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"Multimodal Surveillance Frameworks for Narcotics Detection on Social Media: A Review"

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Abstract: The rapid growth of social media and encrypted messaging platforms has created new challenges for detecting online drug trafficking. Existing monitoring systems struggle with multimedia content, evolving slang, and hidden identities. This review surveys recent AI-based approaches, including multimodal detection, NLP pipelines, computer vision, blockchain forensics, and OSINT frameworks. Key limitations such as static vocabularies, high computational latency, and barriers posed by end-to-end encryption are highlighted. By synthesizing current methodologies and research gaps, this paper provides a comprehensive overview of the state of the art and outlines directions for future development in cyber-enabled narcotics detection.

Keywords: Artificial Intelligence in Cybersecurity, Multimodal Detection Frameworks, Drug Trafficking on Social Media, Encrypted Messaging Platforms (E2EE), Dynamic Slang and Identity Attribution.

I. INTRODUCTION

1.1 Background Social media and encrypted apps like WhatsApp, Telegram, and Instagram have become major channels for drug trafficking. Their anonymity and encryption make it difficult for law enforcement to track and stop these activities.

1.2 The Evolving Threat Traffickers use coded language, slang, emojis, and multimedia to evade detection. They operate across multiple platforms simultaneously, making traditional keyword-based monitoring ineffective.

1.3 Motivation Most current investigations happen after crimes occur. Police need a proactive system that can monitor in real time, detect suspicious text and images, and alert investigators instantly. DrugShield AI aims to fill this gap by enabling faster, preventive action.

II. LITERATURE SURVEY / RELATED WORK

The detection of online drug trafficking has been widely studied using artificial intelligence techniques across social media and encrypted platforms. This section reviews prior research, highlighting methodologies, findings, and limitations to identify gaps addressed in the proposed framework.

Sl. No	Paper Name	Author(s) & Year	Methodology	Findings	Limitations
1	Deep Learning Solution for Monitoring Social Media Drug Sales	P. S. et al., 2026	Gemini LLM, SmolVLM, Whisper Ensemble	Processes text, imagery, and audio concurrently to automate narcotics alerts.	High computational complexity and latency due to heavy model ensembles.
2	Cross-Layer Analysis of Darknet and Telegram Narcotics Distribution Networks	Moreno et al., 2026	Behavioral Pattern Mapping	Established structural links between darknet markets and Telegram syndicates.	Focuses on telemetry; lacks payload parsing or automated text detection.
3	Forensic Analysis of Blockchain Transactions in Illicit Networks	Zhao et al., 2026	Graph Neural Networks (GNNs)	De-anonymized criminal wallet clusters via immutable ledger audits.	Struggles against mixers, tumbling, and zero-knowledge privacy tokens.
4	Investigating Drug Trafficking Using Encrypted Messengers	Anonymous, 2025	NLP + Data Analysis	Classified hidden distribution requests in encrypted ecosystems.	Limited by data sparsity and ethical extraction issues in E2EE networks.

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Sl. No	Paper Name	Author(s) & Year	Methodology	Findings	Limitations
5	AI Detection of Drug Activity in Telegram Bots and Groups	Sonawane et al., 2025	Lightweight Pipeline Classifiers	Flagged illicit merchant behavior in Telegram bots and groups.	Lacks access control and data security guarantees.
6	Proposed Model to Identify Drug Trafficking on Social Media	Padole et al., 2025	CNN + Linguistic Architecture	Proposed model to identify suspicious storefront patterns on social media.	High false positives; lacks real-world deployment metrics.
7	Identifying Drug Traffickers on Encrypted Messaging Apps	Karthikeyan et al., 2025	OSINT Mining + Network Analysis	Mapped localized distribution hubs managed by cartels.	Cannot breach closed, invite-only rings without manual intervention.
8	Narcotrace: Advanced Detection System for Social Media-Based Drug Trafficking	Gautam et al., 2025	Multi-tier ML Framework	Combined text scraping with image processing for trafficking detection.	Vulnerable to adversarial obfuscation and slang manipulation.
9	Testing the Reliability of OSINT Network Data	Breuer, 2025	OSINT Reliability Metrics	Verified organized crime infiltration in legal markets.	Raw OSINT data suffers from noise, incompleteness, and temporal decay.
10	HMLM: Intelligent AI Strategy for P2P Fraud Detection	Anonymous, 2025	Automated Financial Audit	High accuracy in detecting P2P transaction frauds.	Not designed to parse conversational social media layers.
11	Medical Informatics Framework for Drug Harm Detection	Anonymous, 2025	ML Health Telemetry	Managed toxicological incidents via PubMed Central data.	Lacks forensic capability to isolate active criminal distribution cells.
12	Integrated CV + ML Indicators	S. L. R. et al., 2026	Computer Vision + ML	Parsed text embedded in social media graphics.	Computational overhead limits edge-device monitoring.
13	Knowledge-Prompted ChatGPT for Drug Trafficking Detection	Hu et al., 2025	Customized ChatGPT Prompts	Achieved zero-shot classification of complex slang.	Privacy concerns via API exposure; static knowledge cutoffs.
14	Digital Forensic Taxonomy for Illicit Transactions	Anonymous, 2025	Forensic Pattern Mapping	Proposed taxonomy for tracking illicit financial transactions.	Largely theoretical; lacks automated API pipelines.
15	Detection of Illicit Drug Trafficking Events on Instagram	Hu et al., 2025	Deep Learning Detection (Instagram)	Tracked visual + contextual indicators across public accounts.	Limited by API rate caps; traffickers migrate quickly to private ecosystems.

III. RESEARCH GAPS

- **Encrypted Channels – Main Gap (Papers 4, 7, 9)** Detection systems lose visibility once traffickers migrate into private peer-to-peer or end-to-end encrypted networks. Payload content becomes inaccessible unless a manual leak or undercover node is introduced.
- **Static Vocabulary in NLP (Papers 6, 13)** NLP and LLM models rely on fixed training datasets. They cannot dynamically update slang or code words, leading to false positives and misclassification of legal medical discussions.
- **High Computational Latency (Papers 1, 12)** Heavy multimodal ensembles (OCR, CV, NLP) demand large processing pipelines. They introduce delays and are unsuitable for smartphones or real-time mobile endpoints.
- **Weak Blockchain Forensics (Papers 3, 10, 14)** Current forensic methods cannot handle advanced obfuscation like mixers, tumbling, and privacy-centric tokens. Real-time mobile app integration is missing.
- **Closed Channel Isolation (Papers 4, 7, 15)** Systems optimized for public channels fail once networks migrate entirely into private groups. Automated monitoring pipelines lose access completely.

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IV. PROPOSED FRAMEWORK / METHODOLOGY

4.1 Multimodal Detection: Combining OCR and Intent-Based NLP

DrugShield AI integrates OCR with NLP to extract hidden text from screenshots and posters, then analyzes it using models like BERT to detect drug-related intent. In parallel, CV models (YOLO, ResNet) identify trafficking objects such as pills, packets, syringes, and currency, ensuring robust detection beyond plain text.

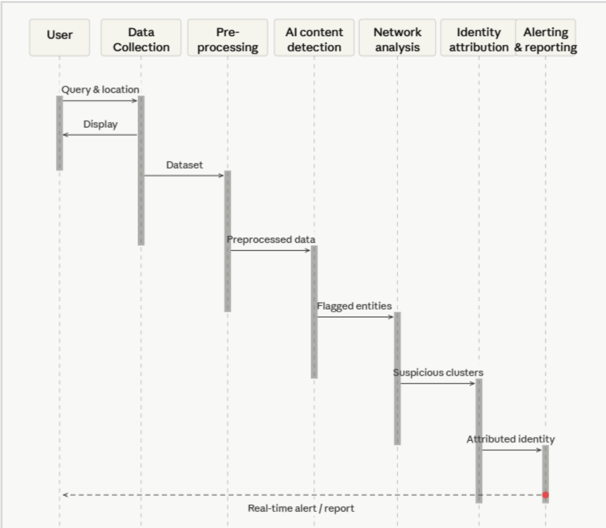

Fig. 1 Sequence diagram

4.2 Dynamic Slang Adaptation

To counter evolving drug slang, DrugShield AI employs continual learning pipelines that update vocabularies in real time. Zero-day slang terms and adversarial spellings are dynamically incorporated, reducing false positives and improving precision.

Region	**Sample Slang Terms**
United States	Snow, Molly, Bars
India	Stuff, Green, Powder
United Kingdom	Gear, Charlie
Australia	Pingas, Bud

Table. 2 Examples of Regional Slang Terms

4.3 Blockchain Forensics Integration

The framework uses Graph Neural Networks and anomaly detection to trace illicit wallet clusters and suspicious P2P transactions. Unlike prior desktop-only systems, DrugShield AI emphasizes mobile-ready forensic modules to address mixers, tumbling, and privacy tokens.

4.4 Real-Time Mobile Deployment

Lightweight model optimization enables deployment on smartphones, overcoming latency issues seen in heavy multimodal ensembles. Edge-device validation ensures faster alerts and practical usability in field operations.

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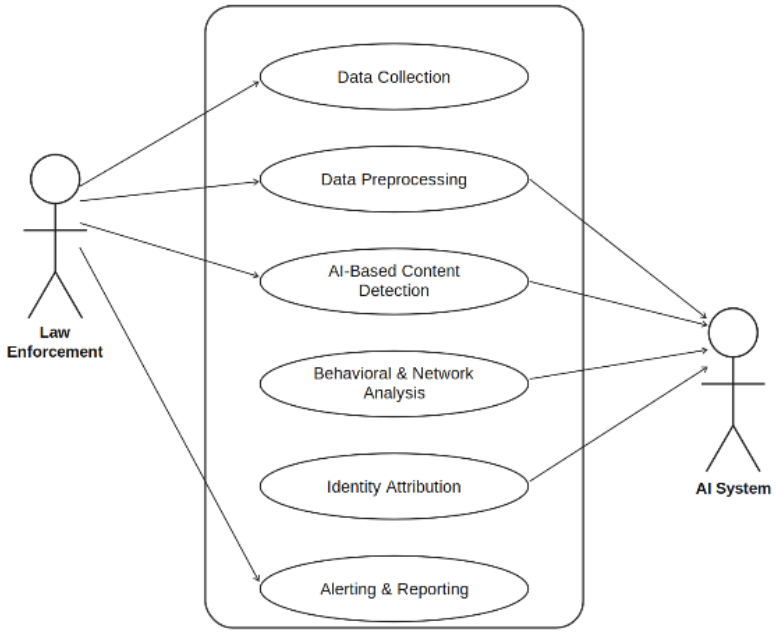

Fig. 2 Use Case diagram

4.5 Closed Channel Monitoring

DrugShield AI incorporates metadata analysis and undercover node integration strategies to regain visibility in private or encrypted ecosystems. This addresses the isolation barrier where conventional monitoring pipelines fail.

4.6 Cross-Platform Correlation

DrugShield AI integrates identity attribution across multiple platforms to link suspicious accounts operated by the same individual. By analyzing usernames, profile photos, phone numbers, device fingerprints, writing styles, and geospatial metadata, the system correlates fragmented digital footprints into unified identities. Stylometric analysis and image matching further strengthen attribution accuracy, enabling law enforcement to track syndicates that exploit anonymity across social media and encrypted messengers.

Platform	**Account Identifier**
Instagram	@greenexpress
Telegram	GreenExpress24
WhatsApp	+91XXXXXXXXXX
Facebook	Green Delivery Bengaluru

Table.**2** Cross-Platform Account Correlation

V. EXPERIMENTAL SETUP AND EVALUATION

5.1 NLP Datasets

DrugShield AI uses NLP datasets to train models for detecting drug-related communication. The *Drug-Related Social Media NLP Dataset* (SEACrowd, Hugging Face) provides slang, coded terms, and intent patterns from online posts. The *DDIE Drug–Drug Interaction Corpus* supports Named Entity Recognition (NER), enabling extraction of drug names and chemical references. Together, these datasets improve contextual understanding and intent detection.

5.2 Visual Datasets

Visual datasets strengthen multimedia analysis. The *NIH RxImage Pill Image Dataset* offers labeled pill images with metadata for CNN-based classification. The *Kaggle Pills Image Dataset* adds high-resolution pill and packaging samples, supporting models like ResNet and EfficientNet. These datasets enable recognition of suspicious drug imagery and packaging patterns across social platforms.

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5.3 Graph and Network Datasets

Graph datasets support analysis of trafficking networks. The *Dark Web Drug Network Graph Dataset* (Harvard Dataverse) provides vendor–buyer records and trafficking graphs for GNN-based community detection. The *Telegram Channel Network Dataset* includes millions of posts and connectivity data, helping trace referral chains, migration patterns, and coordinated communication among suspicious entities.

VI. CONCLUSION

The growth of media and encrypted platforms has made it hard for police to stop online drug trafficking. Traffickers use fake names, secret codes, slang, and pictures to hide their crimes and avoid being caught by monitoring sys tems. DrugShield AI shows how AI can help police by using language analysis to understand coded messages, image analysis to identify suspicious pictures, behavioral analysis to track behavior, and network analysis to monitor con nections between people and accounts. This helps identify suspicious activity, understand hidden intentions, and monitor multiple platforms in real time. Po lice can get alerts and act fast to stop drug trafficking networks. DrugShield AI helps police improve their monitoring, investigate cybercrimes, and respond to changing drug trafficking networks. The system supports investigators by pro viding real-time alerts and proactive detection so police can respond effectively to evolving narcotics trafficking networks..

REFERENCES

[1]. P. S., V. S. B., and S. S. B., "Deep Learning Solution for Monitoring Social Media Drug Sales," ITM Web Conf., vol. 82, p. 03013, 2026. [Online].Available: https://doi.org/10.1051/itmconf/20268203013.

[2]. A. Moreno et al., "Cross-Layer Analysis of Darknet and TelegramNarcotics Distribution Networks," in Proc. Int. Conf. Cyber Security, 2026.

[3]. H. Zhao and K. Williams, "Forensic Analysis of Blockchain Transac-tions in Illicit Networks," IEEE Trans. Information Forensics and Security,vol. 21, pp. 45–58, 2026.

[4]. "Investigating Drug Trafficking Using Encrypted Messengers: NLPand Data Analysis," in Proc. 14th Int. Conf. Digital Forensics, SciTePress,2025, pp. 112–120.

[5]. M. S. Sonawane et al., "AI Detection of Drug Activity in Telegram Botsand Groups," in Proc. IEEE Int. Conf. Advanced Electrical and ComputerApplications (ICAECA), 2025. doi: 10.1109/ICAECA63854.2025.11012406.

[6]. T. B. Padole et al., "Proposed Model to Identify Drug Trafficking onSocial Media," Int. Journal of Innovative Research in Computer and Commu-nication Engineering, vol. 13, no. 2, 2025.

[7]. R. Karthikeyan et al., "Identifying Drug Traffickers on En-crypted Messaging Apps," ResearchGate, 2025. [Online]. Available:https://www.researchgate.net/publication/390724052.13

[8]. R. Gautam et al., "Narcotrace: Advanced Detection System for So-cial Media-Based Drug Trafficking," SciTePress Digital Library, 2025.

[9]. N. Breuer, "Testing the Reliability of OSINT Network Data for In-vestigating Organised Crime Infiltration of Legal-Market Businesses," Trendsin Organized Crime, 2025. doi: 10.1080/17440572.2025.2567277.

[10]. "HMLM: Intelligent AI Strategy to Identify UPI Frauds," Journal ofFinancial Crime, vol. 32, no. 1, pp. 88–102, 2025.

[11]. "Automating Detection of Drug-Related Harms: A Machine Learn-ing Framework," PubMed Central (PMC), 2024. [Online]. Available:https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1101240/.

[12]. S. L. R., H. J. D., J. M. B., M. M., and R. Ravi, "AI-Powered De-tection of Drug Trafficking on Social Media Platforms Using Image Processingand Machine Learning," Diagnostics, vol. 15, no. 15, p. 1914, 2024.

[13]. C. Hu, B. Liu, X. Li, and Y. Ye, "Unveiling the Potential of Knowledge-Prompted ChatGPT for Enhancing Drug Trafficking Detection on SocialMedia," Information and Management, vol. 61, no. 4, 2023.

[14]. "Financial Pattern Analysis in Illicit Transactions," Journal of Digi-tal Investigation, vol. 40, pp. 201–215, 2022.

[15]. C. Hu, M. Yin, B. Liu, and X. Li, "Detection of Illicit Drug TraffickingEvents on Instagram," in Proc. ACM Conf. Computer and CommunicationsSecurity.