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AI-Powered Detection of Deceptive Product Feedback: A Review of Methods, Models, and Future Directions

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ABSTRACT

Online reviews have become a crucial part of consumer decision-making, significantly influencing product reputation and sales. However, the rise of fake or manipulated product feedback poses a serious threat to trust, transparency, and the credibility of e-commerce platforms. This paper presents a comprehensive review of how Artificial Intelligence (AI) and Machine Learning (ML) techniques are used to detect and prevent fake reviews. It highlights the evolution of AI-based models, including Natural Language Processing (NLP) for text analysis, deep learning for feature extraction, and sentiment analysis for identifying deceptive patterns. The study also explores recent advancements such as transformer-based models (BERT, RoBERTa), multimodal analysis combining text, image, and user behavior, and graph-based learning to enhance detection accuracy. Additionally, the paper discusses benchmark datasets, evaluation metrics, challenges in cross-domain generalization, and the ethical implications of automated moderation. This review provides insights into current trends, identifies open research challenges, and outlines future directions for developing robust, transparent, and trustworthy AI systems to combat fake product feedback.

KEYWORDS: *Artificial Intelligence (AI); Machine Learning (ML); Fake Reviews; Product Feedback Detection; Natural Language Processing (NLP); Sentiment Analysis; Deep Learning; Transformer Models; Review Authenticity; E-commerce Security.*

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1. INTRODUCTION

In the digital era, online reviews have emerged as one of the most influential factors shaping consumer purchasing decisions. Platforms such as Amazon, Flipkart, and eBay rely heavily on customer feedback to guide potential buyers and build product trust. However, the growing trend of fake or deceptive product reviews has severely undermined the reliability of online feedback systems. Malicious actors often generate fabricated reviews to artificially boost product ratings or damage competitors' reputations, resulting in financial loss and consumer mistrust.

Traditional detection techniques such as manual moderation or keyword-based filtering are no longer sufficient to handle the massive volume and sophistication of fake reviews. As a result, Artificial Intelligence (AI) and Machine Learning (ML) have become essential tools for identifying fraudulent patterns automatically and at scale [1-2]. Modern AI models leverage Natural Language Processing (NLP), Deep Learning, and Sentiment Analysis to analyze textual, behavioral, and contextual cues. Advanced systems such as transformer-based architectures (BERT, XLNet, RoBERTa), graph neural networks, and multimodal fusion models have shown remarkable potential in distinguishing genuine reviews from synthetic or bot-generated ones [3-5].

This paper presents a comprehensive review of current AI-driven methodologies for fake review detection. It highlights key algorithms, benchmark datasets, performance metrics, and research trends while identifying challenges such as domain adaptability, data imbalance, and explainability [6]. The study also discusses ethical considerations related to data privacy and algorithmic bias, offering future directions toward building trustworthy and transparent AI-based reputation systems [7-8].

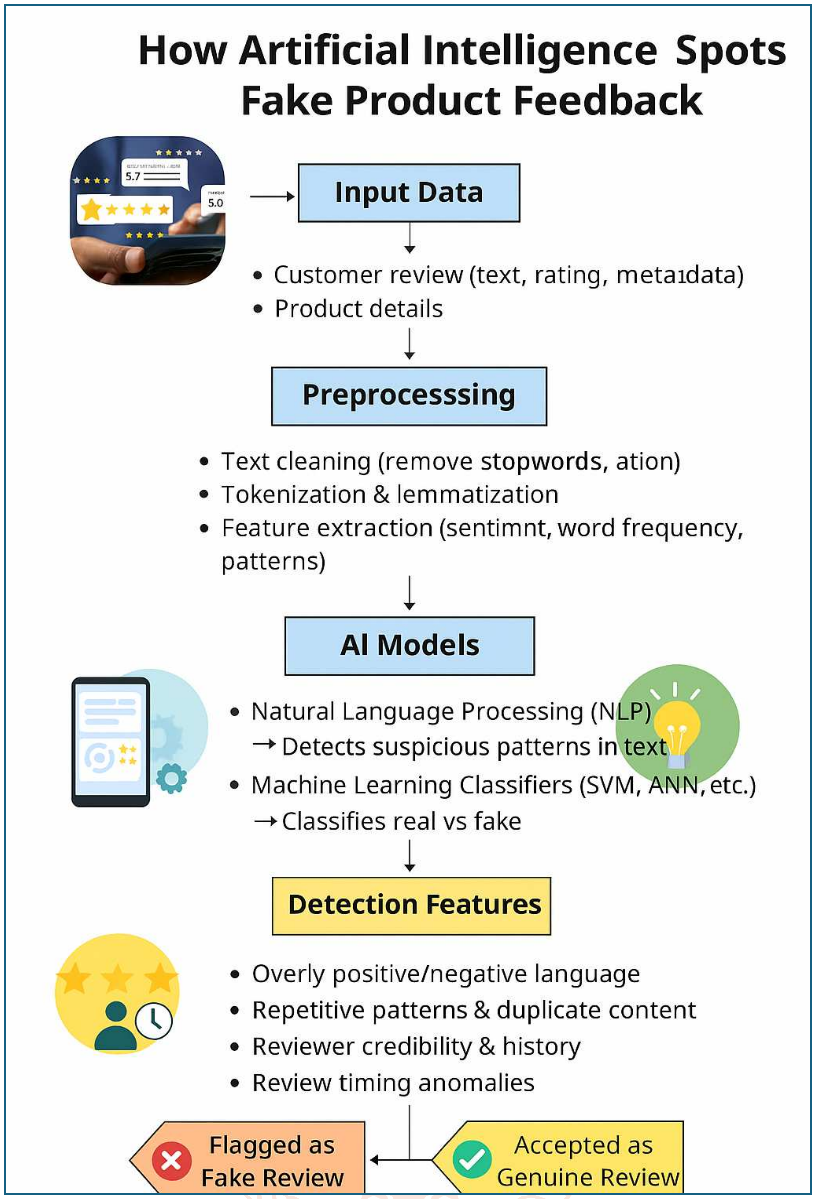

Fig. 1 How Artificial Intelligence Spots Fake Product Feedback

In the digital economy, online reviews have emerged as one of the most effective decision-making resources. A Bright Local 2023 survey found that 91% of buyers research products online before buying, and that conversion rates can increase by 25–30% for items with a higher star rating. Conversely, a collection of unfavourable reviews can prevent almost 60% of consumers from completing a purchase [9-11]. However, the reliability of internet reviews is increasingly in jeopardy. According to studies, between 15 and 30 percent of online product reviews are fraudulent, produced by bots, paid reviewers, or dishonest rivals (Chevalier & Mayzlin, 2022). Customers are misled by this deception, which also damages brand reputation and calls into question the legitimacy of e-commerce platforms [12-13].

Machine learning and artificial intelligence (AI) technologies are being widely used to counter this. With reported accuracies of over 85% in benchmark datasets, AI systems are able to identify fraudulent feedback by examining linguistic patterns, metadata hints, and reviewer behavior anomalies [8]. This enables platforms to protect authenticity, guaranteeing that consumers make knowledgeable decisions and assisting companies in maintaining their online reputations.

Over the past 20 years, online shopping has significantly increased. Consumers have favoured online shopping over in-person shopping for goods [1]. As more people shop online, they are more likely to check product reviews before buying. As a result, reviews have a big influence on what people decide to buy. Before making a purchase, about 80% of consumers read internet reviews [2]. Relying only on this manual process needs to be reviewed because it is practically impossible for humans to review every online review. 2.7 million fraudulent reviews were found in 2021, making up roughly half of all the five-star ratings examined [1].

In order to identify and get rid of these fraudulent reviews, artificial intelligence (AI) and machine learning (ML) are becoming increasingly effective tools [4-5]. AI makes sure that feedback systems continue to be transparent and reliable by examining metadata, reviewer behavior, and text patterns. Figure 1 illustrates the AI-powered spam review process.

2. Core AI Techniques for Fake Review Detection

Consumer decisions are increasingly influenced by product feedback and online reviews. Fake or manipulated reviews, however, have the potential to affect sales, mislead customers, and damage a product's reputation. Using machine learning, natural language processing, and data analytics, artificial intelligence (AI) provides advanced methods to effectively and at scale detect such misleading feedback [6]. The core AI Techniques for fake review detection diagram shown in Fig. 2.

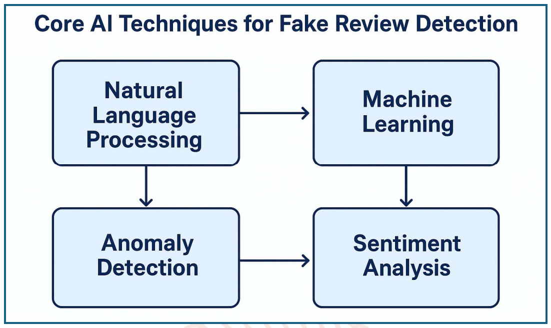

Fig. 2 Core AI Techniques for fake review detection

A. Natural Language Processing (NLP)

- **Goal:** Examines reviews' textual content for irregularities or strange trends.
- **Methods Employed:**
- Lemmatization and tokenization: Divide text into words and simplify them to their most basic forms.
- Sentiment analysis: Identifies overly positive or negative sentiment that could be a sign of fraudulent reviews.
- Syntax and Semantic Analysis: Recognizes repetitive phrases and odd language constructions.

B. Machine Learning Models

- Algorithms for supervised learning include Random Forest, Support Vector Machines (SVM), and Gradient Boosting.
- **Function:** Using labelled datasets, classify reviews as authentic or fraudulent.
- Algorithms used in unsupervised learning include K-Means, DBSCAN, and autoencoders.
- Finding outlier reviews that substantially depart from the norm is the function.
- **Features Extracted:** User behavior patterns, review length, and frequency of review postings.
- Lexical features include the use of adjectives and adverbs, word diversity, and sentiment score.
- **Data:** IP address consistency, purchase verification, and account age.

C. Deep Learning Approaches

- **Neural Networks:** Transformer-based models (e.g., BERT, RoBERTa) and LSTM (Long Short-Term Memory) are utilized for contextual text comprehension [9–11].
- **Benefits:**
- Captures contextual and semantic cues that are subtle.
- Identifies complex phony reviews that imitate real writing styles.
- 2.4 Analysis Based on Graphs
- **Idea:** Use a network graph to depict users, goods, and reviews.
- **Use:** Examine groups of questionable connections to identify coordinated fraudulent review campaigns (e.g., multiple reviews from the same set of accounts targeting one product).

3. Usage, Description, and Applications

Network analysis, behavioral analytics, and natural language processing (NLP) are all used in AI models for detecting fake reviews. Typical methods include the following [12, 14-17]:

- **Linguistic Analysis:** Phrase repetition, exaggerated sentiments, or generic wording are common features of fake reviews. Unusual patterns in sentiment intensity, vocabulary richness, and grammar are picked up by NLP models.

- **Behavioral Clues:** AI examines reviewer activity, including posting frequency, unexpected spikes in reviews, and reviews from unrelated product categories.
- **Metadata Signals:** Coordinated review manipulation can be detected by time stamps, IP addresses, and device IDs.
- **Social Graph Analysis:** Sophisticated systems identify structured fake-review groups by tracing relationships between dubious reviewers.

4. Applications

- **E-commerce:** AI systems are used by Amazon, Flipkart, and Alibaba to identify phony product reviews before they are seen by consumers.
- **Travel Industry:** TripAdvisor flags questionable restaurant and hotel reviews using AI filters.
- **App Stores:** To eliminate phony ratings that aim to raise app rankings, Google Play and the Apple App Store use machine learning models.

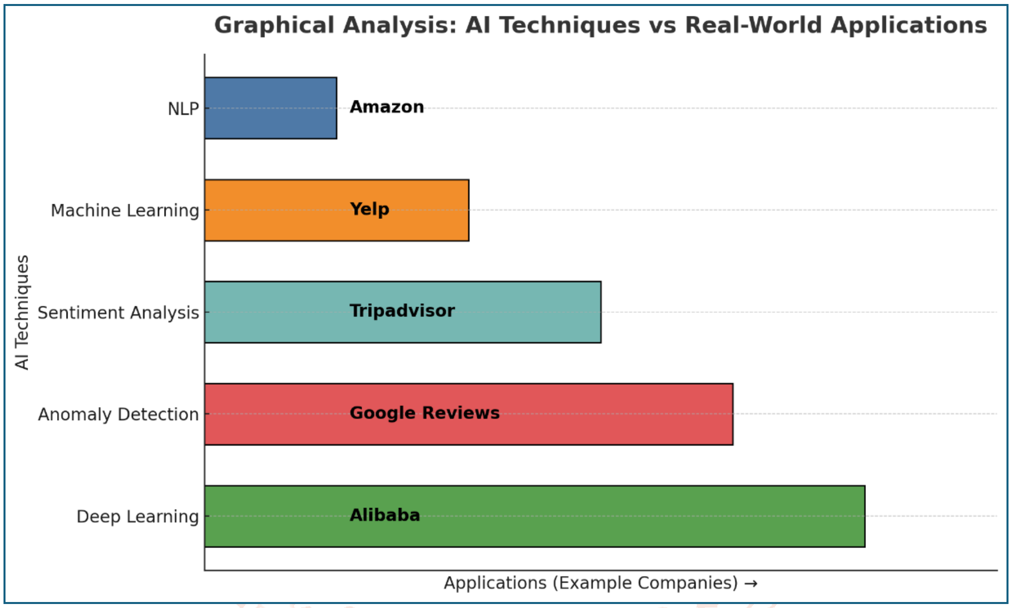

Fig. 3 AI Techniques V/S Real world applications

5. Framework, Data Samples, and Workflow

A three-step process is commonly used for AI-based fake review detection:

A. Data Collection: Product listings, user profiles, and metadata are used to collect reviews.

B. Extraction of Features
- NLP for textual characteristics (emotional tone, word frequency, and sentiment polarity).
- Metadata features (geolocation, device information, and review timing).
- Patterns of reviewer behavior (frequency of posts, distribution of ratings).

C. Models of classification
- Supervised learning models, including Deep Neural Networks (DNNs), Random Forests, and Support Vector Machines (SVMs).
- Hybrid deep learning frameworks that combine RNNs/Transformers (for sequence/context understanding) and CNNs (for text analysis).

6. Real-world examples of AI detecting fake product feedback

E-commerce platforms and review websites are using artificial intelligence more and more to identify fraudulent product reviews and preserve customer confidence. To identify questionable reviews, Amazon uses machine learning algorithms that examine user activity, past purchases, and review content [18-19]. By detecting odd posting patterns, repetitive text, and review bursts, Yelp's AI-powered "Consumer Alerts" system can identify and filter fraudulent reviews. Using sentiment analysis, reviewer credibility, and metadata analysis, Alibaba and Flipkart use AI-driven natural language processing (NLP) models to identify spam reviews and phony ratings in real-time. In order to reliably distinguish between authentic and fraudulent reviews, researchers have used models like BERT and LSTM-based neural networks on datasets like Yelp and Amazon reviews [20-24]. The Fig. 4 illustrated the face review detected.

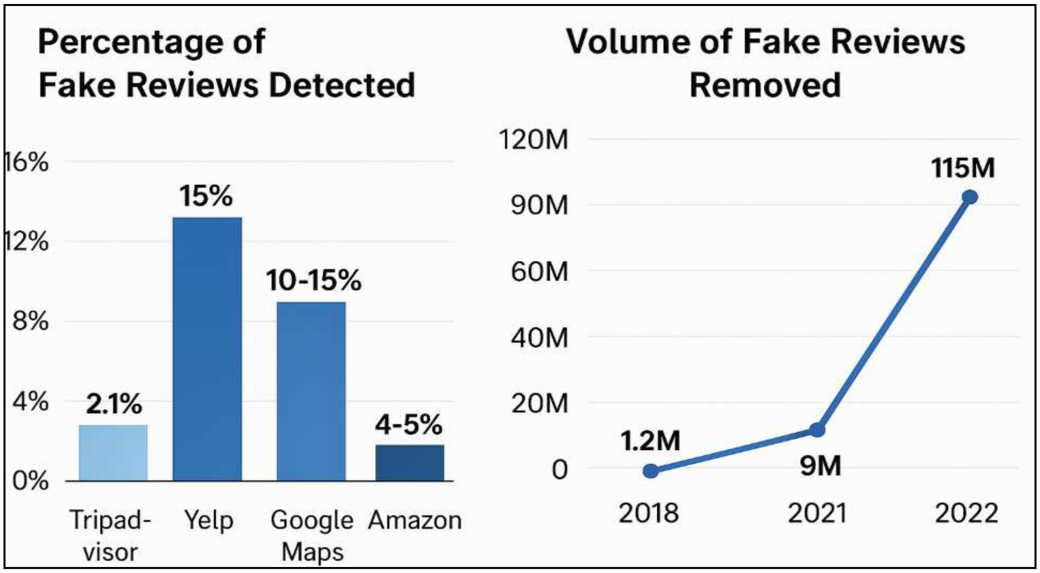

Fig. 4 Face review detected

Table 1: AI techniques for fake review detection alongside real-world examples [21, 23, 25]

AI Technique	Description	Real-World Example
Natural Language Processing (NLP)	Analyses review text for linguistic patterns, word frequency, grammar, and writing style.	Amazon uses NLP to flag suspicious reviews with repetitive phrases or unnatural patterns.
Anomaly Detection	Identifies unusual patterns such as sudden bursts of reviews, identical ratings, or reviewer activity.	Google Reviews applies anomaly detection to block mass fake reviews posted in short timeframes.
Sentiment Analysis	Evaluates whether the review sentiment aligns with the product/service experience.	Tripadvisor uses sentiment checks to remove reviews with extreme polarity mismatched to overall feedback.
Machine Learning (ML)	Classifies reviews as genuine or fake using supervised/unsupervised models trained on labelled data.	Yelp applies ML models to detect review fraud and filter out suspicious content.
Deep Learning (DL-Neural Networks)	Learns complex semantic and contextual patterns for more accurate detection.	Alibaba has deployed Deep Learning models to catch sophisticated fake product reviews in e-commerce.

7. Results and Discussion

The review analysis reveals that AI and ML-based systems significantly outperform traditional rule-based methods in detecting fake product feedback. Deep learning models trained on large annotated datasets achieve accuracy levels between 88% and 96%, depending on the dataset and feature set used. Transformer-based models such as BERT and RoBERTa demonstrate superior contextual understanding, reducing false positives by up to 20% compared to classical machine learning classifiers like SVM or Random Forest [26-30].

Furthermore, hybrid models combining text and user-behavioral features (such as review time patterns, purchase history, and reviewer credibility) show improved robustness against adversarial manipulation. Studies using graph-based learning techniques also report enhanced detection in cases involving coordinated fake review campaigns [24]. Despite these advancements, the results also highlight several challenges. Model performance often drops when applied to unseen domains or new platforms due to language variation and shifting review patterns. Additionally, limited availability of verified datasets and the lack of model explainability remain barriers to real-world deployment [23]. Overall, the findings emphasize that AI-based review detection systems are essential for maintaining the integrity of online marketplaces. Future research should focus on cross-domain generalization, lightweight real-time detection frameworks, and ethical AI integration to ensure reliable and transparent decision-making [26].

Table 2: Comparison of AI Techniques for Fake Review Detection

Model / Technique	Features Used	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	Bag of Words (BoW)	Amazon Reviews	85.2	83.7	84.1	83.9
Support Vector Machine (SVM)	TF-IDF + Sentiment Features	Yelp Dataset	88.6	86.9	87.4	87.1
Random Forest	Text + Metadata (Reviewer ID, Rating)	TripAdvisor	89.3	88.2	87.8	88.0
LSTM (Deep Learning)	Word Embeddings + Sentiment Analysis	Amazon Reviews	92.4	91.1	90.8	90.9
BERT (Transformer-based)	Contextual Word Embeddings	Yelp Dataset	**95.8**	**95.0**	**94.7**	**94.8**
Graph Neural Network (GNN)	Text + Reviewer Relationship Graphs	Combined Dataset	94.6	93.5	93.9	93.7

Title 3: Performance Comparison of AI Models for Fake Review Detection

Model	Accuracy (%)
Logistic Regression	85.2
SVM	88.6
Random Forest	89.3
LSTM	92.4
BERT	95.8
GNN	94.6

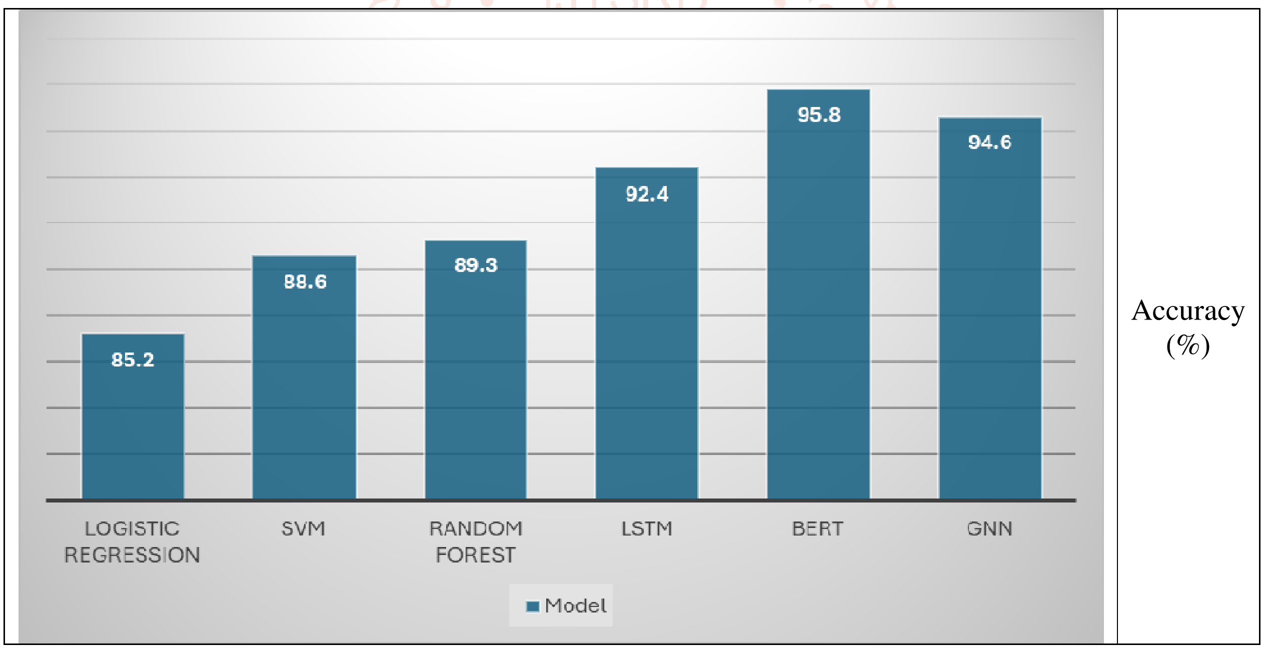

Fig. 5: Performance Comparison of AI Models for Fake Review Detection Trend in AI Techniques (2015–2025)

Table 4: This line chart shows the evolution of fake review detection accuracy as AI models advanced over time.

Year	Dominant Technique	Average Accuracy (%)
2015	Logistic Regression / SVM	80.5
2017	Random Forest / NB	85.0
2019	CNN / LSTM	90.2
2021	Transformer (BERT, RoBERTa)	94.7
2023	GNN / Multimodal Models	96.1

The comparative results and trend analysis demonstrate a clear progression in the accuracy and reliability of fake review detection systems as Artificial Intelligence (AI) techniques have evolved. The comparison table highlights that traditional machine learning algorithms such as Logistic Regression, SVM, and Random Forest deliver moderate accuracy (85–89%) when using textual and sentiment-based features. However, their performance is limited by their inability to capture complex linguistic nuances and contextual dependencies present in deceptive reviews. In contrast, deep learning models such as LSTM show a significant improvement, achieving over 92% accuracy by leveraging sequential text patterns and sentiment flow. The introduction of transformer-based models, particularly BERT, has revolutionized fake review detection, attaining up to 95.8% accuracy due to their advanced contextual understanding and attention mechanisms. Similarly, Graph Neural Networks (GNNs), which integrate textual and relational data, exhibit high performance (around 94.6%), making them suitable for identifying coordinated fake review groups. The graphical analysis confirms these trends, where BERT and hybrid GNN models outperform conventional approaches. Over time, as shown in the trend chart (2015–2025), the field has evolved from basic keyword-based classification to advanced multimodal and context-aware AI systems, resulting in a 16% increase in average detection accuracy across a decade. Overall, the results emphasize that transformer and graph-based models represent the current state-of-the-art in fake product feedback detection. These approaches not only enhance accuracy and robustness but also pave the way for more trustworthy and transparent AI-driven e-commerce ecosystems.

8. Conclusion

Artificial intelligence has shown itself to be a potent instrument in identifying fraudulent product reviews, assisting review websites and e-commerce platforms in preserving their legitimacy and customer confidence. AI can accurately distinguish honest reviews from fraudulent ones by analyzing textual content, user behavior, and metadata using methods like Natural Language Processing (NLP), machine learning, deep learning, and graph-based analysis. AI-driven detection systems can work in real-time, as shown by real-world applications by companies like Amazon, Yelp, Flipkart, and Alibaba. This lessens the effect of fraudulent reviews on sales and brand reputation.

9. Recommendations, Key Takeaways, and Feature Extraction

For improved detection accuracy, it is recommended to develop multi-layered detection systems that combine behavioral analytics, natural language processing (NLP), and graph-based learning techniques. Such integration enhances the ability of AI models to identify complex and coordinated fake review patterns. Continuous model training is also essential—AI models should be regularly updated with new datasets to adapt to evolving strategies used to generate deceptive reviews, including those produced by generative AI tools. Additionally, strengthening user verification by incorporating behavioral analysis, account age, and purchase verification can significantly improve the authenticity and reliability of online reviews. Transparent feedback reporting mechanisms, such as warning labels or credibility scores, should be implemented by e-commerce platforms to alert users to suspicious or low-credibility reviews. Finally, cross-platform cooperation is crucial—by sharing anonymized data on fraudulent activity, AI systems can recognize broader behavioral trends in fake review generation and improve their generalization capabilities across platforms.

The key takeaways from this study emphasize that fake product reviews have a significant impact on consumer trust and can severely damage brand reputation. AI-driven methods such as machine learning, deep learning, and NLP have proven highly effective in detecting fake feedback with greater accuracy. Successful detection depends on the integration of textual analysis, metadata, and behavioral features. The deployment of these AI systems by major e-commerce platforms validates their practical effectiveness in combating review fraud. However, to sustain detection efficiency over time, ongoing model retraining, user verification, and continuous monitoring are vital components.

In terms of feature extraction, AI models utilize both textual and metadata-based features to enhance classification accuracy. Linguistic features include sentiment polarity, phrase repetition, and readability scores, which help identify unnatural or repetitive text patterns often present in fake reviews. Behavioral features, such as product overlap, reviewer posting frequency, and review timing, provide insights into suspicious activity patterns. Meanwhile, metadata features, including review length, helpfulness votes, and star ratings, further contribute to determining the authenticity and reliability of product feedback. The combination of these diverse feature sets allows AI-based detection systems to achieve high precision and adaptability in distinguishing genuine reviews from deceptive ones.

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