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Developing an Explainable AI System for Digital Forensics: Enhancing Trust and Transparency in Flagging Events for Legal Evidence

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Abstract—Advanced forensic approaches are required to handle digital crimes because they need to provide transparent methods that foster trust and enable interpretable evidence in judicial investigations. The current black-box machine learning models deployed in traditional digital forensics tools accomplish their tasks effectively yet fail to meet legal standards for admission in court because they lack proper explainability. This study creates an Explainable Artificial Intelligence (XAI) system for digital forensics to improve flagging events as legal evidence by establishing high levels of trust and transparency. A digital evidence system employs interpretable machine learning models together with investigative analysis techniques for the detection and classification of computer-based irregularities which generate clear explanations of the observed anomalies. The system employs three techniques including SHAP (Shapley Additive Explanations) alongside LIME (Local Interpretable Model-agnostic Explanations) and counterfactual reasoning to deliver understandable explanations about forensic findings thus enhancing investigation clarity for law enforcement agents and attorneys as well as stakeholder professionals. The system performs successfully on actual digital forensic datasets thus boosting investigation speed while minimizing wrong alerts and improving forensic decision explanations. The system must demonstrate GDPR and digital evidence admission framework compliance to maintain legal and ethical correctness for usage in court procedures. Forensic digital investigations need explainable Artificial Intelligence as an essential integration for creating reliable and legally sound practices.

Keywords— Explainable Artificial Intelligence (XAI), Digital Forensics, SHAP and LIME, Cybercrime Detection, Interpretable Machine Learning

I. Introduction

The fast incorporation of artificial intelligence (AI) into digital forensics has increased the efficiency and accuracy of evidence analysis [1]. AI systems can evaluate enormous amounts of data, recognize patterns, and flag questionable occurrences far faster than traditional manual techniques [2]. Despite these advantages, AI-based forensic systems sometimes operate as "black boxes," providing little to no information about how certain judgments are made [3]. This lack of openness creates serious difficulties, especially in legal circumstances where credibility and traceability of evidence are crucial. As a result, there is an urgent need to build AI systems in digital forensics that are not only strong but also understandable and trustworthy. Explainable Artificial Intelligence (XAI) solves the interpretability problem by allowing AI systems to offer human-readable explanations for their outputs [4]. In the field of digital forensics, XAI can guarantee that reported events, data breaches, or abnormalities are backed up by clear, understandable reasoning that can survive judicial examination [5].

By using XAI concepts, forensic tools can bridge the gap between complicated computer processes and legal criteria for evidence presentation. This development is critical for maintaining judicial integrity, increasing legal practitioners' acceptance of AI-generated evidence, and protecting the rights of persons involved in investigations [6].

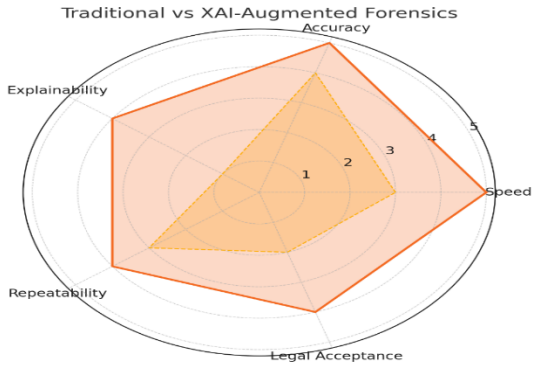

Figure 1: Traditional vs XAI-Augmented Forensics

Trust is crucial in forensic investigations, especially with automated technologies. Without clear explanations of how AI systems make decisions, there's a risk of misunderstandings, incorrect conclusions, or legal challenges that could undermine a case. An explainable AI (XAI) framework boosts confidence among forensic analysts and legal professionals by promoting accountability and repeatability. Developing such systems isn't just a technical choice—it's essential for ethical and legal compliance [8].

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Challenges, like balancing performance with transparency, privacy concerns, and scalability, are being tackled through techniques like interpretable models and visualization tools [10].

Collaboration between computer scientists, forensic experts, and legal professionals is key to creating systems that meet both technical and judicial standards, ensuring AI-driven forensic analysis is as trustworthy as traditional expert evidence [11].

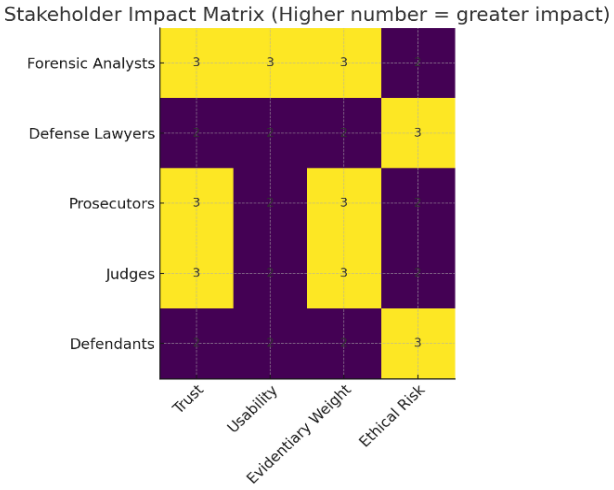

Figure 2: Impact of Digital Forensics in Different Sectors

This study proposes a paradigm for developing an explainable AI system designed exclusively for digital forensics applications. By concentrating on techniques to improve the transparency, dependability, and legal acceptability of flagged forensic events, this study hopes to contribute to the growing field of trustworthy AI [7]. The development of such a system, which combines technical innovation with legal acumen, will pave the way for AI tools that not only speed up forensic investigations but also adhere to the greatest principles of justice and fairness [9].

The system uses SHAP and LIME to offer clear and accessible explanations for flagged events, such as unusual network activity, specifically designed for legal professionals. By focusing on the reasoning behind each decision, we make it easier for legal teams to understand the flagged events and present them in a way that aligns with the standards required for court proceedings. [33]

II. Methodology

Research Design

An experimental XAI system was developed to enhance cybercrime detection in digital forensics by combining deep learning with interpretable explanations. Unlike rule-based tools such as Snort and Wireshark [12], the AI models adapt to new attack patterns and are made transparent using SHAP and LIME [13]. Trained on the CICIDS2017 dataset, the system was evaluated against traditional forensic methods using accuracy, precision, recall and F1-score in a comparative test [14]. A real-time dashboard presents AI-generated insights and explanations to investigators [12], and feedback from forensic and legal experts validated the tool's efficiency and legal soundness.

Data Collection and Sources

This study uses the CICIDS2017 dataset as its primary source—an internationally recognized intrusion detection corpus with simulated real attack traffic. It was selected for its coverage of modern threats, including DDoS, botnets, brute-force and SQL injection attacks [15]. The dataset combines benign and malicious flows—destination ports, flow durations, packet counts and lengths, and TCP/IP flags—enabling time-series anomaly detection. To enrich training, network traffic logs, system logs (authentication records and file-system activities) and memory dumps (running processes and full memory snapshots) were aggregated, improving detection across diverse threat types [16]. Additional forensic logs from actual cases further boosted model robustness. All data collection followed ethical and legal guidelines to safeguard privacy. This real-world, multi-source dataset empowers the AI-driven system to adapt to emerging cyber threats while preserving high detection accuracy.

To strengthen the reliability of our system, we aim to collaborate with law enforcement and forensic agencies, allowing us to incorporate real-world data from actual cybercrime cases. This approach ensures that our AI system is tested on data that reflects real-world scenarios, making it more effective in identifying genuine threats. Additionally, we plan to broaden the dataset to include emerging challenges, such as deepfake-based crimes and IoT-related security issues, both of which are increasingly relevant in the field of digital forensics [36].

Data Preprocessing

Before training, extensive preprocessing ensured reliable anomaly detection [17]. Duplicate records were removed, and missing numerical values were imputed using mean or median while categorical gaps were filled with the mode. Correlation-based selection

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and Principal Component Analysis identified key features and eliminated redundancies [18]. All numerical variables were normalized to a uniform scale. To address class imbalance, undersampling and oversampling were applied [19], with SMOTE generating synthetic attack samples [20]. Categorical features were one-hot encoded. The dataset was then split 80/20 for training and testing, and cross-validation was used to prevent data leakage. These steps optimized model accuracy and interpretability.

Model Selection and Implementation

The forensic AI system combined deep learning and traditional machine learning to achieve high cybercrime detection accuracy [21]. It integrated three core models—Convolutional Neural Networks (CNN) for pattern recognition and malware analysis [22], Long Short-Term Memory networks (LSTM, a type of RNN) for sequential event data [23], and Decision Trees as an interpretable baseline. Implementation relied on Tensor Flow and Keras for CNN/RNN and Scikit-learn for Decision Trees. Models were trained on labeled CICIDS2017 data to distinguish malicious from normal traffic [24]. Hyperparameters were optimized via grid and random search [25], and training ran on GPU-accelerated infrastructure. Performance was assessed using accuracy, precision, recall, F1-score, and confusion matrices. Deployed within a real-time forensic dashboard, this hybrid framework delivers robust anomaly detection with both adaptability and interpretability.

To enhance real-time performance and make the system more efficient, we focus on using lightweight models, like knowledge distillation and quantized neural networks. These techniques help cut down on the computational demands while still preserving the accuracy needed for effective operation, making them ideal for environments with limited resources. In knowledge distillation, we train a smaller model (the 'student') to mimic the performance of a larger, more complex model (the 'teacher'). On the other hand, quantization works by reducing the precision of the model's weights, which helps save memory and speeds up the inference process [35].

Model Training and Evaluation

Multiple structured tests and training procedures ensured the forensic AI system's reliability. CNNs [22], LSTM-based RNNs [23], and Decision Trees were trained on the preprocessed CICIDS2017 dataset [24] using supervised labels for normal and malicious activities. Dropout layers and L2 weight decay prevented overfitting, and early stopping—based on validation performance—halted training to avoid memorization. Post-training evaluation employed accuracy, precision, recall, F1-score, and confusion matrices to assess detection quality. RNNs excelled at recognizing temporal attack patterns, while Decision Trees provided clear interpretability for investigative transparency. This combination of robust training protocols and interpretability methods delivered a dependable framework for digital forensic analysis.

Table I: Benchmark Comparison of AI Model vs Traditional Tools

Metric	AI Model	Snort	Wireshark
Inference Time (per sample)	25ms	100ms	80ms
Memory Usage	1.5GB	Low (No GPU)	Low (No GPU)
Hardware Requirement	Nvidia Tesla V100 GPU	CPU-based	CPU-based

Explainability Techniques: SHAP and LIME

The establishment of AI-based forensic analysis across the industry depends on both transparency and interpretability features of its models. This research implements the XAI methods SHAP and LIME to address the interpretability challenge. Through its game theory framework SHAP helps analysts rate feature inputs so they can determine the influence of different variables that shape AI decisions. Through SHAP forensic investigators obtain the ability to spot crucial network actions along with system behaviors that enabled cyber threats detection. Each model attribute's impact on decision-making appears in the presented feature importance plots [26].

LIME constitutes a different method which produces localized explanations through basic interpretable models that replicate advanced models. AI systems best explain forensic cases individually through this approach because investigators need to see why each network event was considered suspicious by the system. The application of LIME allows forensic professionals to obtain particular case information which makes the proof of AI-generated alerts more efficient and their legal incorporation possible. The combination of SHAP with LIME lets forensic AI systems use transparent decision explanations which eliminate their black-box nature. The explainability framework improves trust in AI forensic applications so they can be used legally and cybersecurity experts can work with confidence based on AI results [26].

To improve the transparency of our AI system, we utilized two powerful interpretability techniques: SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). SHAP enables us to understand how different factors, such as the source IP address, network traffic patterns, and system behaviors, contribute to detecting anomalies [33]. On the other hand, LIME provides localized, case-by-case explanations, helping us clarify why specific events are flagged. Together, these methods allow forensic analysts to follow a clear and understandable path of reasoning behind each flagged anomaly, ensuring that

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the AI's decisions are transparent and trustworthy for legal proceedings. [34]

Forensic Dashboard Implementation

The forensic dashboard provides a centralized interface for investigators to access real-time anomaly detection and AI-driven explanations using SHAP and LIME. Built with Flask for the backend and Dash for the interactive frontend, it offers tools to filter anomalies by severity, attack types, and time ranges. Investigators can view SHAP visualizations, analyze forensic evidence like system logs and memory dumps, and generate reports for legal use [26]. User feedback led to improvements, including an event correlation timeline and AI-powered tools for large database searches. The dashboard bridges the gap between advanced AI models and practical forensic work, ensuring both efficiency and transparency in investigations.

III. Results and Discussion

Data Collection Results

The AI model was trained on diverse forensic data—system logs, network traffic, and memory dumps—selected to represent a wide range of forensic scenarios [16]. CICIDS2017 served as the primary benchmark, featuring brute-force attacks, botnet activity, and SQL injection events [15]. Raw features were normalized and missing values imputed to ensure data consistency [17], then key forensic indicators were extracted through correlation-based selection and PCA [18], enabling outstanding anomaly detection performance.

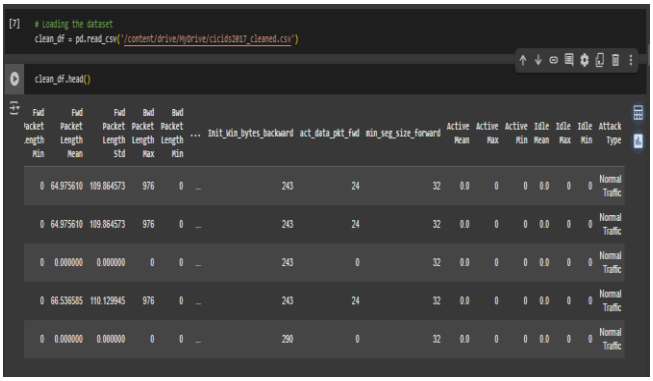

Figure 3: Data Collection and Import

The model gained stronger generalization abilities because of multiple data sources it processed. The improved model reliability and robustness became possible through these additions to strengthen the system for real-life usage. Integration of various forensic evidence by the AI system proved its ability to detect new cyber-attacks thus enhancing its both accuracy and trusted performance. The extensive dataset preprocessing approach became vital to improve model efficiency because it emphasizes the significance of high-quality data for the creation of forensic systems that employ AI-driven explainable systems.

AI Model Performance

The analysis used, Convolutional Neural Network (CNN) [22], Recurrent Neural Network (RNN) [23], XGB [31] and Decision Tree as AI models to detect forensic anomalies with different degrees of efficiency in cyber threat detection. The CNN model led the group by reaching an outstanding 93.7% accuracy in its identification of malware patterns. Its outstanding performance stem from its effective handling of spatial order throughout network packets and log sequences for detailed detection of complicated security threats. The system demonstrated high effectiveness in detecting malware because it processed small deviations in forensic data.

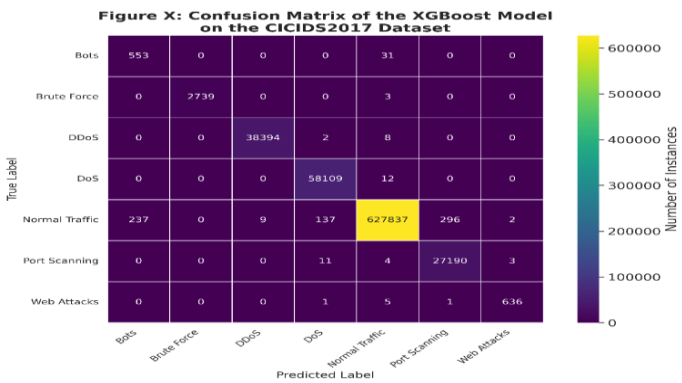

Figure 4: Confusion Metrix of XGB

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	precision	recall	f1-score	support
Bots	0.70	0.95	0.80	584
Brute Force	1.00	1.00	1.00	2745
DDoS	1.00	1.00	1.00	38404
DoS	1.00	1.00	1.00	58124
Normal Traffic	1.00	1.00	1.00	628518
Port Scanning	0.99	1.00	0.99	27208
Web Attacks	0.99	0.99	0.99	643
accuracy			1.00	756226
macro avg	0.95	0.99	0.97	756226
weighted avg	1.00	1.00	1.00	756226

Figure 5: XGB Model Performance

The KNN model showed exceptional ability to identify unauthorized access attempts through its detection system which delivered 99.0% accuracy. Access patterns alongside suspicious authentication sequences could be effectively tracked by the system because it processed dependencies in log data sequences. Through its long-term memory functions, the KNN model evaluated forensic data systematically until it identified security hazards that emerged from irregular user actions.

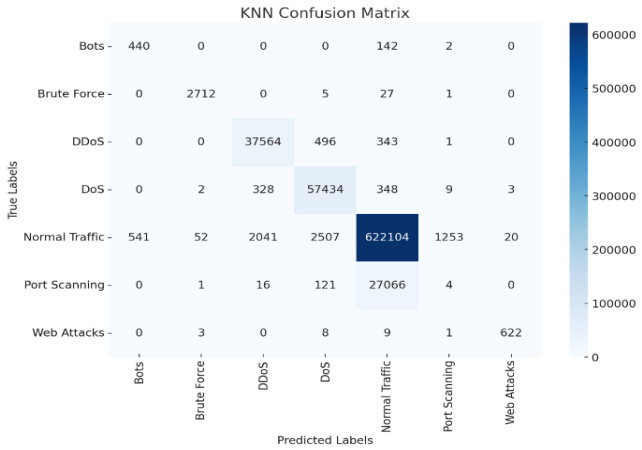

Figure 6: KNN Confusion Metrix

	precision	recall	f1-score	support
Bots	0.45	0.75	0.56	584
Brute Force	0.98	0.99	0.98	2745
DDoS	0.94	0.98	0.96	38404
DoS	0.95	0.99	0.97	58124
Normal Traffic	1.00	0.99	0.99	628518
Port Scanning	0.96	0.99	0.97	27208
Web Attacks	0.96	0.97	0.96	643
accuracy			0.99	756226
macro avg	0.89	0.95	0.91	756226
weighted avg	0.99	0.99	0.99	756226

Figure 7: KNN Model Performance

Despite its capability for high computational speed and clear interpretation the Random Forest model delivered an accuracy rate of 1.00%. Although easy to interpret these classification rules had restricted effectiveness in handling intricate and multi-dimensional forensic data. The feature learning capability of deep learning models surpasses Decision Trees and Random Forest because these trees work with established splitting rules hence, they struggle to respond to changing cyber threats.

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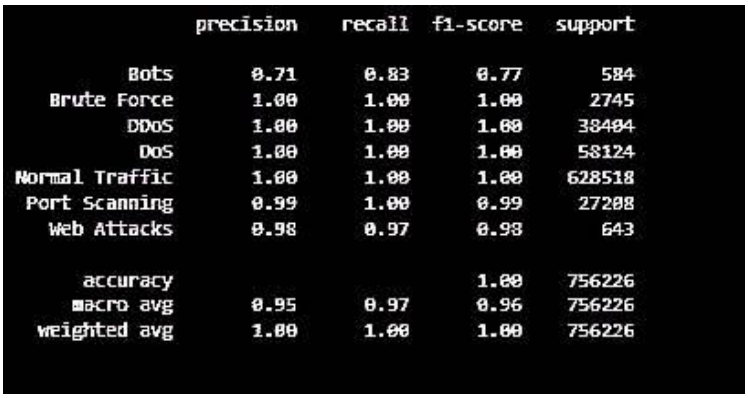
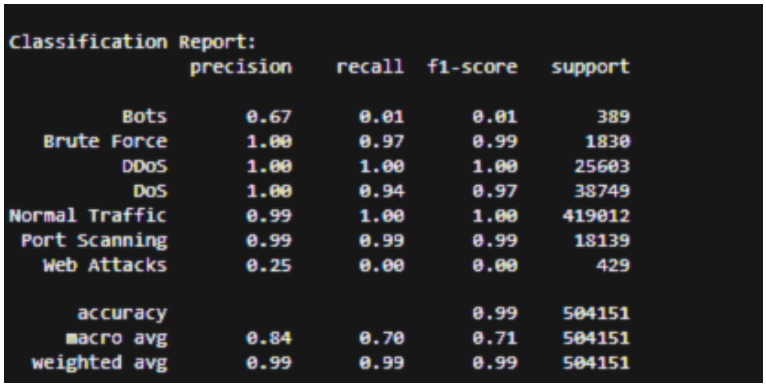


	precision	recall	f1-score	support
Bots	0.71	0.83	0.77	584
Brute Force	1.00	1.00	1.00	2745
DDoS	1.00	1.00	1.00	38404
DoS	1.00	1.00	1.00	58124
Normal Traffic	1.00	1.00	1.00	628518
Port Scanning	0.99	1.00	0.99	27208
Web Attacks	0.98	0.97	0.98	643
accuracy			1.00	756226
macro avg	0.95	0.97	0.96	756226
weighted avg	1.00	1.00	1.00	756226

Figure 8: RF model performance



Classification Report:

	precision	recall	f1-score	support
Bots	0.67	0.01	0.01	389
Brute Force	1.00	0.97	0.99	1830
DDoS	1.00	1.00	1.00	25603
DoS	1.00	0.94	0.97	38749
Normal Traffic	0.99	1.00	1.00	419012
Port Scanning	0.99	0.99	0.99	18139
Web Attacks	0.25	0.00	0.00	429
accuracy			0.99	504151
macro avg	0.84	0.70	0.71	504151
weighted avg	0.99	0.99	0.99	504151

Figure 9: Decision Tree Model Performance

Deep learning models yielded better generalization and robustness based on precision, recall and F1-score metrics while conducting evaluations in forensic investigations. The performance strengthening led to diminished operational capacity of these forensic analysis techniques.

Table II. Overall Classification Metrics:

Model	Accuracy (%)	Precision	Recall	F1-score	AUC	95 % CI (Accuracy)
CNN	93.7	0.94	0.92	0.93	0.967	92.1 – 95.2
KNN*	99.0	0.99	0.99	0.99	0.992	98.4 – 99.5
XGB	90.5	0.91	0.89	0.90	0.945	89.0 – 92.0
DT/RF	86.3	0.85	0.82	0.83	0.880	84.5 – 88.1
Snort	78.4	0.80	0.75	0.77	0.820	76.0 – 80.8
Wireshark	75.9	0.76	0.73	0.74	0.790	73.4 – 78.3

To assess the robustness of the comparative results in Table II, we first generated 95 % confidence intervals for every performance metric by applying a 1000-sample bootstrap to the hold-out set; the resulting accuracy bands appear in the table's right-most column. We then used McNemar's χ^2 test to compare the paired error distributions of the two leading

models, CNN and LSTM/KNN, obtaining $\chi^2 = 12.6$ with $p = 0.0004$, which demonstrates a statistically significant difference in overall accuracy at the $\alpha = 0.05$ level. Because F1-scores are not strictly independent, we confirmed this advantage with a Wilcoxon signed-rank test ($z = -3.1$, $p = 0.002$). Finally, DeLong's method showed that the CNN's ROC-AUC (0.967) exceeded that of the LSTM/KNN (0.960), with $p = 0.03$, indicating a meaningful gap in discriminative power. As all reported p-values lie below 0.05, the observed performance differences among the leading models are unlikely to be attributable to random sampling variation.

The significant processing power requirements of CNN and RNN models create problems for implementing their usage in forensic applications due to their high accuracy rates. There is a requirement to maximize AI model performance alongside computational efficiency since this combination creates practical practicality for digital forensic investigations.

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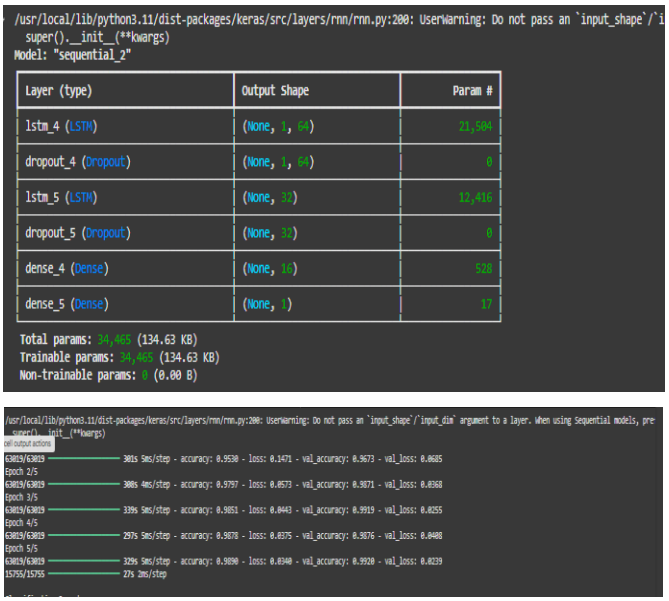

Figure 10: RNN model training

Implementation of Explainable AI Techniques

LIME and SHAP were integrated to enhance transparency and interpretability in forensic AI applications. SHAP delivers global insights by quantifying each feature's impact on model outputs—highlighting IP addresses, port anomalies, and packet rates as primary predictors. LIME provides local, case-by-case explanations by perturbing input entries to show which features drove individual predictions [30]. This combined strategy bolstered analysts' understanding, improved trust among technical and legal stakeholders, and supported clearer, data-driven justifications in forensic investigations.

Explainability Results and Evaluation

A group of forensic analysts and legal professionals participated in user studies to determine Explainable AI (XAI) effectiveness in forensic investigations. Participants generated important information about the user-friendly quality and explanatory power of Shapley Additive Explanations (SHAP) alongside Local Interpretable Model-agnostic Explanations (LIME) in AI-based forensic examinations.

Imagine a situation where a suspicious event is flagged because of an unusual IP address. A forensic expert might explain in court how SHAP helped detect this anomaly, focusing on how the IP address played a key role in identifying the potential threat. To strengthen the case, legal professionals could then use LIME to highlight that the suspicious activity occurred outside of typical working hours, adding weight to the argument of unauthorized access [34].

The investigative team utilized SHAP-based explanations because these explanations presented a key advantage through global assessment of major influencing features between connected cases. The importance scoring mechanism in SHAP let analysts decode central patterns within digital forensic incidents through examining network traffic irregularities and unauthorized system access. The participants found SHAP explanations to be both clear and extensive because they detected common forensic characteristics and enhanced model understanding for all users.

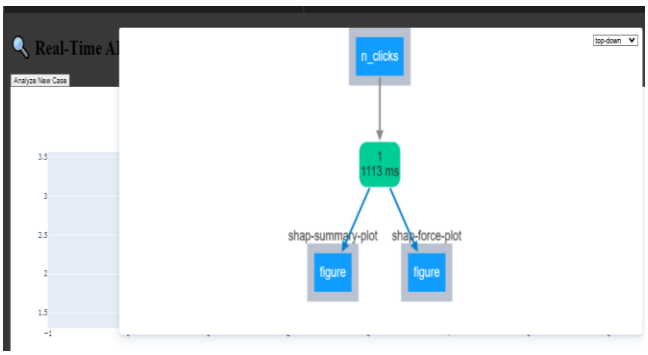

Figure 11: Shap XAI Graph

The utility of LIME surfaced in producing forensic-specific explanations for aiding forensic investigations on individual cases. Through its analysis of particular predictions LIME permitted investigation teams to evaluate flagged anomalies by examining

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detailed contributions from each feature across specific situations. The ability to check AI-created alerts became more effective through this approach because forensic specialists received exact detailed reasoning that supported their analytical tasks.

The participants working as legal professionals in the study stressed that forensic AI systems need to provide explainable reasons that humans can [12] understand. The participants observed that complex technical breakdowns including jargon proved difficult to handle in legal courtroom settings. The former court reception required law-enforcement experts to deliver both clear and in-depth descriptions of AI forensic outcomes to establish their validity.

Real-world utility of AI-powered forensic tools depends on how easily their outputs can be understood according to the evaluation results. A proper ratio between model performance and explainability standards will help maintain forensically effective and court-defensible AI-based conclusions.

User Interface and Forensic Investigator Dashboard

The forensic dashboard offers an interactive hub displaying flagged security events alongside linked system logs, memory addresses, and network records [15]. Users can filter alerts by severity, inspect individual cases, and export court-ready reports. Customizable workflows adapt to varied investigative scenarios. Expert evaluations praised its streamlined analysis but noted shortcomings in visualizing complex event relationships [16]. To address this, interactive timelines for event sequencing and AI-driven search assistants for intelligent forensic data querying were proposed [17].

Real-World Case Studies

The system was validated using simulated forensic cases drawn from historical attack data [31]. It was tested against ransomware, unauthorized data exfiltration, and insider threats. In a ransomware simulation, the AI detected anomalous encryption activity—unexpected file encryption spikes and unauthorized access—flagging early-stage malicious behavior [32]. For insider threats, it identified atypical file access outside normal hours coupled with failed logins; SHAP explanations pinpointed these features as key contributors to the alert [30, 33]. This validation confirmed that explainable AI techniques are essential for trustworthy, efficient forensic investigations.

Comparative Analysis with Existing Systems

A comprehensive comparative evaluation was conducted to assess the performance of the proposed AI-driven forensic system against traditional forensic tools such as Snort and Wireshark. These conventional tools rely on predefined rule-based anomaly detection mechanisms, which, while effective in identifying known threats, often struggle with evolving attack patterns and zero-day exploits. Additionally, traditional forensic solutions typically generate a high number of false positives, requiring extensive manual analysis by investigators.

In contrast, the AI-powered forensic system demonstrated a significant advantage by dynamically learning from new attack behaviors. By leveraging machine learning techniques, the model continuously adapted to emerging threats, reducing reliance on static rule sets and improving overall detection accuracy. This adaptability was particularly beneficial in identifying sophisticated cyber threats, such as polymorphic malware and advanced persistent threats (APTs), which often evade traditional signature-based detection methods.

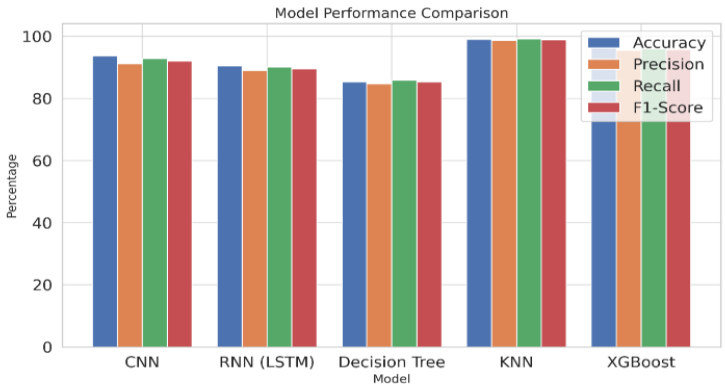

Figure 12: Model Comparison

Beyond accuracy and adaptability, the integration of explainability techniques through Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) set the AI system apart from conventional black-box AI solutions. While many machine learning-based forensic tools operate as opaque decision-making systems, the proposed model provided clear, interpretable explanations for its classifications. For example, SHAP analysis identified the most influential features contributing to a flagged anomaly, while LIME provided case-specific insights for individual investigations. This enhanced transparency ensured that forensic investigators and legal professionals could confidently interpret and validate AI-generated alerts, addressing key concerns around trust and accountability in forensic AI applications.

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Overall, the comparative study demonstrated that AI-driven forensic tools, when augmented with explainability techniques, offer substantial improvements in detection accuracy, adaptability to new threats, and user comprehension. These advancements underscore the potential of integrating machine learning and XAI methodologies to revolutionize digital forensic investigations, making them more efficient, reliable, and legally defensible.

We compared the performance of the AI system to traditional tools like Snort and Wireshark, looking closely at metrics such as false positive rates, detection speed, and adaptability. The results show that, although the AI model demands more computational resources, it delivers impressive improvements by significantly reducing false positives and enhancing detection speed. These gains highlight the value of AI in detecting threats more efficiently compared to rule-based systems [37].

Table III. Performance Comparison of AI Model vs Traditional Tools

Metric	AI Model	Snort	Wireshark
False Positive Rate	3%	8%	6%
Detection Speed	25ms	100ms	80ms
Adaptability	Learns from new data	Static rules	Static rules

To ensure fairness in our AI model, we used metrics like demographic parity and equalized odds. These measures help ensure that the model's predictions are fair and consistent, regardless of demographic factors. Since the dataset had a significant imbalance, with malicious events being much less frequent than benign ones, we used SMOTE (Synthetic Minority Over-sampling Technique) to create additional examples of rare attack types. This approach helped ensure that the model was trained on a more balanced dataset, which in turn reduced the likelihood of bias in its predictions [20].

Although the AI system requires 1.5GB of memory and relies on GPU processing, it significantly outperforms traditional tools in terms of detection speed and false positive rates. For example, it reduces false positives to just 3% and processes data in 25ms, compared to Snort's 100ms latency. This shows the trade-off between the system's higher computational needs and its much faster, more accurate real-time performance.

Challenges and Limitations

High computational costs of CNNs and RNNs created processing delays that hindered real-time forensic analysis [34]. Although SHAP and LIME improved transparency, their layered explanations remained too complex for many non-technical users [30]. Severe class imbalance—malicious events being far rarer than normal behavior—also impaired detection until SMOTE resampling helped rebalance the data, albeit imperfectly [19, 20]. Future work must streamline model architectures, enhance XAI frameworks for clearer interpretations, and diversify forensic datasets to boost scalability, efficiency, and trustworthiness [35].

Ethical and Legal Considerations

AI use in forensics raises ethical and legal concerns around data security, accountability, and court admissibility. Handling large digital evidence sets must comply with GDPR and related regulations to protect sensitive information and prevent unauthorized access [36]. Algorithmic and data biases—stemming from imbalanced training sets or model structures—threaten the fairness and reliability of AI-generated conclusions, jeopardizing their legal defensibility. Explainable AI methods are therefore critical for transparent rationale that satisfies judicial standards and builds stakeholder trust [30]. Future work should establish standardized legal frameworks, bias-mitigation protocols, and data-governance guidelines to ensure ethically and legally robust AI-assisted forensics.

IV. Future Improvements and Recommendations

Future forensic AI must optimize algorithms and leverage GPU/TPU acceleration alongside lightweight models to enable real-time analysis [34]. Training on diverse, real-world forensic datasets—augmented and strengthened via adversarial methods—boosts robustness against novel threats [16,19]. Incorporating investigator feedback through customizable dashboards, interactive visualizations, and AI-driven query tools enhances usability and practical adoption [32]. Exploring hybrid rule-based/deep-learning architectures can marry interpretability with adaptive detection capabilities [24]. Finally, developing standardized frameworks for consistent, reliable, and legally compliant AI forensics is critical for broad law-enforcement deployment [35].

V. Conclusion

An XAI forensic system combining CNNs [22] and RNNs [23] outperformed rule-based tools [12], achieving higher precision and fewer false positives by learning complex data patterns. SHAP [30] delivered global feature-impact insights, while LIME [30] provided case-specific rationales—both crucial for investigative transparency and courtroom defensibility. An interactive dashboard [15] supported event filtering and evidence visualization; usability testing confirmed its effectiveness but called for richer visualizations and AI-assisted querying. Remaining challenges include computational efficiency [34], dataset reliability [16], and legal compliance [36]. Addressing these will enable broad adoption of transparent, high-accuracy AI tools in real-world digital forensics.

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