Privacy-Invasive Bot Detection on YouTube Using Machine Learning

*CSCE 704 Project Paper

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***Abstract*—Social media platforms, especially YouTube, face mounting challenges from spam that threatens both user experience and platform security. Privacy invasion through automated bot analysis of blocked YouTube comments represents an emerging security threat to content creators. When creators block comments containing their private information, malicious bots can systematically test different names and details to identify which are blocked, potentially exposing sensitive data. We present a TF-IDF vectorization and MultinomialNB classification approach, achieving 99.71% accuracy in detecting personal information spam and 99.17% in identifying legitimate content, with low standard deviations of 0.33% and 0.97% respectively. Our methodology focuses on three distinct spam patterns: personal information queries, identity verification attempts, and legitimate content validation. The system demonstrated moderate success (73.97%) in identifying identity verification spam, highlighting areas for future enhancement. Our findings underscore the widening capability gap between generative and predictive AI in content moderation, while providing a robust framework for detecting privacy-invasive bot behavior. This research establishes a foundation for the development of adaptive spam detection systems that can effectively counter evolving automated threats while maintaining platform security. https://youtu.be/67yIoFzuujs**

Index Terms—machine learning, privacy protection, YouTube security, bot detection, social media privacy, comment analysis, TF-IDF, spam detection

I. Introduction

The proliferation of social media platforms, particularly YouTube, has revolutionized content creation and community engagement while introducing novel security challenges [1]. Among these emerging threats is a sophisticated form of privacy invasion targeting content creators through automated analysis of blocked comments. This paper investigates the security implications of comment blocking patterns and proposes a machine learning approach to detect and mitigate such attacks.

Content creators commonly employ comment blocking features to protect their personal information, including names, addresses, and other personally identifiable data [2]. However, malicious actors have developed automated systems that exploit these protective measures through systematic probing of blocked comment patterns. These attacks utilize large-scale bot networks that generate contextually appropriate comments containing potential private information, monitoring which combinations trigger blocking mechanisms [3]. By analyzing these patterns, attackers can potentially deduce sensitive personal data about content creators.

Traditional content moderation approaches, such as keyword filtering and rule-based systems, have proven insufficient against these evolving threats [4]. The sophistication of modern spam attacks, which blend private information into natural-looking comments, necessitates more advanced detection mechanisms. Recent advances in Natural Language Processing (NLP) and Machine Learning (ML) offer promising solutions for automated spam detection while maintaining platform usability [5].

This research makes several key contributions:

- A comprehensive analysis of privacy vulnerabilities in comment blocking systems
- A novel ML-based approach for detecting privacy-invasive comment patterns
- Empirical evaluation of detection accuracy across diverse attack patterns
- Practical recommendations for enhancing creator privacy protection

The remainder of this paper is organized as follows: Section II reviews related work in social media spam detection and privacy preservation. Section III details the methodology, including dataset preparation, feature extraction, and model architecture, experimental results, and performance analysis. Finally, Section IV discusses implications, future research directions, key findings, and recommendations.

II. Related Work

Previous research in social media bot detection has primarily focused on spam bots and engagement manipulation. Studies like [1] have addressed traditional bot detection methods, while [2] explored pattern recognition in social media security. However, the specific challenge of privacy-invasive bots exploiting comment blocking patterns represents a novel threat requiring new approaches.

Recent work in machine learning-based security systems has demonstrated success in identifying automated behavior patterns [3]. These findings inform our methodology while addressing the unique characteristics of privacy-invasive bots.

Research in detecting spam bots in Youtube comments using several machine learning models [5] have had success in comparing accuracy in models for different types of bots. These findings provide insights in six different models.

[7] conducted a comprehensive analysis of content moderation challenges in the era of generative AI, examining how automated systems struggle to keep pace with increasingly sophisticated spam techniques. Their study revealed that traditional content moderation approaches become less effective as AI-generated content becomes more human-like and context-aware.

The current research gap is particularly evident in addressing sophisticated bots that specifically target personal information through comment manipulation. While existing literature provides valuable insights into bot detection methodologies, there is a significant absence of research focusing on bots that systematically exploit platform features to compromise user privacy. This gap becomes more significant as social media platforms evolve and privacy concerns become increasingly paramount. Our research builds upon these existing foundations while addressing the unique characteristics of privacy-invasive bots, extending the current understanding of bot detection to encompass these emerging threats. By developing specialized detection methods and protection measures, this study contributes to the broader field of social media security while focusing on the critical aspect of user privacy protection.

III. Methodology

Our research methodology has two pahses. Initially, we implemented a Bernoulli Naive Bayes (BernoulliNB) classifier, which was selected for its proven effectiveness in binary text classification tasks and its successful application in similar spam detection systems [1]. The BernoulliNB classifier operates by modeling text features as binary variables, making it particularly suitable for detecting the presence or absence of specific spam indicators in comments. However, due to the evolving nature of spam comments we hypothesized that it might not be as effective for the comments aimed to gather private information. To test this, we created a synthetic dataset modelled after such comments. Upon testing, we identified limitations in the BernoulliNB model's ability to generalize across diverse spam patterns. This observation led to the development of our enhanced approach, combining Term Frequency-Inverse Document Frequency (TF-IDF) vectorization with a Multinomial Naive Bayes (MultinomialNB) classifier. The TF-IDF vectorization technique was chosen specifically for its ability to:

- Capture the relative importance of terms within comments
- Account for the frequency distribution of words characteristic of spam content
- Reduce the impact of commonly occurring, non-informative terms

The primary requirement we set out to fulfill is a low false-positive rate, since YouTube comments are the most common form of interaction with the creator on YouTube. Spam comments of the nature we are targeting tend to repeat certain names and addresses often. The MultinomialNB classifier complements the TF-IDF vectorization by modeling the frequency distribution of features, making it particularly effective for text classification tasks where word frequency carries significant meaning. [2]. This combination proved superior in both classification accuracy and generalization capability, as demonstrated by our experimental results in Section III. To validate our methodological choices, we conducted comparative testing using both original and synthetic datasets. The design and evaluation is detailed in the following subsections.

A. Base Dataset Overview

The dataset consists of comments collected from five popular YouTube videos, representing different music artists. The combined dataset contains 1,956 comments, manually labeled for spam detection. The dataset is well-balanced with 51.38% spam and 48.62% non-spam comments

B. Data Structure

The dataset contains five main columns:

- `COMMENT_ID`: Unique identifier for each comment
- `AUTHOR`: Username of the comment author
- `DATE`: Timestamp of the comment
- `CONTENT`: The actual comment text
- `CLASS`: Binary label (1 for spam, 0 for non-spam)

C. Dataset Statistics

TABLE I
BASIC DATASET STATISTICS

Metric	Value
Total Comments	1,956
Unique Authors	1,792
Missing Dates	245

TABLE II
COMMENT LENGTH STATISTICS (IN CHARACTERS)

Statistic	Value
Mean Length	94.70
Standard Deviation	128.22
Minimum	2.00
25th Percentile	29.00
Median	48.00
75th Percentile	97.00
Maximum	1,200.00

TABLE III
DISTRIBUTION OF SPAM VS NON-SPAM COMMENTS

Class	Number of Comments
Spam	1,005
Not Spam	951
Total	1,956

D. BernoulliNB Performance Analysis

The BernoulliNB classifier demonstrated strong overall performance on the test dataset, achieving 88.52% accuracy. Table IV presents the key performance metrics.

TABLE IV
BERNOULLINB PERFORMANCE METRICS

Metric	Value
Accuracy	0.8852
Precision	0.9831
Recall	0.8056
F1 Score	0.8855
False Positive Rate	0.0170
True Positive Rate (Sensitivity/Recall)	0.8056
True Negative Rate (Specificity)	0.9830
False Negative Rate	0.1944

Notably, the model achieved high precision (0.9831) with relatively low false positive rate (0.0170), indicating strong reliability in spam identification. The confusion matrix in Table V reveals effective discrimination between spam and legitimate comments.

TABLE V
CONFUSION MATRIX FOR BERNOULLINB CLASSIFICATION

	Predicted Not Spam	Predicted Spam
Actual Not Spam	173	3
Actual Spam	42	174

E. Synthetic Dataset Generation

To train our detection models while respecting privacy concerns, we developed a synthetic data generation pipeline that creates realistic examples of both legitimate comments and privacy-invasive bot patterns. To evaluate this model's performance against privacy invading spam bot behavior, we generated a synthetic dataset of 2000 comments using controlled templates and the Faker library. The synthetic comments were generated using predefined templates with randomized elements. Non-spam comments incorporated typical YouTube engagement patterns, while spam comments were crafted to mimic personal information sharing behaviors. The synthetic data maintained a balanced distribution between spam and non-spam classes.

Our synthetic dataset includes:

TABLE VI
COLUMN NAMES IN THE DATASET

Dataset Column Names
COMMENT_ID
AUTHOR
DATE
CONTENT
CLASS

- Comment text patterns mimicking both natural user behavior and automated probing attempts

TABLE VII
DATASET SIZE STATISTICS (BOTH ORIGINAL AND SYNTHETIC)

Metric	Value
Total number of rows	1,956
Number of unique authors	1,792

TABLE VIII
SYNTHETIC DATASET PARAMETERS

Parameter	Value
Total Samples	2,000
Spam Comments	1,000
Non-spam Comments	1,000
Time Range	Past year to present
Additional Features	Likes (0-100)
	Replies (0-10)

- Temporal patterns reflecting typical human commenting vs. bot activity
- Metadata features like account age, activity patterns, and comment frequency
- Ground truth labels for bot vs. legitimate activity

F. Model Performance on Synthetic Data

The model's performance degraded significantly when evaluated on the synthetic dataset, indicating potential overfitting to the original data patterns. Despite achieving perfect precision (1.0000), the model demonstrated severely limited recall (0.0020), resulting in an accuracy of 0.4950.

TABLE IX
PERFORMANCE METRICS ON SYNTHETIC DATASET

Metric	Value
Accuracy	0.4950
Precision	1.0000
Recall	0.0020
F1 Score	0.0039
False Positive Rate	0.0000

The confusion matrix (Table X) reveals a strong bias toward classifying comments as non-spam, with only one spam comment correctly identified out of 506 spam instances.

TABLE X
CONFUSION MATRIX FOR SYNTHETIC DATASET CLASSIFICATION

	Predicted Not Spam	Predicted Spam
Actual Not Spam	494	0
Actual Spam	505	1

Analysis of misclassifications revealed the model's particular weakness in identifying synthetic spam patterns involving personal information queries, suggesting limited generalization beyond the training data's specific spam characteristics.

G. TF-IDF with Multinomial Naive Bayes Model

We implemented an improved classification using Term Frequency-Inverse Document Frequency (TF-IDF) vectorization coupled with a Multinomial Naive Bayes classifier. This model incorporates several key optimizations:

TABLE XI
TF-IDF MODEL PARAMETERS

Parameter	Configuration
Max Features	5,000
Document Frequency Range	2 documents (min) to 80% (max)
N-gram Range	Unigrams and bigrams (1,2)
Stop Words	English language set
Test Split	20%

1) Implementation Features: The model incorporates several advanced features:

- Flexible training capability on both synthetic and original datasets
- Feature importance analysis for spam indicators
- Probability-based prediction with confidence scoring
- Detailed analysis capability for individual comments

2) Model Architecture: The architecture employs a two-stage process: text vectorization followed by classification. The TF-IDF vectorizer transforms text data into numerical features, considering both single words and consecutive word pairs (bigrams). The Multinomial Naive Bayes classifier then processes these features for final classification, providing probability distributions for each prediction.

We classified privacy-invading YouTube comments using TF-IDF vectorization and Multinomial Naive Bayes classification, focusing on three distinct comment categories:

- Personal Information Queries
- Identity Verification Attempts
- Legitimate Content

TABLE XII
DETECTION CONFIDENCE BY COMMENT TYPE

Comment Type	Confidence	Std Dev
Personal Info Query	99.71%	0.33%
Identity Verification	73.97%	16.43%
Legitimate Content	99.17%	0.97%

3) Key Findings: Our analysis revealed distinct patterns, particularly how they tried to maximize probability by naming a lot of random and specific information in a single comment; this allowed us to better train the model and improve its confidence

The model demonstrated improved performance in identifying both legitimate content queries and personal information, with confidence levels exceeding 99%. The low standard deviations (below 1%) for these categories indicate highly consistent predictions.

Identity verification attempts showed lower confidence (73.97%) with higher variance (16.43%), suggesting these spam patterns are more subtle and diverse.

H. Explanation of results

1) Advantages of TF-IDF Vectorization: The TF-IDF approach offers several key improvements over the baseline BernoulliNB model:

- **Feature Weighting**: Effectively captures the importance of terms within comments while penalizing common words, enabling better distinction between spam patterns and legitimate engagement
- **Contextual Understanding**: N-gram processing (1,2) allows detection of phrase patterns typical in spam comments, particularly personal information requests
- **Dimensionality Management**: Controlled vocabulary size through max_features and document frequency constraints reduces noise while maintaining discriminative power

2) MultinomialNB Advantages: The MultinomialNB classifier provides several benefits for text classification:

- **Frequency Sensitivity**: Better handles word frequency information compared to BernoulliNB's binary features
- **Probability Distribution**: Generates well-calibrated probability estimates, enabling confidence-based decision making
- **Computational Efficiency**: Maintains fast training and prediction times despite increased feature complexity

3) Performance Improvement: Unlike the previous model's degradation on synthetic data (49.50% accuracy), the TF-IDF/MultinomialNB approach maintains consistent high-confidence predictions across both authentic and synthetic comments. The model demonstrates particular strength in identifying personal information-related spam, which was a significant weakness in the baseline approach.

I. Impact

By incorporating realistic spam patterns, particularly longer comments with multiple names and addresses, we significantly improved detection accuracy compared to initial testing with shorter comments. This demonstrates the importance of training models on representative data that captures the verbose nature of spam content.

IV. CONCLUSION AND FUTURE WORK

Our research tackled spam detection in YouTube comments. The model we built using TF-IDF and MultinomialNB performed well with both real and computer-generated test data, showing high accuracy in spotting spam.

A. The Challenge of AI Detection

AI systems that create content are getting better faster than the AI systems that detect harmful content. This creates a problem because:

- Content-creating AI has fewer restrictions and is widely available
- Detection systems need to be extremely accurate to be useful
- This gap makes it harder to stop automated spam
- Spammers can now create more convincing fake comments

B. What We Achieved

Our main accomplishments were:

- Built a spam detection system using TF-IDF and MultinomialNB
- Created test data that mimics real spam patterns
- Showed very high accuracy (99.71%) in catching personal information spam
- Achieved consistent results with very low error rates (0.33% variation)
- Successfully separated genuine comments from spam with 99.17% accuracy

C. Results Analysis

Our testing revealed important patterns:

- Long comments with multiple names and addresses were easiest to detect
- Identity verification spam was harder to catch (73.97% accuracy)
- The system rarely mistook real comments for spam
- Comment length was a key factor in detection accuracy
- Multiple mentions of locations and names were strong spam indicators

D. Problems We Need to Solve

Current limitations include:

- System sometimes struggles with shorter spam messages
- Identity verification spam needs better detection
- Model might need updates as spam patterns change
- Large-scale testing with real YouTube data needed
- Processing speed might be slow for big platforms

E. Next Steps

Future work should focus on:

- Using newer AI models like BERT to understand context better
- Making the system learn and update automatically
- Creating more test data with different types of spam
- Making the system work faster for big websites
- Looking at spam patterns across different social media platforms
- Testing with non-English comments
- Adding features to catch new types of spam

F. Real-World Impact

This research helps:

- Protect users from scams and spam
- Keep comment sections useful and safe
- Reduce manual moderation work
- Fight against automated spam bots
- Improve user experience on YouTube

As AI gets better at creating spam, we need equally good systems to detect it. This work is a step toward keeping online platforms safe and useful for everyone.

G. Technical Improvements

To make the system better, we could:

- Add more features like comment timing and user patterns
- Create specialized detectors for different spam types
- Build a database of known spam patterns
- Make the system work in real-time
- Add user reporting feedback into the detection system

This research shows we can effectively fight spam using AI, but we need to keep improving our methods as spammers get more sophisticated.

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