The Invisible Crime, The Exploding Data: Leveraging Explainable AI for Automated Victim Identification in Encrypted Trafficking Networks

M Kheekshitha

Student, Department of Forensic Science, Maris Stella College, Vijayawada, Andhra Pradesh, India.
keethumodugu@gmail.com

Abstract:

Modern Human Trafficking (HT) exploits the seamless anonymity of digital platforms, migrating the crime scene from the street to the server. This transformation presents a critical forensic paradox: exploitation is ubiquitous, yet evidence is vast, volatile, and encrypted. Traditional manual review methods are overwhelmed, leading to catastrophic delays in victim identification and intervention.This poster unveils these challenges—and the core motivation of analyzing technology-facilitated trafficking footprints (Latonero, 2012)—by unveiling a comprehensive AI-Integrated Cyber-Forensic Pipeline designed specifically to combat this data saturation crisis. The framework goes beyond standard extraction by coupling OSINT Network Mapping with advanced Machine Learning (ML) for rapid evidence triage. We detail the development and validation of an Explainable AI (XAI) model utilizing Natural Language Processing (NLP), which automates the identification of subtle coercion patterns and code-words within billions of communication logs. Concurrently, Computer Vision is applied for rapid, automated authentication and hash-matching of high-risk multimedia content across multiple platforms, effectively addressing evidence duplication and integrity challenges.Our findings demonstrate that this automated triage approach dramatically reduces the time-to-first-relevant-evidence by an estimated 85%, shifting the investigative focus from data collection to intervention. The work critically addresses the non-technical constraints, particularly the friction points of Mutual Legal Assistance Treaties (MLATs) and the ethical imperative for victim-centric forensic protocols that minimize re-traumatization during digital evidence handling. We advocate for the immediate standardization of this validated, high-efficiency framework to effectively scale the global response against digitally facilitated human trafficking.

Keywords:
Explainable AI (XAI), Digital Forensics, Human Trafficking, Evidence Triage, OSINT, MLAT, NLP, Encryption, Victim Identification.

1. Introduction:

The proliferation of digital platforms has fundamentally changed Human Trafficking (HT) operations, shifting the crime scene from physical locations to encrypted networks and social media. This transition has driven a global data saturation crisis for law enforcement: investigations now involve collecting and processing vast, cross-jurisdictional, and often encrypted digital evidence that manually reviewing traditional forensic methods cannot manage efficiently. This bottleneck causes critical delays in victim identification and intervention, severely undermining prosecution efforts.

D. R. Reddy et al. (eds.), *Proceedings of the First International Conference on Advances in Forensics and Cyber Technologies (ICFACT 2025)*, Advances in Computer Science Research 127,
https://doi.org/10.2991/978-94-6239-610-4_3

While Machine Learning (ML) offers a solution for triage, current AI-based forensic tools largely operate as "black box" models. This lack of transparency compromises the legal admissibility of evidence, as courts require verifiable and interpretable reasoning for automated decisions. A crucial gap thus exists for a scalable, high-throughput digital evidence framework that is also legally accountable.

This paper proposes a novel AI-Integrated Cyber-Forensic Pipeline to address these technical and legal challenges. Our primary contribution is the deployment of an Explainable AI (XAI) framework that couples Natural Language Processing (NLP) for identifying coercion code-words and Computer Vision for automated multimedia authentication. By integrating XAI, our pipeline provides human-readable explanations for every flag, ensuring the evidence is not only rapidly identified but also transparent, traceable, and defensible in a court of law. This research builds upon early examples of using AI for detecting trafficking indicators (Alvari et al., 2016) and the broader operational impact of AI in digital forensics (Jarrett & Choo, 2021).

2. Materials And Methods:

1) DATASET AND ETHICAL PREPARATION:

The pipeline was developed using a dual-modal dataset comprising both publicly accessible and synthetically generated data to model real-world high-volume cyber-trafficking scenarios ethically. The final corpus included approximately 1.2 million textual communications (annotated for coercion/deception) and 450,000 multimedia files (processed for forensic hash values). Strict ethical guidelines were followed to ensure no personally identifiable information (PII) or actual victim data was utilized.

2) SYSTEM ARCHITECTURE OVERVIEW:

The pipeline operates in four logical stages: Ingestion, Triage, XAI Layer, and Reporting. The system ensures end-to-end chain-of-custody logging. The Triage Layer rapidly processes data using two specialized deep learning models, whose predictions are immediately routed to the XAI Layer for interpretation before final reporting.

3) MACHINE LEARNING MODELS:

3.1) NLP MODEL: A fine-tuned BERT (Bidirectional Encoder Representations from Transformers) model classifies text for high-risk indicators, focusing on semantic coercion patterns and low-frequency trafficking code-words.

3.2) COMPUTER VISION MODEL: A Convolutional Neural Network (CNN) performs initial classification and feature extraction for multimedia. Its primary function is automated hash-matching against databases of known exploitation material and flagging visual indicators of staging or exploitation.

4) EXPLAINABLE AI (XAI) IMPLEMENTATION: The core novelty is the XAI Layer, which generates legally transparent explanations for all predictions, addressing the "black box" problem. This implementation follows established conceptual frameworks for XAI in digital forensic contexts (Hall et al., 2022; Kelly et al., 2020). We employed two post-hoc, model-agnostic techniques:

4.1) LOCAL INTERPRETATION (LIME): Applied to individual data points to identify and highlight the specific features (words, pixel clusters) that contributed most to the risk score (Ribeiro et al., 2016). This provides the investigator with a direct, per-instance rationale (e.g., specific terms flagged in a chat log).

4.2) GLOBAL INTERPRETATION (SHAP): Used to consistently attribute the prediction outcome across the entire dataset, generating overall feature importance rankings that inform broader investigative strategy and model validation (Lundberg & Lee, 2017).

5) EXPERIMENTAL VALIDATION: Validation focused on operational effectiveness and legal feasibility. Triage Efficiency was measured by the Time-to-First-Relevant-Evidence reduction compared to manual review. Interpretability Score was assessed by Subject Matter Experts (SMEs) to determine the legal defensibility and actionability of the XAI-generated reports.

3. Results:

This section presents the quantitative performance metrics of the proposed AI-Integrated Cyber-Forensic Pipeline, focusing on the efficacy of the Triage Layer and the legal defensibility achieved by the Explainable AI (XAI) implementation.

1) PREDICTIVE ACCURACY: The Machine Learning Triage Layer demonstrated robust performance, prioritizing the detection of true positives to minimize the risk to victims.

1.1) NLP MODEL (COERCION DETECTION): Achieved a high Recall of 94.7% for the High-Risk (Coercion/Grooming) class, ensuring that nearly all potentially critical text evidence was flagged. The overall macro-average F1-Score was 0.91.

1.2) COMPUTER VISION MODEL: Achieved 98.2% detection accuracy for known exploitation media using cryptographic hash matching, and an 89.1% F1-Score for classifying deceptive multimedia.

2) OPERATIONAL GAINS: The integration of the AI pipeline drastically reduced the time required to initiate an investigation compared to manual methods.

2.1) TIME-TO-FIRST-RELEVANT-EVIDENCE (TFRE): The average time taken to identify and flag the top 10 highest-risk evidence files was reduced from a baseline of 4.8 hours to 0.84 hours (50 minutes). This represents an overall 82.5% reduction in triage time.

3) LEGAL INTERPRETABILITY (XAI): The deployment of Explainable AI (XAI) successfully transformed opaque predictions into legally defensible rationales.

3.1) SME INTERPRETABILITY SCORE: A panel of legal and forensic experts rated the XAI-generated reports (featuring LIME and SHAP explanations) with a mean score of 4.52 out of 5.0 for clarity, actionability, and admissibility in court.

3.2) FEATURE ATTRIBUTION: Local explanations generated by LIME successfully identified and highlighted the specific "coercive words" or semantic

shifts that contributed most to the risk classification, providing direct evidence for the investigator.

4) EXPLANATION FIDELITY: This metric confirms the reliability of the XAI explanations by assessing how accurately they reflect the true behavior of the underlying black-box models.

4.1) FIDELITY SCORE: The pipeline achieved a mean explanation fidelity score of 96.1%. This result verifies that the simpler LIME/SHAP explanations are highly faithful to the complex predictions made by the deep learning models, establishing trust in the XAI layer's output for investigative purposes.

4. Discussions:

The validation of the AI-Integrated Cyber-Forensic Pipeline confirms its role as a disruptive technology that optimizes both speed and legal compliance in digital investigations.

1) CORE IMPACT: SPEED AND SAFETY: The 82.5% reduction in Time-to-First-Relevant-Evidence (TFRE) is the central finding. This speedup is transformative, shifting investigations from a time-consuming manual review to rapid, proactive triage. In exploitation cases, this drastically reduces the time to identify victims and intervene. The model's 94.7% Recall for high-risk evidence ensures that critical evidence of coercion is rarely missed, prioritizing victim safety above all else.

2) LEGAL DEFENSIBILITY AND TRUST: The integrated Explainable AI (XAI) layer successfully solves the "black-box" problem. The high SME Interpretability Score (4.52/5.0) confirms that the system's rationales (generated by LIME/SHAP) are clear, actionable, and suitable for courtroom use. However, as noted in recent forensic literature, while explanation is desirable for transparency, rigorous validation remains a technical and legal necessity for AI-based evaluation in court (Ypma et al., 2023). Crucially, the 96.1% Explanation Fidelity verifies that these simple explanations are true to the complex underlying model, establishing technical trust and allowing for the automated extraction of legally defensible evidence features.

5.Conclusion: This study successfully validates the AI-Integrated Cyber-Forensic Pipeline as a highly effective tool for high-volume digital investigations.

The key achievements are:

1) TIME EFFICIENCY: A critical 82.5% reduction in Time-to-First-Relevant-Evidence (TFRE) was realized, enabling rapid, life-saving interventions.
2) LEGAL COMPLIANCE: The integrated Explainable AI (XAI) layer delivers legally defensible transparency. It produced highly faithful explanations (96.1% Fidelity) rated as actionable and courtroom-ready (4.52/5.0 Interpretability Score).

In conclusion, the pipeline offers a scalable and ethically grounded solution that significantly improves the speed and integrity of digital evidence triage, directly enhancing the fight against complex cybercrimes. Future work will focus on expanding language support and continuous validation against evolving criminal tactics.

References:

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