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Fake Mobile Product Review Detection Using Machine Learning

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Abstract: *Online product reviews are an important source of information for consumers before making purchasing decisions. However, the growing availability of misleading, promotional, spam-like, and otherwise unreliable reviews can reduce consumer trust. This study presents a lightweight machine-learning approach to classify mobile-phone product reviews as Genuine or Fake, based on the experimental labels used in the dataset. Review text was cleaned and represented using term frequency–inverse document frequency (TF–IDF). Naive Bayes and Logistic Regression were compared using accuracy, precision, recall, and F1-score. Evaluation of two feature configurations: text-only features and text combined with eight mobile-specific parameters—battery, camera, display, performance, heating, charging, storage, and price. Logistic Regression outperformed Naive Bayes in the reported comparison. Its text-only configuration achieved 92.225% accuracy, while adding the mobile-specific parameters increased accuracy to 92.450% and improved the fake-class F1-score from 0.817595 to 0.825231. The final model was integrated into a simple web application that returns a predicted class and confidence value. Because the dataset labels were generated through the project's experimental labelling procedure rather than independently verified reviewer investigations, the results measure agreement with those labels and should not be interpreted as proof that a review is fraudulent in the real world.*

Keywords: Fake Review Detection, Machine Learning, Mobile Product Reviews, Logistic Regression, Naive Bayes, TF-IDF, Natural Language Processing.

I. INTRODUCTION

The rise of online shopping has changed how consumers search for products and make purchasing decisions. Before purchasing a product, customers often check ratings and written reviews posted on websites. These reviews can provide information about product quality, performance, usability, advantages, and disadvantages. Product reviews are particularly important in the mobile phone market. Before purchasing a mobile phone, consumers usually search for details about battery life, camera quality, display, performance, heating issues, charging, storage, and price; as a result, online reviews can strongly shape what people think and how they decide to buy.

Not all reviews are helpful; some can be fake, misleading, or written by people paid to promote a product, so spam or biased content can affect customer trust. Manually inspecting a large number of reviews is time-consuming and difficult. Therefore, automated approaches are needed to check large numbers of reviews.

Machine-learning methods can learn from labelled examples. They can classify new reviews using text, product details, reviewer details, or behaviour details. In this research, machine learning methods have been used with features like text content, user behaviour, reviewer details and product information. The literature reviewed for this project includes supervised learning, sentiment analysis, detecting groups of reviewers, feature selection and advanced models for fake-review detection.

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This study focuses specifically on mobile phone reviews. It looks at whether information is specific to mobile-domain and can be added to the review text to help detect fake reviews. Selected mobile-specific parameters such as battery, camera, display, performance, heating, charging, storage and price are included as data points. Two machine learning algorithms, Naive Bayes and Logistic Regression, are compared during the model-development stage; the better-performing approach is selected for the final prediction system. A simple web application is then developed to demonstrate the practical use of the trained model.

This study is deliberately lightweight and does not claim that machine learning can independently verify every real-world reviewer's identity or purchase history. to verify reviewer identity, purchase history or coordinated manipulation. Instead, this study predicts the review based on the patterns and labels used during model training.

II. PROBLEM STATEMENT

Online reviews significantly influence consumer purchasing decisions. However, fake or misleading reviews can affect customer trust and damage a product's reputation. Manually identifying such reviews is difficult due to the large volume of online content. Thus, this study aims to use a lightweight machine-learning technique to classify mobile-phone reviews into Genuine or Fake categories using review text and selected mobile-specific parameters.

III. RESEARCH OBJECTIVES

The objectives of this research are:

- To study the problem of unreliable and fake product reviews in online shopping environments.
- To develop a machine learning-based model for review classification.
- To compare Naive Bayes and Logistic Regression algorithms and evaluate model performance using Accuracy, Precision, Recall, and F1-score.
- To investigate whether selected mobile product-specific parameters improve classification performance.
- To select the better-performing model for the final prediction system.
- To develop a simple web-based application for review prediction.

IV. LITERATURE REVIEW

Fake-review detection has been studied using supervised classification, feature engineering, sentiment analysis, reviewer behaviour, reviewer–product relationships, and deep-learning methods. The literature surveyed for this project includes studies on supervised learning with e-commerce review data, surveys of machine- and deep-learning approaches, sentiment-based analysis, and graph-based detection of coordinated reviewer groups.

Text is an accessible feature source because it is present in many public review datasets. TF–IDF is suitable for a lightweight baseline because it converts documents into sparse numerical vectors without requiring a computationally expensive language model. However, text alone may not capture reviewer behaviour, account relationships, verified-purchase status, or coordinated activity. Graph-based and behavioural approaches can model some of these signals, but they require data that is often unavailable in a small public dataset.

The research gap addressed here is therefore practical rather than foundational. Instead of proposing a new general fake-review algorithm, the study tests whether product-domain information can complement TF–IDF text features in a mobile-phone review setting while retaining a simple implementation.

V. METHODOLOGY

A. Dataset

The analysis was performed using a publicly available dataset containing mobile-phone reviews. The available variables include product name, brand, price, rating, review text, and review votes. Review text was the main input for the text-classification task.

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The available project materials do not specify the dataset name or URL, collection date, original number of records, duplicate-handling procedure, or train/test split procedure. These details should be added from the experiment log before submission.

B. Data Pre-processing

Before model training, the dataset was prepared for machine-learning analysis. The main pre-processing steps included:

- Handling missing review values.
- Standardising the text format.
- Converting text to lowercase.
- Removing unnecessary characters.
- Cleaning the review content.
- Preparing the processed reviews for feature extraction.

C. Experimental Labels

The labels were assigned according to the criteria used during data preparation. However, these labels have not been independently verified as proof of actual fraud. In this study, the target variable is defined as the Genuine or Fake label assigned during the experiment. The model predicts the class based on these dataset labels; it does not confirm whether a reviewer intentionally provided a misleading review, whether a purchase was actually made, or whether different accounts are connected.

D. Feature Representation

The cleaned review text was converted into TF–IDF vectors. The general form of the TF–IDF weight of a term t in document d is:

$$TF\text{–}IDF(t, d) = TF(t, d) \times \log(N / df(t))$$

Here, N represents the total number of documents, and df(t) represents the number of documents containing the term. The available project details do not specify the tokenizer, n-gram range, vocabulary limit, stop-word handling, or TF–IDF normalisation settings.

In the second configuration, eight binary mobile-specific parameters were identified from the review text using related terms: battery, camera, display, performance, heating, charging, storage, and price. For example, if a review contains terms related to both the camera and battery, the Camera and Battery indicators are set to 1. The remaining indicators are set to 0 if no related terms are detected.

E. Classification Models

Naive Bayes was used as a simple and computationally efficient model for text classification. Logistic Regression was also applied to classify reviews as Genuine or Fake by estimating the probability of each class. Both models were trained using the prepared feature matrix.

F. Experimental Configurations and Evaluation

Two configurations were used for the experiments:

- Configuration A: TF–IDF text features only.
- Configuration B: TF–IDF text features combined with the eight mobile-specific indicators.

Model performance was evaluated using accuracy, precision, recall, and F1-score.

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VI. RESULTS AND DISCUSSION

A. Algorithm Comparison

TABLE I. PERFORMANCE COMPARISON OF MACHINE-LEARNING MODELS

Model	Accuracy	Precision	Recall	F1-score
Naive Bayes	0.883750	0.843697	0.574371	0.683458
Logistic Regression (Text Only)	0.922250	0.838748	0.797483	0.817595

In the reported comparison, Logistic Regression performed better than Naive Bayes in terms of accuracy, recall, and F1-score. Although Naive Bayes achieved higher precision, its recall and F1-score were lower than those of Logistic Regression.

B. Effect of Mobile-Specific Parameters

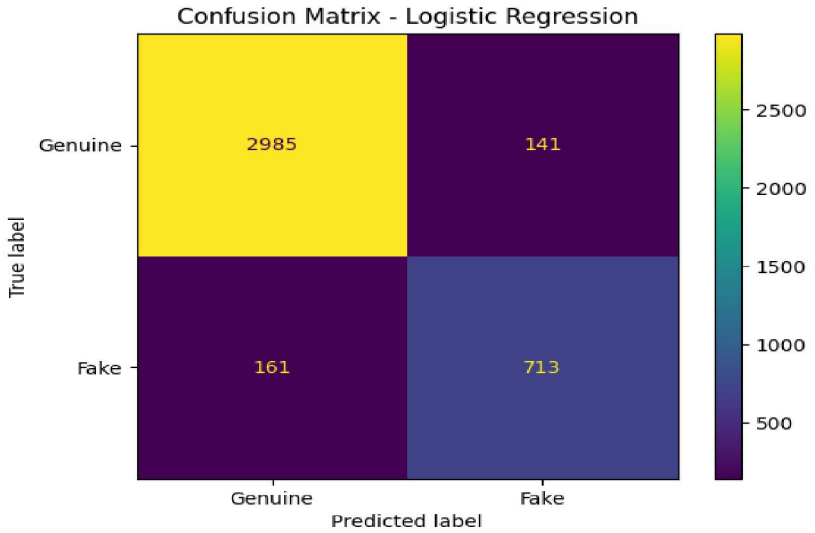
TABLE II. COMPARISON OF LOGISTIC REGRESSION CONFIGURATIONS

Configuration	Accuracy	Precision	Recall	F1-score
Text Only	0.922250	0.838748	0.797483	0.817595
Text + Mobile Parameters	0.924500	0.834895	0.815789	0.825231

Adding the mobile-specific parameters increased accuracy by 0.225 percentage points and increased the F1-score from 0.817595 to 0.825231. Precision decreased slightly from 0.838748 to 0.834895, while recall increased from 0.797483 to 0.815789. This indicates a small improvement in the detection of the dataset-labelled Fake class, although not every metric improved.

C. Confusion Matrix Analysis

The final Logistic Regression model produced the following confusion matrix for 4,000 evaluated reviews:



The matrix contains 3,698 correct predictions and 302 incorrect predictions out of 4,000 evaluated reviews, corresponding to 92.45% accuracy. The model correctly classified 713 labelled Fake reviews and missed 161; it incorrectly flagged 141 labelled Genuine reviews.

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D. Classification Report

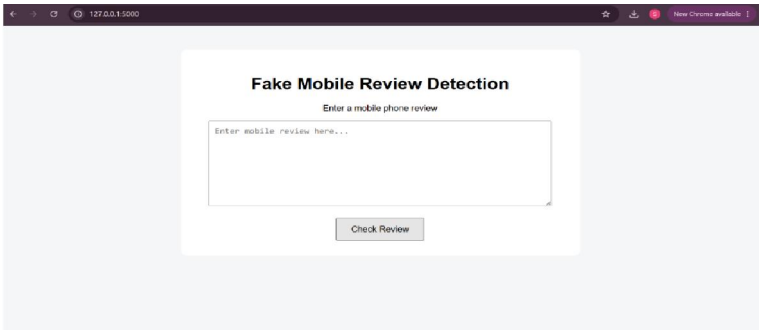
TABLE III. CLASSIFICATION REPORT OF THE FINAL MODEL

Class / Average	Precision	Recall	F1-score	Support
Genuine	0.95	0.95	0.95	3126
Fake	0.83	0.82	0.83	874
Accuracy	—	—	0.92	4000
Macro average	0.89	0.89	0.89	4000
Weighted average	0.92	0.92	0.92	4000

For the final model, 3,126 reviews were labelled Genuine and 874 were labelled Fake. Performance was stronger for the Genuine class than for the Fake class, which is consistent with the unequal class distribution and the higher number of Genuine reviews.

VII. PROPOSED WEB-BASED SYSTEM

The selected Logistic Regression model was integrated into a simple web application. Users can enter a mobile-phone review, and the application processes the text using the same preprocessing and feature-generation steps applied during training. It then combines the TF–IDF features with the mobile-specific indicators and predicts whether the review is Genuine or Fake, along with a confidence value. The prototype demonstrates how the trained model can be used in a web application, but it does not overcome the limitations of the evidence used to train and evaluate the model.



VIII. LIMITATIONS

The study has several limitations. The dataset labels may not be independently verified as completely Fake or Genuine, and the study is limited to mobile-phone reviews, so the results may not apply to other product categories. The system also does not analyse detailed reviewer behaviour such as purchase history, multiple accounts, or coordinated groups. Mobile parameters are identified using selected keywords, which may not capture all possible expressions. Finally, the study compares only Naive Bayes and Logistic Regression, while other algorithms can be explored in future research.

IX. CONCLUSION

This paper presented a lightweight approach for classifying mobile-phone product reviews using TF–IDF text features and selected mobile-specific parameters. Logistic Regression performed better than Naive Bayes, and adding eight domain indicators improved accuracy from 92.225% to 92.450% and F1-score from 0.817595 to 0.825231. The contribution is best understood as a domain-focused modelling experiment and a deployable prototype. The results are promising for the prepared dataset, but they do not independently validate the real-world authenticity of individual reviews. Stronger labels, transparent reproducibility details, leakage controls, and external validation are required before claims about operational marketplace fraud detection can be made.

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REFERENCES

1. Soldner, F., Kleinberg, B., and Johnson, S. D. (2021). Work on supervised machine learning for fake-review detection using Amazon product-review data. Complete title, venue, volume, pages, and DOI/URL remain to be verified.
2. Mohawesh, R. (2021). Survey work on machine-learning and deep-learning techniques for fake-review detection. Complete title, venue, volume, pages, and DOI/URL remain to be verified.
3. Yousif, A., and Buckley, J. (2022). Work on sentiment analysis in fake-review research. Complete title, venue, volume, pages, and DOI/URL remain to be verified.
4. Cao, C., Li, S., Yu, S., and Chen, Z. (2021). Work on graph-based detection of potentially coordinated fake-reviewer groups. Complete title, venue, volume, pages, and DOI/URL remain to be verified.