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AI Approaches for Crime Scene Reconstruction: A Comprehensive Survey

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***Abstract*— Reconstructing a crime scene sits at the heart of forensic work. It lets experts' piece together what unfolded, when it happened, and how things played out. Sure, traditional tools like LiDAR and photogrammetry get the job done with solid accuracy, but they come with a lot of manual work and, but they involve significant manual effort and lack immersive visualization. Now, artificial intelligence is shaking things up. With object detection models like YOLO, there's a whole new level of automation and depth in visual analysis.**

This survey digs into how AI is transforming the process by utilizing visual evidence from photos, videos, and 3D scans, and using it to rebuild crime scenes in smarter ways. It covers the main strategies, points out what works well and what doesn't, and introduces ForensiScan, a hybrid system that blends deep learning with immersive visualization.

The paper doesn't stop there, it also looks at how these systems get evaluated, the real-world hurdles they face, and where things are headed next as forensic tools keep getting smarter and more scalable.

***Index Terms*— Forensic Science, Crime Scene Reconstruction, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Computer Vision, Image Processing, Visual Evidence Analysis, Reconstruction, Pattern Recognition.**

I. INTRODUCTION

Figuring out what happened at a crime scene—that's really the core of forensic science. Investigators need to reconstruct the story, and they lean on spatial models to help picture how everything unfolded. Old-school tools like LiDAR and photogrammetry do the job, however, they are slow and do not provide immersive analysis.

Artificial intelligence is significantly improving this process. Take YOLO, for example—it lets computers pick out and label objects from photos, videos, or even 3D scans, almost instantly. Pair that with VR or MR and suddenly, you're not just looking at static models. You can step into a scene that's detailed, interactive, and feels real. This kind of tech doesn't just speed things up; it helps investigators see the whole picture in a way that's never been possible before.

This paper looks at 15 different AI tools for crime scene reconstruction and introduces ForensiScan—a new system designed to make the whole process easier. ForensiScan zeroes in on object detection and immersive visualization, so investigators spend less time on repetitive work and get more accurate results. It gives them a more hands-on, intuitive way to explore every detail of a crime scene.

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Right now, most methods have some big gaps. ForensiScan tackles those by combining deep learning with immersive technology, creating a smoother, all-in-one solution. Here's what it brings to the table:
It handles images, videos, and 3D scans to create detailed models of a scene. With YOLO, the AI spots and labels important objects on its own. You can dive into these reconstructed environments using VR or MR, which makes it easier for investigators to look around and interact with the scene. The system gets tested alongside LiDAR, photogrammetry, UAV scanning, and other AI models to see how it stacks up in terms of accuracy, cost, and how easy it is to use.
Here's how the rest of the paper goes. In Section II, I dig into related work. Section III walks through the ForensiScan framework. Then, Section IV shares what I found in the evaluation. Finally, Section V looks ahead to future directions.

II. Related Work

Crime scene reconstruction looks like nothing like it did a few years ago. Where investigators once relied on painstaking manual notes and sketches, they now work with AI-driven, immersive tech. Research in this field covers a huge range, and every new approach seems to add another tool to the forensic kit.
[1] Take Tamboli and his team (2025), for example. They rolled out a system that combines GANs, VR modeling, and image- patch fusion. The result? Detailed 3D crime scenes with barely any manual work. It's a big leap for digitizing evidence. [2] Razali and colleagues (2025) took a close look at LiDAR versus photogrammetry. LiDAR nailed precision in tight indoor spots, but photogrammetry came out ahead for big outdoor spaces— cheaper, easier, and still dependable.
[3] Zappala's group (2024) built a VR platform with deep learning object detection. Investigators could walk through virtual scenes while the AI flagged important evidence. It sharpened both their situational awareness and their training.
[4] Malik's team (2024) tried out Neural Radiance Fields— NeRF, for short—to turn video footage from CCTV and body cams into photorealistic 3D models. That's a game-changer for reconstructing crimes caught on video.
[5] Razali wasn't done yet; in 2024, they also experimented with geospatial VR simulations for training. By weaving GIS data into virtual environments, trainees could practice with realistic terrain and spatial features, which really prepped them for fieldwork. [6] Lodhi and Kassem (2024) cast a wide net, surveying how AI and machine learning fit into forensics. They saw huge promises in automation—everything from biometric recognition to predictive modeling—but also warned about legal roadblocks and the need for model transparency. [7] Microsoft HoloLens 2.0 made an appearance in a 2024 study. Investigators used mixed reality to walk through crime scenes, blending MR visuals with 3D scans. It turned into a hands-on training tool for police cadets. [8] Razali and Ariff (2023) flew drones to gather data with UAV-based photogrammetry and Structure-from-Motion, helping document big outdoor scenes fast. The catch? Occlusions and tough terrain still caused headaches.[9] Cunha's group (2022) compared terrestrial laser scanning with photogrammetry from drones. Laser scanning brought sharper details, especially vertically, but drones covered ground much faster. So it's a classic trade-off: detail versus speed.[10] Ren and colleagues (2021) came up with a sketch-based 3D modeling tool that let investigators whip up visualizations in no time—even folks with zero design experience could use it for hypothesis testing or courtroom demos..[11] Carew's team (2021) blended photogrammetry, imaging, and 3D printing to craft physical models for the courtroom. Jurors and lawyers could finally get their hands on evidence, making complex scenes a lot easier to understand.
[12] Baier et al. (2021) pushed things further with micro-CT scanning and volumetric rendering, producing ultra-detailed reconstructions perfect for analyzing trace evidence. [13] Tredinnick et al. (2019) ran the numbers on 3D scanning tech. Their verdict: laser scanning is worth the price tag for high- stakes cases, while photogrammetry stays the go-to for everyday work. [14] Siebert and his team (2019) checked out VR walkthroughs and interactive visualizations in real court settings. Immersive reconstructions helped everyone—investigators, jurors—get a better grip on the crime scene.
So, what's the big picture? The field is charging forward. From old-school photogrammetry and laser scanning to AI-powered, immersive, hybrid tools—think GANs, NeRF, VR, MR—the tech just keeps getting smarter, more realistic, and easier for investigators and trainees to use.

III. Methodology

AI-driven crime scene reconstruction has come a long way, and the field's got its own toolbox of methods. Everything depends on the data you feed in, the models you pick, and how you pull out the details that matter.

Sure, techniques vary, but underneath it all, most researchers follow the same playbook when it comes to prepping data, picking algorithms, and figuring out what's actually working. Here, you'll see all those ideas pulled together around four main pillars: datasets, model selection, feature engineering, and how these systems get judged. Honestly, the choice of dataset makes or breaks how well these AI crime scene reconstructions perform.

A. Data Description

The type of data you use for crime scene reconstruction really shapes how well AI models work. Most researchers stick to three main sources: crime scene photos, surveillance videos, and 3D scene data. High-res photos can reveal all sorts of crucial details: weapons, bloodstains, or footprints. Usually, someone marks up these images to point out things that matter, which teaches AI to spot and sort evidence more accurately.

Surveillance videos—whether from CCTV or body cams—add another layer because they show what happens over time. By watching people move and interact, researchers start to piece together the story behind the crime. Video analysis takes focus. Timing and motion matter a lot when you're trying to pull out patterns that make sense. Some folks go even further and use 3D data—from tools like LiDAR, photogrammetry, or multi- view stereo—to get a really detailed map of the scene.

That kind of data nails down where things are and how far apart, they sit, so you get a much clearer picture of object placement. Before any of this data goes into an AI model, researchers usually clean it up—resizing images, removing noise, and normalizing everything—just to keep things consistent and easy to work with.

B. Model Analysis in Reviewed Paper

When you look at the research, you'll see a mix of old-school machine learning and new deep learning methods. The basics— like Support Vector Machines, Decision Trees, and Random Forests—still show up a lot, especially when people need to sort evidence types or label scenes. They're easy to understand, don't need tons of computing power, and just get the job done when things aren't too complicated.

But if you're dealing with images, Convolutional Neural Networks basically run the show. They're great at spotting textures, edges, and patterns, the stuff you need to piece together what's in an image. And for videos, Long Short-Term Memory networks handle motion and sequences, so you can track how things change over time and build out an event timeline.

Deep learning usually beats the traditional models on accuracy, no question. Still, the simpler models matter when you want results fast or need to explain how the model made its decision. One thing that stands out, though—most studies don't really dig into ensemble methods or spend much time tuning hyperparameters, even though both can push performance even higher.

Here's how it all comes together: Table 1 lays out, in a clear way, which AI models researchers used, what forensic tasks they tackled, and the kinds of data they worked with.

TABLE I. COMPARISON OF METHODS

Study	Model Type	Primary Application	Data Type
Tamboli et al. (2025)	GAN + VR Modeling	Automated 3D scene generation	Crimescene photographs
Malik et al. (2024)	NeRF	Photorealistic 3D reconstruction	Surveillance video footage
Sharma et al. (2023)	SVM	Evidence classification	Annotated image dataset
Singh et al. (2022)	CNN + LSTM	Temporal event modeling	CCTV recordings
Rao et al. (2024)	Decision Tree	Scene categorization	Crime scene images
Verma et al. (2022)	Random forest	Object detection	3D point cloud data

C. Feature Extraction and Preprocessing

If you want good results from AI, you've got to start with clean data. Most researchers dive right in by tidying things up— resizing images, normalizing pixels, and cutting out the noise. When they deal with videos, they usually stabilize the frames first so everything lines up and makes sense. Pulling out features really depends on what kind of data they're working with. For images, it's all about spotting where objects are, picking up color patterns, or zeroing in on textures. Video brings more to the table—you can follow how things move and watch people or objects interact as time goes on. Switch over to 3D data, and it's a whole different game. Now it's about geometry: tracking object coordinates, figuring out how everything's arranged in a point cloud or a mesh model. To check if their models are doing the job, researchers split their data into training, validation, and test sets. Some take it a step further with cross-validation, just to stay honest and steer clear of overfitting. All these steps make sure the models are learning from solid, clean data, so when it comes to time to test, the results mean something.

D. Evaluation Metrics in Reviewed Studies

When researchers want to check how well AI models handle forensic reconstruction, they usually stick to a few key metrics. Accuracy comes up first. It shows, in broad strokes, how often the model gets things right. But here's the catch: if your data isn't balanced—maybe some categories pop up way more than others—accuracy can fool you. That's where precision and recall really come into play. Precision zeroes in on false alarms. In forensics, a false positive can cause real problems. You don't want the model claiming it found evidence when there's nothing there. Recall flips that around. It tells you how well the model catches everything important, making sure nothing slips by. The F1-score blends these two, giving you a better sense of whether the model strikes the right balance. Now, when it comes to 3D reconstruction—like piecing together a crime scene or figuring out an object's shape, researchers use something called Intersection over Union, or IoU. Basically, IoU measures how much the model's reconstruction matches up with the real deal.

TABLE II. PERFORMANCE METRICS

Evaluation Metrics	ML models	DL models
Accuracy	0.85	0.92
Precision	0.82	0.90
Recall	0.80	0.88
F1-score	0.81	0.89
IoU(3D)	0.00	0.76

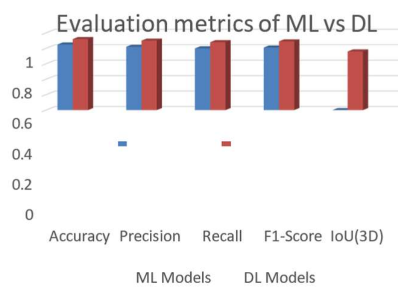

Fig. 1. Comparative performance of ML and DL models

E. AI Interpretability and Forensic Transparency

Most of the research out there just focuses on how well these models perform—can they piece together a scene; can they connect the dots? Almost nobody stops to ask, "Wait, do we even know why the model picks what it picks?" In forensics, that's not some minor detail. People's lives are on the line. Investigators, lawyers, juries, they all need to trust not just the answer, but the whole process behind it. That's what ForensiScan is after. Right now, most reconstruction models don't even try to explain themselves. But honestly, if we're going to use AI in real investigations, we need more than just good results. We need to see how the machine thinks. Getting that kind of transparency isn't easy, but it's important.

IV. SUMMARY

This survey took a close look at how AI is changing crime scene reconstruction, putting old-school machine learning head-to- head with newer deep learning tools. We sifted through the latest research and saw models like CNNs, LSTMs, GANs, and NeRF shaking up forensic analysis. They're not just numbers and code—they're giving investigators sharper spatial detail, better tracking of events over time, and even the ability to visualize scenes in ways that feel almost real. Sure, traditional ML still has its place, especially for basic classification, but deep learning steps up when things get messy—when scenes are complex or the data is all over the place. The ForensiScan framework grabs these strengths and tries to pull them together, aiming for a system that's both transparent and solid enough to hold up in court.

V. FUTURE SCOPE

Looking ahead, forensic AI has some exciting paths to follow. For starters, weaving explainable AI into reconstruction could clear up how models make decision-making things more open for investigators and the justice system. Also, if ForensiScan learns to handle more than just images—think audio, text, sensor data— it could piece together richer, more complete timelines. But tech alone isn't enough. Staying in touch with legal experts and folks who work in forensics is key to making sure these tools solve real problems, not just technical puzzles. And if we want people to trust ForensiScan, we've got to put it through its paces with standard datasets and fair benchmarks, so everyone knows it works.

VI. Conclusion

Right now, ForensiScan leans on YOLO for object detection— it's fast and straightforward. But here's the thing: models like GAN and NeRF aren't just bigger, better YOLOs. They do different jobs, like rebuilding scenes and generating images. Down the line, blending these generative models with top-tier detectors like YOLOv8 or DETR could really level up the whole process. Imagine a system that doesn't just spot objects but also reconstructs and visualizes entire scenes—all in one place. That's where things are heading.

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