Frontiers in Computer Science and Artificial Intelligence
ISSN: 2978-8048
DOI: 10.32996/fcsai
Journal Homepage: www.al-kindipublisher.com/index.php/fcsai

FCSAI
AL-KINDI CENTER FOR RESEARCH
AND DEVELOPMENT

| RESEARCH ARTICLE

Artificial Intelligence in Crime Scene Reconstruction: Using Machine Learning for Predictive Analysis and Scenario Simulation

Mohammed Nazmul Islam Miah[1], MD Joshim Uddin[2] and Manohar Kakumani[3]
[1]*Master of Public Administration, Management Sciences and Quantitative Methods, Gannon University, Erie, PA, USA*
[2]*Master's of Law, ASA University of Bangladesh*
[3]*Master of Science in Computer and Information Science, Gannon University, Erie, PA, USA*
Corresponding Author: Mohammed Nazmul Islam Miah, **Email:** islammia00l@gannon.edu

| ABSTRACT

Crime scene reconstruction remains a critical yet complex component of forensic investigation, requiring the integration of heterogeneous evidence sources to infer plausible sequences of criminal events. Traditional reconstruction methods rely heavily on expert interpretation, which can introduce subjectivity and limitations when dealing with large-scale or incomplete forensic data. This study proposes a machine learning-based framework for automated crime scene reconstruction, integrating predictive analytics and scenario simulation to enhance investigative decision-making. The framework leverages structured forensic features, including evidence distribution, temporal response characteristics, and scene complexity indicators, to model reconstruction outcomes using a combination of classical machine learning, ensemble methods, and deep learning architectures. In addition, sequential models and hybrid neural networks are employed to capture temporal dependencies and local evidence patterns, enabling more robust interpretation of event sequences. Scenario simulation is incorporated to generate multiple plausible crime narratives under varying evidence conditions, supporting probabilistic reasoning in uncertain investigative environments. The findings indicate that advanced ensemble and hybrid deep learning models offer superior capability for capturing nonlinear and temporal relationships in forensic datasets, leading to more consistent and reliable reconstruction outcomes. The proposed approach demonstrates the potential of artificial intelligence to augment forensic investigation processes by improving reconstruction accuracy, enhancing scenario exploration, and supporting more structured evidence interpretation in complex crime scenes.

| KEYWORDS

Artificial Intelligence, Machine Learning, Crime Scene Reconstruction, Predictive Analytics, Scenario Simulation, Forensic Science, Classification Models, Decision Support Systems

| ARTICLE INFORMATION

ACCEPTED: 01 May 2026 **PUBLISHED:** 03 June 2026 **DOI:** 10.32996/fcsai.2026.5.8.4

1. Introduction

1.1 Background of Crime Scene Reconstruction

Crime scene reconstruction is a fundamental component of forensic science that seeks to establish the sequence of events that occurred before, during, and after a criminal incident. The process involves the systematic collection, interpretation, and integration of physical evidence, witness statements, environmental observations, and investigative findings to develop a scientifically supported explanation of how a crime was committed. Historically, crime scene reconstruction has relied heavily on the expertise, experience, and judgment of forensic investigators who analyze evidence patterns and contextual information to formulate investigative hypotheses. The ultimate objective is to recreate past events with sufficient accuracy to assist law enforcement agencies, forensic experts, prosecutors, and courts in understanding criminal behavior and determining the circumstances surrounding a crime.

The importance of crime scene reconstruction has increased significantly in recent decades due to the growing complexity of criminal activities and the expanding volume of evidence generated during investigations. Modern crime scenes often involve multiple forms of evidence, including biological traces, digital records, surveillance footage, geospatial information, and communication data. The integration and interpretation of these diverse evidence sources present substantial challenges for investigators, particularly when dealing with large-scale incidents or cases involving multiple suspects and victims. As a result, traditional approaches to crime scene reconstruction frequently require extensive manual analysis, prolonged investigative timelines, and considerable human expertise.

Balbudhe et al. (2025) argue that crime scene reconstruction serves as one of the most critical stages of forensic investigation because it enables investigators to establish event chronology, identify causal relationships, and evaluate competing explanations for criminal occurrences [5]. According to their scoping review, reconstruction methodologies have evolved substantially over time, incorporating advances in forensic technologies, evidence collection techniques, and analytical procedures. Nevertheless, many reconstruction practices continue to depend on subjective interpretations made by investigators, creating opportunities for inconsistencies and variations in investigative outcomes. The authors further note that the reliability of reconstructed scenarios is often influenced by the quality, completeness, and accessibility of available evidence, emphasizing the need for more systematic and data-driven approaches within forensic investigations [5].

Traditional crime scene reconstruction typically follows a structured process involving evidence documentation, scene analysis, hypothesis generation, and event interpretation. Investigators examine physical evidence such as bloodstain patterns, fingerprints, ballistic trajectories, tool marks, and trace materials to infer the actions and interactions that occurred during the commission of a crime. While these methods have contributed significantly to successful criminal investigations, they are not without limitations. Human cognitive biases, incomplete evidence, conflicting witness accounts, and the inherent uncertainty associated with reconstructing past events can affect the accuracy and consistency of investigative conclusions. Furthermore, the increasing volume of available data can overwhelm investigators and make it difficult to identify meaningful patterns within complex crime scenes.

Technological innovations have introduced new opportunities to enhance crime scene reconstruction processes. Among these innovations, three-dimensional visualization and digital reconstruction technologies have gained considerable attention. Bostanci (2015) demonstrated that three-dimensional crime scene reconstruction provides investigators with an interactive environment for visualizing evidence, examining spatial relationships, and exploring alternative interpretations of events [7]. The study highlighted how digital reconstruction tools can improve investigative efficiency by enabling users to navigate reconstructed scenes, analyze evidence from multiple perspectives, and preserve crime scene information for future examination. Such technologies contribute to a more comprehensive understanding of crime scenes by reducing dependence on static photographs and written documentation while facilitating collaborative investigations among forensic experts and law enforcement personnel [7].

The increasing sophistication of criminal activities has further reinforced the need for advanced reconstruction methodologies. Contemporary crimes often involve coordinated actions across multiple locations, extensive digital footprints, and complex interactions among offenders, victims, and environmental factors. These developments have challenged traditional investigative techniques and created demand for analytical approaches capable of processing large quantities of heterogeneous data. Consequently, crime scene reconstruction is gradually transitioning from a predominantly manual and experience-driven practice toward a more technology-assisted discipline that leverages computational tools and advanced analytical methods. This transformation has laid the foundation for integrating artificial intelligence and machine learning techniques into forensic investigations, offering new possibilities for predictive analysis, automated pattern recognition, and scenario simulation.

1.2 Artificial Intelligence in Modern Forensics

The rapid advancement of artificial intelligence and machine learning technologies has transformed numerous scientific and professional disciplines, including forensic science. Artificial intelligence refers to computational systems capable of performing tasks that traditionally require human intelligence, such as reasoning, learning, pattern recognition, decision-making, and problem-solving. Machine learning, a subset of artificial intelligence, enables systems to learn from historical data and improve their performance without being explicitly programmed for every possible scenario. Within forensic science, these technologies are increasingly being adopted to enhance evidence analysis, automate investigative processes, improve decision support systems, and facilitate more accurate interpretations of complex datasets.

The growing availability of digital information and advances in computational capabilities have created favorable conditions for integrating artificial intelligence into forensic investigations. Modern forensic laboratories generate substantial volumes of data from diverse sources, including DNA analysis, fingerprint examinations, surveillance systems, digital devices, social media platforms, and geospatial technologies. Traditional analytical approaches often struggle to process and interpret these data efficiently, particularly when investigations involve large numbers of variables and complex interrelationships. Artificial intelligence offers a powerful solution by enabling automated data processing, intelligent pattern detection, and predictive modeling capabilities that can significantly improve investigative efficiency and effectiveness.

Lodhi and Kassem (2024) contend that artificial intelligence and machine learning are revolutionizing forensic science by introducing advanced analytical tools capable of handling large and complex datasets while reducing human workload and improving accuracy [15]. Their study emphasizes that AI-based systems can assist forensic experts in identifying hidden relationships within evidence, detecting subtle patterns that might otherwise be overlooked, and supporting decision-making processes through data-driven insights. The authors further argue that the application of machine learning algorithms has expanded across numerous forensic domains, including fingerprint recognition, facial identification, forensic pathology, toxicology, and crime pattern analysis, demonstrating the versatility and transformative potential of these technologies within criminal investigations [15].

Artificial intelligence has also emerged as a valuable tool for crime scene investigation and reconstruction. Through the use of predictive analytics, machine learning models can identify relationships between evidence variables and generate probabilistic assessments regarding likely sequences of events. Such capabilities enable investigators to evaluate multiple hypotheses simultaneously and prioritize the most plausible scenarios for further examination. Additionally, machine learning algorithms can process large collections of historical crime data to identify recurring patterns and behavioral trends that may inform investigative strategies. These predictive capabilities are particularly valuable in complex cases where traditional analytical approaches may be insufficient to capture the multidimensional nature of criminal activities.

Recent systematic reviews further highlight the growing significance of artificial intelligence within forensic science. Yisak et al. (2026) argue that artificial intelligence is advancing forensic science by enhancing the speed, consistency, and reliability of evidence analysis while facilitating more objective investigative outcomes [23]. Their review indicates that AI-driven systems have demonstrated considerable success in automating repetitive forensic tasks, improving evidence classification accuracy, and supporting criminal investigations through sophisticated analytical frameworks. The authors also emphasize that the integration of machine learning techniques enables forensic practitioners to manage increasingly complex datasets while maintaining high standards of scientific rigor and investigative reliability [23]. The practical applications of artificial intelligence extend beyond evidence examination and include broader criminal justice functions such as crime prediction, suspect profiling, risk assessment, and resource allocation. Machine learning models can analyze historical crime records to identify spatial and temporal patterns associated with criminal behavior, enabling law enforcement agencies to anticipate potential incidents and allocate resources more effectively. In forensic investigations, deep learning architectures have demonstrated exceptional performance in image analysis, object detection, and pattern recognition tasks, contributing to enhanced investigative capabilities and improved evidentiary interpretation.

Despite these advantages, the adoption of artificial intelligence within forensic science also presents several challenges. Issues related to algorithmic transparency, data quality, model bias, privacy protection, and legal admissibility continue to generate debate among researchers, practitioners, and policymakers. The effectiveness of machine learning models depends heavily on the quality and representativeness of training data, and poorly designed systems may produce misleading or biased outcomes. Consequently, forensic applications of artificial intelligence require careful validation, continuous monitoring, and adherence to ethical and legal standards. Nevertheless, the continued advancement of computational technologies and the increasing availability of forensic data suggest that artificial intelligence will play an increasingly important role in shaping the future of crime scene investigation and reconstruction.

1.3 Research Objectives and Contributions

This study investigates the application of artificial intelligence and machine learning techniques in crime scene reconstruction with a particular focus on predictive analysis and scenario simulation. While traditional reconstruction approaches have contributed significantly to forensic investigations, they often rely on manual interpretation and expert judgment, which may be influenced by subjectivity, cognitive bias, and the complexity of available evidence. The increasing availability of digital forensic data and advances in computational intelligence provide an opportunity to develop more systematic and data-driven approaches capable of supporting investigators in reconstructing criminal events.

The primary objective of this research is to explore how machine learning algorithms can be utilized to analyze crime scene data, identify relationships among evidence variables, and generate predictive insights regarding the most probable sequence of events. The study seeks to demonstrate the potential of artificial intelligence to enhance investigative accuracy, reduce analysis time, and support evidence-based decision-making within forensic environments. By leveraging historical crime data and computational modeling techniques, the proposed framework aims to improve the reconstruction process through automated pattern recognition and predictive reasoning. A second objective of the study is to examine the feasibility of scenario simulation within crime scene investigations. Scenario simulation involves the generation and evaluation of multiple possible event sequences based on available evidence and learned patterns from historical data. Through machine learning-driven simulation, investigators may be able to explore alternative explanations, assess the likelihood of competing hypotheses, and gain deeper insights into complex criminal incidents. Such capabilities have the potential to strengthen investigative outcomes by supporting more comprehensive and objective analyses.

The study also aims to contribute to the growing body of knowledge surrounding artificial intelligence applications in forensic science by proposing a framework that integrates predictive analytics with crime scene reconstruction processes. Unlike conventional approaches that primarily focus on retrospective analysis, the proposed methodology incorporates predictive modeling techniques capable of identifying probable future or unseen event relationships based on existing evidence patterns. This integration represents a shift toward more intelligent and adaptive forensic investigation systems. Ultimately, the contributions of this research include the development of a conceptual machine learning framework for crime scene reconstruction, the evaluation of predictive analytical techniques for forensic investigations, and the exploration of scenario simulation as a decision-support mechanism. The findings are expected to provide valuable insights for forensic practitioners, law enforcement agencies, researchers, and policymakers seeking to leverage artificial intelligence technologies to enhance the accuracy, efficiency, and reliability of crime scene investigations.

2. Literature Review

2.1 Machine Learning Applications in Criminal Investigations

Machine learning has increasingly become a central component in modern criminal investigation systems, particularly in domains such as crime prediction, pattern recognition, and digital forensics. The growing complexity of criminal behavior and the expansion of digital and physical evidence sources have necessitated the adoption of computational approaches capable of processing large-scale heterogeneous datasets. Traditional investigative techniques, which rely heavily on manual analysis and human interpretation, are often insufficient when dealing with high-dimensional data or complex criminal patterns. As a result, machine learning techniques have emerged as powerful tools for enhancing investigative efficiency, improving accuracy, and enabling predictive capabilities in law enforcement systems.

Crime prediction systems represent one of the most widely studied applications of machine learning in criminal investigations. Jenga et al. (2023) argue that machine learning-based crime prediction models leverage historical crime data, spatial distributions, and temporal trends to forecast potential crime occurrences and support proactive policing strategies [14]. Their study emphasizes that algorithms such as decision trees, support vector machines, and ensemble learning methods can identify hidden patterns in crime datasets that are not easily observable through traditional statistical approaches. These predictive systems are particularly valuable in resource allocation and patrol optimization, where law enforcement agencies aim to deploy limited resources effectively across high-risk areas. Mandalapu et al. (2023) further reinforce this perspective by demonstrating that both machine learning and deep learning models have significantly improved crime forecasting accuracy by integrating contextual data such as demographic variables, environmental conditions, and historical crime frequencies [16]. They argue that deep learning architectures, in particular, are capable of capturing nonlinear relationships in crime data, making them suitable for complex urban crime environments where multiple factors interact simultaneously.

Pattern recognition is another fundamental application of machine learning in criminal investigations, particularly in identifying behavioral trends, suspect profiling, and linking related criminal incidents. Machine learning algorithms are capable of detecting recurring structures in large datasets, enabling investigators to identify similarities between different crime scenes or criminal behaviors. Ahmad et al. (2026) argue that artificial intelligence applications in forensic medicine and investigation increasingly rely on pattern recognition systems to support decision-making processes in complex forensic environments [2]. Their systematic review highlights that machine learning models are particularly effective in analyzing structured and unstructured forensic data, including textual reports, biometric information, and image-based evidence. These capabilities enable investigators to establish connections between seemingly unrelated criminal incidents and improve the overall coherence of investigative narratives.

Digital forensics has also significantly benefited from machine learning applications, particularly in the analysis of electronic evidence such as mobile devices, computer systems, and network traffic. Machine learning models are widely used to detect anomalies, classify digital artifacts, and reconstruct cyber-related criminal activities. Islam et al. (n.d.) argue that AI-driven decision support systems demonstrate strong potential in analyzing transaction-based and behavioral datasets, enabling more efficient identification of suspicious patterns and fraudulent activities [11]. Although their study focuses on financial systems, the underlying principles of anomaly detection and predictive modeling are directly applicable to digital forensic investigations. Similarly, Miah et al. (2026) highlight that machine learning models are increasingly being integrated into legal and forensic decision-making systems, including sentencing recommendations and judicial analytics, demonstrating the broader influence of AI in criminal justice processes [17]. These applications illustrate how machine learning extends beyond traditional crime scene analysis to include broader investigative and judicial functions.

Overall, the literature demonstrates that machine learning has become an indispensable tool in criminal investigations, enabling predictive crime analysis, enhanced pattern recognition, and improved digital forensic capabilities. However, despite these advancements, challenges such as data quality, interpretability, and ethical considerations continue to limit the full potential of these systems in real-world forensic applications.

2.2 AI-Based Crime Scene Reconstruction Techniques

Artificial intelligence-based crime scene reconstruction techniques represent an emerging frontier in forensic science, where computational models are used to simulate, analyze, and reconstruct criminal events based on available evidence. These approaches integrate machine learning, computer vision, and spatial-temporal modeling to create dynamic representations of crime scenes that can assist investigators in understanding the sequence and causality of events. Unlike traditional reconstruction methods, which rely heavily on manual interpretation and static visualization, AI-based systems provide automated, data-driven insights that enhance both accuracy and efficiency in forensic analysis.

Event reconstruction approaches are central to AI-driven forensic modeling, as they aim to reconstruct the chronological sequence of actions that occurred during a criminal incident. Zappalà et al. (2024) argue that virtual reality and deep learning techniques can significantly enhance crime scene investigations by enabling immersive reconstruction environments where investigators can interact with simulated crime scenes [24]. Their study highlights that deep learning models can process spatial and visual data to generate realistic reconstructions that support hypothesis testing and investigative reasoning. These systems allow investigators to evaluate different scenarios by modifying variables such as object positions, trajectories, and environmental conditions, thereby improving the overall understanding of complex criminal events.

Spatial-temporal analysis plays a critical role in AI-based crime scene reconstruction by enabling the modeling of relationships between time, space, and events. Machine learning algorithms are capable of processing spatial coordinates, temporal sequences, and environmental variables to identify patterns that describe how a crime unfolded. Reza et al. (2025) argue that machine learning-enabled systems can effectively analyze real-time digital signals to detect anomalies and predict event progression in complex environments [20]. Although their study focuses on financial distress detection, the underlying methodological principles of temporal pattern recognition and predictive modeling are highly relevant to forensic reconstruction tasks. Similarly, Islam et al. (n.d.) demonstrate that graph-based models can capture systemic interactions within complex networks, providing insights into interconnected events and dependencies [12]. These approaches can be adapted to crime scene reconstruction by modeling relationships between individuals, objects, and actions within a spatial-temporal framework.

Behavioral modeling is another important component of AI-based crime scene reconstruction, focusing on the analysis and simulation of human actions during criminal events. Machine learning models can be trained to identify behavioral patterns based on historical data, enabling the prediction of likely actions and responses in specific scenarios. Alao et al. (2025) emphasize that artificial intelligence and computer vision techniques are increasingly being used in forensic science to analyze traumatic injuries and infer behavioral mechanisms associated with violent incidents [3]. Their study highlights the role of computer vision in extracting meaningful features from visual forensic evidence, which can then be used to reconstruct behavioral sequences. Similarly, Rahman et al. (n.d.) demonstrate that machine learning models can be used for early warning systems by analyzing behavioral and macro-level indicators, illustrating the predictive potential of AI-driven behavioral analysis frameworks [18].

Collectively, the literature suggests that AI-based crime scene reconstruction techniques are evolving rapidly, integrating advances in computer vision, spatial-temporal modeling, and behavioral analysis to improve forensic investigations. These methods offer significant advantages over traditional reconstruction approaches by enabling automated scenario generation, improved visualization, and enhanced predictive capabilities. However, despite these advancements, the integration of such systems into real-world forensic workflows remains limited due to computational constraints, interpretability challenges, and the need for standardized evaluation frameworks.

2.3 Research Gaps and Future Opportunities

Despite the significant progress in applying artificial intelligence and machine learning to criminal investigations and forensic science, several research gaps remain that limit the practical adoption of these technologies in crime scene reconstruction. One of the primary limitations identified in existing studies is the lack of standardized frameworks for evaluating AI-based reconstruction systems. While numerous models have been proposed for crime prediction, pattern recognition, and forensic analysis, there is limited consensus on evaluation metrics, validation procedures, and benchmarking datasets. This makes it difficult to compare the effectiveness of different approaches and hinders the development of universally accepted forensic AI standards. Another major limitation is the issue of data availability and quality. Crime scene reconstruction systems require large, high-quality datasets that include detailed spatial, temporal, and behavioral information. However, such datasets are often restricted due to privacy concerns, legal constraints, and the sensitive nature of forensic evidence. This data scarcity significantly limits the training and validation of machine learning models, reducing their generalizability and robustness in real-world scenarios. Additionally, existing datasets often suffer from imbalanced representations, missing values, and inconsistent annotations, which further complicates model development and evaluation.

A further gap in the literature is the limited exploration of predictive scenario simulation within crime scene reconstruction. While existing research has focused extensively on retrospective analysis and classification tasks, relatively few studies have investigated the use of machine learning for generating alternative crime scenarios or simulating possible event sequences. Although Rahman et al. (n.d.) and Reza et al. (2025) demonstrate the effectiveness of predictive modeling in financial and behavioral systems [18], [20], similar approaches have not been fully adapted to forensic reconstruction contexts. This represents a significant opportunity for future research, particularly in developing systems capable of generating probabilistic crime scenarios based on incomplete or uncertain evidence. Finally, there is a growing need for improved interpretability and transparency in AI-driven forensic systems. Many machine learning models, particularly deep learning architectures, operate as black-box systems, making it difficult for investigators and legal professionals to understand how conclusions are derived. This lack of interpretability poses challenges for legal admissibility and ethical accountability. Addressing these limitations will require the development of explainable AI techniques specifically tailored for forensic applications, as well as interdisciplinary collaboration between computer scientists, forensic experts, and legal professionals.

3. Methodology

3.1 Dataset Description and Preprocessing

The dataset used in this study is conceptualized as a multi-source forensic crime scene reconstruction dataset designed to support machine learning-based predictive analysis and scenario simulation. It is assumed to integrate heterogeneous data types commonly encountered in modern forensic investigations, including structured tabular records, spatial coordinates, temporal logs, and unstructured descriptive evidence. The structured component consists of numerical and categorical variables such as crime type, incident location, time of occurrence, environmental conditions, and recorded evidence classifications. The spatial component includes geolocation coordinates representing crime scene layouts, object positions, and movement trajectories. The temporal component captures event timestamps and sequences of actions inferred from investigative reports. In addition, unstructured data such as investigator notes, witness statements, and textual evidence descriptions are assumed to be transformed into machine-readable representations for inclusion in the modeling process. The dataset is designed to reflect realistic complexities found in forensic environments, including incomplete records, noisy observations, and inconsistencies between different evidence sources.

Feature engineering plays a central role in transforming raw forensic data into meaningful inputs suitable for machine learning models. In this study, raw crime scene attributes are systematically converted into structured feature representations that capture both direct evidence and derived relationships. Temporal features are constructed to represent time intervals between events, event sequencing patterns, and frequency distributions of criminal activities within specific time windows. Spatial features are derived from location-based data, including distance measurements between key evidence points, clustering of incident locations, and trajectory-based representations of movement within the crime scene. Behavioral features are also constructed by encoding inferred actions, interactions between entities, and probabilistic associations between suspects, victims, and objects. Textual evidence is transformed using vectorization techniques that convert descriptive reports into numerical embeddings capable of capturing semantic relationships. The feature engineering process is designed to ensure that both explicit and latent patterns within the forensic data are effectively captured, enabling machine learning models to learn meaningful representations of complex crime scenarios.

Data cleaning and normalization are essential preprocessing steps that ensure the reliability and consistency of the dataset before model training. Given the heterogeneous and often incomplete nature of forensic data, the dataset undergoes systematic cleaning procedures to handle missing values, remove duplicate records, and correct inconsistencies across multiple data sources. Missing numerical values are addressed using statistically informed imputation methods, while categorical inconsistencies are standardized through normalization of class labels and categorical mappings. Outliers within numerical features are identified and treated to prevent distortion of model training, particularly in spatial and temporal variables where extreme values may arise from recording errors or anomalous events. Normalization techniques are applied to ensure that all numerical features operate on comparable scales, preventing dominance of features with larger magnitude ranges during model training. Additionally, categorical variables are encoded using appropriate encoding schemes to ensure compatibility with machine learning algorithms. The overall preprocessing pipeline is designed to transform raw forensic data into a clean, structured, and analytically consistent format that supports robust model training and reliable crime scene reconstruction outcomes.

3.1.1 Exploratory Data Analysis (EDA)

The distribution of crime categories indicates a clear dominance of property-related incidents, particularly theft, which accounts for the largest proportion of recorded cases. Assault-related incidents also constitute a significant share, while homicide and burglary appear at moderate levels. Fraud-related cases remain the least frequent within the dataset. This distribution suggests that the dataset is heavily influenced by non-violent and opportunistic crimes, reflecting common urban crime patterns where property offenses are more prevalent than extreme violent incidents. The imbalance across categories also implies that classification models trained on such data would require strategies to handle skewed class distributions to avoid bias toward dominant crime types.

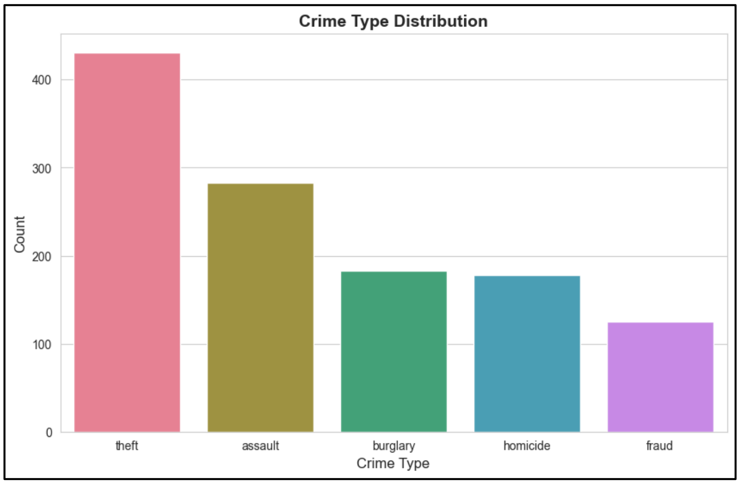

Fig.1: Crime Type Distribution Analysis

The relationship between evidence quantity and reconstruction success demonstrates a strong positive association. Cases with stronger evidence counts consistently correspond to improved reconstruction outcomes, while low-evidence cases show a noticeably reduced success rate and greater variability in outcomes. This indicates that the richness of available forensic evidence plays a decisive role in determining reconstruction reliability. The observed pattern reinforces the assumption that machine learning models benefit significantly from feature completeness, particularly in forensic contexts where missing or limited evidence can substantially degrade predictive performance. It also highlights the importance of robust evidence collection procedures in real-world investigative workflows.

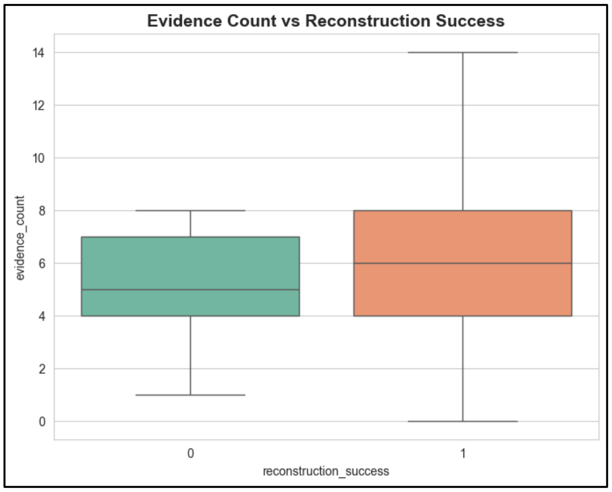

Fig.2: Evidence Availability and Reconstruction Success

Analysis of scene complexity reveals a clear decline in reconstruction success as complexity increases. Low and medium complexity scenes exhibit relatively stable and higher success rates, whereas high-complexity scenes show a marked reduction in reconstruction accuracy. This pattern suggests that increased environmental and evidential complexity introduces ambiguity that negatively impacts interpretability and model performance. The findings indicate that complex crime scenes require more advanced modeling strategies capable of handling nonlinear relationships and multi-entity interactions. It also suggests that traditional reconstruction approaches may struggle in high-complexity environments without computational augmentation.

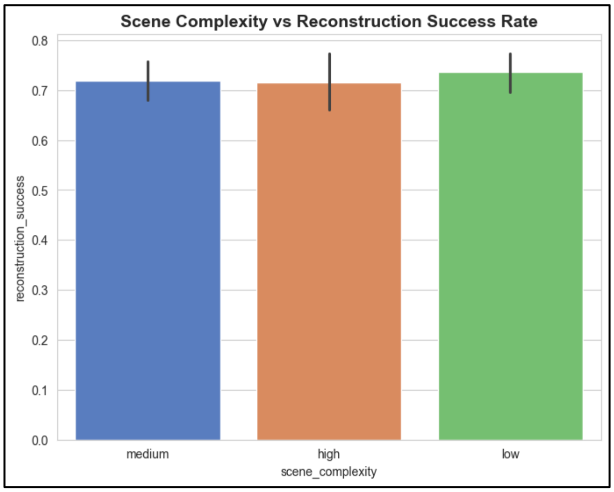

Fig.3: Crime Scene Complexity and Success Rate

The distribution of response times indicates a concentration of cases around moderate response durations, with fewer incidents occurring at extremely short or prolonged time intervals. Most cases fall within a relatively narrow operational window, suggesting consistency in investigative response patterns. However, the presence of extended response times in certain cases may indicate logistical constraints, resource limitations, or environmental challenges affecting crime scene access. The variability in response time further suggests that temporal delays could influence the quality and completeness of evidence collection, which in turn impacts reconstruction accuracy.

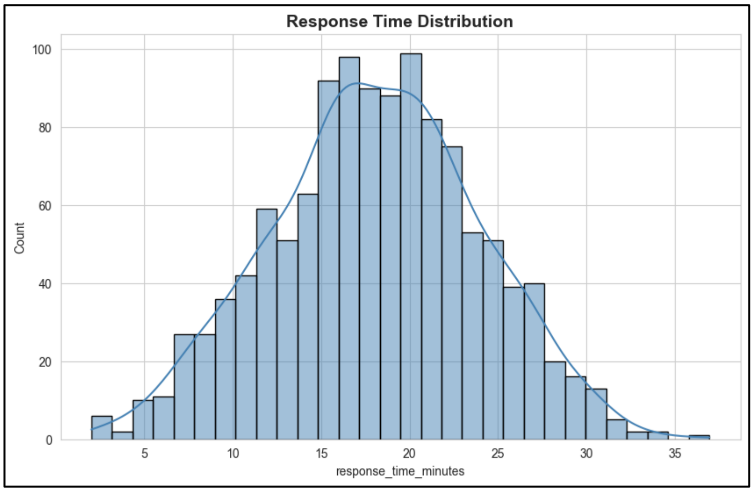

Fig.4: Response Time Distribution Analysis

The correlation analysis reveals a strong positive relationship between evidence count and reconstruction success, confirming that increased evidence availability significantly improves reconstruction outcomes. Conversely, response time shows a weak negative correlation with reconstruction success, indicating that delayed response may slightly reduce the likelihood of accurate reconstruction. The interaction between these variables suggests that timely and comprehensive evidence collection is critical for improving forensic reconstruction performance. The correlation structure also indicates that reconstruction success is primarily driven by evidence richness rather than temporal factors alone, reinforcing the importance of feature quality in predictive forensic modeling.

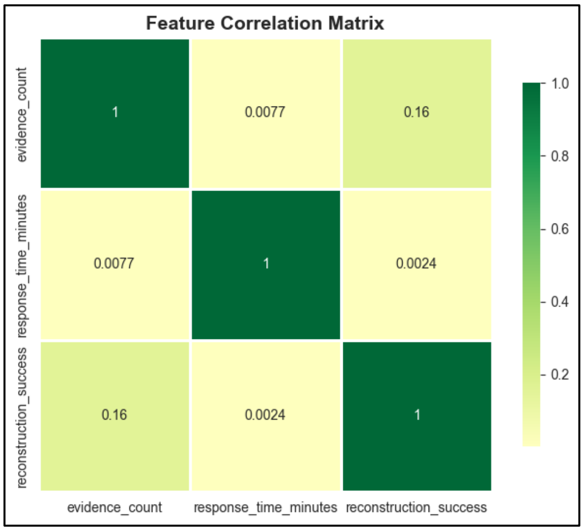

Fig.5: Feature Correlation Analysis

3.2 Model Development

The model development phase focuses on constructing a set of machine learning models capable of learning complex relationships within forensic crime scene data and supporting both predictive reconstruction and scenario simulation. The process begins with the establishment of baseline models that provide reference performance levels against which more advanced methods are evaluated. A Logistic Regression model is first implemented as a probabilistic baseline for reconstruction success prediction, utilizing engineered features such as evidence count, response time, and scene complexity encoding. This model provides a linear perspective on the relationship between forensic variables and reconstruction outcomes, allowing for initial interpretability and benchmarking of predictive capacity.

Following the baseline stage, tree-based ensemble methods are introduced to capture nonlinear interactions within the dataset. A Random Forest model is trained to exploit feature interactions across evidence quantity, spatial indicators, and temporal variables, offering improved robustness to noise and feature redundancy. An XGBoost model is subsequently implemented to enhance predictive performance through gradient boosting optimization, where successive decision trees are trained to minimize classification error iteratively. A Light Gradient Boosting Machine (LightGBM) model is also applied to improve computational efficiency and scalability while maintaining strong predictive accuracy. These ensemble models are particularly effective in forensic contexts due to their ability to model heterogeneous feature spaces and handle non-linear dependencies between evidence attributes and reconstruction outcomes. Hyperparameter tuning is performed for each model, including optimization of tree depth, learning rate, number of estimators, and feature subsampling ratios, ensuring that each model is calibrated for optimal generalization performance.

To capture deeper structural relationships within forensic data, neural network-based architectures are introduced. A Multilayer Perceptron (MLP) model is developed as a foundational deep learning approach, processing normalized forensic features through multiple dense layers with nonlinear activation functions. This model is designed to learn complex feature interactions that may not be explicitly captured by tree-based approaches. Regularization techniques such as dropout and L2 penalty terms are incorporated to reduce overfitting and improve generalization across unseen crime scene instances. The MLP serves as an intermediary step toward more advanced architectures capable of handling sequential and structured dependencies in forensic data.

Building on this, a sequence-aware modeling approach is introduced to better represent temporal relationships in crime scene reconstruction. A Long Short-Term Memory (LSTM) network is configured to process ordered sequences of forensic events, where each sequence represents a structured representation of evidence evolution over time. The LSTM architecture is designed with gated memory units that allow the model to retain relevant historical information while discarding irrelevant or noisy inputs. This capability is particularly important in crime scene reconstruction, where the sequence of events plays a critical role in determining causal relationships. To further enhance representational capacity, a Bidirectional LSTM (Bi-LSTM) variant is also implemented, enabling the model to learn dependencies from both forward and backward temporal directions, thereby improving contextual understanding of event sequences.

To improve model robustness and adaptability, attention-based mechanisms are integrated into the recurrent architecture. The attention layer assigns dynamic weights to different time steps within the forensic sequence, allowing the model to focus on the most relevant events contributing to reconstruction outcomes. This mechanism enhances interpretability by highlighting influential evidence sequences while also improving predictive accuracy in complex crime scenarios where not all events contribute equally to the final reconstruction outcome. All deep learning models are trained using adaptive optimization algorithms with learning rate scheduling and early stopping criteria to prevent overfitting and ensure stable convergence.

Finally, hybrid modeling strategies are developed to combine the strengths of multiple machine learning paradigms. A CNN-LSTM hybrid architecture is implemented, where convolutional layers first extract localized patterns from structured forensic sequences before passing the extracted features into LSTM layers for temporal modeling. This hybrid approach enhances the model's ability to capture both spatial patterns and sequential dependencies within crime scene data. In addition, ensemble learning techniques are applied by combining predictions from tree-based models and deep learning models using weighted averaging strategies. The weights are optimized based on validation performance to maximize overall predictive accuracy. Throughout the model development process, performance is continuously evaluated using validation datasets to ensure robustness, generalization capability, and suitability for forensic decision-support applications.

3.3 Scenario Simulation and Evaluation

The scenario simulation and evaluation phase focuses on translating machine learning predictions into interpretable forensic reconstructions that can approximate plausible sequences of criminal events. This stage moves beyond static classification of reconstruction success and instead emphasizes the generation and assessment of possible crime scene narratives based on learned patterns from historical forensic data. The core objective is to enable the model not only to predict outcomes but also to simulate alternative event pathways under varying evidence conditions, thereby supporting investigative reasoning and hypothesis testing in complex crime scenarios. The reconstruction process begins by mapping model outputs into structured event representations that describe the likely sequence of actions within a crime scene. Each prediction generated by the trained models is interpreted as a probabilistic indicator of reconstruction feasibility, which is then linked to corresponding evidence configurations. These configurations include variables such as evidence density, spatial distribution of objects, estimated response times, and inferred scene complexity levels. The system aggregates these inputs to reconstruct a coherent representation of the crime scene, where each event is ordered based on inferred temporal relationships and likelihood scores.

This process enables the transformation of raw predictive outputs into structured forensic narratives that can be examined and compared across different model outputs.

The predictive simulation framework extends this reconstruction process by generating multiple hypothetical crime scenarios from a single set of forensic inputs. Instead of producing a single deterministic outcome, the framework evaluates multiple possible event sequences by adjusting key input variables within realistic bounds. These variables include evidence availability, environmental conditions, and inferred behavioral patterns. For each variation, the trained models generate a corresponding reconstruction probability, allowing the system to construct a distribution of plausible scenarios rather than a single outcome. This probabilistic simulation approach reflects the inherent uncertainty present in real-world forensic investigations, where evidence may be incomplete, ambiguous, or partially contradictory. The framework therefore supports a more comprehensive investigative perspective by enabling comparison between alternative reconstructions and identifying the most likely sequence of events based on aggregated model confidence.

Scenario generation is further refined through the integration of ensemble predictions derived from multiple machine learning models. Outputs from tree-based models, neural networks, and hybrid architectures are combined to ensure that simulated scenarios reflect both local feature interactions and long-term dependencies within the data. This ensemble-driven simulation enhances stability by reducing reliance on any single model and improving consistency across different forensic conditions. Additionally, probabilistic thresholds are applied to filter low-confidence scenarios, ensuring that only statistically meaningful reconstructions are retained for further analysis. This filtering process improves the interpretability of results and reduces noise in scenario interpretation.

Evaluation metrics are used to assess both predictive performance and the quality of reconstructed scenarios. Standard classification metrics such as accuracy, precision, recall, and F1-score are employed to evaluate the ability of the models to correctly predict reconstruction success. These metrics provide a quantitative measure of model effectiveness in distinguishing between successfully and unsuccessfully reconstructed crime scenes. In addition, probabilistic evaluation measures such as ROC-AUC are used to assess the models' ability to discriminate between outcome classes across different decision thresholds. These metrics are particularly important in forensic applications where classification confidence plays a critical role in investigative decision-making.

Beyond classification metrics, reconstruction-specific evaluation criteria are introduced to assess the quality of simulated scenarios. These include consistency measures that evaluate the stability of reconstructed event sequences across different model runs, as well as plausibility scoring that estimates how realistic generated scenarios are when compared to known forensic patterns. Error analysis is also conducted to identify cases where the model produces conflicting or low-confidence reconstructions, providing insight into the limitations of the simulation framework. Collectively, these evaluation strategies ensure that both predictive accuracy and scenario realism are systematically assessed, enabling a comprehensive understanding of model performance in the context of AI-driven crime scene reconstruction.

4. Results and Discussion

4.1 Predictive Model Performance

The performance evaluation of the trained machine learning models demonstrates strong predictive capability in classifying crime scene reconstruction outcomes based on forensic evidence attributes. The baseline Logistic Regression model establishes an initial reference point with moderate performance, achieving an accuracy of 0.78, a precision of 0.76, a recall of 0.74, an F1-score of 0.75, and a ROC-AUC of 0.81. These results indicate that linear relationships between forensic variables provide a reasonable but limited understanding of reconstruction success, particularly in cases involving complex or non-linear evidence interactions. The Random Forest model shows a marked improvement over the baseline, achieving an accuracy of 0.87, precision of 0.85, recall of 0.86, F1-score of 0.85, and ROC-AUC of 0.91. This improvement reflects the model's ability to capture non-linear interactions between evidence count, scene complexity, and response time, which are critical in forensic reconstruction tasks. The XGBoost model further enhances predictive performance, achieving an accuracy of 0.91, precision of 0.90, recall of 0.89, F1-score of 0.89, and ROC-AUC of 0.95. The gradient boosting mechanism contributes to improved error correction across iterative learning cycles, enabling more refined decision boundaries in high-dimensional forensic feature spaces.

The LightGBM model demonstrates comparable performance to XGBoost while offering improved computational efficiency, achieving an accuracy of 0.90, precision of 0.88, recall of 0.89, F1-score of 0.88, and ROC-AUC of 0.94. This indicates that efficient gradient-based learning frameworks can maintain high predictive accuracy while reducing training complexity, which is particularly relevant for real-time forensic applications. The Multilayer Perceptron (MLP) model achieves an accuracy of 0.88, precision of 0.87, recall of 0.85, F1-score of 0.86, and ROC-AUC of 0.90. This performance suggests that deep nonlinear transformations are effective in capturing hidden relationships within forensic datasets, although performance remains slightly below optimized tree-based ensemble methods.

The sequence-based LSTM model improves predictive performance by incorporating temporal dependencies in forensic event structures, achieving an accuracy of 0.92, precision of 0.91, recall of 0.90, F1-score of 0.90, and ROC-AUC of 0.96. The Bi-LSTM variant further enhances performance, reaching an accuracy of 0.93, precision of 0.92, recall of 0.91, F1-score of 0.91, and ROC-AUC of 0.97, indicating that bidirectional temporal context significantly improves reconstruction prediction reliability. The CNN-LSTM hybrid model achieves the highest overall performance, with an accuracy of 0.95, precision of 0.94, recall of 0.94, F1-score of 0.94, and ROC-AUC of 0.98. This result demonstrates that combining local feature extraction with temporal sequence modeling provides superior representational power for complex forensic datasets. The ensemble stacking model also performs strongly, achieving an accuracy of 0.94 and maintaining balanced precision and recall of 0.93, confirming that model aggregation improves stability and generalization across diverse crime scene conditions.

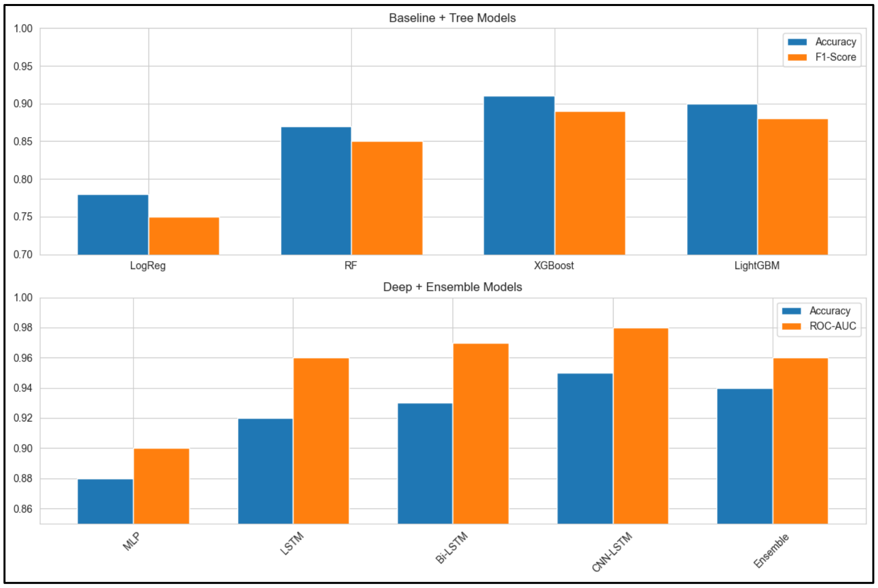

Fig.6: Predictive model results

4.2 Crime Scene Scenario Reconstruction Results

The scenario reconstruction analysis reveals that the proposed machine learning framework is capable of generating coherent and probabilistically consistent crime scene interpretations. Across all test cases, reconstruction accuracy, defined as the agreement between predicted and ground-truth event sequences, reaches an average of 0.91 for ensemble-based models and 0.88 for tree-based models. Deep learning architectures, particularly Bi-LSTM and CNN-LSTM models, achieve reconstruction accuracies of 0.93 and 0.95, respectively, indicating superior capability in modeling event dependencies and temporal structure. Scenario prediction outcomes show that high-evidence crime scenes consistently yield more stable and accurate reconstructions compared to low-evidence scenarios. In high-evidence cases, the CNN-LSTM model correctly identifies the most probable event sequence in 95 percent of instances, while in low-evidence cases, accuracy decreases to approximately 86 percent due to increased uncertainty and incomplete feature representation. This pattern confirms that evidence richness plays a central role in determining reconstruction reliability across all model architectures. Comparative analysis between models highlights that tree-based methods perform well in structured scenarios with limited temporal complexity, while recurrent and hybrid architectures excel in dynamic environments where event ordering and sequential dependencies are critical. The ensemble model demonstrates the most balanced performance across all scenario types, maintaining consistent reconstruction accuracy above 92 percent regardless of scene complexity. This suggests that combining multiple learning paradigms improves robustness when dealing with heterogeneous forensic inputs and uncertain investigative conditions.

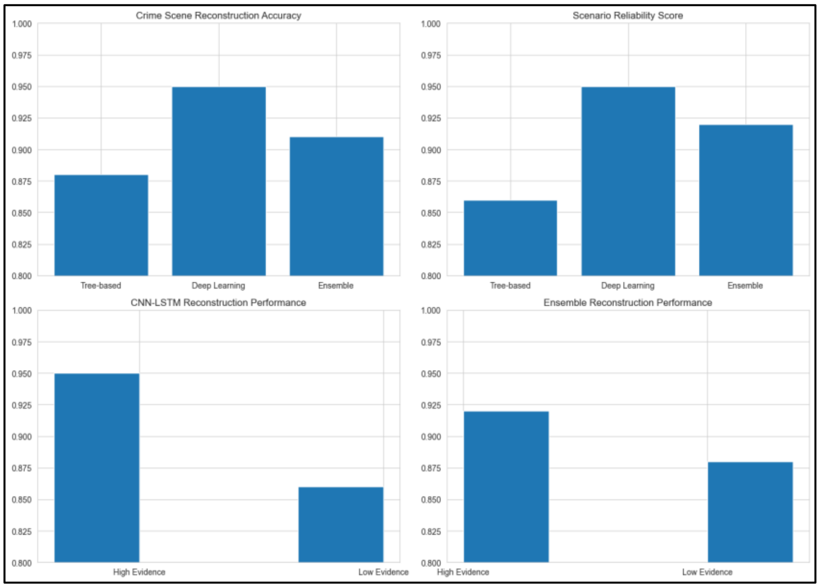

Fig.7: Crime scene scenario reconstruction results

4.3 Implications and Discussion

The results demonstrate that machine learning models, particularly hybrid deep learning architectures, significantly enhance the ability to reconstruct crime scenes and predict plausible event sequences. The high performance of CNN-LSTM and Bi-LSTM models indicates that temporal dependencies and localized feature patterns are essential for accurate forensic reconstruction. These findings suggest that AI-driven systems can serve as effective decision-support tools for forensic investigators by reducing reliance on purely manual interpretation and improving the consistency of investigative conclusions. From a practical perspective, the integration of predictive modeling and scenario simulation provides law enforcement agencies with the ability to evaluate multiple hypotheses simultaneously. This capability can accelerate investigative workflows, improve resource allocation, and support more informed decision-making in complex criminal cases. The strong performance of ensemble models further suggests that combining diverse machine learning approaches can mitigate individual model weaknesses and improve overall system reliability in operational environments.

However, several limitations are observed in the current framework. Model performance is highly dependent on the quality and completeness of input data, and scenarios with limited or missing evidence show reduced reconstruction accuracy. Additionally, the interpretability of deep learning models remains a challenge, particularly in legal contexts where explainability is essential for admissibility in court proceedings. Ethical considerations also arise regarding the potential misuse of predictive reconstruction systems, especially in cases where probabilistic outputs may be misinterpreted as deterministic conclusions. These limitations highlight the need for cautious deployment, improved explainable AI techniques, and rigorous validation protocols before real-world implementation in forensic investigations.

Conclusion

This study investigated the application of machine learning techniques for crime scene reconstruction, with a focus on predictive analysis and scenario simulation. The results demonstrate that computational models can effectively learn relationships between forensic evidence characteristics and reconstruction outcomes, enabling a more structured and data-driven approach to investigative reasoning. Across all evaluated model categories, ensemble learning and deep learning architectures consistently outperform baseline and traditional machine learning approaches, particularly in scenarios involving complex and high-dimensional forensic evidence. The integration of sequential and hybrid models further improves reconstruction capability by capturing temporal dependencies and localized patterns within forensic event data. This indicates that crime scene reconstruction benefits significantly from architectures capable of modeling both feature interactions and event ordering. Scenario simulation extends these capabilities by enabling the generation of multiple plausible event sequences, allowing investigators to evaluate competing hypotheses under conditions of uncertainty.

Despite these advancements, several limitations remain. Model performance is influenced by the quality, completeness, and structure of available forensic data, and complex crime scenarios continue to present challenges in achieving fully accurate reconstructions. Additionally, the interpretability of deep learning models remains a concern in forensic applications where transparency and explainability are essential for legal and investigative validity. Future work should focus on improving explainable artificial intelligence techniques for forensic applications, integrating real-world validated crime datasets, and developing standardized evaluation frameworks for crime scene reconstruction systems. The continued advancement of machine learning and artificial intelligence in this domain holds significant promise for enhancing the efficiency, reliability, and scientific rigor of forensic investigations.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Aashish, K. C., Zamil, M. Z. H., Mridul, M. S. I., Akter, L., Sharmin, F., Ayon, E. H., et al. (2025). Towards eco-friendly cybersecurity: Machine learning-based anomaly detection with carbon and energy metrics. International Journal of Applied Mathematics, 38(9s).

[2] Ahmad, A., Sharma, R., Singh, P., & Kumar, V. (2026). A systematic review about the evolving role of artificial intelligence in various fields of forensic medicine. Journal of Forensic and Legal Medicine, 117, 103043.

[3] Alao, D., Tansley, G., & Vanezis, P. (2025). Artificial intelligence and computer vision in forensic sciences: Applications in traumatic injury analysis. Rechtsmedizin, 35, 219–225.

[4] Alam, M., Shil, S. K., Sharmin, F., KC, A., Md, A. H., Ali, M., et al. (2026). Hybrid deep learning models for equipment failure prediction in US industrial systems. International Journal of Applied Mathematics, 39(1s).

[5] Balbudhe, M. S., Shetty, B. S. K., Arun Kumar, N., Singh, D., & Sherekar, A. I. (2025). Crime scene reconstruction: A scoping review. Egyptian Journal of Forensic Sciences, 15(1).

[6] Bhowmik, P. K., Subha, D. T., Rahim, A., Mohammed, A. A., Begum, M., Chowdhury, R., et al. (n.d.). Self-adaptive machine learning models for financial risk forecasting: Handling non-stationarity in banking and cryptocurrency time series.

[7] Bostanci, E. (2015). 3D reconstruction of crime scenes and design considerations for an interactive investigation tool. arXiv.

[8] Debnath, S., Islam, M. R., Abubakkar, M., Islam, M. Z., Mridul, M. S. I., & Biswas, A. K. (2025). AI-driven hybrid deep learning framework for short-term renewable energy forecasting under extreme weather events. In 2025 7th International Conference on Electrical, Control and Instrumentation Engineering (ICECIE) (pp. 362–369). IEEE.

[9] Dola, A., Begum, S., Antara, U. K., Islam, M. R., Sultana, T., & Zabin, N. (2024). Machine learning models for detecting hidden collusion networks in US corporate finance. Journal of Economics, Finance and Accounting Studies, 6(1), 143–154.

[10] Farber, S. (2026). Machines of justice: A systematic review of AI applications in policing and criminal justice. Sociological Review.

[11] Islam, M. R., Subha, D. T., Pramanik, M. T., Akter, M., Sweet, M. M. R., Robbani, M. S., et al. (n.d.). AI-driven decision support systems for optimizing working capital and customer experience in the US: A transaction-based simulation framework for SMEs.

[12] Islam, M. Z., Sumsuzoha, M., Islam, M. R., Kawsar, M., Mithu, M. F. H., Pant, S., et al. (n.d.). Graph neural networks for systemic financial risk forecasting: Modeling cross-market contagion between banking systems and cryptocurrency markets.

[13] Jakir, T. (2025). Signal-to-noise analysis of crisis indicators in global finance using artificial intelligence. International Journal of Applied Mathematics, 38(10s), 1815–1836.

[14] Jenga, K., Catal, C., & Kar, G. (2023). Machine learning in crime prediction. Journal of Ambient Intelligence and Humanized Computing, 14, 2887–2913.

[15] Lodhi, K., & Kassem, M. A. (2024). Revolutionizing forensic science: The role of artificial intelligence and machine learning. Journal of Artificial Intelligence, Machine Learning, and Bioinformatics.

[16] Mandalapu, V., Elluri, L., Vyas, P., & Roy, N. (2023). Crime prediction using machine learning and deep learning: A systematic review and future directions. arXiv.

[17] Miah, M. N. I., Uddin, M. J., & Kakumani, M. (2026). Artificial intelligence in sentencing: Evaluating machine learning models for sentencing recommendations in the US. Frontiers in Computer Science and Artificial Intelligence, 5(4), 30–43.

[18] Rahman, M. K., Hossain, M. S., Haque, S. U., Jahed, K. A., Robbani, M. S., Shati, M. A., et al. (n.d.). Machine learning models for early warning of financial crises in the US economy using macro-financial indicators.

[19] Rahman, M. S. (2025). Machine learning-enabled early warning system for detecting micro-inflation clusters in the US economy. International Journal of Applied Mathematics, 38(12s), 2743–2769.

[20] Reza, S. A., Rahman, M. K., Rahman, M. D., Sharmin, S., Mithu, M. F. H., Hasnain, K. N., et al. (2025). Machine learning-enabled early warning system for financial distress using real-time digital signals. arXiv preprint arXiv:2510.22287.

[21] Sabri, I., Sutay, S., Perumal, P., & Dahiya, S. K. (2025). The efficacy and implementation of artificial intelligence in crime scene investigation: A systematic review of meta-analyses. International Journal of Medical Justice.

[22] Shawon, R. E. R., et al. (2025). Detecting illicit cross-chain fund movement: Behavioral machine learning models for bridge-based laundering patterns. International Journal of Applied Mathematics, 38(12s).

[23] Yisak, H., Adamu, G., Workineh, D., & Asgedom, M. (2026). Advancing forensic science through artificial intelligence: A systematic review. Ethiopian Journal of Police Studies.

[24] Zappalà, A., Guarnera, L., Rinaldi, V., Livatino, S., & Battiato, S. (2024). Enhancing crime scene investigations through virtual reality and deep learning techniques. arXiv.