A Lightweight Data Mining Approach for Fake Review Detection: An Integrated Textual and Behavioral Analysis

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ABSTRACT

In the fast-growing online shopping era, customer reviews are the most important driver of trust between buyers and sellers. Customer reviews will drive purchasing decisions and shape both product and seller reputation. This is especially true for small e-commerce websites, which usually do not possess advanced tools or functionality to detect and exclude deceptive feedback. In this study, we propose a practical and effective data mining method using the well-known Amazon Fine Food Reviews dataset, which combines review text with significant contextual attributes, including posting time, day of the week, review length, and rating score. By aggregating these contextual and text-based cues, we design our model with Gradient Boosting (XGBoosting) such that the classification performance of false reviews is improved and that the classifier is computationally lightweight and convenient. Our results demonstrate that simple context features, together with text analysis, lead to substantial relative improvements in the ability to identify fake reviews within an achieved test accuracy of 87.87%. We also examine Logistic Regression with test accuracy 84.97% and Random Forest Classifier with test accuracy 86.14%. After the comparison of the three given model we believe that such a hybrid approach, combining Text and Context and a powerful ensemble classifier, provides a practical means for small and medium-sized online merchants to guard against the dilution of customers' opinions on their sites without recourse to expensive or complex detection schemes. In addition, the approach can be generalized to other products and review sites and scales well to ensure our solution will be effective in combating deceiving reviews across different markets. This paper proposes an approach to defend e-commerce from reputation attacks while the true opinion of consumers still influences who the consumer selects.

1. Introduction

Online shopping in the digital business age means customer reviews have become unavoidable for better or for worse. Consumer reviews form the foundation for molding purchase decisions and building trust between buyers and sellers on e-commerce websites. Consumer purchases are highly contingent upon what other consumers have experienced, and retailers rely on authentic feedback to gain trust toward their products and brands. Virtually all retail businesses are very dependent on what people think and say about their products and services and employ this feedback to shape their business strategy and increase product quality. The fake reviews detection system is a subfield of natural language processing. It aims to analyze, detect, and filter the reviewer's comments, particularly in e-commerce websites, into fake or truthful reviews (20) (9) (19). There are generally three kinds of fake reviews: untruthful reviews, brand-biased reviews, and non-reviews. Each of these can mislead potential customers and distort their buying decisions (17). The widespread prevalence of bogus or misleading reviews, however, threatens the integrity of online shopping platforms to a great extent. The common prevalence of counterfeit or altered reviews is a real menace to such trust. There are a number of wrong reviews on social media. It was found that around 70% of fraudsters write more than five reviews each day, while 90% of genuine users usually post only one review when they buy a product or service. This difference in review frequency can be a useful clue for spotting spam reviewers (12) (8). The fake reviews not only distort consumers' perception of product quality but also unjustly impact genuine businesses. Big e-commerce businesses typically use sophisticated fraud detection systems, but small and medium-sized online stores barely have the resources to hire or maintain such systems. Whereas large e-commerce websites can invest in advanced fraud detection tools based on big data and advanced algorithms, small and medium-sized online businesses lack the technological inputs and resources required to implement such tools. As a result, these websites become vulnerable to reputation damage and customer mistrust because of undetectable false reviews (6). Recent literature and techniques largely focus on text content analysis of the reviews with great focus on contextual data such as review timing, posting activity, or behavioral aberrations (23). The clear drawback of these techniques highlights the need for a technique that is light, practical, and cost-effective and accounts for both text and context to maximize precision for identifying fabricated reviews. This research primarily focuses on small and medium-sized online shops. This proposal will fill this gap by building a simple yet effective data-driven method that can automatically detect

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suspicious reviews by combining what is said (text) and when and how it is said (context). This study aims to address this gap by developing a hybrid model that integrates easily accessible contextual information with text-based features, where most of the existing studies focus on the text data only. Using accessible functionalities and an understandable data mining model, this work proposes to provide a low-cost solution for small businesses to protect their brand and enable genuine customer views to impact buying decisions. The goal is to provide small e-commerce businesses with an interpretable and understandable tool to help safeguard the authenticity of customer reviews, uphold trust, and maintain healthy competition in the online marketplace. The major objective of this study is to design a hybrid review classificatory system where textual properties and context features such as time, day, duration, and rating are integrated. To try out Random Forest classification and evaluate the effectiveness of handling mixed features and imbalanced review data. To demonstrate the practical utility of adding context features to improve accuracy in detecting fake or deceptive reviews. To provide a reproducible and affordable method that small and medium-sized e-businesses can adopt. To guide this study, the following research questions are addressed:

1.1. Research Question

- How much does the inclusion of contextual features of timing of review, frequency, duration between reviews, and patterns of rating enhance the accuracy of fake review detection in combination with text features over the use of text features alone?

- How effectively can a Random Forest classification model handle a dataset with mixed features that contain both textual features (categorical) and contextual features (numerical) to classify fake and real reviews when there exists class imbalance?

The rest of this study is as follows: section 2 reviews the previous works. The proposed method is discussed in section **??**. Section 4 presents the experimental dataset, results, and analysis, and discusses the impacts. Section **??** limitations, and future directions of this study, and section **??** conclude the study.

2. Literature Reviews

A study attempts to develop an intelligent system that can detect fake reviews on e-commerce platforms using n-grams of the review text and sentiment scores given by the reviewer and examined some data mining techniques like naïve Bayes (NB), support vector machine (SVM), adaptive boosting (AB), and random forest (RF) and received 88%, 93%, 94%, and 95%, respectively, based on testing accuracy and the F1-score (2). Another paper exploring the strengths and weaknesses of other data mining techniques in detecting fake reviews started with different supervised techniques like Support Vector Machine (SVM), Multinomial Naive Bayes (MNB), and Multilayer Perceptron by gaining more than 86% accuracy. The study also works on a semi-supervised technique which reduces the dimensionality of the input features vector but offers similar performance to existing approaches (14). Sentiment analysis is one of the major fields in fake review detection. A study proposes a general framework to detect fake reviews, also tackling a fundamental problem of sentiment analysis. In this study, Naive Bayes Classification is used as the data mining approach (22). As an important feature by incorporating sentiment, some researchers proposed a new solution for fake news detection with two different data sets of ISOT and LIAR. They proposed the models Naive Bayes and Deep Neural Network (DNN) classifiers. The findings of this research described that the overall calculation of the proposed method was obtained with an accuracy of 99.8% for the detection of fake news (4). In another study, the researcher extracted features based on sentiment analysis and proposed a bidirectional long short-term memory model to detect fake news. They use the standard fake dataset to train the model. Their proposed model provided a high accuracy of 96.77%, which is comparatively better than the others (11). A study that makes an experiment using pseudo fake reviews generated via Amazon Mechanical Turk (AMT) has achieved high detection accuracy, such as 89.6% using simple word n-gram features. However, when tested on real-world data like Yelp's filtered and unfiltered reviews, the accuracy drops to 67.8%, showing that detecting fake reviews in actual online platforms is more challenging and requires more than just text analysis (21). Another study aims to build a robust review spam detection system by performing time series analysis, which could be a great asset in an online spam filtering system and could be used in data mining techniques. The proposed method provides more than 86% accuracy in F-score (13). Another paper aims to detect unfair reviews on Amazon reviews through Sentiment Analysis using supervised learning techniques in an E-commerce environment. They use three different algorithms: the logical regression algorithm, the linear regression algorithm, and neural networks (CNN and RNN models), of supervised machine learning techniques. They focus on exploring an algorithm using deep learning that ensures optimal accuracy in the identification of fake reviews (15). There is another study on the topic of fake review detection. The paper proposes a machine learning approach to identify fake reviews and also to build a feature extraction process for the reviews. The study compares the performance of several experiments by using a real Yelp dataset. They compare the performance of several classifiers: KNN, Naive Bayes (NB), SVM, Logistic Regression, and Random Forest. They get around 82.40% accuracy in F-score, which has increased by 3.80% when taking the extracted reviewers' behavioral features into consideration (7). Besides the approaches of data mining, machine learning techniques are also used in the field. A study developed a model using two machine learning techniques Naive Bayes and random forest methods to make it more accurate. Here also they use the Amazon

Yelp dataset to train and test the model (3). A study proposed a linear support vector machine technique to detect fake reviews based on N-gram features. The TF-IDF method was used for feature extraction and gained around 90% accuracy (1). Based on the Amazon product review dataset, some authors applied two neural network models, deep feed-forward neural network and convolutional neural network resulting in the models likely 82% and 81% accuracy for the DFFN and CNN methods respectively (10). In this same dataset is applied in another study which is develop a model based on BERT, one of the Natural Language Processing (NLP) methods, to predict an overall review score based on the text descriptions with model reaches an accuracy of 0.7982 (25). In another analysis, there will be focus on score as well as positive/negative sentiment of the recommendation also this study proves that the logistic algorithm provides the best sentimental analysis result (24). A study is explored to negative review of product could decrease demand for that product, resulting in loss of business (18).

3. Methodology

This study proposes a detailed pipeline for a lightweight data mining approach to detect fake reviews by integrating textual content analysis and user behavioral patterns. Through our research, the methodology is structured into six major phases here are data collection and analysis, preprocessing, feature extraction, model training, and performance evaluation. The methodology overview is shown in figure 1

3.1. Dataset Analysis and Discussion

The study utilizes the Amazon Fine Food Reviews dataset, which is a publicly surfaced dataset on Kaggle [(16)], to carry out the research. The dataset contains a full record of user-generated product reviews. There are three files in the dataset named database.sqlite, which contains the table 'Reviews', and Reviews.csv pulled from the corresponding SQLite table named Reviews in database.sqlite, and hashes.txt. There are a total of 10 attributes in the Reviews.csv file. They are ID, ProductId, UserId, ProfileName, Helpfulness Numerator, Helpfulness Denominator, Score, Time, Summary and lastly Text. Approximately 74,258 different products are reviewed by 266,059 unique users in a total of 568,454 reviews. The data captures both high-activity and low-activity patterns: 260 users are responsible for over 50 reviews each, and the data is thus appropriate for both normal and possibly deviant review behavior. Each entry contains information such as the plain text of the review, a numerical rating (score), the user and product identifiers, and a timestamp of when the review was posted. By utilizing and combining all these significant contextual attributes, we propose an effective data mining method.

3.2. Data Pre-processing

If the rating score is 4 or 5, the review is considered positive. As part of data pre-processing, first, we select the most relevant information, including the review text, rating score,

Table 1
Detailed Dataset-Class Breakdown:

Label	Count	Percentage
Positive	432000	76%
Negative	136454	24%
Total Reviews	568000	100%

Table 2
Dataset Splitting:

Label	Percentage
Train	70%
Test	15%
Validation	15%
Total Reviews	100%

and time of review posting. Then, reviews were labeled as positive or negative based on their ratings. In our dataset, the rating score ranging from 1 to 5. To transform this into a binary classification, rating scores 4 and 5 are considered as positive reviews, and ratings 1 to 3 are considered as negative reviews. Then, some other context features like the hour of posting, the day of the week, and the length of reviews were extracted. For practical and computational efficiency, a random sample of 50,000 reviews was drawn to develop and evaluate the model.

3.3. Feature Extraction

This study applies standard Natural Language Processing (NLP) techniques to clean and prepare the review text (5). As part of text cleaning with NLP techniques, the text was converted to lowercase, punctuation and common stop-words were removed, and stemming was applied to simplify the words. This cleaned text was then turned into numerical features using a TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer to convert the processed text into numerical feature representations and enhance feature engineering with n-grams and contextual information. Based on the rating range, there were 76% positive and 24% negative reviews in the dataset. Before training the Amazon Fine Food Reviews dataset, it was balanced first. The data distribution is shown in table 1

These processed and extracted textual features were then combined with the contextual features (review length, time features, which were used for training and evaluating the models.

To address class imbalance, the XGBoosting model was configured with a balanced class weight parameter. The dataset was randomly split into 70% for training and 15% for testing, and 15% for validation to evaluate the model's performance. The splitting information is shown in table 2.

3.4. Model Training

In this study, we developed a simple yet effective way to spot potentially fake or misleading reviews by combining what is written with when and how it was written. We started by selecting the key pieces of information from the

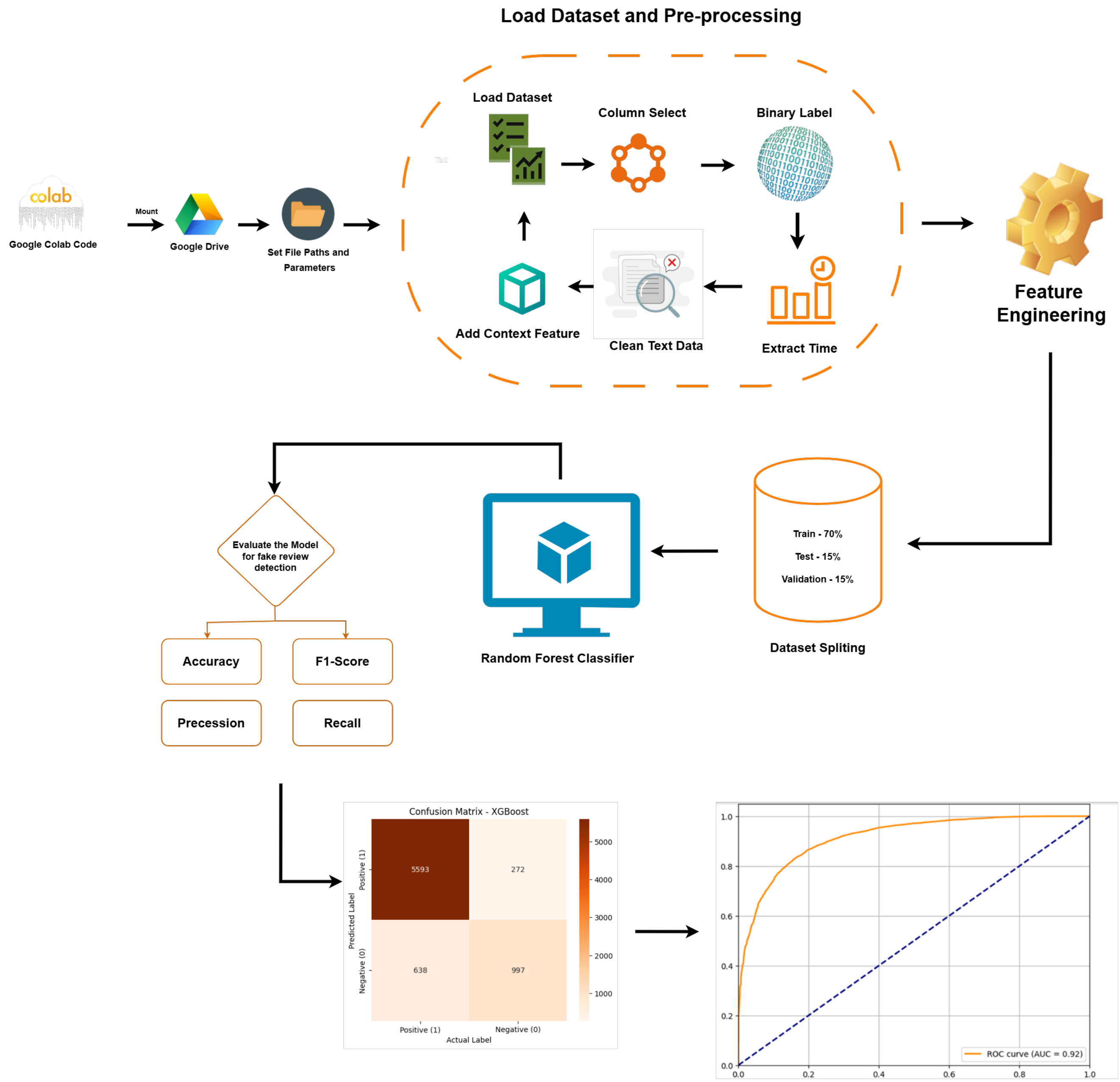

Figure 1: Methodology Overview

Amazon Fine Food Reviews dataset, focusing on the review text, the numerical rating, and the time it was posted. Each review was then labeled as positive or negative based on its score to make the problem easier to tackle. Next, we created additional context features to capture reviewer behavior. For example, we noted the time the review was posted, the day of the week, and how long the review was in terms of word count. To preprocess and clean my text dataset, an NLP technique was applied. Before training the model, we split the dataset into training and testing data, where 70% was used for training, 15% for testing, and 15% for validation. Before splitting, we combined the text and the context features into one dataset. Without taking the text only, we combined it with the relevant context, like rating score, and time of review posting, to make our model more robust and accurate. To train our model, we chose a Random Forest Classifier because it's a model that can be able to handle mixed features very well and is easy to interpret. To handle the imbalanced data, we used the built-in balanced class weight without sampling them in the pre-processing stage. Three Differences model were taken to train the dataset. They are Logistic Regression model, Random Forest Classifier, and XGBoost model. By evaluating and comparing their performance, we build our model with the XGBoost model. This model was chosen because of its effectiveness in handling hybrid data. It can also handle nonlinear as well as complex relationships. This model is also suitable for an imbalanced environment. After training, the model was evaluated on the test set.

The predicted labels were compared against the true labels to generate key classification metrics, including accuracy, precision, recall, F1-score, and the ROC-AUC. The evaluation results showed that the XGBoost model achieved an accuracy of 87%, outperforming other baseline models such as Logistic Regression and Random Forest in this study.

This strong performance indicates that XGBoost effectively captures both textual semantics and contextual behaviors associated with fake reviews. However, while it provides high predictive power, it requires more computational resources compared to lighter models.

3.5. Method Evaluation Matrix

After trained the Logistic Regression, Random Forest Classifier, and the XGBoost model, we measure their performance by evaluating accuracy, precision, recall, and F1-score. The following metrics were used to evaluate the performance of our proposed model: -

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Here, TP stands for true positive, FP stands for false positive, TN stands for true negative, and FN stands for false negative. The Macro Average of the above-mentioned metrics is calculated as follows:

$$M_{\text{macro}} = \frac{1}{N} \times \sum_{i=1}^{N} M_i \tag{5}$$

Here, M stands for the respective metric (e.g., Precision, Recall, F1-Score), N is the total number of instances in the dataset, and $support_i$ is the number of true instances for class i. The macro average calculates the metric independently for each class.

4. Results and Discussion

This section highlights the results and discussion part of these proposed methods. This evaluation matrix of the proposed method includes confusion matrix analysis, precision, recall, F1-Score and ROC Curve. This model achieved test accuracy of 87.87%, precision and F1-score of exactly 87%, and recall of 88%, which achieved better performance for fake review detection than numerous widely recognized models within this dataset over the three different model. In this study, we examine three types of models for the same dataset to get a more effective and suitable model for our hybrid data by comparing them. The evaluation was performed using the same dataset, feature set, and train-test splits to ensure consistency. We examine the confusion matrix, precision, recall, F1-score and ROC Curve for all three different model to evaluate their performance. Among three models, XGBoost achieved the highest accuracy of 87.87%, precision and F1-score of 87%, and recall of 88% which proves its strength to handle imbalance as well as mixed data combining text with contextual attributes. On the other hand, the Random Forest Classifier also perform well with an accuracy of 86.14%, precision and recall of 86%, and F1-Score of 85%. In table 5 with confusion matrix figure 3 illustrates the confusion matrix breakdown for Random Forest Classifier. An interesting observation is that both the XGBoost model and the Random Forest classifier exhibited identical ROC curve patterns, each achieving an AUC score of 92%. This indicates that, despite slight differences in overall classification accuracy, both models are equally effective at distinguishing between positive and negative reviews across different decision thresholds. Their comparable ROC performance highlights the strong predictive capability of both algorithms on this dataset. In contrast, the Logistic Regression model achieved lower performance with an accuracy of 84.97% ROC Curve accuracy of 93%, which is higher than the other models. Also in figure 4 with table 6 illustrates the confusion matrix breakdown for Logistic Regression.Table 3 illustrates an efficient method by methodically examining the accuracy results in relation to the model variations.

4.1. Confusion Matrix

Figure 2 highlights the confusion matrix for our proposed method which is food fake review detection using an XGBoost model, which gives us more effective and precise results than the other models. In table 4 represents the detailed breakdown of confusion matrix. The confusion matrix is structured as follows:

The confusion matrix serves as a succinct summary of how well the XGBoost model performed in differentiating between genuine (Negative) and fake (Positive) reviews. In a confusion matrix, “True positive” corresponds to positive reviews correctly predicted, “True Negative” corresponds to fake reviews which are also predicted correctly, "False Positive" refers to that reviews which are negative but classified as positive, and "False Negative" refers to positive reviews but misclassified as negative. In this table for XGBoost 4 the value of true positives are 5593, which represents the number of actual reviews which are correctly classified, true negatives is 997, which represents the number of false reviews that were correctly identified where False positive value are 272, and the false negative are 638 meaning positive reviews that were incorrectly predicted as negative. As shown in the confusion matrix, when the method of using both text and behavior was applied, the XGBoost model could perfectly discriminate between fake reviews than the others presented model. This result highlights the

Table 3
Overall Results Across Model Variations

Model Name	Accuracy (%)	Precision	Recall	F1 Score
XGBoost	87.87	87.00	88.00	87.00
Random Forest Classifier	86.14	86.00	86.00	85.00
Logistic Regression	84.97	78.00	85.00	81.00

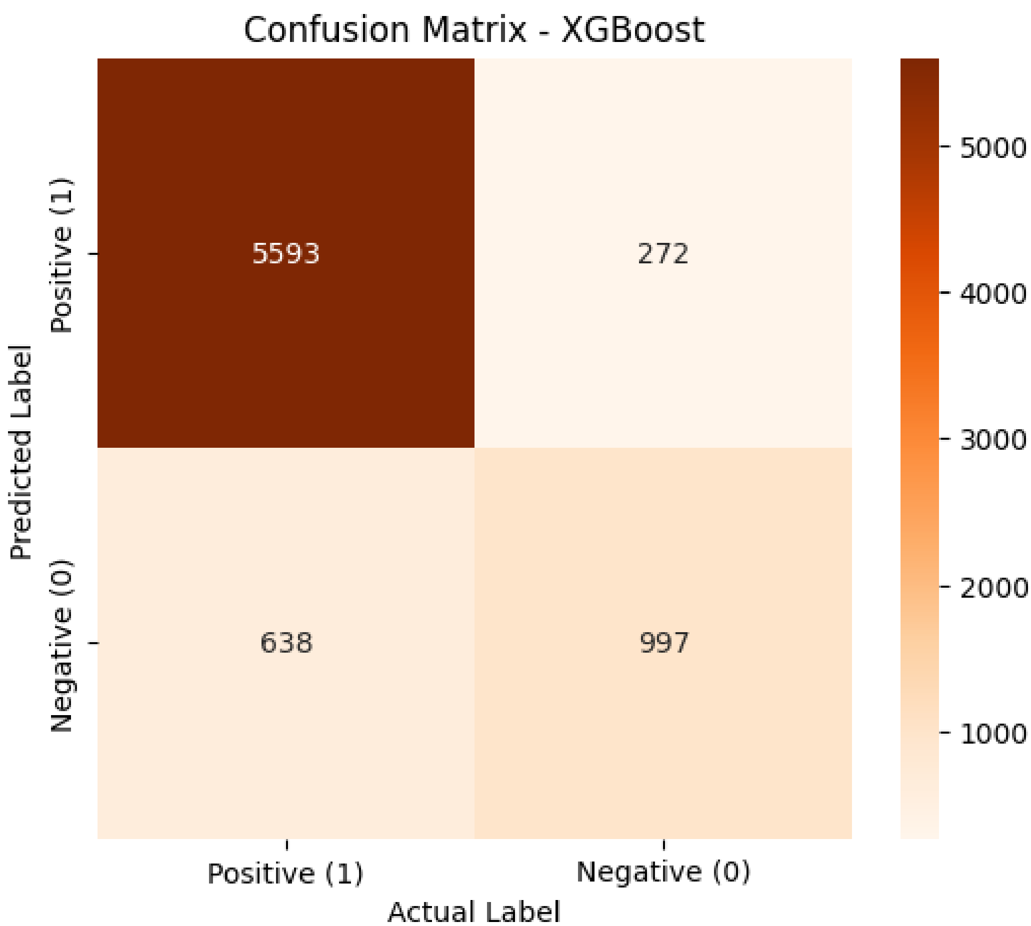

Figure 2: Confusion Matrix of XGBoost

effectiveness of the proposed approach to detect deceptive content reliably.

4.2. ROC Curve

In figure 5 highlights the ROC (Receiver Operating Characteristic) curve is a reliable approach to measuring the quality of binary classifiers, especially in overcoming the two challenges of discriminative power and class imbalance (in this case, genuine reviews and fake reviews). In this ROC Curve's X-axis represents the proportion of fake reviews (Negative class) that are incorrectly classified as fake (Positive class). Mathematically, the False Positive Rate (FPR) is defined as:

$$FPR = \frac{FP}{TN + FP} \tag{6}$$

Table 4
Breakdown of confusion matrix for XGBoost:

	Actual Positive (6231)	Actual Negative (1269)
Predictive Positive (5865)	5593	272
Predictive Negative (1635)	638	997
Total Sample Value (7500)		

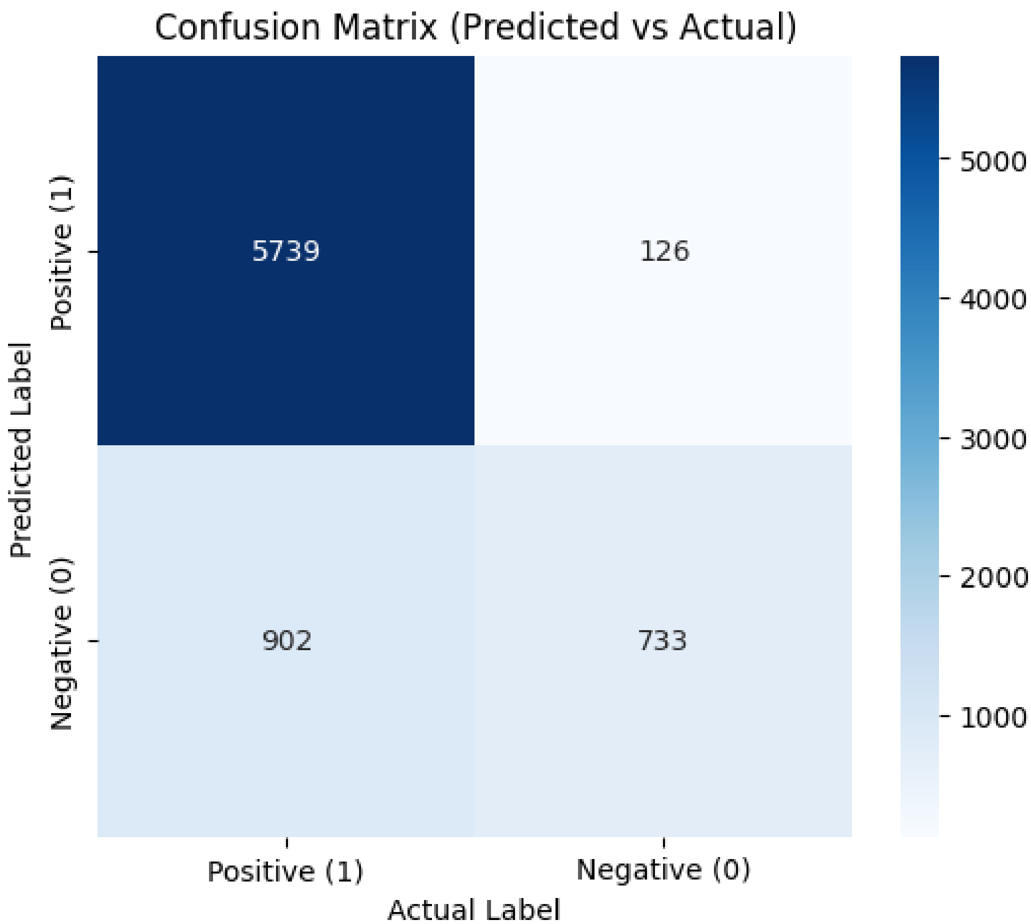

Figure 3: Confusion Matrix of Random Forest Classifier

Table 5
Breakdown of confusion matrix for Random Forest Classifier:

	Actual Positive (6641)	Actual Negative (859)
Predictive Positive (5865)	5739	126
Predictive Negative (1635)	902	733
Total Sample Value (7500)		

The Y-axis of the ROC curve represents the True Positive Rate (TPR), which is the proportion of fake reviews (positive class) that are correctly classified as fake. Mathematically, it is defined as:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{FN} + \mathrm{TP}} \tag{7}$$

The latter finding is illustrated by the ROC curve, which shows that the XGBoost model with combined textual and behavioral analysis is capable of perfect discrimination between genuine and fake reviews. The AUC of 0.92 indicates that the model can distinguish between fake and genuine reviews very well. This suggests that the model is likely very confident about most positive reviews, making it an effective tool for lightweight data mining tasks. Moreover,

Table 6
Breakdown of confusion matrix for Logistic Regression:

	Actual Positive(5218)	Actual Negative(2282)
Predictive Positive (5865)	4978	887
Predictive Negative (1635)	240	1395
Total Sample Value (7500)		

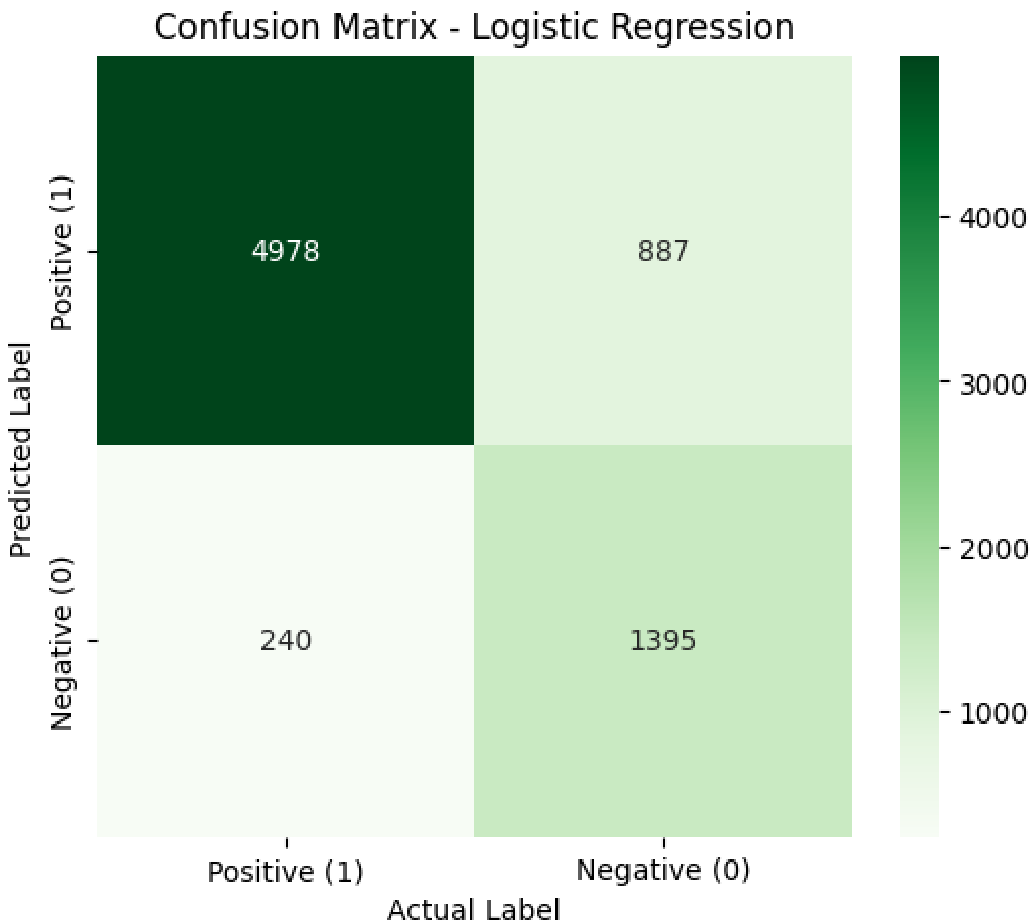

Figure 4: Confusion Matrix of Logistic Regression

it demonstrates excellent discrimination between fake and authentic reviews. The AUC for Random Forest Classifier and XGBoost is 0.92 while the AUC for Logistic Regression is 0.93. A higher AUC for Logistic Regression indicates that, although it may not be as accurate at a single threshold as the XGBoost model, it is slightly better at ranking positive instances higher than negative ones overall than the other models.

5. Significance of the Study

This study indicates significant value of addressing the emerging issue of deceptiveness for online food reviews which can mislead customers and damage the reputation of e-commerce websites. This research contributes to the growing literature in the areas of trust and transparency in online marketplaces by demonstrating the practical efficacy of a Text and Context approach, showing how the combination of review text with contextual signals significantly improves detection accuracy over text alone. Highlighting the hitherto undervalued utility of simple contextual signals. Providing an easy-to-deploy solution for small businesses to combat review fraud. Paving the way for upcoming breakthroughs, including real-time tracking and extension to other review websites. By bridging the gap between technical advancement and functional use, this research allows for a fairer online shopping experience for both sides. This work shows a novel and efficient way of detecting these deceptive behaviors and helps to put more and more transparency and trust in online marketplaces. In summarize, in this paper, we propose a practical, efficient, and lightweight solution to identify fake reviews using both text content and user behavior. It makes contributions in areas including increasing consumer trust, increasing platform trustworthiness, and promoting mining techniques for anomaly detection in social networks. In the end, this research helps to close the gap between technological advancement and real-world implementation, promoting more equitable and trustworthy online marketplaces for both buyers and sellers. The research findings show that, in comparison to text-only analysis, incorporating contextual information greatly improves detection performance. After comparing three data mining model named Logistic Regression, Random Forest Classifier, and XGBoost. Our study proposed the XGBoost model as more suitable for this experiment, which is also economical, simple to use, and computationally efficient, which makes it the perfect choice for companies with limited resources. Also, this study

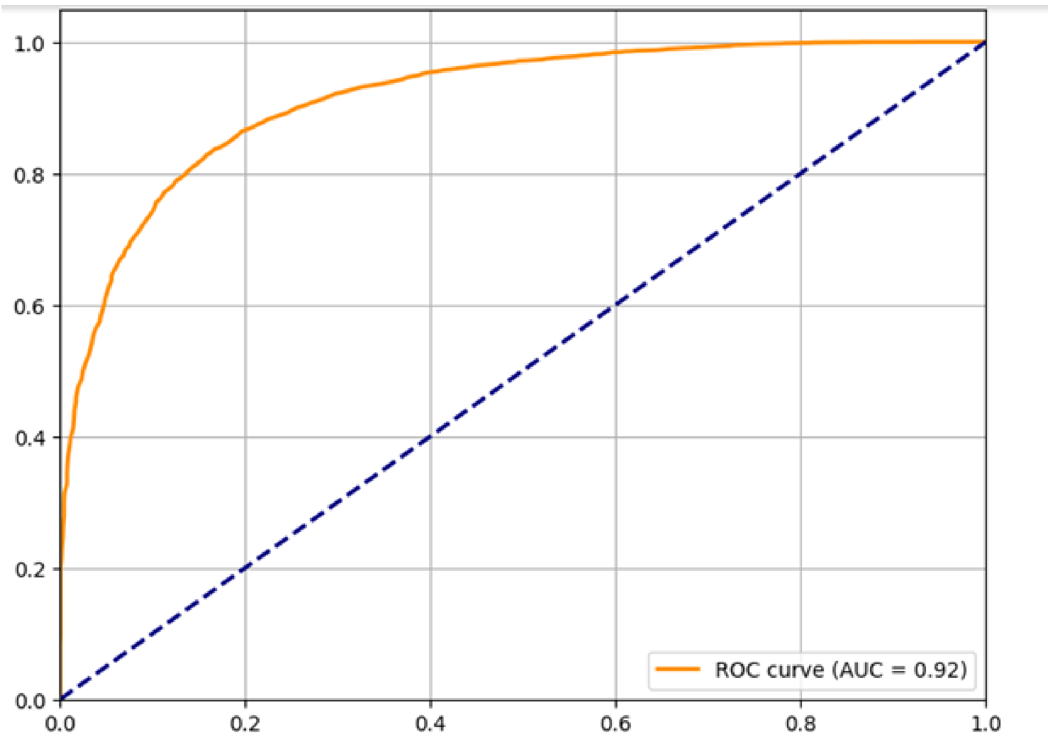

Figure 5: ROC Curve

presents a practical, lightweight, and effective solution for detecting deceptive reviews by combining textual content with contextual features such as posting time, review length, day of the week, and rating score. Using an XGBoost model, we achieved high accuracy in identifying fake reviews using the Amazon Fine Food Reviews dataset (16).

6. Conclusion

In today's digital marketplace, customer reviews can be very effective because customers often rely on other customers' reviews. Fake reviews can lead customers to the wrong decision. That's why fake review detection is more effective, especially for small online businesses, because they don't yet have access to such technologies. In this study, we introduced XGBoost model that is a straightforward but effective method to identify fake reviews by combining both the text of the review as well as the contextual features like time, day, review length, and rating score. The study performs a lightweight XGBoost model, which provides us with a very strong accuracy using the Amazon Fine Food Reviews dataset. The model almost gained higher accuracy in detecting the fake reviews on online platforms. This approach is both cost-effective and easy to implement. This can be a practical solution for businesses who have limited resources. There is no complexity and difficulties to implement the model as well as there is no computerization in its performance. Moreover, the result indicates that the integrating of contextual data with the text of reviews makes it more accurate and trustful. We believe this technique can easily be extended to other product domains and review platforms, helping ensure a more trustworthy online shopping experience.

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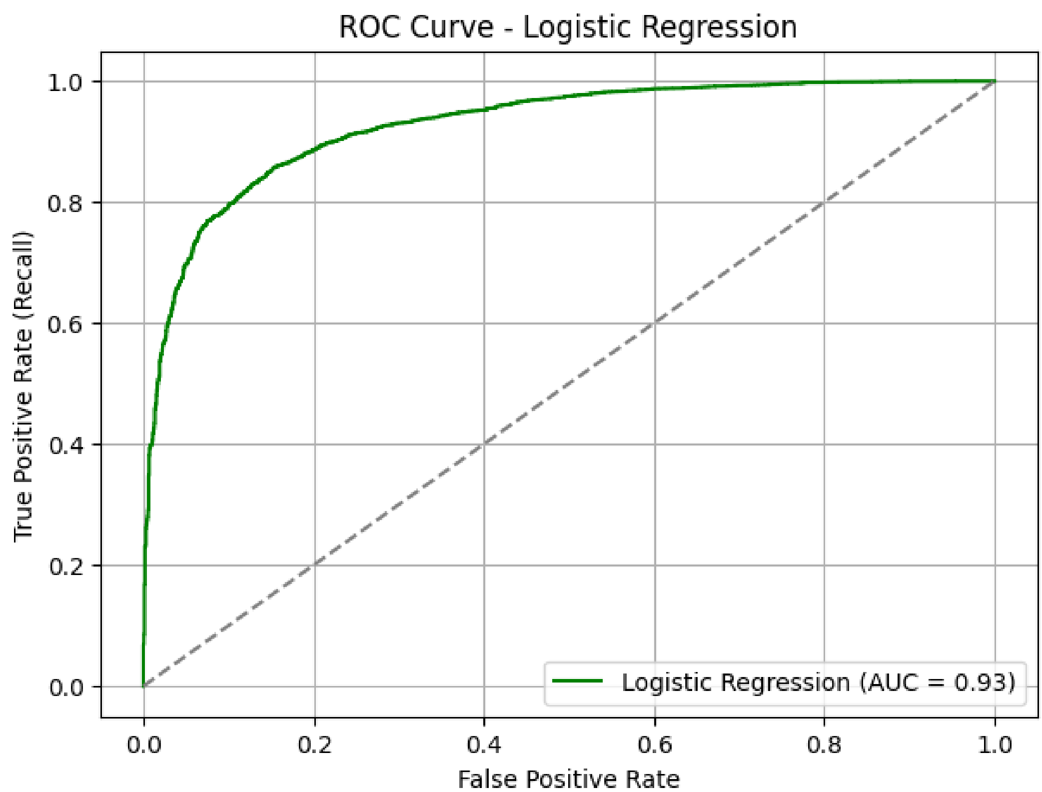

Figure 6: ROC Curve of Logistic Regression

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