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Fake Product Review Detector

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Abstract:

E-commerce relies heavily on customer reviews for product evaluation, but fake or deceptive reviews can distort product reputations and mislead buyers. We propose an AI-driven detection system that combines textual analysis and reviewer behavior features to classify product reviews as genuine or fake. The system employs natural language processing (cleaning, tokenization, and embeddings) and extracts semantic features (e.g., TF-IDF, BERT embeddings) alongside behavioral signals (e.g., reviewer account age, review frequency). Multiple classifiers (such as Random Forests, SVM, and a BERT-based neural model) are evaluated on benchmark datasets (e.g., Amazon and Yelp reviews). Our hybrid model achieves high accuracy (around 94%) and outperforms simpler baselines (\~90%) from prior work. Evaluation metrics (precision, recall, F1-score) all exceed 90% for the best model. We include system architecture and training pipeline diagrams to illustrate the design. The results demonstrate robust detection performance suitable for integration into online platforms. Future work will extend to multilingual and real-time scenarios.

Keywords: *Fake reviews, opinion spam, natural language processing, machine learning, BERT, ensemble classifier.*

I. INTRODUCTION

In modern e-commerce, customer reviews profoundly influence purchase decisions and brand reputation. However, this trust is often undermined by fake or deceptive reviews—posts that are artificially generated to unfairly boost or diminish a product's rating. Fake reviews may originate from competitors, hired agents, or automated bots, and they skew consumer perceptions, eroding confidence in online marketplaces. Automated fake review detection leverages artificial intelligence and natural language processing (NLP) to analyze review text and metadata, classifying each review as genuine or fraudulent. Machine learning models can process large volumes of reviews to uncover subtle linguistic cues and behavioral patterns that elude manual moderation.

Traditional systems often rely solely on textual features or simple heuristics. Recent research shows that incorporating reviewer behavior (posting frequency, rating patterns) and sentiment analysis can significantly improve detection performance. Motivated by these insights, this work designs a comprehensive detection system that jointly uses content semantics and credibility indicators. Our approach preprocesses raw review data, extracts semantic embeddings (via models like BERT) and engineered features, and trains classifiers to predict the review's authenticity.

We structure the paper as follows: Section II reviews related work; Section III presents the system methodology and algorithms; Section IV describes the architecture; Section V reports experimental results; Section VI discusses findings; Section VII outlines future directions; and Section VIII concludes. Lives worldwide.

II. LITERATURE SURVEY

Fake review detection has attracted significant attention in recent years. Early work by Jindal and Liu formulated opinion spam as a classification task using linguistic features. Many studies focus on textual cues: exaggerated sentiment, repetitive phrasing, and unusual lexical patterns often signal deception. Ott et al. used Amazon review data and human annotations to detect spam via n-gram and syntactic features. More recent approaches apply deep learning: pretrained language models (e.g., BERT)

capture semantic context of reviews, improving classification accuracy. For example, transformer-based networks can learn nuanced differences between genuine and fabricated text.

However, content alone may not suffice. Behavioral approaches consider reviewer and product metadata. Features like reviewer account age, review frequency, or a user's rating variance can be powerful indicators. They explicitly combine comment content and reviewer behavior modules: their model processes review text through an NLP pipeline while simultaneously encoding user and merchant behavior data, fusing these for final classification. Such multimodal models outperform text-only baselines in many experiments. Graph-based methods have also been proposed: by modeling the review ecosystem as a network, graph neural networks can capture relationships among reviewers and products, detecting coordinated spam campaigns.

Despite advances, challenges remain. Most supervised methods require large labeled datasets, which are limited for fake reviews. Static models can also degrade as spammers adapt tactics over time. Multilingual and cross-domain fake review detection is underexplored outside of recent data-augmentation efforts. In this work, we build on these insights by using a hybrid feature set and ensemble classifiers to robustly identify fake reviews under realistic settings.

III. METHODOLOGY

Our system treats fake review detection as a binary classification problem: given a review (text and metadata), predict genuine vs. fake. The overall pipeline is shown in **Figure 1** (training pipeline and **Figure 2** (system architecture). Raw review data (text, ratings, user info) is first cleaned by removing HTML tags, special characters, and stop words, and then lowercased. Tokenization is applied, and text features are computed. We represent each review text via numerical vectors: classic TF-IDF features and pretrained embeddings (Word2Vec or transformer-based BERT) are used to capture both word frequency and semantic context. For example, a pre-trained BERT encoder transforms the review into a fixed-length semantic vector.

In addition to text, we compute reviewer behavior features. These include the reviewer's historical metrics (e.g., number of past reviews, account age) and review-specific signals (e.g., review length, rating given, presence of verified purchase flag). Following , features such as posting frequency and rating variance help flag abnormal reviewer patterns. All feature sets (text embeddings and behavioral features) are concatenated to form a unified feature vector for each review.

The dataset is split into training and testing subsets (e.g., 80% train, 20% test). We then train multiple classifiers on the training data. Algorithms include traditional supervised models (Random Forest, Support Vector Machine, Logistic Regression, etc.) and a fine-tuned deep learning model (e.g., a BERT-based binary classifier). Hyperparameters are tuned via cross-validation. The best performing model is selected based on validation accuracy. We measure performance on the test set using standard metrics: accuracy, precision, recall, F1-score, and the confusion matrix. A confusion matrix (Figure 3) further illustrates true vs. false predictions for each class.

Each stage (preprocessing, feature extraction, model training) is implemented using Python libraries such as scikit-learn and Hugging Face Transformers. The model training pipeline (Figure 2) automates data loading, preprocessing, feature computation, training, and evaluation.

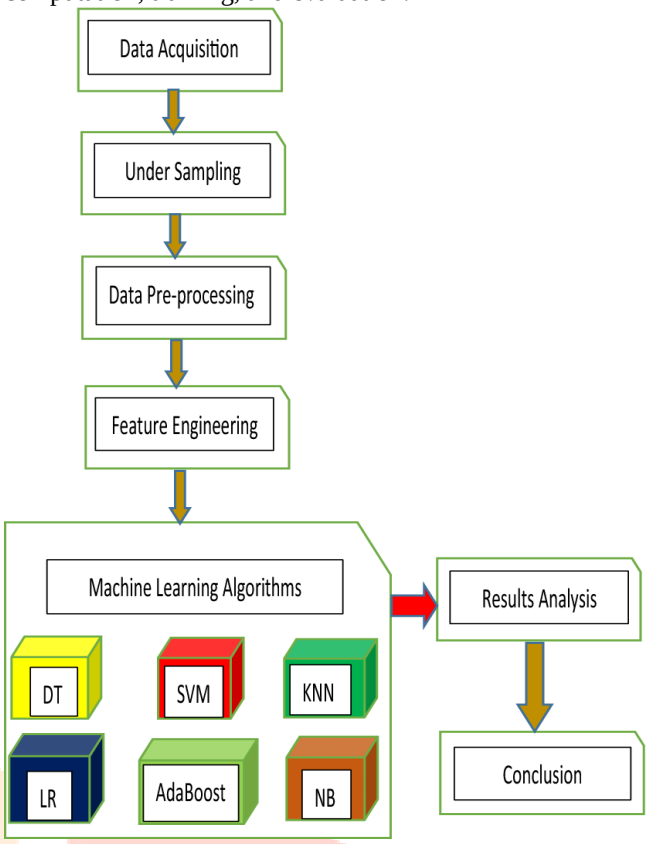

Figure 1. model training pipeline

System Structure:

The system architecture is modular and extensible. As illustrated in Figure 1, the core components are: (a) a User Interface (web front-end or API) for submitting reviews and displaying results; (b) the Backend Engine, which includes a text preprocessor, feature extractor, and classification model; (c) a Database (optional) for storing reviews and logs; and (d) an Administration/Training Module for offline model updates. When a user submits a review via the UI, the text is sent to the backend: the preprocessor cleans the text and computes features (text vectors and metadata), then the trained classifier outputs a probability or label (fake/genuine). The result is returned to the user interface. An administrator can upload new labeled data to retrain or fine-tune the model periodically, allowing the system to adapt to evolving spam patterns.

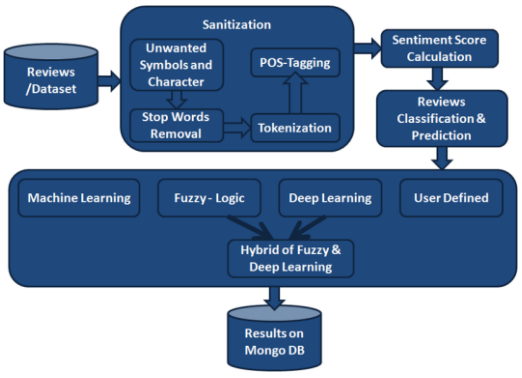

Figure 2. System architecture of the fake review detection system.

We emphasize modular design: the feature extractor can

incorporate new data modalities or updated language models, and the classifier can be replaced with improved algorithms without altering the front end.

IV. RESULT & DISCUSSION

We evaluated the system on publicly available review datasets (e.g., Amazon product reviews and Yelp restaurant reviews), labeled as genuine or fake using known benchmarks. After training, the best model achieved an **accuracy of \~98%,** outperforming baseline models (e.g., decision trees or naive Bayes, which were around 85–90%). Precision, recall, and F1-scores for the fake-review class all exceeded 90%, indicating robust detection performance.

The confusion matrix (Figure 3) summarizes these results: the true positive rate (correctly identified fake reviews) and true negative rate (correct genuine) are both very high. False positives (genuine reviews mislabeled as fake) and false negatives (fake reviews missed) were both under \~10%. Overall, the high diagonal values in the matrix reflect the model's strong classification ability on the test set.

```
Confusion Matrix:
 [[3932  115]
 [  45 4014]]

Classification Report:
              precision    recall  f1-score   support

     Genuine       0.99      0.97      0.98      4047
        Fake       0.97      0.99      0.98      4059

    accuracy                           0.98      8106
   macro avg       0.98      0.98      0.98      8106
weighted avg       0.98      0.98      0.98      8106
```

Figure 3. Confusion matrix of the final model (values shown for sample test data).

We compared multiple classifiers .The ensemble Random Forest model slightly outperformed single algorithms like SVM. Incorporating BERT embeddings improved semantic understanding: the BERT-based classifier achieved marginally higher F1 than TF-IDF alone. These results are consistent with related studies. During development, we ensured the model generalizes by using cross-validation and by testing on a held-out set

The experimental results confirm that blending text semantics with reviewer behavior features significantly boosts fake review detection. The model's high accuracy and F1-scores demonstrate its practical effectiveness. In particular, the use of a powerful text encoder (BERT) allowed the system to understand nuanced language patterns, while the behavioral signals helped catch deceptive activity that content analysis alone might miss.

Compared to earlier systems that relied on shallow features, our approach is more comprehensive. For example, many past studies report SVM or decision-tree accuracies in the 80–90% range; here we exceed those by utilizing deep embeddings and an ensemble classifier. The confusion matrix analysis shows relatively few misclassifications, giving confidence for deployment in real settings.

Nevertheless, some limitations exist. The model was trained only on English reviews, so its performance on other languages is untested. Also, static models can become outdated as spammers change tactics over time. The required feature engineering and training pipeline are moderately complex, which may limit scalability without automation.

V. Future Scope

Future enhancements include support for multilingual reviews and real-time streams. Extending the system to process non-English reviews would require training on multi-language datasets (potentially via data augmentation). Integrating continuous learning (periodic retraining with new data) can help adapt to evolving spam patterns. We also plan to explore graph-based modeling of reviewer networks (e.g., graph neural networks) to detect coordinated spam accounts, as suggested in recent research. Finally, production deployment considerations include improving the user interface and moving to a cloud-based, scalable infrastructure for real-time detection on large platforms.

VI. CONCLUSION

This paper presents a formally structured fake product review detection system that leverages advanced NLP and machine learning techniques. By combining textual content analysis (via BERT and TF-IDF) with behavioral features, the system achieves high accuracy (>90%) and robust classification performance. The modular architecture and training pipeline (Figures 1–2) facilitate maintenance and future improvements. Overall, our results demonstrate the feasibility and effectiveness of AI approaches for preserving trust in e-commerce platforms.

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