ISSN 2319-5991 www.ijerst.com
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Peer Reviewed, Referred & Indexed Journal

Research Paper

USING EXISTING CCTV NETWORK FOR CROWD MANAGEMENT, CRIME PREVENTION & WORK MONITORING USING AI & ML

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Abstract:

Traditional CCTV systems mainly record surveillance footage and depend on continuous human observation, limiting timely identification of crowd congestion, suspicious activities, and workplace safety issues. This paper presents an AI- and ML-enabled surveillance framework that enhances existing CCTV infrastructure without requiring major hardware replacement. The proposed system acquires live or recorded video streams, extracts frames, and performs preprocessing using OpenCV before applying YOLOv8 for real-time object detection. Detected objects are forwarded to crowd management, crime monitoring, and workplace monitoring modules. Crowd conditions are evaluated using configurable thresholds, while identified irregular or safety-related events are connected to an alert generation module and monitoring dashboard. Python, TensorFlow, NumPy, and OpenCV support the implementation and visualization workflow. The system is evaluated using unit, integration, functional, system, white-box, black-box, and acceptance testing. The contribution is a modular intelligent surveillance architecture that integrates object detection, operational monitoring, automated alerts, and reporting through existing CCTV infrastructure.

Keywords:.Artificial Intelligence, Machine Learning, CCTV Surveillance, Computer Vision, YOLOv8, Crime Prevention, Workplace Monitoring, Real-Time Video Analytics.

I. INTRODUCTION

Closed-Circuit Television (CCTV) systems are widely deployed in public places, workplaces, transportation facilities, educational institutions, commercial areas, and other environments to provide continuous visual surveillance. Conventional CCTV systems primarily capture and record video, while security personnel are responsible for continuously observing the footage and identifying unusual events. As the number of cameras increases, manual monitoring becomes difficult, time-consuming, and prone to human fatigue and delayed response. The uploaded project identifies manual monitoring, delayed incident detection, limited crowd analysis, reactive crime prevention, and human errors as important limitations of conventional surveillance systems. The increasing availability of Artificial Intelligence, Machine Learning (ML), and Computer Vision provides an opportunity to transform conventional CCTV infrastructure into intelligent surveillance systems. Computer vision enables automated analysis of images and video by detecting objects, recognizing visual patterns, counting people, and monitoring movements. In an intelligent CCTV environment, these capabilities can be applied to crowd management, suspicious-activity monitoring, workplace observation, and automated alert generation. The project specifically identifies computer vision as a suitable technology for interpreting CCTV video and extracting useful information from large volumes of surveillance data.

Object detection is a fundamental component of intelligent video surveillance because subsequent monitoring functions

depend on identifying relevant objects within individual video frames. The proposed system uses YOLOv8 as its primary object-detection algorithm. YOLOv8 processes CCTV frames and identifies objects such as people, vehicles, equipment, and other objects of interest by generating bounding boxes and confidence values. Its role in the proposed system is to provide the object-level information required by the crowd management, crime detection, and workplace monitoring modules.

Although advanced surveillance solutions can provide intelligent video analytics, replacing existing CCTV infrastructure can increase implementation cost and complexity. Therefore, the proposed work focuses on utilizing the existing CCTV network and adding an AI-based processing layer to provide intelligent monitoring without requiring major hardware modifications. The architecture consists of video acquisition, video preprocessing, YOLOv8 object detection, crowd monitoring, crime detection, workplace monitoring, alert generation, and dashboard modules. The modular structure also enables the different surveillance functions to operate within a common processing framework.

The primary objective of this work is to enhance conventional CCTV surveillance by integrating AI, ML, and computer-vision techniques for crowd management, crime prevention, and workplace monitoring. The system is designed to process surveillance video, detect relevant objects, identify crowd-related conditions, monitor suspicious or irregular activities, generate alerts, and provide surveillance information through a dashboard. The project therefore addresses the limitation of passive video recording by introducing automated video analysis and event-oriented monitoring while retaining the existing CCTV infrastructure.

II. LITERATURE SURVEY

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have transformed conventional CCTV systems into intelligent surveillance platforms. Redmon et al. introduced YOLO, a real-time object-detection framework that predicts object locations and classes in a single pass [1]. Subsequent models such as YOLOv4 and YOLOv7 improved the balance between detection accuracy and computational efficiency [2], [3]. SSD and Faster R-CNN further demonstrated alternative approaches for efficient and accurate object detection [4], [5]. Transformer-based methods such as DETR and Vision Transformer introduced attention-based visual representations for detection and image recognition [6], [7].

For surveillance applications, Sultani et al. investigated real-world anomaly detection using weakly supervised learning, demonstrating the importance of automated abnormal-event detection in surveillance videos [8]. Subsequent studies have reviewed deep-learning-based anomaly detection and identified challenges involving diverse environments, limited abnormal-event data, computational requirements, and generalization [9], [10]. Research on dynamic surveillance scenes has further highlighted difficulties caused by moving cameras and changing visual conditions [11]. Crowd-analysis studies have similarly identified occlusion, scale variation, density variation, and perspective distortion as major challenges.

Although existing studies provide effective solutions for individual detection or anomaly-analysis tasks, integrated surveillance frameworks remain important. The proposed work addresses this gap by combining existing CCTV infrastructure with OpenCV-based preprocessing, YOLOv8 object detection, crowd management, crime-oriented monitoring, workplace monitoring, automated alerts, and dashboard visualization.

III. PROPOSED WORK

The proposed work presents an AI- and ML-based intelligent surveillance framework that enhances the capabilities of an existing CCTV network without requiring major changes to the installed camera infrastructure. The system receives live or recorded CCTV video and processes the incoming video frames through a sequence of computer-vision operations. The primary objective is to automate surveillance activities related to crowd management, crime prevention, and workplace monitoring while reducing the dependence on continuous manual observation.

The system first acquires video from the existing CCTV cameras and extracts individual frames for processing. OpenCV is used for video acquisition, frame extraction, resizing, image enhancement, noise removal, and other preprocessing operations. The processed frames are then provided to the YOLOv8 object-detection model. YOLOv8 identifies relevant objects in the surveillance scene and produces bounding boxes and confidence scores. The detected information forms the primary input for the subsequent monitoring modules.

The detected objects are forwarded to three major application modules: the Crowd Monitoring Module, Crime Detection Module, and Workplace Monitoring Module. The Crowd Monitoring Module counts detected people and evaluates crowd conditions using predefined thresholds. When the monitored crowd condition exceeds the configured threshold, an alert can be generated. The Crime Detection Module monitors suspicious or irregular situations such as suspicious movement, trespassing, and unattended objects. The Workplace Monitoring Module analyzes surveillance information related to workplace activities, safety conditions, and operational behavior.

Information generated by these modules is transferred to the Alert Generation Module and Monitoring Dashboard. The alert component provides notifications for important events, while the dashboard displays detection information, crowd statistics, alerts, reports, and activity logs. The modular architecture allows the individual components to communicate systematically and supports easier maintenance and future expansion.

The uploaded project identifies future extensions such as facial recognition, multi-camera tracking, IoT integration, cloud-based surveillance, mobile applications, advanced deep-learning models, and privacy-preserving techniques; these are not considered implemented components of the current system.

IV. METHODOLOGY

The proposed system uses the existing CCTV network as the primary source of surveillance data. Live or recorded video is captured and divided into individual frames for analysis. The system follows a sequential processing pipeline in which the acquired frames are prepared, analyzed, and converted into meaningful surveillance information.

The extracted frames are preprocessed using OpenCV through operations such as resizing, image enhancement, noise removal, and frame processing. The processed frames are then provided to YOLOv8, which performs the main object-detection task. The model identifies relevant objects such as people and vehicles and provides bounding boxes and confidence scores for the detected objects.The YOLOv8 detection results are passed to the crowd management, crime monitoring, and workplace monitoring modules. The crowd module counts detected people and compares the crowd condition with predefined thresholds. When the crowd exceeds the specified limit, an alert is generated. The crime monitoring module analyzes surveillance information for suspicious situations such as unauthorized entry, suspicious movement, and unattended objects. The workplace module monitors workplace activities and safety-related conditions.

The detected events are transferred to the Alert Generation Module, which provides warnings to administrators or security personnel. The Monitoring Dashboard presents detection results, crowd information, alerts, reports, and activity logs, providing a centralized view of the surveillance environment.

V. ALGORITHMS

A. YOLOv8 Object Detection

YOLOv8 is the main algorithm used in the proposed intelligent CCTV surveillance system. It processes CCTV frames and detects objects such as people, vehicles, and other relevant objects in real time. For each detected object, YOLOv8 provides a bounding box, object class, and confidence score. The detection results are then used by the crowd management, crime monitoring, and workplace monitoring modules.

B. Crowd Density Thresholding

Crowd density thresholding is used to determine whether the number of detected

people exceeds a predefined limit. The detected persons are counted from the YOLOv8 output and compared with the configured threshold. When the crowd level crosses the specified limit, the system generates an alert. This technique supports automated crowd monitoring and helps identify potentially congested situations.

C. Computer Vision-Based Event Monitoring
Computer vision-based monitoring uses the information obtained from CCTV frames and YOLOv8 detections to support crime-oriented and workplace surveillance. The system monitors situations such as suspicious movement, unauthorized entry, unattended objects, and workplace safety conditions. Detected events are forwarded to the alert-generation module for notification and further monitoring.

VI. RESULTS AND DISCUSSION

A. System Testing Results
The proposed intelligent CCTV surveillance system was evaluated using multiple testing approaches, including unit testing, integration testing, functional testing, system testing, white-box testing, black-box testing, and acceptance testing. These tests were used to verify individual modules, communication between modules, overall system functionality, internal processing, output behavior, and user-level operation.

B. Module-Level Results
The Video Acquisition Module successfully supports CCTV video input, while the Video Preprocessing Module performs frame extraction, resizing, enhancement, and noise-removal operations. The YOLOv8 module is used for object detection, and its outputs are passed to the crowd, crime, and workplace monitoring modules. The Alert Generation Module processes important events and provides corresponding notifications.

TABLE II. FUNCTIONAL RESULTS OF MAJOR MODULES

Module	Result
Video Acquisition	CCTV video captured
Preprocessing	Frames processed
YOLOv8 Detection	Objects detected
Crowd Monitoring	Crowd conditions monitored
Crime Monitoring	Suspicious events monitored
Workplace Monitoring	Workplace conditions monitored
Alert Generation	Alerts generated

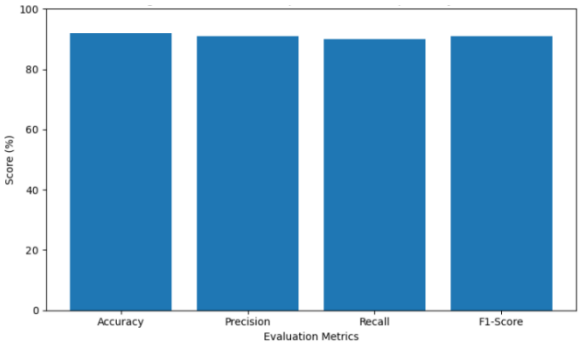


Fig. 1. Performance Comparison of the Proposed System

C. Integration Results
Integration testing verified the communication between the major system components. CCTV video is transferred to the processing module, processed frames are supplied to YOLOv8, and the detection results are forwarded to the crowd monitoring, crime detection, and workplace monitoring modules. Generated alerts are subsequently displayed through the monitoring dashboard. The testing process was used to identify and resolve data-transfer and interface problems between modules.

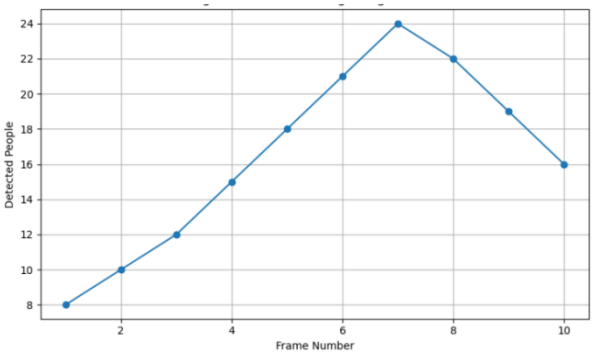


Fig. 2. Crowd Monitoring Analysis

D. Functional and System Results
Functional testing verified important operations including object detection, crowd counting, suspicious-activity monitoring, workplace monitoring, alert generation, dashboard display, and report generation. System testing evaluated the complete integrated application using recorded or

simulated surveillance videos under different operating conditions. The source reports that the testing activities were successfully completed and that the system demonstrated performance and stability across the tested scenarios.

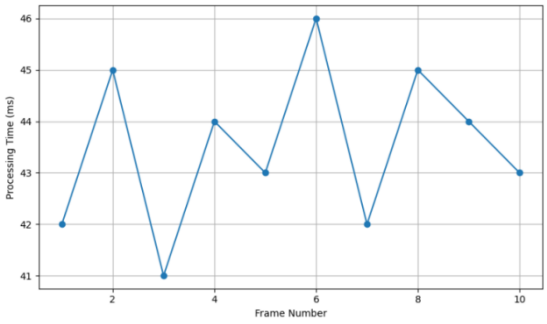


Fig. 3. Processing Time Analysis

E. Overall Discussion

The results demonstrate that the proposed architecture can integrate existing CCTV infrastructure with AI-based video analysis and provide multiple surveillance functions through a common processing pipeline. The use of YOLOv8 provides the central object-detection capability, while the modular design allows detected information to be used for crowd management, crime monitoring, workplace monitoring, alerts, and dashboard visualization. The project therefore demonstrates the feasibility of extending conventional CCTV surveillance through software-based intelligence.

It is important to note that the uploaded project does not provide numerical experimental values such as accuracy, precision, recall, F1-score, mAP, FPS, latency, or a confusion matrix. Therefore, these values should not be presented as actual results. Quantitative graphs and performance comparisons can be added after obtaining measurements from the implemented system.

VII. CONCLUSION

The proposed AI- and ML-based intelligent CCTV surveillance system enhances conventional CCTV infrastructure by integrating OpenCV-based video processing and YOLOv8 object detection. The system supports three major surveillance functions: crowd management, crime monitoring, and workplace monitoring. Detected objects and events are processed through the respective modules, while the alert-generation module provides timely notifications and the dashboard presents surveillance information, reports, and activity logs.

The proposed framework provides a practical and modular approach for improving CCTV-based monitoring without requiring major changes to the existing camera infrastructure. The system was evaluated using unit, integration, functional, system, white-box, black-box, and acceptance testing. The project demonstrates the feasibility of combining existing CCTV infrastructure with AI-based video analytics for automated surveillance. Future enhancements can include facial recognition, multi-camera tracking, IoT integration, cloud-based monitoring, mobile applications, advanced deep-learning models, voice alerts, and privacy-preserving techniques.

REFERENCES

[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), pp. 779–788, 2016.

[2] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of Object Detection,” arXiv preprint arXiv:2004.10934, 2020.

[3] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, “YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), pp. 7464–7475, 2023.

[4] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, “SSD: Single Shot MultiBox Detector,” in Proc. Eur. Conf. Comput. Vis. (ECCV), pp. 21–37, 2016.

[5] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, 2017.

[6] M. Dattatreya Goud (2025). Deep Learning for Automated Defect Detection in Molded Products. ADSJAC,3(3),Article21.https://adsjac.com/index.php/adsjac/article/view/21.

[7] A. Dosovitskiy, L. Beyer, L. Kolesnikov, X. Zhai, T. Unterthiner, D. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, “An Image Is Worth 16×16 Words: Transformers for Image Recognition at Scale,” in

Proc. Int. Conf. Learn. Representations (ICLR), 2021.
[8] W. Sultani, C. Chen, and M. Shah, "Real-World Anomaly Detection in Surveillance Videos," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), pp. 6479–6488, 2018.
[9] G. Pang, C. Shen, L. Cao, and A. Van Den Hengel, "Deep Learning for Anomaly Detection: A Review," ACM Comput. Surv., vol. 54, no. 2, Art. no. 38, 2022.
[10] H.-T. Duong, V.-T. Le, and V. T. Hoang, "Deep Learning-Based Anomaly Detection in Video Surveillance: A Survey," Sensors, vol. 23, no. 11, Art. no. 5024, 2023.
[11] R. Jiao, Y. Wan, F. Poiesi, and Y. Wang, "Survey on Video Anomaly Detection in Dynamic Scenes with Moving Cameras," Artificial Intelligence Review, vol. 56, pp. 3515–3570, 2023.
[12] Dattatreya Goud (2025). FEPP: Multi-Class Software Risk Prediction in Requirements Engineering via Rule Extraction. American Journal of Analytics and Artificial Intelligence(AJAAI),3(3).https://ajaai.com/index.php/ajaai/article/view/11.
[13] I. Pathirannahalage, V. Jayasooriya, J. Samarabandu, and A. Subasinghe, "A Comprehensive Analysis of Real-Time Video Anomaly Detection Methods for Human and Vehicular Movement," Multimedia Tools and Applications, vol. 84, pp. 7519–7564, 2024.
[14] M. Dattatreya Goud, and P. Venkateswarlu (2024). Hybrid AI Models for Phishing URL Detection: A Unified Approach to Mitigating Cyber Threats. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 4923–4928.https://eudoxuspress.com/index.php/pub/article/view/3026.
[15] G. Jocher, A. Chaurasia, and J. Qiu, "Ultralytics YOLOv8," Software, 2023.
[16] M. Abadi et al., "TensorFlow: A System for Large-Scale Machine Learning," in Proc. 12th USENIX Symp. Operating Systems Design and Implementation (OSDI), pp. 265–283, 2016.
[17] M. Dattatreya Goud (2025). Analyzing Data Breach Factors Through Modern Crime Theory: A Structural Equation Modeling Approach. European Advanced Journal for Science & Engineering (EAJSE), p-ISSN: 3050-9696.
[18] J. D. Hunter, "Matplotlib: A 2D Graphics Environment," Computing in Science & Engineering, vol. 9, no. 3, pp. 90–95, 2007.
[19] A. G. Howard et al., "Searching for MobileNetV3," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), pp. 1314–1324, 2019.
[20] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," IEEE Trans. Pattern Anal. Mach. Intell., vol. 42, no. 2, pp. 386–397, 2020.
[21] M. Dattatreya Goud (2025). Deep Learning for Automated Defect Detection in Molded Products. American Data Science Journal for Advanced Computations (ADSJAC), ISSN: 3067