IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.1511198

AI-DRIVEN DIGITAL CRIME PATTERN ANALYSIS

Neha Sarashetti[1], Manjula Bhajantri[2], Pooja Hullannavar[3], Kavita Mantanavar[4], Pradnya Rama[5]*

Department of Computer Science and Engineering, Basaveshwara Engineering College (affiliated to Visvesvaraya Technological University), Bagalkot, Karnataka, India[1,2,3,4]

Assistant Professor, Department of Computer Science and Engineering, Basaveshwara Engineering College (affiliated to Visvesvaraya Technological University), Bagalkot, Karnataka, India[5]

*Corresponding Author

Abstract: Crime pattern analysis requires the organised examination of visual evidence and contextual details across images. This paper presents a crime scene review prototype whose main purpose is to compare an uploaded scene with related reference images and summarise similarities in weapon category, detected person count, scene setting, time of day description, and clothing descriptors. The application uses a React and TypeScript frontend with a Python FastAPI backend and a configured Roboflow inference workflow. After image validation, the backend returns object detections, bounding boxes, weapon categories, person count, and available scene descriptions. The frontend selects up to four reference images and applies descriptive comparisons to their stored text descriptions. Weapon matching is based on category labels; person matching compares the detected count with a count parsed from reference descriptions; area and time matching use descriptive keywords; and dress matching checks for shared clothing terms. Pattern records are stored in browser IndexedDB, displayed in a direct image comparison page, and used to generate a PDF report. The current local reference directory contains 35 images: 16 gun, 15 knife, and 4 bat images. The displayed match percentages describe agreement with the selected references and are not detector accuracy or forensic certainty. The prototype supports structured human review and does not independently establish identity or prove that separate incidents are connected.

Keywords: Crime pattern analysis, weapon detection, image comparison, clothing-pattern comparison, scene analysis, reference-image matching.

I. INTRODUCTION

Crime pattern analysis involves examining incident-related information to identify recurring characteristics and possible similarities between cases. Images collected during an incident may contain several useful visual details, including objects, people, clothing, and the surrounding environment. Reviewing these details manually across multiple images can be time-consuming, particularly when the images must be compared and organised consistently.

The proposed system focuses on image-based pattern analysis rather than weapon detection alone. When a user uploads a crime-scene image, the application obtains object detections and available scene descriptions from a configured inference workflow. It then compares the uploaded image information with reference-image descriptions using weapon category, person count, scene area, time-of-day, and clothing descriptors. The comparison results are organised as a pattern summary and can be reviewed through one-to-one image comparison and PDF reporting.

The project is implemented as a web application with a React and TypeScript frontend and a Python FastAPI backend. The backend communicates with an external Roboflow workflow for image inference. The project does not train a new detector; its main contribution is the integration of detection outputs with rule-based reference comparison, record storage, and reporting.

 This work is licensed under a Creative Commons Attribution 4.0 International License

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.1511198

II. LITERATURE REVIEW

A. Weapon Detection in Computer Vision

Debnath and Bhowmik [1] surveyed computer-vision methods for automatic gun and knife detection. They discussed the variation in weapon shape and appearance, occlusion, background clutter, and the difficulty of locating weapons held by people. Their survey also identifies research directions involving human activity, behaviour, and hand-position analysis. This work provides the background for the weapon-detection stage of the present system.

Santos, Oliveira, and Cunha [2] reviewed deep-learning approaches for weapon detection in surveillance footage. Their review groups studies by general weapon detection, small-object detection, lighting enhancement, and weapon orientation or human pose. They report that performance can deteriorate under challenging image conditions, supporting the need to treat automated detections as candidate observations that require review.

B. Detection and Surveillance Systems

Bhatti et al. [3] presented a deep-learning-based approach to weapon detection in real-time CCTV videos. Their work evaluates object-detection performance using measures such as precision, recall, and mean average precision. These measures are relevant when designing a separate evaluation protocol. The present project consumes predictions from a configured hosted workflow and does not claim the metrics reported by Bhatti et al.

Lim et al. [4] proposed deep multi-level feature pyramids for detecting non-canonical firearms in video surveillance. Their study addresses firearm appearance and scale variation in realistic CCTV imagery. It demonstrates that small or unusually oriented weapons can be difficult to detect, a limitation that should also be considered when interpreting outputs from the external inference service used in this project.

Jadhav et al. [5] studied weapon detection from surveillance footage using deep-learning models, including CNN, YOLOv7, YOLOv8, and VGG-based approaches. Their work compares model behaviour and discusses precision and recall as useful evaluation measures for detection tasks. The current project differs by focusing on the comparison and organisation of image-level observations after inference.

Yadav, Gupta, and Sharma [6] reviewed classical machine-learning and deep-learning methods for weapon detection. Their study provides a taxonomy of approaches and discusses datasets, reported performance, advantages, and limitations. The review highlights the need to consider dataset quality and differences between evaluation settings when comparing detection methods.

C. Research Gap

The reviewed studies primarily address weapon detection methods, surveillance models, datasets, and detector performance [1]–[6]. The present project places emphasis on the subsequent pattern-review stage. It combines category-based reference retrieval with descriptive comparisons of person count, scene area, time of day, and clothing terms, and presents the comparison in a saved record and one-to-one view. The current implementation uses text descriptions associated with reference images and rule-based comparisons; it does not perform learned visual similarity, biometric identification, or statistical linkage of real-world cases.

III. BLOCK DIAGRAM

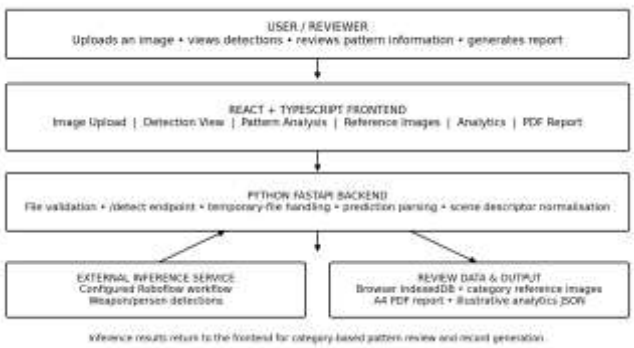


Fig. 1 System architecture of the crime pattern analysis prototype.

 This work is licensed under a Creative Commons Attribution 4.0 International License

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.1511198

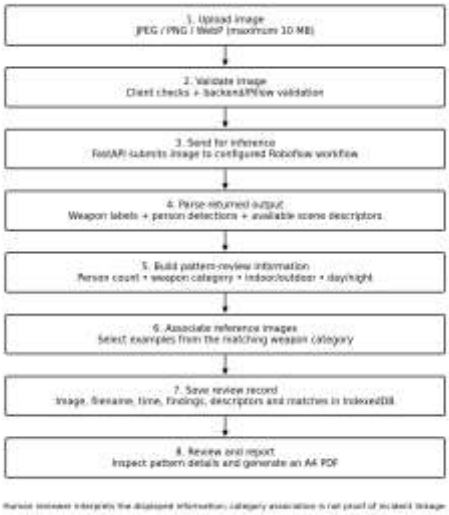


Fig. 2 Workflow from image upload to pattern review and report generation.

IV. METHODOLOGY

A. System Architecture

The application uses a client–server architecture. The React/TypeScript frontend provides image upload, detection display, pattern analysis, one-to-one comparison, analytics, and report pages. The Python FastAPI backend validates uploaded files and calls the configured Roboflow workflow. The returned prediction data is parsed and sent to the frontend, where category-based reference selection and pattern comparison are performed. Analysis records are saved in browser IndexedDB. Optional database and object-storage operations are available only when the required environment configuration is present.

The main processing path is: image upload → file validation → FastAPI detection endpoint → Roboflow inference → prediction and scene parsing → reference-image selection → pattern comparison → IndexedDB storage → one-to-one review and PDF report.

B. Image Upload and Validation

The frontend accepts JPEG, PNG, and WebP images up to 10 MB. The backend reads the uploaded data and validates the file using Pillow before inference. Unsupported, empty, malformed, or oversized files are rejected. A temporary file is used for the inference request and removed after the request completes.

C. Object Detection and Scene Description

The backend invokes the configured Roboflow workflow through the inference client. It parses returned prediction categories and bounding-box coordinates. Weapon categories supported by the application include gun, pistol, rifle, knife, sword, and bat. Person labels are parsed separately and used to calculate the number of person detections. The frontend overlays the returned bounding boxes on the uploaded image.

The scene parser normalises available descriptions into indoor/outdoor and day/night values and retains a people-presentation description when returned. Unknown or unavailable values remain unclassified. These descriptions are not verified GPS coordinates, capture timestamps, or identity information. The backend does not expose a meaningful confidence value for the current workflow, so no confidence-based performance claim is made.

D. Reference-Image Collection

The uploaded project directory contains 35 local reference images distributed across three folders: 16 gun images, 15 knife images, and 4 bat images. Each reference path is associated with a text description and, where available, a body-style or clothing description. The frontend selects up to four reference images for a given upload, prioritising categories returned by the detector and avoiding immediate reuse where possible. These images are reference examples for comparison; they are not identified in the code as training or independent test data for the external detector. The planned future expansion is to build the reference collection to 100+ independently sourced and appropriately labelled images

 This work is licensed under a Creative Commons Attribution 4.0 International License

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940



International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.1511198

across the gun, knife, and bat categories. This is a future target and is not the size of the collection in the current submitted project version.

E. Pattern-Analysis Method

Pattern Analysis is the central module of the project. It compares the uploaded scene record with up to four selected reference records. The comparisons are rule-based and use the available detection output and reference text descriptions rather than a trained image-embedding or person-recognition model.

Weapon-category comparison checks whether the weapon category detected in the uploaded image is also assigned to a reference image. Person comparison extracts a person count from the reference description, where possible, and compares it with the uploaded image's detected person count. Scene-area comparison identifies indoor or outdoor terms in the reference description and compares them with the uploaded scene setting. Time comparison looks for explicit day or night terms. Dress comparison extracts clothing descriptors—such as uniform, hoodie, shirt, jacket, jeans, trousers, and colour terms—from the uploaded people description and reference body-style description, then checks whether at least one descriptor is shared.

For each attribute, the interface displays the number of matching references divided by the selected reference set, expressed as a percentage. Comparisons that lack sufficient descriptive information are reported as unavailable rather than treated as a mismatch. The percentage is a descriptive match proportion for the selected references only; it is not a probability, detector accuracy, or a measure of forensic certainty.

F. Record Storage and One-to-One Comparison

After the comparison is prepared, the frontend saves a record in IndexedDB. The record contains the uploaded image blob, file name, analysis time, person count, scene descriptors, detection findings, and selected reference matches. The One to One Image page displays the uploaded image alongside each selected reference image and presents a text summary of the category and scene information. It explicitly states that category and context similarities do not establish person identity or an incident match.

G. PDF Report Generation

The report module retrieves the latest saved pattern record and creates an A4 PDF using jsPDF. The report includes the uploaded image, weapon-category information, analysis time, up to four comparison descriptions, people description when available, reference body-style descriptions, and a safety notice. The report is intended to document the automated review output for subsequent human examination.

H. Analytics Module

The analytics dashboard uses a local JSON file containing 40 illustrative records with month, area, gender, weapon category, and image path fields. The data file explicitly labels these entries as illustrative demonstration records rather than verified crime statistics. The dashboard demonstrates the presentation of sample records by month, area, gender, and weapon category; it must not be interpreted as an empirical crime-trend analysis.

V. RESULTS AND DISCUSSION

The supplied application screenshots demonstrate the main stages of the implemented workflow. The detection screen shows weapon and person bounding boxes, grouped object labels, a person count, and available scene information. In the illustrated detection example, the interface displays firearm-related detections and two person detections, together with outdoor and day scene descriptors. These are observations from the displayed example, not a general detector-performance evaluation.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.1511198

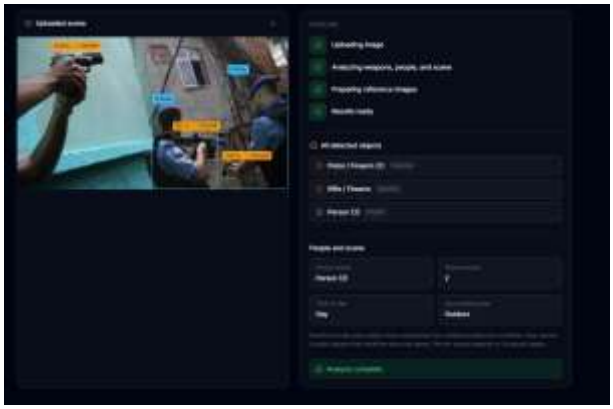


Fig. 3 Detection interface showing object boxes, weapon labels, person count, and available scene descriptors

The Pattern Analysis screen displays a saved uploaded image and a pattern-match summary. In the illustrated example, the interface reports Weapon: 100% match (4/4), Person: 50% match (2/4), Area: 0% match (0/4), and Dress: 50% match (2/4). These values represent rule-based comparison outcomes against four selected reference records in that example. They do not represent classification accuracy or validation against ground-truth labels.

A second supplied Pattern Analysis example shows an uploaded image containing two people and one knife detection. The scene descriptor reports an indoor setting, while the time-of-day field is not reported. The interface presents four selected knife-category references and describes similarities in weapon category and visible scene context. The four displayed references are all category matches; the text descriptions include knife-defence or staged self-defence activity involving two people. This example demonstrates how the system presents the uploaded image summary alongside individual reference descriptions. It does not establish that the same people, weapon, or incident appear in the reference images.



Fig. 6 Latest Pattern Analysis output showing the uploaded image summary and four category-related reference comparisons.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026

DOI: 10.17148/IJARCCE.2026.1511198

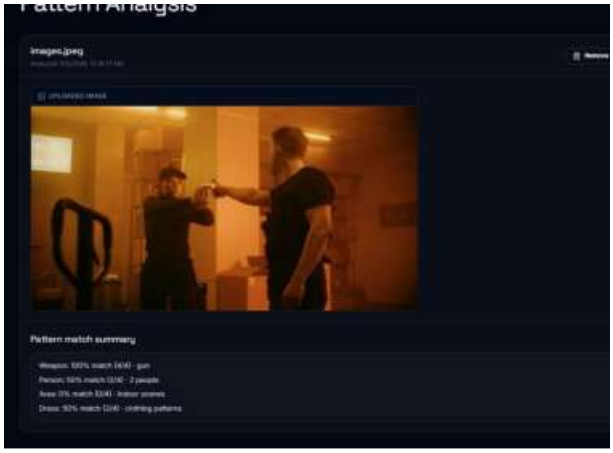


Fig. 4 Pattern Analysis screen showing the attribute-wise match summary for one saved image.

The one-to-one comparison page presents the uploaded image beside selected category-related references and provides text descriptions of the detected category, person count, scene setting, and reference content. The PDF report presents the uploaded image and comparison details in a structured format, allowing the reviewer to inspect the basis of each category match.



Fig. 5 Example PDF report generated from a saved image-analysis record.

The analytics interface displays the illustrative JSON records in dashboard form. Because these records are not verified incident data, no real-world crime frequency, geographic concentration, gender distribution, or temporal trend is inferred from them.

The results demonstrate that the project connects object-detection output with a multi-attribute reference-review process. Its main contribution is not the development of a new weapon detector but the organisation of several image-level attributes into a single pattern-analysis record. Weapon category provides the initial reference grouping, while person count, scene setting, time-of-day description, and clothing terms provide additional comparison dimensions.



International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 11, November 2026
DOI: 10.17148/IJARCCE.2026.1511198

The dress comparison is implemented as descriptor overlap. For example, a shared term such as uniform, hoodie, shirt, or jeans contributes to a clothing-pattern match when it appears in both the uploaded people description and a reference body-style description. This is a text-based comparison and does not establish that the same person or same clothing item appears in both images. Likewise, person-count and scene matches are based on parsed descriptions and should be interpreted as supporting observations.

The displayed percentage summary helps reviewers understand which attributes agree with the selected references and which do not. However, the small reference collection, dependence on generated descriptions, and rule-based matching method limit the strength of the conclusions. A larger curated reference set, verified annotations, and a formal evaluation protocol would be needed before measuring the reliability of these comparisons.

VI. CONCLUSION

This paper presented an image-based digital crime pattern analysis prototype that integrates external object detection with descriptive reference comparison and report generation. The main module compares weapon category, detected-person count, scene area, time-of-day description, and clothing descriptors across an uploaded image and up to four selected reference images. It stores the analysis record, supports one-to-one image review, and generates a PDF report. The current implementation demonstrates an organised workflow for human-assisted comparison, while its rule-based matching, limited reference collection, and illustrative analytics data restrict the conclusions that can be drawn. Future work should expand and curate the reference collection, add verified annotations, evaluate each comparison attribute against ground truth, and investigate visual similarity methods under a documented evaluation protocol.

VII. FUTURE SCOPE

The future scope of this project includes expanding the reference image collection with more diverse and verified crime-scene images to improve comparison results. Verified annotations can be added to increase the reliability of image analysis. Advanced visual similarity techniques can be introduced to improve matching beyond the current rule-based approach. Weapon detection and person-count analysis can be further enhanced to provide more reliable results. Clothing and scene descriptions can be improved using advanced image-processing techniques. Each comparison attribute can be evaluated using verified data to measure its performance. The system can also be extended with detailed analytical reports and improved visualizations. In the future, human verification and expert review should remain essential before using the results for investigative or forensic purposes.

VIII. ACKNOWLEDGE

The authors gratefully acknowledge the guidance and support of Prof. Pradnya Rama, Department of Computer Science and Engineering, Basaveshwar Engineering College, Bagalkot, Karnataka, India.

REFERENCES

[1]. R. Debnath and M. K. Bhowmik, “A comprehensive survey on computer vision based concepts, methodologies, analysis and applications for automatic gun/knife detection,” Journal of Visual Communication and Image Representation, vol. 78, Art. no. 103165, 2021, doi: 10.1016/j.jvcir.2021.103165.
[2]. T. Santos, H. Oliveira, and A. Cunha, “Systematic review on weapon detection in surveillance footage through deep learning,” Computer Science Review, vol. 51, Art. no. 100612, 2024, doi: 10.1016/j.cosrev.2023.100612.
[3]. M. T. Bhatti, M. G. Khan, M. Aslam, and M. J. Fiaz, “Weapon detection in real-time CCTV videos using deep learning,” IEEE Access, vol. 9, pp. 34366–34382, 2021, doi: 10.1109/ACCESS.2021.3059170.
[4]. J. Y. Lim, M. I. Al Jobayer, V. M. Baskaran, J. M. Y. Lim, J. See, and K. S. Wong, “Deep multi-level feature pyramids: Application for non-canonical firearm detection in video surveillance,” Engineering Applications of Artificial Intelligence, vol. 97, Art. no. 104094, 2021, doi: 10.1016/j.engappai.2020.104094.
[5]. V. Jadhav, R. Deshmukh, P. Gupta, S. Ghogale, and M. Bodireddy, “Weapon detection from surveillance footage in real-time using deep learning,” in Proc. 7th International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune, India, 2023, doi: 10.1109/ICCUBEA58933.2023.10392003.
[6]. P. Yadav, N. Gupta, and P. K. Sharma, “A comprehensive study towards high-level approaches for weapon detection using classical machine learning and deep learning methods,” Expert Systems with Applications, vol. 212, Art. no. 118698, 2023, doi: 10.1016/j.eswa.2022.118698.

 This work is licensed under a Creative Commons Attribution 4.0 International License