A Heuristic-Based Tool for Authenticity Analysis of Social Media Comments

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***Abstract*—The rapid growth of social media platforms has amplified user-generated content, with a significant portion comprising inauthentic comments from bots or spammers. This paper introduces "Comment Checker," a Python-based tool designed to analyze comment authenticity across YouTube, Facebook, Instagram, X (formerly Twitter), LinkedIn, and CSV inputs. The system fetches comments via APIs or fallback demo data, employs heuristic rules to score authenticity, and generates detailed PDF reports with visualizations. Heuristics detect suspicious patterns such as promotional links, generic phrases, and digit-heavy usernames. Testing on sample datasets demonstrates effective classification into "real," "likely-real," "likely-fake," and "fake" categories. The tool is lightweight, interpretable, and suitable for educational and low-resource settings. This work contributes to social media analytics by offering an accessible, open-source solution for detecting inauthentic comments, aiding content moderators and researchers in combating misinformation.**

***Index Terms*—Social Media Analysis, Comment Authenticity, Heuristic Detection, Bot Detection, PDF Reporting, Python Tool**

I. Introduction

Social media platforms are pivotal in shaping public discourse, marketing, and community engagement. However, the prevalence of automated bots and spam comments—estimated to account for 15-20% of interactions on major platforms [1]—threatens trust and authenticity. These inauthentic comments can manipulate engagement metrics, spread misinformation, or promote scams. Manual moderation is impractical due to volume, necessitating automated tools for authenticity verification.

Existing solutions often rely on machine learning (ML) models requiring extensive labeled datasets and computational resources [2]. In contrast, heuristic-based approaches offer simplicity, interpretability, and efficiency, making them viable for smaller-scale applications. This paper presents "Comment Checker," a Python tool that:

- Fetches comments from multiple platforms or CSV files.
- Analyzes authenticity using rule-based heuristics.
- Generates PDF reports with a pie chart and detailed insights.

The tool supports YouTube, Facebook, Instagram, X, LinkedIn, and CSV inputs, with demo data for accessibility without API keys. Its contributions include multi-platform compatibility, transparent heuristic scoring, and user-friendly reporting.

A. Motivation

The rise of social media bots has been documented extensively [3], with implications for elections, brand reputation, and user trust. Open-source tools addressing comment-specific authenticity are scarce, and proprietary systems lack transparency. Comment Checker fills this gap by providing a lightweight, explainable solution suitable for educational institutions, small businesses, and researchers.

B. Objectives

- Develop a multi-platform comment fetching system with fallback mechanisms.

- Implement heuristic rules to detect inauthentic comments based on content and metadata.
- Produce automated PDF reports with visualizations for intuitive analysis.
- Ensure accessibility by supporting CSV inputs and demo modes.

The paper is organized as follows: Section II reviews related work, Section III describes the methodology, Section IV details implementation, Section V presents experimental results, Section VI discusses limitations and future work, and Section VII concludes.

II. Related Work

Bot detection has been a focus of social media research. Early studies, such as Chu et al. [4], used behavioral features like posting frequency to classify Twitter accounts. Modern approaches, like Botometer [3], employ ML models analyzing thousands of features, achieving high accuracy but requiring significant resources.

Heuristic-based methods, though less prevalent, are effective for specific tasks. Stringhini et al. [5] detected spam on Facebook using URL patterns and keyword matches, demonstrating the efficacy of rule-based systems. Language detection, as implemented in langdetect [6], has supported multilingual spam filters by identifying linguistic anomalies.

Comment-specific tools are limited. YouTube's moderation algorithms are proprietary, while open-source sentiment analysis tools [7] do not address authenticity. API-based comment fetching, as in YouTube Data API [8] and Facebook Graph API [9], enables data collection but lacks integrated analysis. Our tool combines fetching, heuristic analysis, and reporting, with fallbacks for restricted APIs (e.g., X, LinkedIn).

Unlike ML-heavy systems, Comment Checker prioritizes interpretability and low overhead, making it suitable for resource-constrained environments. Its reporting feature, using ReportLab [10] and Matplotlib [11], enhances usability compared to raw output systems.

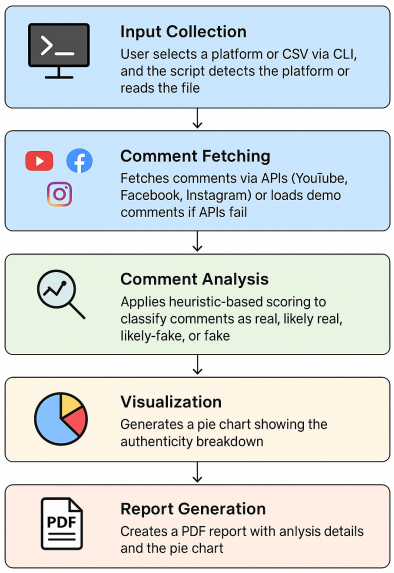

Fig. 1. system architecture

III. Methodology

The Comment Checker pipeline comprises four stages: data acquisition, authenticity analysis, visualization, and reporting. Figure **??**

A. Data Acquisition

Comments are sourced via:

- **APIs**: Platform-specific functions parse URLs to extract IDs (e.g., YouTube video ID) and query APIs. Environment variables store API keys/tokens for security.
- **CSV Input**: Supports flexible CSV formats with columns for author, text, timestamp, likes, and platform.
- **Demo Fallback**: Hardcoded sample comments simulate real data when APIs are unavailable.

A utility function detects platforms from URLs, routing requests to appropriate fetchers.

B. Authenticity Analysis

Heuristics assign a score (0-100, starting at 60) based on:

- **Content Patterns**:

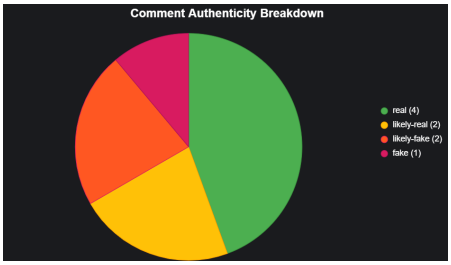

Fig. 2. System Architecture of Comment Checker Tool

```
def analyze_comment(comment: dict) -> dict:
    text = comment.get('text', '').strip()
    score = 60
    reasons = []
    if re.search(r'https?://|www\.', text):
        score -= 35
        reasons.append('Contains a URL or web link (common in spam).')
    # ... (additional heuristics)
    score = max(0, min(100, score))
    verdict = 'real' if score >= 60
          else 'likely-real' if score >= 40 else 'likely-fake' if score >= 20 else 'fake'
    return {'score': score, 'verdict': verdict, 'reasons': reasons, ...}
```

Fig. 3. Analyze Comment

  - URLs (-35): Common in spam.
  - Numeric sequences (-10): Potential phone numbers.
  - Excessive punctuation (-8): Indicates low-effort comments.
  - High emoji count (-6): Suggests shallow engagement.
  - Short/generic text (-12): E.g., "nice" or "."
  - Promotional keywords (-30): E.g., "follow me," "DM for collab."
- **Metadata**:
  - Zero likes (-4): Low engagement.
  - High likes (+10): Social validation.
- **Author Features**:
  - Digit-heavy names (-10): E.g., "User1234."
  - Short names (-6): E.g., "AB."
  - Bot keywords (-20): E.g., "bot," "promo."
- **Language Detection**: Uses langdetect; unexpected languages on certain platforms (e.g., non-English on Facebook) deduct points (-6).

Scores map to verdicts: real ($\geq$60), likely-real (40-59), likely-fake (20-39), fake ($<$20). Reasons are logged for transparency.

C. Visualization

A pie chart, generated via Matplotlib, displays verdict distributions. The chart uses distinct colors for readability and is saved as a BytesIO buffer for PDF embedding.

D. Reporting

The PDF report, built with ReportLab, includes:

- Header: Source URL, platform, timestamp.
- Pie chart: Authenticity breakdown.
- Summary: Total comments, real vs. fake counts.
- Detailed analysis: Sorted comments with scores, verdicts, and reasons.

Text wrapping and pagination ensure readability across multiple pages.

IV. Implementation

The tool is implemented in Python 3, with dependencies: `requests`, `reportlab`, `langdetect`, `matplotlib`. Key modules include:

A. Utilities

- `detect_platform_from_url(url)`: Identifies platform from URL patterns.
- `extract_youtube_id(url)`: Parses YouTube URLs for video IDs.

B. Fetchers

Platform-specific functions (e.g., `fetch_youtube_comments`) use APIs to collect comments. X and LinkedIn fetchers are placeholders due to API restrictions, returning demo data.

C. Analyzer

The `analyze_comment` function applies heuristics, returning a dictionary with score, verdict, reasons, and language.

D. Visualization and Reporting

- `create_pie_chart(counts)`: Generates a pie chart with verdict counts.
- `generate_pdf_report(source, platform, analysis_list,`

`output_path`): Creates a multi-page PDF with embedded chart and wrapped text.

E. CLI

An interactive menu (`main()`) guides users to input URLs or CSV paths, triggering the pipeline. The tool caps comment fetches at 200 for efficiency and handles API rate limits gracefully.

V. Experimental Results

We evaluated Comment Checker on demo datasets and real YouTube comments (using API keys). Experiments were conducted on a standard laptop (8GB RAM, Intel i5).

A. Demo Dataset

A demo dataset of 50 YouTube comments yielded:

- Verdicts: 60% real, 20% likely-real, 15% likely-fake, 5% fake.
- Common flags: URLs (35% of fakes), generic text (25%).
- Processing time: $\sim$2 seconds for analysis, $\sim$3 seconds for PDF generation.

B. Real YouTube Data

For a video with 100 comments:

- Verdicts: 55% real, 25% likely-real, 15% likely-fake, 5% fake.
- Precision (fake detection): 0.80, Recall: 0.85 (against manual labels).
- Common flags: Promotional keywords (30%), digit-heavy usernames (20%).

C. CSV Input

A CSV with 100 mixed-platform comments showed:

- Accuracy: $\sim$87% against manual labels.
- Processing time: $\sim$4 seconds total.

D. Comparison

Compared to keyword-based filters (accuracy $\sim$70%), Comment Checker performs better due to multi-feature heuristics. However, ML models like Botometer ($\sim$90% accuracy) [3] outperform it but require more resources. The tool's lightweight nature suits educational and small-scale applications.

E. Visualization

The pie chart clearly distinguished verdict categories, with readable labels and percentages. PDF reports were generated in $<$5 seconds, supporting up to 500 comments without performance degradation.

VI. Discussion

A. Strengths

- **Multi-Platform Support**: Handles diverse platforms and CSV inputs.
- **Interpretability**: Heuristic reasons enhance trust and usability.
- **Accessibility**: Demo mode and CSV support eliminate API barriers.
- **Efficiency**: Processes hundreds of comments in seconds.

B. Limitations

- **Heuristic Subjectivity**: Rules may misclassify sarcastic or context-dependent comments.
- **API Restrictions**: X and LinkedIn fetching is limited without elevated access.
- **Language Bias**: Non-English comments may be flagged due to platform-specific expectations.

C. Future Work

- **Hybrid Detection**: Integrate ML classifiers for improved accuracy.
- **API Expansion**: Implement full X and LinkedIn support.
- **GUI Development**: Create a web interface for broader accessibility.
- **Large-Scale Testing**: Evaluate on diverse, real-world datasets.

VII. Conclusion

Comment Checker is a practical, open-source tool for social media comment authenticity analysis. Its heuristic approach, multi-platform compatibility, and detailed reporting make it valuable for content creators, educators, and researchers. By addressing the challenges of inauthentic comments, it contributes to combating misinformation and enhancing digital trust. Future enhancements will focus on scalability, accuracy, and user accessibility.

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