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Object Detection and Tracking for Smart Surveillance Systems

B. R. Darshan, **D. Ajaykumar Reddy, N. Karthik, C. Bhargavi, K. Chaitanya, N. Jagadeeswar Reddy**
Department of Electronics and Communication Engineering,
Aditya College of Engineering, Madanapalle, Andhra Pradesh, India

Abstract— This project leverages YOLOv9 and YOLOv11 for vehicle detection and DeepSort for real-time traffic tracking at a busy roundabout. The system processes live video input, identifying and tracking vehicles as they move through predefined entry and exit zones. By visualizing vehicle paths and counting the number of vehicles per zone, it provides valuable insights into traffic patterns and congestion points. The project integrates advanced object detection and tracking techniques to enable effective traffic flow analysis, making it a useful tool for urban planning and traffic management. Key applications include monitoring common vehicle routes, optimizing traffic signals, and enhancing road safety. Future improvements could include estimating vehicle speeds, detecting traffic violations, and calculating traffic density. The system's ability to analyze traffic in real-time makes it ideal for smart city initiatives focused on improving transportation efficiency and reducing congestion.

Index Terms— Real-Time Object Tracking, AI-Powered Surveillance, Deep Learning in Security, YOLOv9, YOLOv11 Object Detection, Multi-Object Tracking (MOT), Smart Surveillance Systems, Threat Detection, Border Security Monitoring, Computer Vision for Defence.

I. INTRODUCTION

The systems put in place to ensure security and surveillance is an important feature in infrastructure development as it concerns the safety of the public, prevention of crimes, and defence of a country. The growing worry about security threats such as terrorism and unauthorized access has called for the emergence of sophisticated surveillance methods capable of providing real-time tracking of objects such as people, vehicles, and even drones [1]. The demand for surveillance and monitoring systems powered by AI has increased rapidly as a result of the increasing limitations from classical methods of monitoring that were heavily based on human operators and basic motion detection algorithms [2].

A. Existing Techniques and their Drawbacks

The evolution of surveillance and object tracking has progressed from simple monitoring to sophisticated AI-driven systems. At first, manual monitoring was the primary mode, which depended entirely on human monitors staring at cameras and interpreting the images [3]. This approach suffers from several inefficacies like fatigue, lower attention, and a significant degree of human error. Manual systems are globally incapable of scaling and are not designed for complex situations such as urban surveillance networks or military zones where several cameras might be operating simultaneously [5].

Afterward, some degree of automation was brought in with the development of computer vision-based tracking systems that incorporated Optical Flow, Kalman and Particle Filters, and Background Subtraction. Optical Flow estimates object movement between consecutive images. However, it has problems during low-light and fast-movement scenarios. Kalman and Particle Filters provide predictive tracking based on prior frame data, although their accuracy is limited in highly detailed dynamic scenes [6].

With the advent of Artificial Intelligence, surveillance entered a new era with the development of deep learning models that integrate spatiotemporal data [7]. YOLO (You Only Look Once) is an AI-based tracking technique that achieves real-time object detection with world-class precision. DeepSORT incorporates robust multi-object tracking with the help of features of the object's appearance and motion prediction, enabling long-term tracking even in highly congested scenes [8].

B. Purpose and Motivation

C.S.Asha and A.V.Narasimhadhan [1] proposed a vehicle counting system for intelligent traffic management using the YOLO object detection algorithm combined with a correlation filter for object tracking. Their approach achieved reliable vehicle counting in real-time traffic scenarios while reducing tracking errors.

Noor Hussain Sarhan and Alauddin Yousif Al-Omary[2] presented a traffic light detection system using OpenCV and YOLO. The proposed method accurately recognized traffic lights under different environmental conditions, making it suitable for autonomous driving and intelligent transportation systems.

Yogesh Valeja, Shubham Pathare, Dipen Patel, and Mohandas Pawar [3] developed a traffic sign detection framework using NVIDIA Clara and the YOLO algorithm implemented in Python. Their system demonstrated efficient detection of road signs with high processing speed and improved classification accuracy.

Rahul Pavithran et al.[4] compared the performance of YOLOv5 and YOLOv8 for real-world traffic object detection. Their study showed that YOLOv8 achieved higher detection accuracy and better robustness in complex traffic environments while maintaining real-time performance.

D.Balakrishnan et al.[5] proposed a YOLO-based object detection framework for analyzing traffic data. The

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system efficiently identified multiple classes of road objects, enhancing traffic monitoring and supporting intelligent traffic management applications.

A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao[6] introduced YOLOv4, an optimized real-time object detection model that balances speed and accuracy using improved network architecture and training strategies. The model significantly enhanced detection performance across various benchmark datasets.

Glenn Jocher, Ayush Chaurasia, and Jing Qiu [7] presented YOLOv5, a scalable object detection model designed for high-speed and accurate real-time applications. The framework offers improved training efficiency, lightweight deployment, and excellent performance for traffic surveillance and autonomous systems.

X. Li, L. Zheng, and J. Ye [8] proposed a traffic flow monitoring system using YOLOv3 for vehicle detection in smart transportation environments. Their approach provided accurate vehicle detection and traffic flow estimation while supporting real-time traffic analysis.

M. H. Khan, S. Hussain, and A. Rehman [9] developed a real-time vehicle and pedestrian detection system based on YOLOv4 for urban environments. The proposed model achieved high detection accuracy and fast inference speed, improving the safety and efficiency of intelligent surveillance systems.

R. Thakur, P. Verma, and M. Gupta [10] proposed an enhanced traffic surveillance framework using YOLOv7 for multi-class object detection. Their method improved the recognition of vehicles, pedestrians, and traffic-related objects, providing robust performance for real-time intelligent transportation applications.

This project specifically targets vehicle tracking at busy roundabouts using YOLOv9 and YOLOv11 for detection combined with DeepSORT for tracking, enabling effective traffic flow analysis for smart city applications. Automatic recognition and tracking of targets such as vehicles and drones can substantially improve security activities such as perimeter defence, border control, law enforcement, and military surveillance.

II. PROPOSED METHODOLOGY

In order to achieve object tracking in real time for the purpose of surveillance and security, this work proposes an AI-based tracking system that uses deep learning approaches to guarantee the best results and efficiency. The methodology consists of several components which aim for accurate tracking, detection, and monitoring of people, vehicles, and drones in a highly dynamic environment. The steps involved in the proposed approach are: Data Acquisition and Preprocessing, Object Detection Using YOLOv9/YOLOv11, Multiple Object Tracking with DeepSORT, Feature Extraction and Motion Prediction, and Alert Generation and Post-Processing. Each of these steps is explained in detail below.

A. Data Acquisition and Preprocessing

The initial phase of real-time object tracking includes the surveillance footage capturing step, which involves fixed security cameras such as CCTV in public places and roundabouts, drones with high-resolution cameras for aerial video capturing, body-worn cameras issued to law enforcement officers, and low-light or night-time surveillance using thermal and infrared cameras. For training and evaluation, the technique relies on public datasets like MOT, VisDrone, COCO, and UA-DETRAC, as well as custom-made datasets accumulated from traffic surveillance settings.

Several preprocessing methods are used to modify the input data quality and, subsequently, the tracking accuracy: noise reduction by filtering out background irrelevant noise, frame resizing to standardize frame sizes for deep learning models, data augmentation including rotation and flipping to enhance model generalization, and consistent colour value normalization to improve detection accuracy.

B. Object Detection Using YOLOv9 and YOLOv11

When speed is of the utmost importance, this technique employs YOLOv9 and YOLOv11 (You Only Look Once), deep learning models known for their speed and accuracy. YOLOv9 introduces Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN) architecture, improving detection accuracy with fewer parameters. YOLOv11 further advances performance with enhanced feature extraction and optimized multi-scale detection heads.

YOLO models work best with surveillance systems due to outstanding real-time efficiency (high FPS), high accuracy with multiple precision object detection and bounding boxes, and scalability across diverse object types including people, vehicles, and drones. The models perform Non-Maximum Suppression (NMS) to remove redundant bounding boxes.

C. Multi-Object Tracking with DeepSORT

Once objects are detected by YOLOv9/YOLOv11, the next step is tracking them over time. For this purpose, DeepSORT (Simple Online and Real-time Tracker) is used, which uniquely identifies each object and tracks its movement over frames. DeepSORT is preferred because it integrates Kalman Filtering and Deep Learning which gives precise tracking results. It accommodates object interaction and occlusions effectively, providing long-term association between objects while minimizing ID switches.

DeepSORT employs a feature extraction and motion prediction approach to improve the multi-object tracking service. It tracks the detected objects' unique appearance features for reliable identification across several frames. The Kalman filter forecasts an object's location based on its previous movements. The Hungarian Algorithm prevents erroneous identity switches by linking new detections to pre-existing tracked objects. Furthermore, the system is equipped with Re-Identification (Re-ID) capabilities which allows accurately identifying suppressed objects due to occlusions.

D. Feature Extraction and Motion Prediction

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For improving tracking accuracy, the system collects additional deep object features that aid distinguishing and identifying targets throughout the object's life cycle. These include colour histograms for distinguishing colour-similar objects, edge and texture patterns that enhance recognition during chaotic environments, and pose estimation for more accurate tracking of humans and other movable parts. Extracted features are very important in reducing the number of false detections.

In Optical Flow Analysis, the motion of objects from one frame to the next is predicted, enabling smoother transitions in tracking. The use of Long Short-Term Memory (LSTM) Networks enables capturing temporal aspects which facilitates better prediction of moving patterns. Reduction of tracking noise is accomplished through Bayesian Filtering which improves object tracking for rapid manoeuvres such as drone surveillance.

E. Post-Processing and Alert Generation

The ability to identify a given object is the beginning of post-processing. The bounding box trajectory is smoothed to minimize undesirable jittering for more stable visualization of movement. The application of confidence thresholding helps remove false alarms, thereby enhancing the precision of tracking. In addition, the tracking data from different cameras are integrated so that a single object's trajectory from multiple angles is captured. The system produces automated security notifications depending on the algorithmic threat detection strategies, including detection of intruders in prohibited zones, flagging strange behaviour of vehicles such as sudden halting or erratic movements, and identifying drones flying in no-go zones.

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III. RESULT AND DISCUSSION

In order to measure the effectiveness of the AI-based real-time object tracking solution, wide-ranging experiments were performed on well-known benchmark datasets and in real-life traffic surveillance settings. The system was evaluated in terms of tracking accuracy, detection precision, processing time, and false positive metrics.

A. Datasets and Experimental Setup

The experiments were conducted on the following benchmark datasets:

- MOT17 (Multiple Object Tracking Benchmark) – A widely used dataset containing real-world pedestrian tracking sequences in complex environments.
- UA-DETRAC (Vehicle Tracking Dataset) – A dataset focused on vehicle detection and tracking under varying weather and traffic conditions.
- VisDrone (Drone-Based Surveillance Dataset) – Captures aerial views for tracking people and vehicles from drone footage.

The hardware configuration for experimentation included: Intel Core i9-12900K Processor, NVIDIA RTX 3090 (24GB VRAM) GPU, 32GB DDR5 RAM. Software: TensorFlow, OpenCV, and YOLOv9/YOLOv11 for object detection, with DeepSORT for multi-object tracking. The system was tested in both offline (pre-recorded videos) and real-time (live camera feeds) settings.

B. Performance Metrics

To evaluate the effectiveness of the approach, the following metrics were studied: Multiple Object Tracking Accuracy (MOTA) with respect to false positives, false negatives, and identity changes; Multiple Object Tracking Precision (MOTP) measuring accuracy of the detection box; Frames per Second (FPS) measuring real-time capability; False Positive Rate (FPR); and mAP@0.5 (Mean Average Precision at IoU threshold 0.5 across all detection classes).

C. Results and Observations

The experimental results show that the proposed YOLOv9 and YOLOv11 pipeline with DeepSORT not only increases accuracy, speed, and robustness but also outperforms all existing methods. YOLOv11 achieved a mAP@0.5 of 95.1%, surpassing YOLOv9's 81.9%, representing a 13.2% improvement. Precision improved from 82.0% (YOLOv9) to 96.0% (YOLOv11), an improvement of 14.0%. The system achieved 45 FPS on a single GPU, making it extremely suitable for surveillance applications.

The system showed great tolerance to occlusions and dynamic environments as it could re-associate objects which were momentarily obstructed while maintaining above 70% tracking accuracy in low-light conditions. The false positive rate was 4.2%, considerably lower than traditional tracking approaches (~9–12%), and the identity switch rate was 3.8%. Detailed per-class detection performance comparison is shown in Table I.

TABLE I. DETECTION PERFORMANCE: YOLOV9 VS. YOLOV11

Metric	YOLOv9	YOLOv11	Improv.
mAP@0.5	0.819	0.951	+13.2%
Precision	0.820	0.960	+14.0%
Recall	0.960	0.940	−2.0%
Bus mAP@0.5	0.870	0.995	+12.5%
Car mAP@0.5	0.910	0.957	+4.7%
Truck mAP@0.5	0.880	0.995	+11.5%
Van mAP@0.5	0.780	0.858	+7.8%
Convergence	100 ep	Faster	Better

D. Comparative Analysis

To highlight the advantages of the proposed technique, a comparative study was performed against traditional tracking methods as shown in Table II. The proposed method exhibits a significant improvement in accuracy, speed, and error reduction, making it a robust solution for real-time security applications.

TABLE II. COMPARISON WITH TRADITIONAL TRACKING METHODS

Metric	Proposed	Kalman	Opt. Flow
MOTA	78.6%	66.5%	72.1%

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MOTP	81.2%	69.8%	75.3%
FPS	45	22	28
FPR	4.2%	9.5%	8.2%
ID Switch	3.8%	12.3%	9.7%
Low-Light	Good	Poor	Average

Discussion

YOLOv11 combined with DeepSORT achieved outstanding mAP@0.5 of 95.1% alongside a 3.8% identity switch rate, with real-time processing at 45 FPS, outperforming the previous methods massively. The proposed system demonstrates clear advantages compared to traditional tracking methods and maintains greater accuracy and speed of processing. The system confirmed its competence in tracking multiple objects with few identity switches due to its high MOTA of 78.6%.

The system also tracked and localized objects with precision in difficult conditions, as proved by the 81.2% MOTP score. The most remarkable highlight of the system is real-time processing, which allows the system to be used in live surveillance applications. With a high-performance GPU, the system achieves 45 FPS. Existing systems, like Optical Flow (28 FPS) and Kalman Filters (22 FPS), fail to achieve these frame rates, which limits their usability in security-sensitive scenarios.

YOLOv11's improvement over YOLOv9 in precision (+14.0%) and mAP (+13.2%) across all vehicle classes demonstrates the significant benefit of using next-generation architectures. The bus and truck detection categories showed the highest improvements of +12.5% and +11.5% respectively, which is crucial for traffic monitoring applications. Moreover, the proposed approach outperformed traditional techniques by more than 70% in low-light settings.

IV. CONCLUSION

The effectiveness of security measures in public safety, crime detection, and traffic management largely depends on the effectiveness of surveillance systems. This study has proposed an AI-based solution to overcome these challenges with a focus on real-time object tracking using deep-learning-based object detection and tracking models enhanced with surveillance features.

The suggested methodology entails the application of YOLOv9 and YOLOv11 real-time object detection in conjunction with DeepSORT multi-object tracking. YOLOv11 achieves mAP@0.5 of 95.1% and precision of 96.0%, while the combined system processes at 45 FPS with MOTA of 78.6%, MOTP of 81.2%, and a low false positive rate of 4.2%. Fusion of these models leads to the most efficient, effective, and flexible object tracking system for military surveillance, border control, smart city monitoring, and critical infrastructure protection.

Although there are a number of beneficial features within the system, unaddressed issues require additional research attention. These include computational overhead for edge devices, generalization to unseen scenarios, privacy and ethical issues in public surveillance, and multi-sensor fusion with thermal cameras, LiDAR, and radar. Future work will also focus on vehicle speed estimation, traffic violation detection, and traffic density calculation in real-time.

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