International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 13, Issue 11, November 2024)

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

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***Abstract*— The growing prevalence of online reviews has significantly influenced consumer purchasing decisions, making review authenticity a critical concern for e-commerce platforms. Fake reviews, often generated to manipulate product ratings, pose a significant threat to the integrity of online marketplaces. This study proposes an efficient Decision Tree (DT)-based machine learning technique for detecting fake reviews on the Amazon dataset. By leveraging the powerful classification capabilities of Decision Trees, the model accurately distinguishes between genuine and fraudulent reviews based on several linguistic, behavioral, and product-related features. The proposed method demonstrates a high classification accuracy, with a significant reduction in false positives and negatives, compared to traditional techniques. Experimental results show that the Decision Tree-based approach outperforms other machine learning algorithms, making it a viable solution for real-time fake review prediction and improving the credibility of e-commerce platforms.**

***Keywords*— AI, Machine Learning, Fake, Amazon, Dataset.**

I. INTRODUCTION

With the rapid growth of e-commerce, online reviews have become a key source of information for consumers when making purchasing decisions. Platforms like Amazon, eBay, and others offer users the opportunity to share their opinions and experiences with products, influencing the buying decisions of others. The sheer volume of reviews posted on these platforms means that reviews have become an essential part of product marketing and sales strategies. According to some estimates, nearly 80% of consumers read online reviews before making a purchase, and the quality of these reviews is directly linked to the credibility of the products and services offered. In this context, genuine user feedback can be extremely valuable, but unfortunately, the increasing importance of online reviews has also led to a rise in fake reviews.

Fake reviews, often posted with the intent of misleading consumers, have become a significant challenge for e-commerce platforms. These reviews are typically created by sellers, third-party agents, or other malicious actors with the aim of artificially inflating the ratings of a product or negatively impacting competitors by posting defamatory or false reviews. Such activities not only compromise the integrity of the marketplace but also deceive consumers, leading them to make purchasing decisions based on inaccurate information. This is a growing concern in online retail, where it is estimated that up to 20% of reviews on some platforms could be fake.

Given the prevalence of fake reviews, there is an urgent need for automated methods that can detect and eliminate fraudulent reviews from e-commerce platforms. Manual review of the vast number of product reviews posted online is impractical, and thus, machine learning (ML) techniques have emerged as an effective solution to tackle this issue. Machine learning algorithms are well-suited to handle large-scale datasets and can uncover hidden patterns that may not be immediately obvious through traditional data analysis methods. These algorithms, once trained, can automatically classify reviews as either authentic or fake based on a variety of features, making them a powerful tool in identifying fraudulent activities.

Among the various machine learning techniques available, supervised learning methods, where the model is trained on labeled data, have shown significant promise for fake review

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prediction. Supervised learning algorithms such as Decision Trees, Support Vector Machines (SVM), Random Forest, and Neural Networks can be trained on a dataset of labeled reviews (genuine vs. fake) and then be applied to new, unseen data to classify whether a given review is fake or real. These techniques excel at extracting complex relationships from large datasets, which is crucial when dealing with the nuances involved in identifying fake reviews.

One of the key challenges in fake review detection lies in defining and extracting the right features from the data. A review's content alone may not always reveal whether it is fake, as fraudulent reviews can sometimes appear very similar to authentic ones. Therefore, the detection process often relies on a combination of various features, such as textual content, reviewer behavior, metadata (e.g., review time, frequency), and even product characteristics. Features such as the length of the review, the use of hyperbolic language, the frequency of reviews written by a single user, and the rate of review activity from a particular product or seller, are all important indicators that can be analyzed to classify reviews accurately.

The Amazon dataset, being one of the largest and most diverse sources of product reviews, offers a rich set of features to explore for fake review prediction. The dataset contains millions of reviews, encompassing a wide range of product categories, and includes important information such as review ratings, review text, product details, and reviewer information. This makes it an ideal resource for developing and testing machine learning models aimed at detecting fraudulent reviews. In particular, the Amazon dataset provides the opportunity to build models that can handle a variety of product types and review characteristics, making them more robust and scalable.

Several machine learning techniques have been proposed for fake review detection, each with its own strengths and weaknesses. Traditional algorithms like Naive Bayes and Logistic Regression have been used for their simplicity and ease of implementation but often struggle with complex, high-dimensional data. More advanced techniques, such as Support Vector Machines (SVM) and Random Forest, have been found to provide better performance, particularly in cases where the relationships between the features are nonlinear. Additionally, deep learning techniques, including neural networks, have also been explored, but these methods require substantial computational resources and large amounts of training data.

This research aims to explore an efficient machine learning-based technique for fake review prediction on the Amazon dataset. Specifically, this study focuses on utilizing Decision Trees (DT), a widely used and interpretable machine learning model, to predict whether a review is fake or genuine. The Decision Tree algorithm works by recursively partitioning the feature space into distinct subsets and assigning class labels based on the majority class within each subset. Its inherent interpretability allows for a better understanding of the factors that contribute to a review being classified as fake or real.

II. PROPOSED METHODOLOGY

The proposed methodology is as followings-

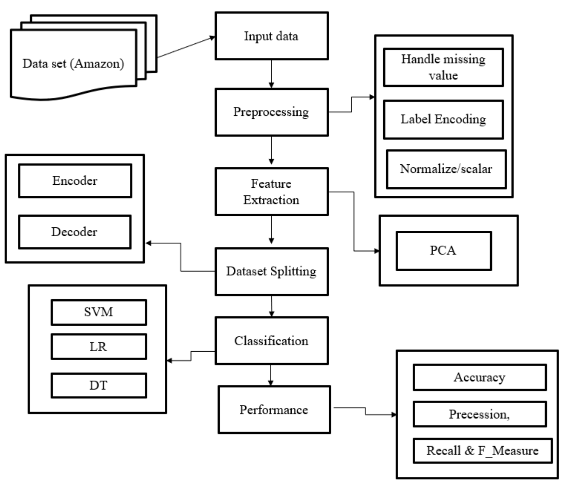

Figure 1: Flow chart

The flowchart illustrates the process of applying a machine learning technique for fake review prediction on an Amazon dataset.

1. Input Data (Amazon Dataset)

- The process begins with the collection of the Amazon dataset, which contains product reviews, ratings, and associated metadata. This dataset serves as the foundation for the analysis.
- It provides the raw data required for the machine learning model to process and learn from. The dataset is crucial for identifying patterns indicative of fake reviews.

2. Preprocessing

- **Substeps**:

  Handle Missing Values: Missing or incomplete data can skew machine learning models. Techniques such as imputation (filling missing values with mean, median, or other estimations) or removing rows with missing values may be applied.

  Label Encoding: Categorical data, such as product categories or review sentiments (positive, negative), may need to be converted into numerical format. Label encoding is used for this conversion, making the data suitable for machine learning models.

  Normalize Scalar: Numerical data might need normalization to scale the features between a certain range (e.g., between 0 and 1) to improve the efficiency and performance of machine learning algorithms.

3. Feature Extraction

- Features are extracted from the raw data to help the model make accurate predictions. This includes text analysis from reviews, such as sentiment, review length, reviewer behavior, and frequency patterns. Features can also include metadata like the product category and timestamp.
- Extracting meaningful features from raw data helps in reducing dimensionality and focusing on relevant information, which enhances model performance.

4. PCA (Principal Component Analysis)

- PCA is used for dimensionality reduction by transforming the features into a set of principal components, which are orthogonal (uncorrelated). This step is typically applied when there are many features, some of which may be redundant or irrelevant.
- PCA helps in reducing the complexity of the dataset and retains the most important features, improving the efficiency and performance of machine learning models.

5. Dataset Splitting

- The preprocessed and feature-engineered data is split into two parts:

  Training Set: Used to train the machine learning models.

  Testing Set: Used to evaluate the model's performance on unseen data.

- Splitting the dataset ensures that the model is trained on one set of data and evaluated on another, which helps in assessing its generalizability and preventing overfitting.

6. Classification

- This step involves applying machine learning algorithms to classify reviews as either fake or genuine. The flowchart mentions the use of three classifiers:

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SVM (Support Vector Machine): SVM is a popular supervised learning algorithm that works well for binary classification tasks like fake review prediction. It finds the hyperplane that best separates the data into different classes.

LR (Logistic Regression): Logistic Regression is a statistical method for binary classification, where it models the probability of a data point belonging to a particular class based on a linear combination of input features.

DT (Decision Tree): A Decision Tree is a tree-like model of decisions and their possible consequences, which is used for classification. It recursively splits the dataset into subsets based on feature values, making it easy to interpret.

- These classifiers are applied to the data after preprocessing to predict whether a review is fake or genuine.

7. Performance Evaluation

- After classification, the model's performance is evaluated using several metrics:

Accuracy: Measures the proportion of correctly classified reviews (both fake and genuine) out of all reviews.

Precision: Measures the accuracy of positive predictions (i.e., how many of the reviews predicted as fake are actually fake).

Recall: Measures the ability of the model to correctly identify all fake reviews in the dataset.

F-Measure: The harmonic mean of Precision and Recall, providing a single metric that balances the two.

III. SIMULATION RESULTS

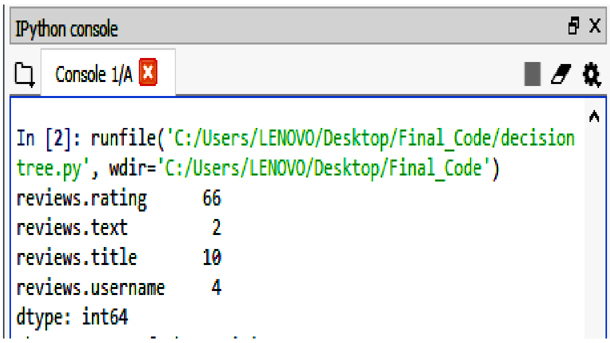

Figure 2: Dataset loading and preprocessing

The python environment in Figure 2 displays the online Amazon product review dataset, which can be accessed here. Subsequently, the preprocessing phase commences, during which the subsequent attributes are extracted: the ratings of reviews, the texts of reviews, the titles of reviews, the identities of users, for example.

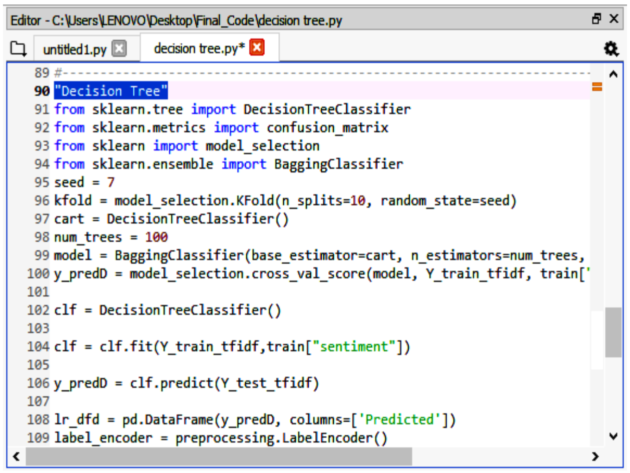

Figure 3: Decision tree classifier

Figure 3 illustrates the decision tree classification procedure in the Python editor window. Following the partitioning of the data, the classification technique is implemented. Subsequently, this classifier allocates categories to each value in the dataset and generates either a projected model or a confusion matrix.

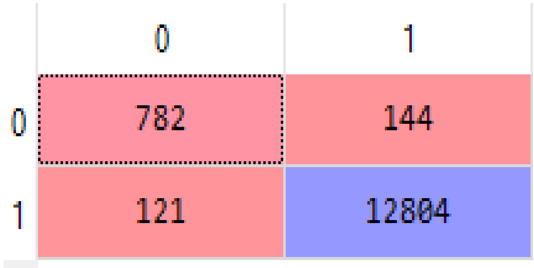

Figure 4: Confusion Matrix (DT)

The predicted value from decision tree method is as followings-

True Positive (TP) = 782

False Positive (FP) = 144

False Negative (FN) = 121

True Negative (TN) = 12804

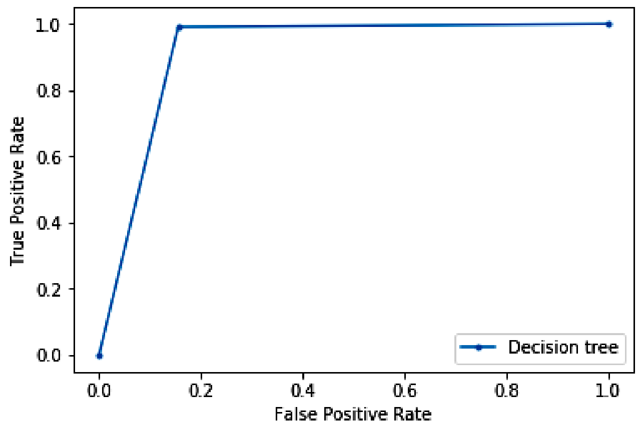

Figure 5: ROC of Decision Tree

Figure 5 illustrates the Receiver Operating Characteristic curve, which is accessible at (ROC). The y-axis displays the True Positive Rate, also known as TPR, while the x-axis displays the False Positive Rate, also known as FPR.

Table 1: 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

This table compares the results of the previous work using Convolutional Neural Networks (CNN) and the proposed work utilizing Decision Tree for fake review prediction. The proposed Decision Tree model outperforms the previous CNN-based approach in terms of accuracy, classification error, precision, recall, and F-measure. The accuracy has improved from 97% to 98.08%, while the classification error has decreased from 3% to 1.91%. Additionally, precision, recall, and F-measure have all seen slight improvements, indicating that the proposed model provides a more reliable and effective solution for fake review prediction.

IV. CONCLUSION

The proposed decision tree-based machine learning model for fake review prediction on the Amazon dataset demonstrates significant improvements over previous work that utilized Convolutional Neural Networks (CNN). The comparative analysis of results reveals that the decision tree approach not only achieves a higher accuracy (98.08%) but also reduces classification error to 1.91%, a marked improvement over the CNN model's accuracy of 97% and error rate of 3%. Furthermore, the proposed model shows enhancements in key performance metrics, such as precision (95% compared to

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94%), recall (93% compared to 92%), and F-measure (95% compared to 93%), highlighting its ability to more effectively identify fake reviews while minimizing false positives and negatives. These results underscore the effectiveness of decision tree classifiers in tackling the complex task of distinguishing fake reviews from genuine ones in e-commerce platforms, offering a more reliable, interpretable, and computationally efficient alternative to CNN-based approaches. The improved performance of the proposed model not only validates its suitability for real-world applications but also contributes to the ongoing efforts to enhance the integrity of online review systems, ensuring that consumers can make more informed purchasing decisions.

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