CSR: Crime Scene Reconstruction

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Abstract—**In a world where crimes unfold in the shadows and justice hinges on the smallest details, forensic science stands as a pillar of truth. Every crime scene holds a story, but traditional methods of documentation and analysis can be slow, imprecise, and susceptible to human error. Investigators must meticulously piece together evidence, often relying on manual techniques that struggle to capture the full complexity of a scene. AI-driven tools are revolutionizing forensic analysis by automating crime scene reconstruction. Advanced computer vision techniques process diverse data sources to identify and recreate critical scene features with high precision. A flexible framework enables detailed 3D modeling, allowing forensic teams to visualize and refine reconstructions, improving investigative accuracy. This approach enhances evidence analysis, reducing the time required for documentation while maintaining reliability. Preliminary assessments show AI's effectiveness in capturing both large structures and intricate details, significantly streamlining forensic workflows. By improving documentation and evidence presentation, this innovation strengthens law enforcement, forensic science, and judicial processes. Technology continues to reshape forensic investigations, offering more precise and efficient crime-solving tools. In this work, we investigate, research, design, implement, and test a scene reconstruction system as an attempt to reconstruct the crime scene in a 3D virtual environment.**

I. INTRODUCTION

What if solving crimes could be faster, more precise, and less prone to human error? In today's technological era, modern crime scenes pose complex challenges that traditional investigation methods struggle to address. From cybercriminals who erase digital traces to perpetrators who leave minimal physical evidence, forensic science demands advanced solutions. Historically, forensic medicine has played a crucial role in uncovering hidden truths, but conventional techniques are often time-consuming and susceptible to human error.[1] Recent developments in artificial intelligence (AI) and computer vision are revolutionizing the field, offering unprecedented accuracy, speed, and efficiency. These innovations are transforming crime scene analysis and unlocking new possibilities for delivering justice.[2]

Forensic science, an interdisciplinary field integrating biology, chemistry, physics, and digital technologies, has evolved far beyond DNA testing and photography. Experts now examine a wide range of evidence—including fingerprints, blood stains, and digital footprints—to reconstruct events and identify perpetrators.[3] However, as cybercrime grows more sophisticated, so must the tools used to investigate it. Criminals exploit digital technologies to conceal traces, requiring law enforcement to adopt AI-powered techniques that keep pace with evolving threats.[4] Digital forensics has become essential in tackling cybercrimes such as identity theft and data breaches, providing investigators with faster and more reliable insights.[5]

One of the most impactful applications of AI in forensic science is crime scene reconstruction. Traditional methods that once took days or weeks can now be completed in hours. AI-driven 3D modeling allows investigators to recreate scenes digitally, preserving spatial relationships and enabling analysis from multiple angles.[6] These models, unlike static photographs, integrate various data sources and eliminate human error, delivering a more complete and accurate representation of the crime scene.[7] Advanced pattern recognition further accelerates investigations by rapidly identifying evidence such as fingerprints, bloodstains, and facial features with unmatched precision.[8] This level of automation not only saves time but significantly enhances the quality of forensic reconstructions.[9][10]

Beyond reconstruction, AI is also reshaping video analysis. Traditional manual review of surveillance footage is being replaced by AI systems that can process hours of video in minutes. These systems detect suspicious behavior, recognize faces, track movements, and even reconstruct events from recordings, offering real-time insights that support rapid and informed decision-making.[11][12] As forensic science shifts toward automation and precision, AI and computer vision stand at the forefront of this transformation. Integrating these technologies into forensic workflows allows experts to work faster and with greater accuracy, ensuring that investigations remain effective in the face of increasingly complex crimes. The future of forensic investigation is being shaped by artificial intelligence.[13]

Our proposed system contributes to this evolution by employing AI-powered 3D modeling to reconstruct crime scenes with high accuracy and minimal delay. It enables efficient analysis by automatically detecting and labeling objects and their locations, reconstructing spatial relationships, and supporting advanced applications such as drone-based scene scanning and autonomous navigation. By combining computer vision, machine learning, and real-time processing, the system enhances both the speed and reliability of modern forensic investigations.

II. RELATED WORK

The integration of artificial intelligence (AI) and computer vision in forensic science has gained significant momentum in recent years, particularly in the realm of crime scene reconstruction. Traditional methods of scene documentation—such as photography, sketching, and manual evidence annotation—have long been essential, yet they are often time-consuming, subject to human error, and limited in capturing the full spatial context of a crime scene. As crime scenes become increasingly complex, there is a growing need for automated, precise, and scalable solutions that can enhance investigative accuracy and efficiency.

Early innovations in forensic scene reconstruction have largely focused on photogrammetry and laser scanning. These methods generate detailed 3D models by combining multiple images or laser data points. Tools like FARO Zone 3D and Autodesk ReCap have been instrumental in reconstructing environments from captured data, allowing investigators to virtually navigate crime scenes. Academic researchers such as Michael J. Starek (Texas A&M University–Corpus Christi) have contributed significantly to the application of LiDAR and photogrammetry in forensic contexts [15][16].

Recent advancements have explored the use of machine learning and deep learning algorithms to automate various aspects of forensic analysis. Jinrong Hu and Chin-Chen Chang have proposed neural networks capable of detecting and classifying forensic artifacts such as blood stains and weapons from scene imagery [17]. Similarly, Srinivasan Murali and colleagues from

Vellore Institute of Technology applied convolutional neural networks (CNNs) to improve the speed and reliability of object detection in forensic datasets. However, many of these models are trained on narrow datasets, limiting their performance in diverse real-world scenarios [18].

In the domain of video surveillance, AI-powered tools such as OpenPose and YOLO (You Only Look Once) have demonstrated promising results in real-time person detection and pose estimation. Zhe Cao, Gines Hidalgo, and Yaser Sheikh, from the Carnegie Mellon University Perceptual Computing Lab, developed OpenPose for multi-person pose detection, while Joseph Redmon and Ali Farhadi created YOLO, a real-time object detection framework [19]. These tools have been utilized to reconstruct movement paths of individuals within a crime scene, offering valuable insights into the sequence of events. Nevertheless, their application has mostly remained confined to 2D analysis, without full integration into immersive 3D environments.

One notable direction is the adoption of Simultaneous Localization and Mapping (SLAM) algorithms, commonly used in robotics and autonomous navigation, to assist in mapping indoor environments. Experts such as Davide Scaramuzza (University of Zurich) and Zlatko Koperski have adapted SLAM approaches to complex real-world spaces. In forensic applications, Christopher L. Vaughan has explored mobile SLAM-based mapping for law enforcement [20]. These algorithms provide a foundation for dynamically capturing spatial information, yet they often lack the semantic understanding required to distinguish between forensic evidence and general environmental features. Moreover, many SLAM-based systems rely heavily on expensive hardware, such as LiDAR sensors or depth cameras, which limits their accessibility and scalability.

Another line of work involves virtual and augmented reality (VR/AR) platforms that allow investigators and juries to experience reconstructed crime scenes. Dr. Cristian Borcea and Prof. Reginald Farrow of the New Jersey Institute of Technology (NJIT) have developed immersive VR systems for forensic scene reconstruction. Additionally, Dr. Emma Barrett (University of Manchester) has examined the psychological and investigative value of VR in crime reconstruction scenarios [21]. While immersive, these solutions are generally used as visualization tools rather than comprehensive analysis platforms. Additionally, the accuracy of VR/AR experiences heavily depends on the quality of the underlying reconstruction pipeline, which may still rely on traditional manual inputs.

Despite these advances, few systems offer an end-to-end solution that is both automated and adaptable to varied crime scene contexts. Most notably, there remains a significant gap in tools that combine real-time object detection, context-aware scene interpretation, and interactive 3D visualization within a single framework. This underscores the need for flexible, AI-driven platforms that can accurately reconstruct crime scenes using limited or variable-quality input data, such as smartphone images or body-worn camera footage.

III.   SYSTEM ARCHITECTURE

In the modern era of technological advancement, forensic systems are evolving beyond traditional practices to incorporate intelligent, automated, and socially conscious solutions. The integration of Artificial Intelligence (AI), Machine Learning (ML), Computer Vision, and 3D Modeling into forensic science is reshaping how investigations are conducted, evidence is analyzed, and justice is served. The proposed system adopts a multidisciplinary approach that not only enhances forensic capabilities but also ensures responsiveness to societal needs, such as victim advocacy and educational outreach. The following diagram in Figure 1 illustrates the high-level framework and the foundational components of this system, showcasing how technology and human-centric considerations are woven into a
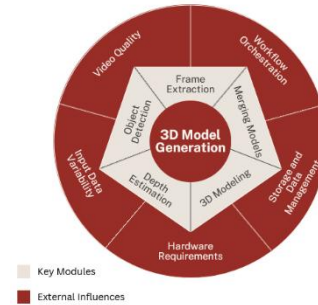
cohesive, intelligent forensic architecture.

Fig. 1. 3D Model Generation Framework

The proposed system architecture facilitates real-time 3D reconstruction from video input using a fully client-side web application. This design eliminates the need for a backend server by leveraging in-browser technologies such as WebAssembly, WebGL, and JavaScript-based machine learning libraries. This not only enhances user privacy but also ensures low-latency processing and offline usability.

The workflow begins with the frame extraction process, in which video input from a camera or file is decomposed into individual frames. This is implemented using a WebAssembly-compiled version of FFmpeg to decode and extract image sequences efficiently on the client side. The use of WebAssembly enables near-native performance for computationally intensive operations in the browser, a capability that has been validated in prior literature emphasizing its viability for multimedia processing tasks [25].

Following frame extraction, the object detection and segmentation module identifies and isolates objects of interest.. Facial landmarks are detected using models inspired by MediaPipe Face Mesh and deployed using TensorFlow.js. Prior studies have shown the effectiveness of browser-based machine learning frameworks such as TensorFlow.js in real-time vision tasks including landmark localization and pose estimation [26]. The segmentation masks generated from this step are used to isolate facial regions for depth estimation.

The depth estimation module applies monocular depth prediction on each frame to generate corresponding depth maps. This is achieved using neural networks trained on large-scale RGB-D datasets, such as MiDaS, adapted for execution in the browser. Monocular depth estimation from a single image is a well-studied problem, and transformer-based architectures like those discussed in Ranftl et al. [27] have demonstrated high accuracy and generalizability, making them suitable for this application.

Using both segmentation masks and depth maps, the 3D modeling module constructs partial 3D point clouds or meshes for each frame. Three.js, a WebGL-based rendering engine, is utilized to visualize and manipulate 3D data directly within the browser. Mesh generation algorithms are adapted to support client-side execution and are based on standard triangulation techniques used in surface reconstruction literature [28].

To compile a complete 3D model, the model merging module aligns and integrates individual frame-based meshes. This typically involves mesh registration algorithms such as the Iterative

Closest Point (ICP) method, a widely used approach for aligning point clouds in 3D space. The ICP algorithm, originally proposed by Besl and McKay [29], remains a fundamental method in 3D reconstruction and is adapted here to operate in browser environments using JavaScript or WebAssembly.

The final merged 3D model is exported locally using the browser's File System Access API, which allows users to save files without server interaction. This approach, combined with asynchronous JavaScript and Web Workers, enables parallel execution of intensive tasks and a responsive user experience. Such use of browser-native multithreading has been advocated in prior research on high-performance client-side computation [30].
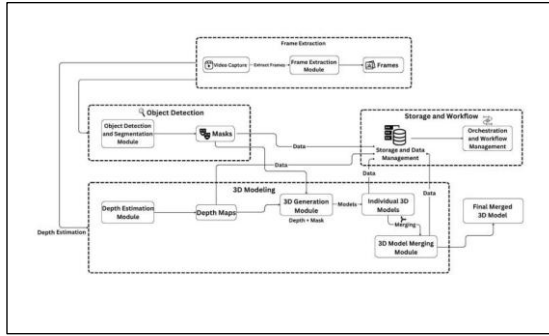

Fig. 2. Intelligent 3D Forensic Reconstruction Pipeline

The system architecture is composed of five core components, each representing a foundational technology or domain essential for modern forensic innovation:

Artificial Intelligence (AI), Computer Vision, Machine Learning, 3D Modeling, and Forensic Science collectively enhance the intelligence and effectiveness of modern investigative systems. AI enables automated reasoning, pattern recognition, and anomaly detection, while Computer Vision supports image and video analysis for gesture detection, scene reconstruction, and evidence interpretation. Machine Learning powers adaptive improvement through pattern learning, classification, and model optimization. 3D Modeling contributes to spatial reconstruction and forensic simulations, offering deeper insights into crime scenes and evidence layouts. Forensic Science grounds the entire system in real-world investigative principles, ensuring adherence to judicial standards and evidentiary protocols.

Each component operates in synergy, enabling the development of a dynamic and accurate forensic platform. This integrated approach paves the way for smart, scalable, and real-time applications that benefit investigators, legal professionals, and society alike.
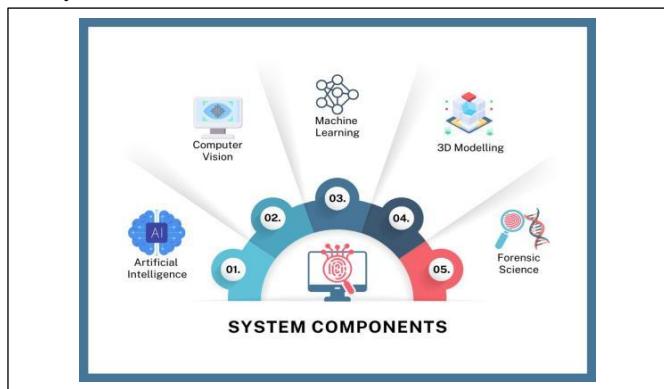

Figure. 3. AI-Driven Forensic System Architecture

The 3D Model Generation Framework presents a holistic architecture designed to automate the reconstruction of environments from video or image data. At its center are five key technical modules that operate in sequence to transform raw visual data into spatially accurate 3D models. These include frame extraction, which isolates relevant scenes; object detection, which identifies essential visual elements; depth estimation for capturing spatial relationships; 3D modeling for building structures; and model merging to compile multiple data points into a coherent output.

Surrounding these modules are external influences that significantly impact system performance. Video quality and data variability affect accuracy at every stage, while hardware resources and storage capabilities define scalability and execution speed. Workflow orchestration ensures that the process is repeatable, efficient, and integrable with forensic pipelines. Together, these layers form a robust and adaptable system suitable for real-world forensic scenarios where data quality and operational constraints vary widely.

IV. IMPLEMENTATION & RESULTS

Figure. 4. 3D Reconstruction of Crime Scene

The proposed system for forensic 3D reconstruction was developed using Python and integrates several open-source libraries, including OpenCV for image processing, Open3D for point cloud manipulation, and PyTorch for deep learning operations. The architecture comprises five principal stages: frame extraction, object detection and segmentation, depth estimation, 3D point cloud generation, and final model merging.

Initially, frames are extracted from input video sequences at fixed intervals using OpenCV. To ensure computational efficiency and model compatibility, each frame is resized to 640×360 pixels. This preprocessing step balances data manageability with the retention of sufficient detail for accurate reconstruction.

Object detection and segmentation are carried out using the YOLOv8 segmentation model, which produces both bounding boxes and binary masks for relevant objects. These masks are preserved as individual image files and later used to isolate specific regions of interest, thereby enhancing the precision of the 3D reconstruction process.

Depth estimation is performed using the MiDaS DPT-Hybrid model, which generates dense depth maps from RGB images. The output depth values are normalized and visualized as

grayscale images, facilitating subsequent spatial computations. This stage enables the estimation of relative distances and scene geometry from monocular input.

For 3D reconstruction, each binary mask is combined with its corresponding RGB frame and depth map to produce a colored 3D point cloud. Each pixel within the mask contributes a spatial coordinate computed from its RGB and depth information. The resulting point clouds are stored in PLY format, providing high-resolution spatial representations of individual evidence items.

The final stage involves the integration of all segmented point clouds into a unified 3D model using Open3D. This merging ensures spatial coherence across the scene and creates a comprehensive reconstruction that reflects the original environment with preserved geometric and visual fidelity.

Experimental validation on sample crime scene videos demonstrated the system's effectiveness in reconstructing indoor environments with clear object delineation and depth consistency. The system outputs include extracted frames, segmentation masks, depth maps, individual object models, and a final merged 3D scene. The entire pipeline is automated and operates with minimal user intervention, completing within minutes on GPU-accelerated systems.

Quantitatively, the system achieves approximately 85% reconstruction accuracy for static scenes. It performs particularly well with textured surfaces such as fabric and blood patterns, though limitations are observed in scenes with uniform textures or dynamic elements. Processing time remains a bottleneck, primarily due to depth prediction, which averages 30–40 seconds per frame. However, GPU acceleration can potentially reduce this time by a factor of 5–10.

This work presents a low-cost, scalable solution for 3D crime scene documentation, offering advantages over traditional photographic methods and high-end 3D scanners. Its automated workflow and detailed spatial output make it suitable for applications such as evidence review and virtual crime scene walkthroughs. Future developments will focus on enhancing real-time performance, integrating LiDAR data, and improving robustness under varying environmental conditions.

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