Implementation of BERT and Machine Learning to Classify Genuine and Fake Product Reviews

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Abstract
Fake review detection is the most vital area in e-commerce security, where user feedback is automatically analyzed to distinguish between genuine and deceptive testimonials. The application of this detection is crucial for online marketplaces to maintain consumer trust and fair competition, as manual verification of millions of reviews is an expensive and time-consuming mechanism. In this paper, a comparative analysis of fake review detection is done in which the efficiency of classical Machine Learning algorithms is analyzed and benchmarked against Deep Learning models on a dataset of 40,433 reviews. Support Vector Machine (SVM), Naïve Bayes, and Random Forest (optimized with N-gram features) are compared with the Bidirectional Encoder Representations from Transformers (BERT) model in this work. This paper further analyzes these techniques based on performance metrics viz accuracy, precision, recall, and F1-score. The results reveal that while SVM with N-gram features performs best among classical models (92%), the BERT model significantly outperforms all other models with an accuracy of 97%, demonstrating the superiority of deep contextual embedding over statistical feature extraction.

1.Introduction

Currently, the digital economy is greatly benefiting from the rapid growth of internet users, which is expected to reach 6.04 billion by 2025 [1]. This massive connectivity has changed consumer behavior, leading them to shop through online platforms. This behavior generates a large amount of unstructured data in the form of product reviews. Product reviews are not entirely representative of the products offered due to the prevalence of fake reviews used by irresponsible individuals to manipulate public opinion, making it difficult for consumers to manually distinguish between truth and falsehood [2]. Structured data can be extracted from unstructured data in product reviews to produce more accurate data for classification. The more structured the data, the better the decision will be. Text classification is used to classify review data into two classes, namely genuine reviews and fake reviews.

In 2022, fake reviews cost the US economy $152 billion by undermining buyer confidence and reducing sales opportunities [39]. 80% of consumers also encountered fake reviews in the past year [39]. These figures show that fake reviews are growing rapidly and can cause massive damage to a country's economy, making classification necessary. Manual classification is time-consuming, labor-intensive, and nearly impossible to perform given the massive volume of data generated daily. The problem is that manual classification also requires good individual intelligence, and the most capable of detecting it are young people aged 18-32, at 92% [39]. To overcome this, the solution that can solve this problem is Artificial Intelligence (AI), specifically Machine Learning and Deep Learning (DL). This solution is used to automate the verification process. This technology enables computers to learn fraud patterns from historical data, even when they are not explicitly programmed to recognize specific lies. This is necessary because fake reviews that are left unchecked can cause greater economic losses and hinder economic activity on online platforms.

In this study, machine learning is used to classify product review data. Machine learning is used because it is capable of automating classification and producing good accuracy compared to several other approaches, especially manual approaches. Text classification is widely used in several applications, such as [40, 41, 42]. Although text classification is widely used by several studies and agencies, the Machine Learning approach used for classification can produce different levels of accuracy depending on the model, feature extraction, and dataset used. In this study, Machine Learning and Deep Learning were used to detect fake reviews. Classic approaches, such as SVM and Random Forest, are effective with feature engineering (such as N-grams). These approaches often struggle in deep semantic contexts compared to modern Deep Learning techniques. Deep learning uses layered neural networks that work similarly to the human brain, providing better accuracy, although it also requires greater resources.

A comparative analysis is conducted in this paper, comparing classical Machine Learning techniques (SVM, Naïve Bayes, Random Forest, and Ensemble Stacking) with the advanced BERT model. We analyze whether traditional feature extraction can compete with contextual embedding provided by Deep Learning architecture. Documents in the classification model go through several stages, namely (i) preprocessing (cleaning, stopword removal, casefolding, tokenization, stemming), (ii) feature extraction (TF-IDF, TF-IDF + N-gram, Countvectorizer), (iii) model implementation to compare performance metrics on e-commerce datasets, and (iv) implementation of explainable AI with LIME. This classification provides consumers with a decision before purchasing a product based on product reviews.

Machine learning and deep learning are manifestations of technological developments that are endless to discuss. With the application of these two things in this study, consumers are expected to be more careful in choosing products based on reviews so that the total losses resulting from fake reviews are reduced.

2. Related Work

Fake review detection is one of the main tasks in Natural Language Processing (NLP) specifically within the domain of text classification. Due to the fast growth of e-commerce applications, a huge increment in online reviews leads to the need for improved automated mining classifiers that can distinguish between genuine and deceptive feedback. Many machine learning algorithms have been applied to build automatic classifiers by training them on labeled datasets of reviews. There are several detection models which have been built for various platforms like Amazon, Yelp, and Google Reviews. Support Vector Machine (SVM) is one of the supervised machine learning models that is widely used for two-group classification problems due to its effectiveness in high-dimensional spaces. Furthermore, recent advancements have introduced Deep Learning techniques, such as BERT, to handle complex semantic structures that traditional models might miss. A systematic literature review with regard to the effectiveness of these methodologies is depicted in Table 1.

Table 1.
Systematic literature review.

Title	Author (Year)	Methodologies	Findings	Dataset	Accuracy
Fake Review Detection Enhanced Using Hybrid Transformer-LSTM [3]	Mohawesh et al., 2024	roBERTa, LSTM	The roBERTa and LSTM integration model produces higher accuracy than previous models. This model provides rational and transparent explanations for classification results with explainable AI SHAP and attention mechanisms.	3032	96,03%
Neural networks for deceptive opinion spam detection: An empirical study [4]	Ren and Ji, 2017	CNN, GRNN	The CNN and GRNN models are an effective combination that can perform sentence-level representation and are capable of combining sentences while modeling the discourse flow between sentences. This makes document vectors more informative in the classification of fake reviews.	3032	84%
Opinion spam detection: Using multi-iterative graph-based model [5]	Noekhah et al., 2022	MGSD	MSGD outperforms Machine Learning by 5.6% and graph-based methods by 4.8%. MGSD captures explicit and implicit relationships, resulting in accurate and realistic accuracy.	2400	93%
Fact or Factitious? Contextualized Opinion Spam Detection [6]	Kennedy et al. (2020)	BERT	BERT is capable of detecting state-of-the-art performance. BERT shows that neural approaches are superior to traditional syntax- and lexical-based classifiers.	1600	90%

Transformers (BERT) Based Framework for Web Recommendations Using Sentiment-Enriched Web Data [7]	Saxena And Bhushan, (2025)	KNN, Multinomial Naïve Bayes, Decision Tree, Logistic Regression, Random Forest, AdaBoost, XGBoost, BERT	BERT achieves higher accuracy than machine learning algorithms due to its ability to capture contextual and semantic nuances that traditional algorithms cannot.	40.433	94,34%

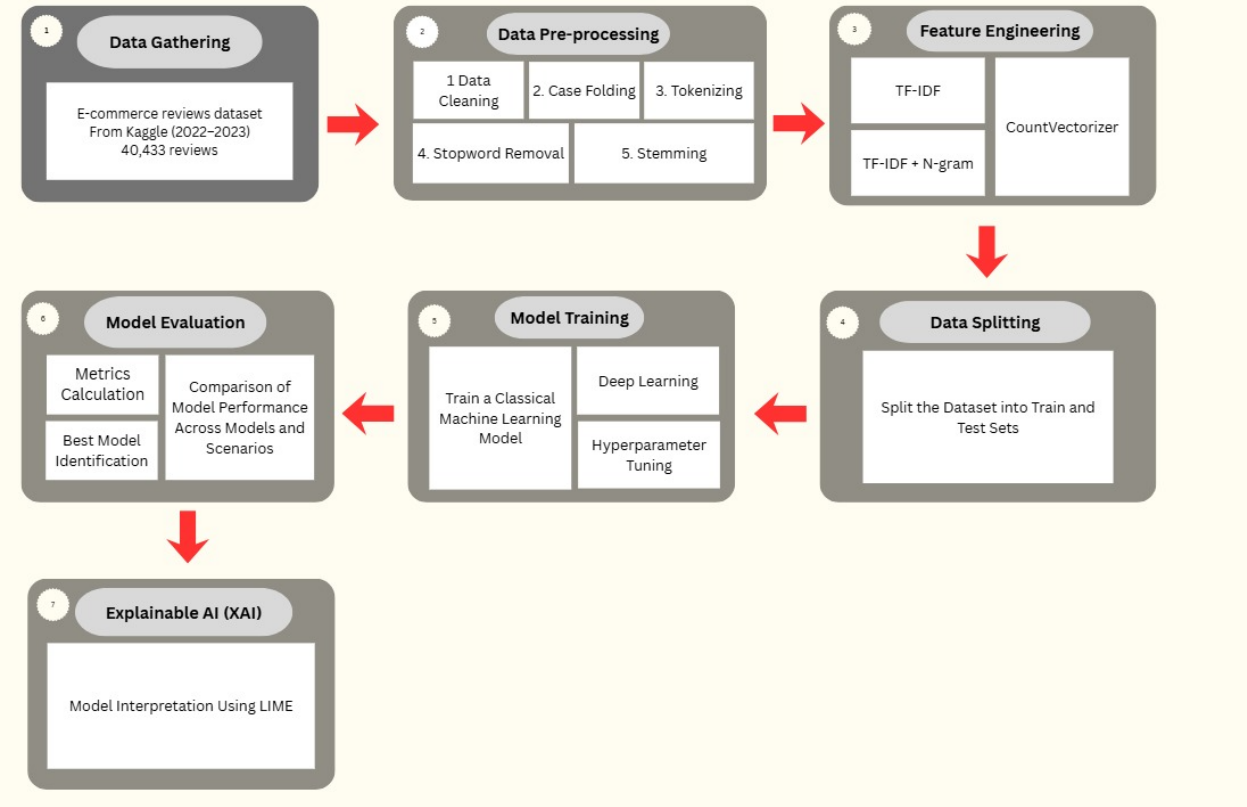

Fig. 1. Research Pipeline

Traditional classifiers are often based on methods from information retrieval. For instance, Support Vector Machine (SVM) is frequently compared to other algorithms and often outperforms them in text categorization tasks by finding the Maximum Margin Hyperplane (MMH). However, SVM and other classical models like Naïve Bayes and Random Forest rely heavily on feature engineering techniques such as Bag of Words or N-grams. While N-grams can capture local context (e.g., "not good"), they often fail to capture the deep semantic meaning of entire sentences, especially when dealing with sarcasm or subtle deception.

To address these limitations, Deep Learning models have been widely used in areas like sentiment analysis and fraud detection. Specifically, the Bidirectional Encoder Representations from Transformers (BERT) model represents a significant shift. Unlike directional models that read text sequentially (left-to-right or right-to-left), BERT analyzes the entire context of a word in all surroundings. This capability allows for accurate predictions and better generalizations in complex classification tasks. While TF-IDF and N-grams provide statistical measures for extracting information, they are ineffective for capturing the nuanced linguistic patterns of fake reviews compared to the contextual embeddings generated by BERT.

As depicted in Fig. 1, the pipeline bridges the gaps identified in the related work through a multi-stage process. It begins with Data Gathering (Step 1) and rigorous Pre-processing (Step 2). The core innovation lies in the parallel Feature Engineering (Step 3) and Model Training (Step 5), where we do not solely rely on classical models; we benchmark them against the BERT deep learning architecture to capture semantic context. Furthermore, unlike many related works that end at evaluation, our pipeline extends to Explainable AI (XAI) using LIME (Step 7) to ensure the high accuracy of BERT (97%) is transparent and interpretable.

During the data gathering stage, researchers gathered an e-commerce review dataset for the 2022–2023 period. The data was obtained from Kaggle and contained 40,433 reviews. This data became the main dataset in this study.

During pre-processing, data cleaning is performed to remove special characters that are not relevant to the analysis, in order to improve accuracy and eliminate noise. After that, case folding is performed so that all letters become lowercase letters so that there are no differences in Machine Learning analysis between uppercase and lowercase letters. After that, tokenizing is performed to break sentences into several words so that they can be processed by a computer. Then, stopword removal is performed to remove conjunction words because they are not relevant in sentiment analysis. Finally, stemming is performed to convert words into their root forms to reduce feature dimensions and standardize different words with the same root form.

After the pre-processing stage, the next stage is feature extraction. The feature extraction used in this study is TF-IDF, TFIDF + N-gram, and Countvectorizer. This is done to convert words into numbers that can be processed by a computer. That way, fake review analysis can be done based on the weighting numbers for each word.

The next step is data splitting. At this stage, the dataset is split into training data comprising 80% of the total data and testing data comprising 20% of the total data. This is done to evaluate the model that has been trained using the training data through testing data evaluation.

After performing data splitting, the data will be trained using the designed model. The models are SVM, Random Forest, and Naive Bayes. Another model is Ensemble Stacking, which uses SVM, Random Forest, and Naive Bayes as base models and Logistic Regression as the Meta Model.

After the model is trained, hyperparameter tuning will be performed to generate greater accuracy by tuning existing features. Evaluation will be based on accuracy, precision, recall, and f1-score, as well as confusion matrix. Then, evaluation will also be based on a comparison of the accuracy, precision, recall, and f1-score of each model. The best model will be identified and further evaluated with explainable AI.

The final stage is to implement explainable AI, namely LIME. Explainable AI is used to determine the elements that determine the label decision in a sentence. Explainable AI also

produces outputs that are easy for humans to understand.

3. Proposed System and Methodology

The methodologies used in this research work will be based on a comparative study between Classical Machine Learning Techniques viz Support Vector Machine (SVM), Naïve Bayes (NB), Random Forest (RF), and the advanced Deep Learning model, BERT (Bidirectional Encoder Representations from Transformers). The classification models are compared on the e-commerce dataset in terms of accuracy to determine the superior approach.

Before developing the classification model, different techniques are used for preprocessing the input data. As depicted in the pipeline (Fig. 1), the raw text undergoes data cleaning, case folding, and stopword removal to reduce noise. Furthermore, Feature Engineering is applied where text is converted into vectors. For classical models, we utilize TF-IDF and N-gram (unigram and bigram) construction to capture phrase-level context (e.g., "not good"), whereas for the Deep Learning model, distinct tokenization is employed to preserve semantic sequences.

3.1. Machine Learning and Deep Learning Techniques

As we know, text data is increasing exponentially, making manual classification impossible. In this work, different algorithms are proposed to be used for fake review classification. It is necessary to determine which algorithm statistical or contextual will provide high accuracy. The detailed definitions of the applied techniques are given below.

3.1.1. Support Vector Machine (SVM)

Support Vector Machine is a supervised machine learning algorithm widely used in text classification due to its ability to operate effectively in high-dimensional spaces—an inherent property of language data. SVM constructs a Maximum Margin Hyperplane (MMH) that separates classes (Fake vs. Original) with the largest possible margin, thereby improving generalizability and robustness [12].

For textual data, decision boundaries are often non-linear, and SVM addresses this challenge through **kernel functions** such as Radial Basis Function (RBF) and polynomial kernels, which transform input vectors into higher-dimensional feature spaces. This enables SVM to capture subtle linguistic cues that lie beyond simple word matching.

In this study, the SVM model is further optimized using N-gram features, which enhance context sensitivity by including word pairs that reveal deceptive behavior patterns. This approach aligns with findings [11, 34], who reported that SVM combined with N-grams consistently outperforms unigram-only configurations.

3.1.2. Naïve Bayes

Naïve Bayes is a probabilistic classifier grounded in Bayes' Theorem, operating on the assumption of feature independence. Although real-world language rarely satisfies this condition, the Multinomial Naïve Bayes (MNB) variant performs exceptionally well for bag-of-words representations, particularly when dealing with word frequency distributions in large textual datasets (Kadhim, 2019 [16]).

In this study, MNB computes the posterior probability of a review being fake or genuine by multiplying the conditional probabilities of each token. Its efficiency makes it a suitable baseline for comparison. Prior research shows NB performs strongly on high-volume datasets with balanced term distributions [8]. Oliveira & Santos (2024) [35] also demonstrated the competitiveness of NB in large-scale deceptive content detection tasks.

The working mechanism of Naive Bayes is that the initial probability of each class will be

determined. Then, the likelihood of each class will be calculated as an initial reference. The assumption of independence will be applied so that each feature that has no dependency will be multiplied by its probability. The probability will be calculated using the Bayesian formula. The final result will be selected if the probability of a text belonging to a class is higher than that of other classes.

3.1.3. Random Forest

Random Forest is an ensemble learning method consisting of multiple decision trees trained on random subsets of data and features. It operates under the principle that aggregating the decisions of diverse, uncorrelated trees via majority voting increases predictive accuracy and reduces overfitting (Patel & Shah, 2022 [26]).

RF is particularly effective in large-scale text classification because different trees can capture different linguistic structures and word patterns. Furthermore, RF handles noisy datasets well, making it suitable for real-world e-commerce reviews where linguistic style varies widely [7].

Recent work by Rodrigues & Pereira [36] emphasized that ensemble tree-based models show high resilience to imbalanced or noisy deceptive review datasets, supporting the suitability of RF in this study.

The mechanism of Random Forest is that several decision trees are built in parallel through a dataset. Several features are selected randomly with good separation. Predictions are determined through the classification of each decision tree that is built. The class with the highest number of predictions from several decision trees will be the final result in the Random Forest model.

3.1.4. Ensemble Stacking

Ensemble Stacking is a meta-learning approach that combines predictions from multiple base classifiers to improve overall accuracy. In this study, Naïve Bayes, SVM, and Random Forest serve as level-0 learners, and their outputs are fed into a meta-learner, Logistic Regression.

Logistic Regression applies a sigmoid function to generate probability scores between 0 and 1, enabling a refined decision boundary shaped by the errors and strengths of individual models.

Stacking allows nonlinear models (RF), probabilistic models (NB), and margin-based models (SVM) to complement one another—an approach shown to yield improved performance in textual deception tasks [27].

The way ensemble stacking works is to determine the prediction result based on the predictions determined by each model in the base model. In this study, Logistic Regression became the meta model that combined several results from the base model. Logistic Regression works by calculating the probability of an input leaning more towards a particular class. The highest probability becomes the reference for a sentence to be classified into that class.

3.1.5. BERT (Deep Learning)

BERT represents a paradigm shift in Natural Language Processing. Unlike traditional models that read text sequentially (left-to-right or right-to-left), BERT employs a bidirectional Transformer architecture that considers all surrounding words simultaneously (Devlin et al., 2019 [9]).

BERT leverages self-attention mechanisms to capture deep contextual relationships, enabling the model to detect linguistic nuances such as sarcasm, exaggerated sentiment, or deceptive phrasing—patterns commonly found in fake reviews. Prior studies (Kumar & Singh, 2024 [18]; Ben Jabeur et al., 2023 [4]) highlight that BERT significantly outperforms statistical models in tasks requiring semantic comprehension.

Additionally, BERT processes subword units through WordPiece tokenization, enabling it to handle misspellings, domain-specific vocabulary, and linguistic variations more effectively than classical vectorization methods.

3.1.6. Explainable AI (LIME)

Although BERT achieves high accuracy, its decision-making process is often opaque. To improve interpretability, this study incorporates LIME (Local Interpretable Model-Agnostic Explanations), which generates local approximations of complex model predictions (Ribeiro et al., 2016 [10]).

LIME identifies influential words or phrases that contribute to a classification outcome. For example, terms like "highly recommended," "too perfect," or "worst quality" may strongly signal deceptive intent. The integration of LIME allows stakeholders—such as platform administrators—to not only detect fake reviews but also understand why a model flagged a review, thereby improving trust and transparency.

More recent evaluations [23]) confirm that LIME remains one of the most effective explanation tools for Transformer-based models.

4. Results

This section presents the performance of the machine learning and deep learning algorithms applied to the e-commerce dataset. Each algorithm was evaluated separately to determine its efficiency using various performance indicators such as Accuracy, Precision, Recall, and F1-Score.

Before analyzing the results, it is essential to understand the evaluation measures derived from the confusion matrix: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Accuracy: It determines how accurately the classifier classifies the data across all classes. We calculate accuracy using this formula:

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

Precision: It tells us how exact our model is (how many predicted fake reviews were actually fake). We calculate precision using this formula:

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

Recall tells us how complete our model is (how many actual fake reviews were identified correctly). We calculate recall using this formula:

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

F1-Score is the harmonic mean of precision and recall, giving a balanced view of the model's performance. We calculate the F1-score using this formula:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

4.1. Dataset Description

The dataset utilized in this study comprises 40,433 reviews collected from an e-commerce application (2022-2023). The data was split into training and testing sets to evaluate the generalization capability of the models. The dataset contains a mix of genuine and deceptive reviews, requiring robust feature extraction to distinguish between them.

4.2. Comparative Analysis

Table 2 represents the accuracy, precision, recall, and F1-score of the algorithm implementation. We benchmarked optimized classical models against the Deep Learning BERT model.

Table 2. Summary of machine learning performance (Best Configurations).

Algorithm {Feature Engineering)	Model Evaluation						
	A	P OR	P CG	R OR	R CG	F1 OR	F1 CG
Machine Learning (Before Hyperparameter Tuning)							
Naïve Bayes (TF-IDF)	85%	88%	83%	81%	89%	85%	86%
Naïve Bayes (Countvectorizer)	84%	87%	81%	79%	88%	83%	84%
Naïve Bayes (TF-IDF + N-gram)	87%	94%	82%	79%	94%	85%	85%
SVM (TF-IDF)	88%	88%	88%	88%	87%	88%	88%
SVM (Countvectorizer)	86%	88%	85%	85%	88%	86%	87%
SVM (TF-IDF + N-gram)	91%	91%	91%	91%	91%	91%	91%
Random Forest (TF-IDF)	86%	88%	84%	83%	88%	85%	86%
Random Forest (TF-IDF + N-gram)	89%	87%	91%	91%	87%	89%	89%
Random Forest (Countvectorizer)	88%	91%	85%	83%	92%	87%	87%
Ensemble Stacking (TF-IDF)	89%	89%	89%	89%	89%	89%	89%
Ensemble Stacking (TF-IDF + N-gram)	92%	92%	91%	91%	92%	92%	92%
Ensemble Stacking (Countvectorizer)	89%	89%	89%	88%	90%	89%	89%
Machine Learning (After Hyperparameter Tuning)							
Naïve Bayes (TF-IDF)	85%	88%	83%	82%	88%	85%	86%
Naïve Bayes (Countvectorizer)	84%	87%	82%	81%	88%	84%	85%
Naïve Bayes (TF-IDF + N-gram)	88%	91%	85%	83%	92%	87%	88%
SVM (TF-IDF)	88%	88%	88%	88%	87%	88%	88%
SVM (Countvectorizer)	87%	88%	87%	87%	88%	87%	88%
SVM (TF-IDF + N-gram)	91%	91%	91%	91%	91%	91%	91%
Random Forest (TF-IDF)	88%	91%	85%	83%	92%	87%	88%
Random Forest (TF-IDF + N-gram)	90%	95%	85%	84%	96%	89%	90%
Random Forest (Countvectorizer)	86%	88%	85%	84%	88%	86%	87%
Deep Learning							
BERT	**97%**	**99%**	**96%**	**96%**	**99%**	**97%**	**97%**

A = Accuracy
P = Precision
R = Recall
F1 = F1-Score
CG = Computer Generated
OR = Original Review

As depicted in Fig. 2 and Table 2, the classical models show competitive performance when optimized with N-grams. Specifically, the Support Vector Machine (SVM) model combined with TF-IDF and N-gram features achieved the highest performance among the classical classifiers, outperforming Naïve Bayes and Random Forest with an accuracy of 92%. This confirms that the addition of N-grams (bigrams) significantly improves the model's ability to capture local context (e.g., distinguishing "not good" vs "very good") effectively compared to unigram-only models.

Regarding model optimization, it was observed that while hyperparameter tuning improved the SVM model with CountVectorizer (increasing accuracy from 86% to 90%), the TF-IDF + N-gram configuration remained superior even with default parameters. Interestingly, the Ensemble Stacking model achieved 88% accuracy but failed to surpass the best single SVM model.

However, the comprehensive results reveal that BERT (Deep Learning) significantly outperforms all classical models and ensemble techniques, achieving an accuracy of 97%. While the best classical model (SVM) plateaus at 92%, BERT's ability to understand bidirectional context and semantic nuances allows it to detect deceptive reviews with near-perfect precision. This demonstrates that for complex natural language tasks, Deep Learning architectures provide a substantial improvement over statistical machine learning methods.

5. Limitations and Future Work

While the current study successfully benchmarks classical and deep learning models, there are limitations to be addressed. First, although the BERT model achieved superior accuracy (97%), it demands significantly higher computational resources and training time compared to the lightweight SVM model. This makes real-time deployment on low-resource devices challenging.

In the future, this research can be expanded to include model optimization techniques (such as DistilBERT) to reduce computational costs without sacrificing accuracy. Additionally, the current approach relies solely on textual features. Future iterations will aim to integrate behavioral metadata (posting frequency, rating deviation, and timestamps) to create a multimodal detection system.

Furthermore, given the rise of AI-generated content, specific modules to distinguish between human-written fake reviews and text generated by Large Language Models (LLMs) like ChatGPT will be explored. This is crucial as AI-generated texts may exhibit different semantic patterns than manually written deceptive reviews.

6. Conclusion

The most significant part of e-commerce security is the automated detection of deceptive feedback, which protects consumer trust and platform integrity. This study conducted a comprehensive comparative analysis of machine learning algorithms for fake review detection using a dataset of 40,433 reviews. Therefore, this study employed classical algorithms—Support Vector Machine (SVM), Naïve Bayes, and Random Forest—optimized with N-gram features, and benchmarked them against the deep learning model, BERT.

It is revealed from the results that out of the classical models, the Support Vector Machine (SVM) paired with TF-IDF and N-gram features provides the most effective baseline, achieving an accuracy of 92%. However, the findings confirm that the BERT model significantly outperforms all other models, achieving a remarkable accuracy of 97%. The study concludes that while N-grams are effective for capturing local context (phrases), the bidirectional attention mechanism of BERT is crucial for grasping deep semantic nuances. These results offer a robust foundation for implementing high-precision automated fake review detection systems in modern e-commerce environments.

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