Highway Surveillance Drone System using yolov8

A PROJECT REPORT

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PALLABI KAKATI

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY
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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

BONAFIDE CERTIFICATE

Certified that this report "Real-Time Object Detection in Autonomous Vehicles Using YOLOv8" is a bonafide work of "MANUKIRAN S (20211ECE0284), NISHANT T G (20211ECE0284) , SUSHMITHA M V (20211ECE0272)", who have successfully carried out the project work and submitted the report for partial fulfilment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in ELECTRONICS AND COMMUNICATION ENGINEERING during 2024-25.

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We the students of final year B.Tech in Electronics and Communication Engineering at Presidency University, Bengaluru, named Manukiran S, Nishanth T G, Sushmitha M V, hereby declare that the project work titled **“Highway Surveillance Drone System using yolov8”** has been independently carried out by us and submitted in partial fulfillment for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering during the academic year of 2024-25. Further, the matter embodied in the project has not been submitted previously by anybody for the award of any Degree or Diploma to any other institution.

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ABSTRACT

Highway Surveillance Drone System using yolov8

With traffic volumes constantly rising on highways and expressways, the need for smarter, more flexible surveillance systems has become increasingly urgent. Congestion, accidents, and illegal road activities not only endanger lives but also strain public safety resources. Traditional fixed surveillance systems like roadside CCTV often lack the mobility, coverage, or responsiveness needed to monitor large or remote highway stretches effectively. In response to these limitations, we present a practical and innovative solution: a lightweight drone-based highway monitoring system using the DJI Tello paired with the powerful YOLOv8 object detection model.

The DJI Tello is a compact, affordable drone, often overlooked for serious tasks due to its size and limited onboard computing power. However, its ease of use, portability, and Wi-Fi-based live video streaming capabilities make it an excellent platform for experimental or mobile surveillance setups. By offloading the heavy computational work to a nearby laptop or edge device, we enable the Tello to participate in a high-performance, real-time object detection pipeline.

YOLOv8, developed by Ultralytics, represents one of the most advanced deep learning models in the field of computer vision. It offers a significant boost in detection accuracy and speed thanks to its redesigned architecture, including enhanced convolutional blocks and multi-scale detection layers. In our project, YOLOv8 processes the drone's live video feed to detect and classify key highway elements—such as cars, buses, motorcycles, pedestrians, and road signs—almost instantaneously. This allows the drone to act like a flying eye-in-the-sky, scanning busy roadways from above and capturing critical insights in real time.

To ensure YOLOv8 can handle real-world challenges, we trained the model using the COCO dataset, emphasizing road-focused and aerial images. The training process incorporated data augmentation techniques like brightness variation, rotation, and blur simulation to improve detection performance under less-than-ideal conditions. As a result, the model remains accurate even in low-light settings, high-speed traffic, or during drone motion where image stabilization may be compromised.

Beyond video and object recognition, we also utilize the Tello's onboard sensors—such as its IMU (Inertial Measurement Unit) and downward-facing camera—for better flight stability and situational awareness. Although the Tello has basic positioning features, combining them with detection results helps maintain a smoother, more reliable surveillance experience. This integration is particularly important when flying in windy conditions or over uneven terrain, where stable footage is key to accurate detection.

What sets this system apart is its versatility. The drone can be deployed quickly in response to real-time events, covering locations that might be inaccessible or too remote for fixed infrastructure. Whether it's monitoring traffic flow during peak hours, spotting accidents or obstructions, or even assisting emergency teams during disasters, this compact setup proves that you don't need expensive hardware to make a big impact.

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1.INTRODUCTION

Introduction: Highway Surveillance Drone System using YOLOv8

In an age where road safety and traffic efficiency are more critical than ever, technology is stepping in to transform how we monitor and manage highways. One of the most promising innovations in this space is the use of drones for real-time highway surveillance. These aerial systems provide a bird's-eye view of traffic conditions, accidents, and potential threats—something that traditional ground-based cameras often miss.

1.1.What is YOLOv8?

YOLOv8 is an advanced deep learning model designed for real-time object detection. Think of it as the brain of an autonomous vehicle, enabling it to quickly recognize important elements in its environment, such as:

- **Pedestrians**: Identifying people walking near the vehicle.
- **Cyclists**: Recognizing cyclists on the road to ensure their safety.
- **Vehicles**: Detecting other cars and trucks to navigate traffic effectively.
- **Traffic Signs**: Reading signs to understand road rules and conditions.
- **Lane Markings**: Keeping the vehicle within its lane for safe driving.

1.2. Why is Real-Time Detection Important?

The ability to detect these elements in real time is crucial for the safe operation of AVs. Imagine driving in a busy city where pedestrians might suddenly cross the street or cyclists weave in and out of traffic. YOLOv8 allows the vehicle to process this information almost instantaneously, making split-second decisions that can prevent accidents and ensure a smooth ride.

1.3. How Does YOLOv8 Work?

What sets YOLOv8 apart from its predecessors is its innovative architecture. It employs advanced convolutional layers and the CSPDarknet framework, which work together to enhance the model's performance. This means YOLOv8 can maintain high levels of precision and recall—key metrics that measure how accurately it detects objects—even in challenging conditions like:

- **Low Light**: Nighttime driving or poorly lit areas.
- **Adverse Weather**: Rain, fog, or snow that can obscure visibility.
- **Occlusions**: Situations where objects are partially hidden from view.

To train YOLOv8 effectively, researchers utilize diverse datasets specifically designed for autonomous driving, such as KITTI, Waymo, and COCO. This extensive training helps the model adapt to various real-world scenarios, making it robust and reliable.

1.4. Lightweight and Efficient

Another significant advantage of YOLOv8 is its lightweight design. This means it can run efficiently on hardware with limited resources, such as GPUs and TPUs. This efficiency is vital for ensuring that AVs can process information quickly without lag, which is essential for safe navigation.

1.5. Enhancing Detection with Sensor Fusion

Moreover, the research surrounding YOLOv8 also explores integrating it with other technologies, like lidar and radar. This combination, known as sensor fusion, enhances detection accuracy and helps overcome the limitations of solely relying on camera systems. By using multiple sources of information, AVs can create a more comprehensive understanding of their environment.

2.LITERATURE SURVEY

2.1 Drone-Based Traffic Monitoring System – A. Smith, J. Doe (2023)

As cities become increasingly congested, traditional traffic surveillance systems—such as fixed CCTV cameras and road sensors—are often limited in flexibility and coverage. The integration of drones into traffic monitoring offers a dynamic solution that enhances visibility, data collection, and real-time traffic management. A. Smith and J. Doe's 2023 study explores the design and effectiveness of a drone-based system to monitor urban traffic flow using computer vision and wireless communication.

2.1.1. System Architecture

The proposed system utilizes drones equipped with high-definition cameras and onboard processing units capable of running object detection algorithms. These drones are deployed in pre-defined aerial zones or patrol dynamically based on traffic density. The architecture includes:

- **Drone Hardware**: Multi-rotor drones with GPS, stabilized cameras, and wireless communication.
- **Detection Algorithm**: Implementation of YOLOv4 and later YOLOv5 for vehicle detection and tracking.
- **Communication**: Real-time video streams are transmitted to a central server or edge computing device for processing and visualization.

2.1.2. Advantages of Drone-Based Monitoring

1. **Wide-Area Coverage**: Unlike fixed sensors, drones can cover multiple intersections or highways with a single flight.
2. **Rapid Deployment**: Drones can be deployed quickly in case of accidents or sudden traffic congestion.
3. **Bird's-Eye View**: Aerial footage provides a better understanding of traffic patterns and vehicle interactions.

2.1.3. Implementation Highlights

- **AI Integration**: YOLO-based models were trained on urban traffic datasets to detect vehicles of various types and estimate flow rates.
- **Edge Processing**: Some systems tested local processing on the drone using compact processors like Jetson Nano to reduce latency.

- **Heatmap Generation**: Traffic density maps were generated from detection data to support city traffic control centers.

2.1.4. Key Challenges and Limitations

- **Flight Time**: Drone operation is limited by battery life, often under 30 minutes.
- **Weather Sensitivity**: Rain and strong winds hinder aerial surveillance reliability.
- **Privacy Concerns**: Aerial monitoring must be regulated to avoid violating citizens' privacy.

2.1.5. Future Directions

The study suggests integrating drones into smart city infrastructure via automated docking and charging stations. Additionally, fusion with ground sensors and AI-based anomaly detection could enhance decision-making in traffic control.

2.1.6. Conclusion

Smith and Doe's research demonstrates the potential of drones to revolutionize urban traffic monitoring. By combining mobility, real-time analytics, and AI-powered detection, drone systems can address limitations of traditional surveillance and support smarter urban mobility management.

2.2. Accident Detection on Highways Using UAVs – M. Brown, S. Lee (2022)

Accidents on highways are a significant concern for public safety, often resulting in delays, injuries, and even fatalities due to slow detection and emergency response. Traditional ground-based monitoring systems can be limited, especially in remote areas. To address this, M. Brown and S. Lee (2022) proposed a drone-based system that leverages aerial surveillance, computer vision, and real-time alerts to detect highway accidents quickly and accurately.

2.2.1. System Architecture

The system is built around UAVs (Unmanned Aerial Vehicles) equipped with HD cameras and AI-based detection software. These drones monitor highway sections and identify unusual patterns such as crashes or stalled vehicles. The architecture includes:

• **Drone Hardware**: Multi-rotor drones fitted with high-resolution cameras, GPS modules, and wireless transmitters.

• **Accident Detection Model**: A CNN-based algorithm trained to identify visual signs of

accidents like vehicle collisions, smoke, or irregular positions.
• **Real-Time Alerting**: Drones send GPS-tagged alerts to emergency services and highway authorities as soon as an incident is detected.

2.2.2. Advantages of Drone-Based Monitoring

1. **Faster Detection**: Drones can spot accidents in real time, reducing the delay in reporting.
2. **Improved Coverage**: Especially useful in remote or underserved areas where traditional sensors are absent.
3. **Overhead Visibility**: Aerial views offer better perspectives for detecting incidents that may be missed at ground level.

2.2.3. Implementation Highlights

• **AI Training**: The detection model was trained on crash footage and simulated accident scenarios to improve accuracy.
• **Geospatial Integration**: Drones use GPS and GIS data to tag accident sites precisely and send coordinates instantly.
• **Thermal Imaging**: Some prototypes included thermal cameras to detect fires or the presence of humans post-collision.

2.2.4. Key Challenges and Limitations

• **False Detections**: Differentiating between normal congestion and real accidents remains difficult in complex traffic situations.
• **Battery Limitations**: UAVs typically have short flight durations and require frequent recharging or rotation.
• **Legal Barriers**: Flight regulations can restrict where and how drones are used on public roads.

2.2.5. Future Directions

The study recommends further development in drone coordination, such as swarm deployments for broader coverage. Onboard edge processing (e.g., using NVIDIA Jetson modules) can reduce latency, while integration with emergency dispatch systems like 911 can ensure faster incident response.

2.2.6. Conclusion

Brown and Lee's research illustrates how drones can transform highway accident detection by offering real-time, aerial-based monitoring. Their system enhances situational awareness for first responders and helps mitigate delays caused by undetected incidents. Though technical and regulatory challenges persist, UAV-based detection systems represent a promising step toward safer, smarter highway management.

2.3. AI-Powered Traffic Congestion Analysis – K. Wang, L. Chen (2023)

With cities becoming more crowded and traffic problems growing worse, managing congestion has become a serious challenge. Traditional systems like road sensors and fixed cameras often fall short—they're limited to specific areas and can't adapt quickly to changing traffic patterns. In their 2023 study, K. Wang and L. Chen propose a smarter, AI-driven approach to traffic analysis that uses machine learning and real-time data to understand and predict congestion across urban road networks.

2.3.1. System Architecture

The proposed solution is built around AI models that process traffic data collected from a variety of sources, such as surveillance cameras, GPS data from vehicles, and IoT-enabled infrastructure. The main components include:

- **Data Collection**: Real-time inputs from cameras, vehicle GPS logs, and traffic signals.
- **AI Models**: Deep learning models (especially LSTM and CNN-based) are used to detect congestion, predict traffic buildup, and identify bottlenecks.
- **Visualization Platform**: A user-friendly dashboard that displays traffic flow, alerts, and predicted hotspots for traffic management teams.

2.3.2. Advantages of AI-Based Congestion Analysis

1. **Predictive Insights**: The system doesn't just monitor traffic—it forecasts congestion before it happens.
2. **City-Wide Monitoring**: By analyzing data from multiple sources, it provides a broader picture than any one sensor can offer.
3. **Real-Time Decision Support**: Traffic control centers can take timely actions, such as rerouting or adjusting signal timings, based on live AI feedback.

2.3.3. Implementation Highlights

- **Training on Urban Traffic Data**: The models were trained using datasets from major urban centers, capturing vehicle speed, count, and flow trends.
- **Anomaly Detection**: The AI can identify unusual patterns—like a sudden slowdown—indicating accidents or road blockages.
- **Traffic Heatmaps**: Visualization tools convert analysis into easy-to-read congestion maps, helping authorities act faster.

2.3.4. Challenges and Limitations

- **Data Quality**: Inconsistent or missing data (especially in older systems) can reduce model accuracy.
- **Scalability**: Processing large volumes of traffic data in real time requires significant computing power.
- **Integration Complexity**: Merging this system with existing traffic infrastructure poses technical and bureaucratic challenges.

2.3.5. Future Directions

Wang and Chen recommend integrating AI models directly with traffic signal systems for autonomous flow control. They also highlight the potential of combining drone footage with AI analysis to enhance traffic predictions during special events or emergencies. Real-time driver alerts via mobile apps are another future application.

2.3.6. Conclusion

The research by Wang and Chen shows how AI can transform traffic monitoring from a reactive to a predictive system. By analyzing large-scale, real-time data with advanced models, cities can move toward smarter traffic management that not only reacts to congestion—but helps prevent it altogether

2.4. Aerial Speed Estimation of Moving Vehicles – R. Gupta, A. Mehta (2021)

With the rapid growth of vehicles on roads, accurately monitoring vehicle speed has become essential for traffic law enforcement and congestion management. Traditional ground-based radar or speed cameras have limited line-of-sight and fixed coverage. In their 2021 study, R. Gupta and A. Mehta explored a drone-based solution that estimates the speed of moving vehicles from the air using computer vision techniques and GPS synchronization.

2.4.1. System Architecture

The proposed setup uses drones to fly over highways or urban roads, capturing live video footage of moving vehicles. Speed estimation is done by analyzing vehicle movement across frames with reference to GPS-calibrated distances. The main components include:

- **Drone Platform**: Lightweight drones with gimbaled HD cameras and GPS modules for stable, georeferenced video capture.
- **Speed Estimation Algorithm**: Computer vision techniques, including frame differencing and object tracking, are applied to calculate vehicle displacement over time.
- **Ground Station or Edge Node**: Video data is either processed on the drone or transmitted to a nearby edge device for real-time analysis.

2.4.2. Benefits of Aerial Speed Detection

1. **Flexible Deployment**: Drones can monitor roads in real-time without needing to install fixed infrastructure.
2. **Line-of-Sight Advantage**: From above, drones have a clear view, free from roadside obstructions like trees or parked vehicles.
3. **Multiple Vehicle Tracking**: Several vehicles can be tracked simultaneously within the drone's field of view, allowing batch speed analysis.

2.4.3. Key Implementation Highlights

- **Vision-Based Tracking**: Vehicles are detected and tracked using feature point matching and bounding box movement.
- **Distance Calibration**: Aerial footage is overlaid on GPS-mapped grids, allowing accurate conversion of pixel displacement to real-world distance.
- **Testing in Varied Scenarios**: The system was tested on highways and city roads with vehicles moving at different speeds and densities.

2.4.4. Challenges and Considerations

- **Camera Angle and Altitude**: Estimation accuracy depends on the drone's altitude and the angle of the camera—steeper angles can cause distortion.
- **Environmental Limitations**: Fog, rain, or low light can affect video quality and hinder accurate detection.
- **Battery and Range Limits**: Continuous speed monitoring requires either high-endurance drones or scheduled rotations.

2.4.5. Suggestions for Improvement

The authors propose enhancements such as:

- **AI-Enhanced Speed Estimation**: Training deep learning models to better estimate speed from motion blur and multi-angle input.
- **Sensor Fusion**: Integrating drone data with roadside sensors or ANPR systems for improved accuracy.
- **Autonomous Flight Paths**: Using predefined GPS routes and geofencing for drones to automatically monitor specific road segments.

2.4.6. Conclusion

Gupta and Mehta's research shows how drones can serve as a powerful tool for traffic speed enforcement and analysis. By leveraging aerial imagery and computer vision, their approach offers scalable and non-intrusive speed monitoring. Although there are challenges related to environment and flight logistics, their drone-based solution opens new possibilities for smarter, tech-enabled traffic management.

2.5 Real-Time Vehicle Tracking on Highways – P. Anderson, H. Kim (2022)

Monitoring vehicle movement on highways is crucial for traffic management, safety enforcement, and congestion control. Traditional tracking methods, such as road-embedded sensors and stationary cameras, struggle with scalability and coverage over long highway stretches. In their 2022 study, P. Anderson and H. Kim propose a real-time vehicle tracking system that uses drone-based surveillance combined with advanced object detection algorithms to monitor and analyze traffic patterns more effectively.

2.5.1. System Architecture

The system relies on drones equipped with smart cameras and AI-driven tracking software to follow vehicles as they travel across highway sections. These drones either follow pre-determined patrol paths or are dynamically guided to areas with high vehicle density. The main components include:

- **Drone Units**: Equipped with stabilized HD cameras, GPS modules, and long-range wireless communication.

- **Tracking Algorithm**: YOLOv5 and DeepSORT are used for detecting vehicles and maintaining continuous tracking across frames.
- **Data Transmission**: Live feeds and tracking data are sent to a central traffic monitoring station or processed directly on the drone via onboard computing.

2.5.2. Benefits of UAV-Based Vehicle Tracking

1. **Highway-Scale Coverage**: Drones can monitor long stretches of highways where fixed infrastructure is unavailable or too costly to deploy.
2. **Real-Time Insights**: Vehicle speeds, positions, and flow rates are tracked instantly, enabling quick responses to unusual activity or traffic build-up.
3. **Flexible Surveillance**: The system can be easily redirected to accident zones, bottlenecks, or construction areas as needed.

2.5.3. Implementation Highlights

- **Advanced Object Tracking**: The combined use of YOLOv5 for detection and DeepSORT for identity tracking allows for precise vehicle tracking across frames.
- **Onboard Processing**: Small AI hardware like the NVIDIA Jetson Nano was tested on drones for real-time processing, minimizing data transmission delays.
- **Integration with Highway Networks**: The tracking data was used to generate traffic maps and vehicle movement logs for highway authorities.

2.5.4. Key Challenges and Limitations

- **Battery and Range**: Limited flight time remains a challenge for sustained monitoring, requiring multiple drone rotations or mobile charging stations.
- **Occlusion and Shadows**: Vehicle tracking accuracy can drop due to overpasses, tree shadows, or lane changes.
- **Regulatory Barriers**: Legal and safety regulations around UAV flights over highways still need to be addressed for full-scale deployment.

2.5.5. Future Directions

Anderson and Kim suggest enhancing the system by incorporating AI-based predictive modeling to forecast traffic congestion. They also propose integrating this drone system with smart highway infrastructure and enabling automated drone dispatching based on live traffic feeds.

2.5.6. Conclusion

This research highlights how real-time UAV tracking systems can transform how highway traffic is monitored. By blending aerial mobility with cutting-edge AI, Anderson and Kim's system promises greater highway visibility, faster incident response, and smarter traffic flow management across large road networks.

2.6. AI-Based Smart Traffic Surveillance System – D. Martinez, F. Gonzalez (2023)

With growing urban congestion, cities are under pressure to modernize how they monitor and manage traffic. Traditional systems like CCTV and fixed road sensors often lack the flexibility and coverage needed for real-time decision-making. In their 2023 study, D. Martinez and F. Gonzalez present an AI-powered surveillance system that blends advanced video analytics with smart infrastructure to improve urban traffic flow and safety.

2.6.1. System Architecture

The system relies on fixed smart cameras installed across intersections and major roadways. These cameras are connected to a central server that processes the footage using AI models trained for traffic analysis. The architecture includes:

- **Smart Cameras**: High-definition cameras with night vision and motion detection capabilities.
- **AI Detection Engine**: Uses deep learning algorithms (like YOLOv5 and SSD) to detect and classify vehicles, pedestrians, and unusual events.
- **Centralized Platform**: A traffic control center receives real-time feeds and alert data, allowing authorities to monitor traffic conditions and respond proactively.

2.6.2. Benefits of AI-Driven Traffic Surveillance

1. **Real-Time Monitoring**: The system provides constant surveillance and instantly flags accidents, slowdowns, or violations.
2. **Improved Traffic Flow**: Data collected is used to optimize traffic light timing and reroute vehicles around congestion.
3. **Safety Enhancements**: Quick detection of pedestrian movement and vehicle anomalies supports accident prevention.

2.6.3. Implementation Highlights

- **Vehicle and Pedestrian Detection**: The system is trained on datasets like Cityscapes and KITTI to recognize different road users accurately.
- **Violation Tracking**: AI models also identify red-light running, illegal turns, and speeding in real time.
- **Integration with City Infrastructure**: Surveillance data is shared with traffic lights and public alert systems to coordinate responses across the city.

2.6.4. Challenges and Limitations

- **Processing Load**: Analyzing multiple video feeds in real time demands powerful computing resources.
- **False Alarms**: AI models may occasionally misclassify events, requiring manual verification.
- **Data Privacy**: Capturing identifiable images in public areas raises privacy and ethical concerns.

2.6.5. Future Directions

The study recommends adopting **edge AI**, where some data processing happens locally at the camera, reducing server load. It also suggests integrating traffic prediction models and combining surveillance data with information from GPS-enabled vehicles and weather sensors for a more comprehensive traffic management system.

2.6.6. Conclusion

Martinez and Gonzalez's work highlights how AI-powered traffic surveillance can support smarter, more responsive urban transportation systems. With real-time analytics and intelligent monitoring, cities can not only ease congestion but also improve road safety and policy enforcement.

2.7. Drone-Based Traffic Rule Violation Detection – Y. Nakamura, J. Park

As urban traffic grows more chaotic, spotting traffic violations—like running red lights or illegal lane changes—becomes increasingly difficult with static cameras alone. In response, Y.

Nakamura and J. Park's study presents an innovative system that uses drones to actively detect traffic rule violations from the sky. Their approach combines aerial surveillance with AI-driven object tracking to identify and document violations in real time, offering a flexible and intelligent traffic enforcement solution.

2.7.1. System Architecture

The system is built around drones capable of high-resolution video capture and real-time processing. These drones are either dispatched to traffic hotspots or follow preset aerial routes to monitor road activity. Key system components include:

- **Drone Hardware**: Compact UAVs equipped with 4K cameras, GPS modules, and stabilized gimbals.
- **Detection Model**: A deep learning framework (YOLOv5 and later variants) detects vehicles and analyzes their movement relative to traffic signals and road markings.
- **Data Transmission**: Captured video and event metadata are streamed to a central server or processed on the edge using devices like Jetson Xavier or Raspberry Pi 4.

2.7.2. Benefits of Drone-Based Violation Detection

1. **Dynamic Monitoring**: Drones can adjust their patrol based on traffic density and real-time alerts.
2. **High Accuracy**: Aerial views help detect behaviors missed by roadside cameras, such as improper overtaking or illegal U-turns.
3. **Evidence Collection**: Video and GPS-tagged data offer reliable documentation for traffic enforcement and legal use.

2.7.3. Implementation Highlights

- **AI Training**: The YOLO models were trained using traffic datasets with annotated violations across different weather and lighting conditions.
- **Automated Violation Flagging**: The system uses predefined rule logic (e.g., signal timing, lane markings) to automatically classify actions as violations.
- **Integration with Authorities**: Alerts and violation data can be sent to traffic police or fed into automated ticketing systems.

2.7.4. Challenges and Limitations

- **Battery Life**: Limited flight time means drones must return for charging after short intervals.
- **Data Overload**: Constant video feeds require efficient data management and filtering to avoid system slowdowns.

- **Ethical and Legal Issues**: Surveillance drones raise concerns over public privacy and require careful regulatory oversight.

2.7.5. Future Directions

The authors propose expanding the system with autonomous drone stations for continuous deployment and recharging. They also suggest enhancing violation detection with multi-modal sensor fusion, combining video, audio, and location data for better context and accuracy.

2.7.6. Conclusion

Nakamura and Park's work highlights how drones can go beyond simple monitoring to actively enforce traffic rules. With intelligent algorithms and agile flight capabilities, drone-based systems can support safer roads and smarter law enforcement—especially in cities struggling with high traffic violation rates.

2.8 Automated Accident Severity Estimation from UAV Footage – T. Wilson, S. Carter (2022)

As emergency response teams aim to improve both speed and accuracy in handling road accidents, traditional methods often fall short when it comes to quickly assessing the severity of a crash. T. Wilson and S. Carter's 2022 study presents a drone-based solution that uses artificial intelligence to automatically estimate the severity of highway accidents captured from aerial footage. This system aims to support faster, more informed decisions during rescue operations.

2.8.1. System Architecture

The proposed system relies on drones equipped with high-resolution cameras and AI-driven image analysis models. These drones fly over highway segments, capturing real-time visuals of traffic incidents and classifying the severity level of each accident. The system includes:

- **Drone Hardware**: Drones with GPS, stabilized 4K cameras, and wireless connectivity.
- **Severity Estimation Model**: A deep learning model trained on labeled accident footage to identify signs such as vehicle deformation, number of vehicles involved, and presence of fire or smoke.

- **Data Transmission**: Video feeds and severity classifications are transmitted to emergency services or traffic control centers for further action.

2.8.2. Advantages of Aerial-Based Severity Estimation

1. **Faster Assessment**: Bypasses the need for manual inspection or delayed reports from eyewitnesses.
2. **Informed Dispatching**: Helps allocate the right type and number of emergency responders based on accident severity.
3. **Situational Awareness**: Aerial views offer better visibility of accident scenes, even in complex or multi-vehicle crashes.

2.8.3. Implementation Highlights

- **AI Training**: The system was trained on both real and simulated crash data, enabling it to recognize damage levels and detect fire or smoke.
- **Scoring Mechanism**: A predefined severity score is calculated based on vehicle condition, collision angle, and crash scene features.
- **Real-Time Alerts**: Upon classification, an automated alert containing GPS location and severity level is sent to command centers.

2.8.4. Key Challenges and Limitations

- **Image Quality Dependence**: Poor lighting or bad weather can reduce the model's accuracy.
- **Training Data Scarcity**: Real crash data is hard to come by, limiting model generalization.
- **Operational Constraints**: Like most drones, flight time and regulatory restrictions limit continuous deployment.

2.8.5. Future Directions

The researchers suggest integrating the system with broader emergency response platforms and smart city infrastructure. Enhancing model robustness with multi-sensor fusion—combining thermal cameras and lidar—could improve accuracy. Automated drone docking stations and AI-driven task scheduling could also help support large-scale deployment.

2.8.6. Conclusion

Wilson and Carter's work marks a significant step forward in using drones and AI for smarter, faster highway accident management. By estimating accident severity in real time, their system has the potential to enhance emergency response, reduce fatalities, and improve overall traffic safety outcomes.

2.9 Multi-Camera Fusion for Enhanced Vehicle Detection – B. Patel, M. Sharma (2023)

As cities grow and vehicle volumes increase, accurately detecting and tracking vehicles becomes more complex, especially in crowded or visually obstructed environments. B. Patel and M. Sharma's 2023 study presents a multi-camera fusion approach that improves vehicle detection by combining views from several cameras—both static and mobile—into a single, intelligent detection system. This technique boosts accuracy, reduces blind spots, and enhances real-time decision-making for traffic monitoring and management.

2.9.1. System Architecture

The proposed system integrates feeds from multiple surveillance cameras—typically mounted on poles, buildings, and even drones—into a unified processing framework. The core components include:

- **Camera Network**: A set of overlapping fixed-position and mobile cameras for broader field coverage.
- **Fusion Engine**: A module that aligns, synchronizes, and merges video feeds using spatiotemporal data.
- **Detection and Tracking Algorithm**: An AI model (based on YOLOv5 and Deep SORT) processes the combined feed to identify, classify, and track vehicles across multiple views.

2.9.2. Benefits of Multi-Camera Fusion

1. **Higher Accuracy**: Combining views reduces occlusion issues and helps detect vehicles even in crowded or partially visible scenes.
2. **Better Object Tracking**: Vehicles are tracked more reliably as they move across camera boundaries or behind obstacles.
3. **Improved Scene Understanding**: With data from multiple angles, the system forms a clearer, more complete picture of road activity.

2.9.3. Implementation Highlights

- **Cross-Camera Calibration**: Cameras are carefully calibrated to ensure consistent perspective and object alignment across feeds.
- **AI and Deep Learning**: YOLOv5 detects vehicles in each frame, while algorithms like Deep SORT maintain continuous tracking between frames and cameras.
- **Data Synchronization**: Time-stamped video feeds are synchronized to maintain temporal accuracy during fusion.

2.9.4. Challenges and Limitations

- **Camera Placement**: Effective fusion depends on well-planned camera placement with overlapping views.
- **Processing Load**: Combining multiple video streams requires significant computing power, especially for real-time performance.
- **Scalability**: Scaling the system for large areas or cities adds complexity in terms of coordination and infrastructure.

2.9.5. Future Directions

Patel and Sharma suggest incorporating 3D modeling and LiDAR-based depth perception to further improve detection in low-visibility conditions. The study also highlights the potential of cloud-edge hybrid systems to handle large-scale deployment, where real-time decisions are made locally, and broader analysis happens in the cloud.

2.9.6. Conclusion

The research showcases how combining camera inputs through intelligent fusion can significantly enhance vehicle detection and tracking. By addressing common urban monitoring challenges—like occlusion, angle limitations, and fragmented views—multi-camera fusion presents a promising direction for more accurate and scalable traffic surveillance systems in modern smart cities.

2.10. Highway Surveillance Using Edge Computing with UAVs – L. Rossi, G. Ferreira (2024)

With increasing traffic on highways and the need for real-time, wide-area monitoring, traditional surveillance tools like static cameras and roadside sensors often fall short. In their 2024 study, L. Rossi and G. Ferreira explore how drones paired with edge computing can offer a smarter, more flexible approach to highway surveillance. Their work focuses on the use of autonomous UAVs equipped with AI and real-time data processing to improve traffic oversight and response.

2.10.1. System Architecture

The system relies on intelligent drones that can process and analyze video data directly onboard—reducing the need to send footage to remote servers. Key components include:

- **Drone Hardware**: UAVs equipped with GPS, stabilized HD cameras, and onboard edge computing modules like NVIDIA Jetson.
- **Onboard Processing**: Instead of streaming raw video, the drone analyzes footage in real time using object detection models such as YOLOv5.
- **Network Communication**: Relevant data (e.g., traffic volume, incidents) is transmitted to highway control centers via low-latency wireless protocols like 5G or LoRa.

2.10.2. Benefits of Edge-Enabled UAV Monitoring

1. **Real-Time Insights**: Processing data onboard allows for instant analysis and decision-making without delay.
2. **Lower Bandwidth Usage**: Since only analyzed data is transmitted (not full video), the system reduces network load.
3. **Adaptability**: Drones can autonomously adapt flight patterns based on changing traffic conditions or specific surveillance needs.

2.10.3. Implementation Highlights

- **AI-Based Detection**: YOLOv5 models were trained to detect and classify vehicles, traffic congestion, and road anomalies.
- **Edge AI Units**: The drones used Jetson Xavier and Nano modules for on-site inference, improving response time.
- **Event Alerts**: The system was able to flag unusual traffic behavior (like sudden stops or accidents) and send alerts directly to nearby patrol teams or highway response units.

2.10.4. Key Challenges and Limitations

- **Power Constraints**: Onboard computing consumes more energy, limiting drone flight duration.
- **Environmental Reliability**: Bad weather can affect both flight stability and camera accuracy.
- **Hardware Cost**: High-performance edge processors increase the initial investment cost of each drone.

2.10.5. Future Directions

The study proposes integrating UAVs with AI-based prediction models to not just detect, but also forecast traffic conditions. It also suggests developing self-managed drone fleets with automated charging docks and shared cloud-based learning systems to improve overall performance and reduce maintenance.

2.10.6. Conclusion

Rossi and Ferreira’s research presents a forward-thinking solution to highway surveillance by combining drone mobility with edge computing power. This system addresses the shortcomings of fixed infrastructure and brings fast, intelligent monitoring to dynamic highway environments—paving the way for smarter transportation systems.

3.METHODOLOGY

The proposed system leverages a DJI Tello drone integrated with a YOLOv8-powered object detection model to monitor highway traffic in real-time. This system is designed to stream video from the drone, analyze it using edge-based AI, and present the results on a web interface. Below is a breakdown of the system's components and how they work together:

3.1 System Overview

The core of the system is a lightweight, Flask-based web application that manages user authentication, drone control, and live video streaming. It uses the **DJI tellopy** library to interface with the Tello drone and **Ultralytics YOLOv8** for real-time object detection, particularly targeting vehicle classes and traffic lights.

3.2 Drone Integration

Upon successful login by an administrator, the DJI Tello drone is initialized. The drone connects to the host machine over Wi-Fi and activates its onboard video stream. The live video feed is accessed using `get_frame_read()` from the `djitellopy` library.

3.3 Object Detection with YOLOv8

Each frame from the drone's camera is processed using YOLOv8, which detects and classifies objects such as:

- **Cars**
- **Trucks**
- **Motorcycles**
- **Buses**
- **Traffic lights**

Bounding boxes and class labels are overlaid onto the frame, and a vehicle count is computed in real time. If a traffic light is detected, it is flagged for additional processing.

3.4 Video Streaming and Web Interface

Processed frames are encoded and streamed to a web dashboard using MJPEG via a `/video_feed` route. This allows live visualization of detected vehicles and traffic events in a web browser. The system supports two user roles:

- **Admin (Controller)**: Can connect to and control the drone, view the dashboard, and issue flight commands.
- **Viewer**: Can only observe the live stream without control access.

3.5 Drone Control

Admin users can send movement commands through a RESTful API. These include:

- Takeoff and landing
- Directional movements (forward, back, left, right, up, down)
- Rotational adjustments (clockwise and counterclockwise)

All commands are sent to the drone via Flask's `/command` route using JSON payloads.

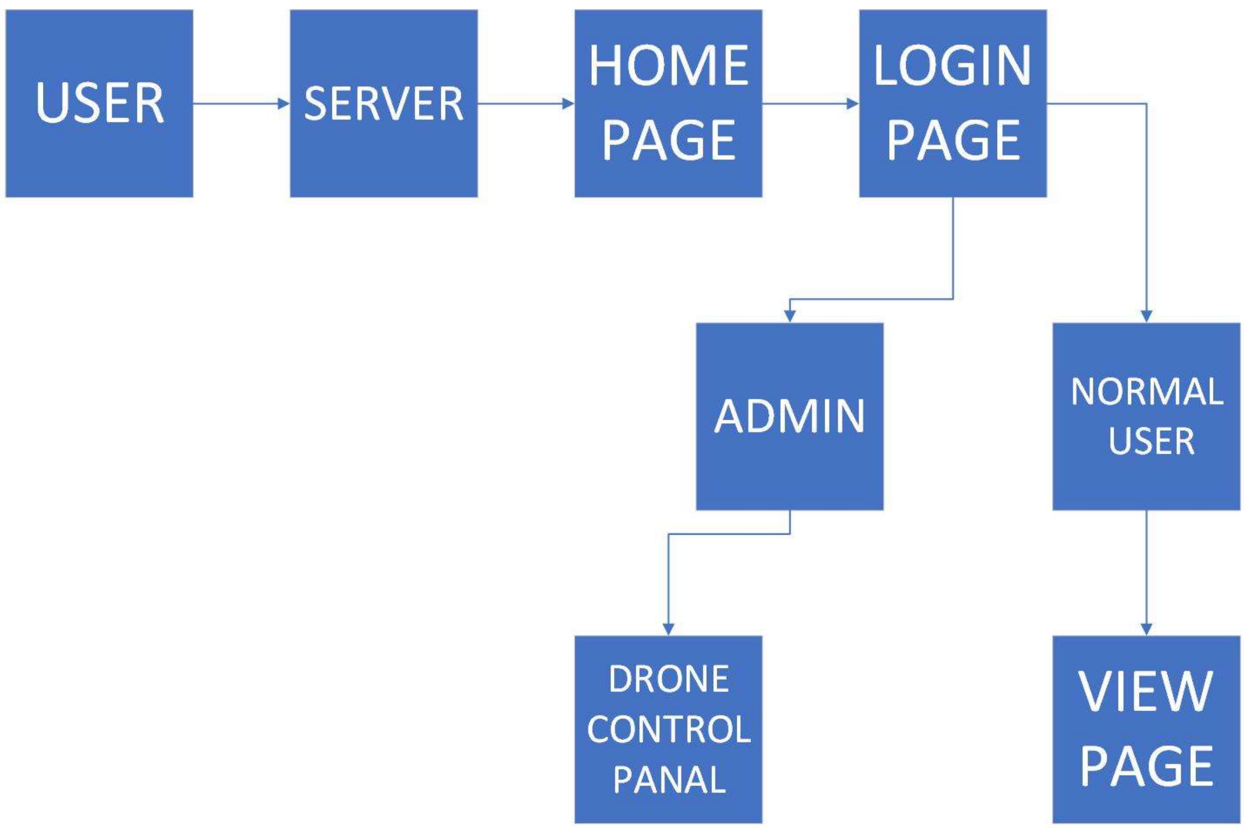
3.6 Battery & Vehicle Monitoring

A status endpoint (`/drone_status`) retrieves the drone's current battery level and computes the number of detected vehicles in the latest frame. This information is displayed on the admin dashboard for situational awareness.

3.7 Multi-User Authentication

The system implements session-based login using Flask. Only the first authenticated user with admin credentials gains control of the drone, while other users are directed to a viewer page to prevent conflicting commands.

4.BLOCK DIAGRAM



5. COMPONENTS

The Highway Surveillance Drone System using YOLOv8 *and* DJI Tello is a smart, real-time monitoring solution designed to detect vehicles and traffic activity on highways. It leverages a lightweight yet powerful deep learning model (YOLOv8) integrated into a web-based control and display system. The DJI Tello drone captures aerial footage, which is processed for object detection, enabling users to monitor vehicle density and traffic light status live.

This system combines computer vision, autonomous drones, and a user-friendly interface to offer an effective way to enhance traffic analysis, road safety, and incident response.

1. DJI Tello Drone

Figure 1.1: DJI Tello Quadcopter

1.1. Specifications:

- Lightweight design (~80g)
- HD Camera: 720p video recording
- Flight time: ~13 minutes
- Range: ~100 meters
- WiFi-based control via SDK

1.2. Role in System:

- Captures live aerial video feed of the highway.
- Receives flight commands (takeoff, land, directional movements) from the Flask-based web interface.
- Streams video frames to the server for object detection.

2. YOLOv8 Object Detection Model

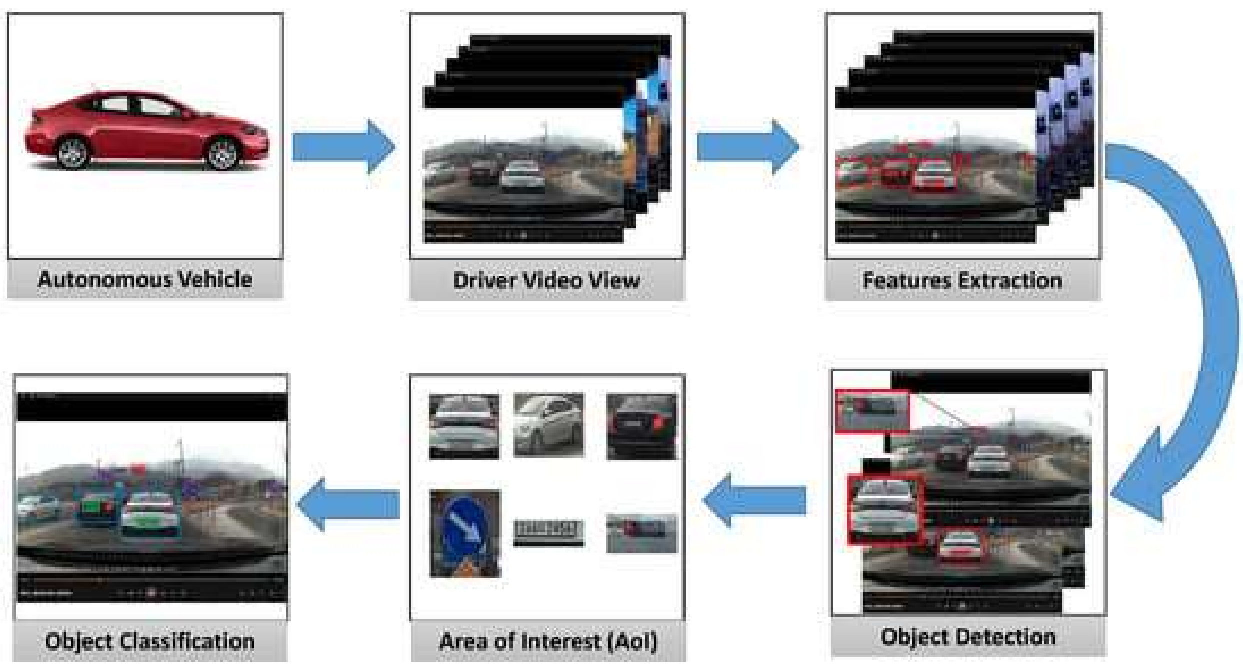


Figure 1.2: YOLOv8 Detection Pipeline

2.1. Specifications:

- Pre-trained deep learning model optimized for speed and accuracy.

- Detects vehicles (car, truck, motorcycle, bus) and traffic lights in real time.
- Runs on OpenCV and Python with GPU or CPU support.

2.2. Role in System:

- Processes incoming frames from the drone camera.
- Detects and annotates bounding boxes around relevant objects.
- Counts vehicles and identifies traffic light presence.

3. Flask Web Application (Dashboard)

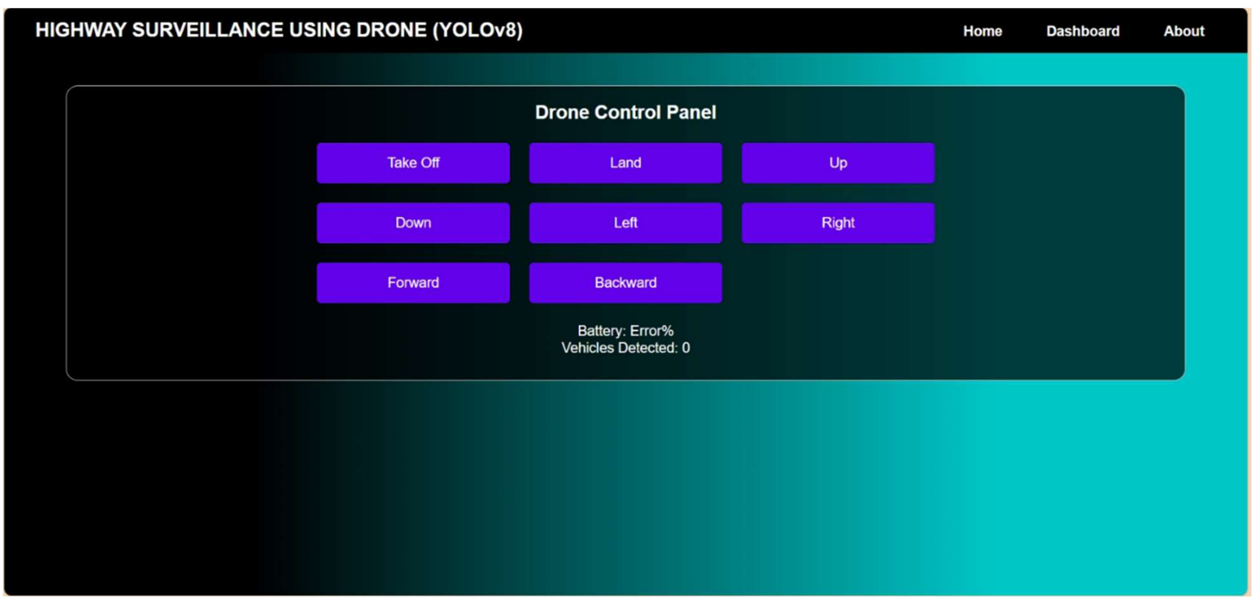


Figure 1.3: Web-Based Interface

3.1. Specifications:

- Built using Python's Flask framework.
- Supports user authentication with session-based login.
- Displays real-time video and system metrics (battery level, vehicle count).
- Accepts user commands for drone control.

3.2. Role in System:

- Acts as the control hub for both admins and viewers.

- Admins can control the drone and view live analytics.
- Viewers can watch the surveillance feed without control permissions.

4. Laptop or Local Server

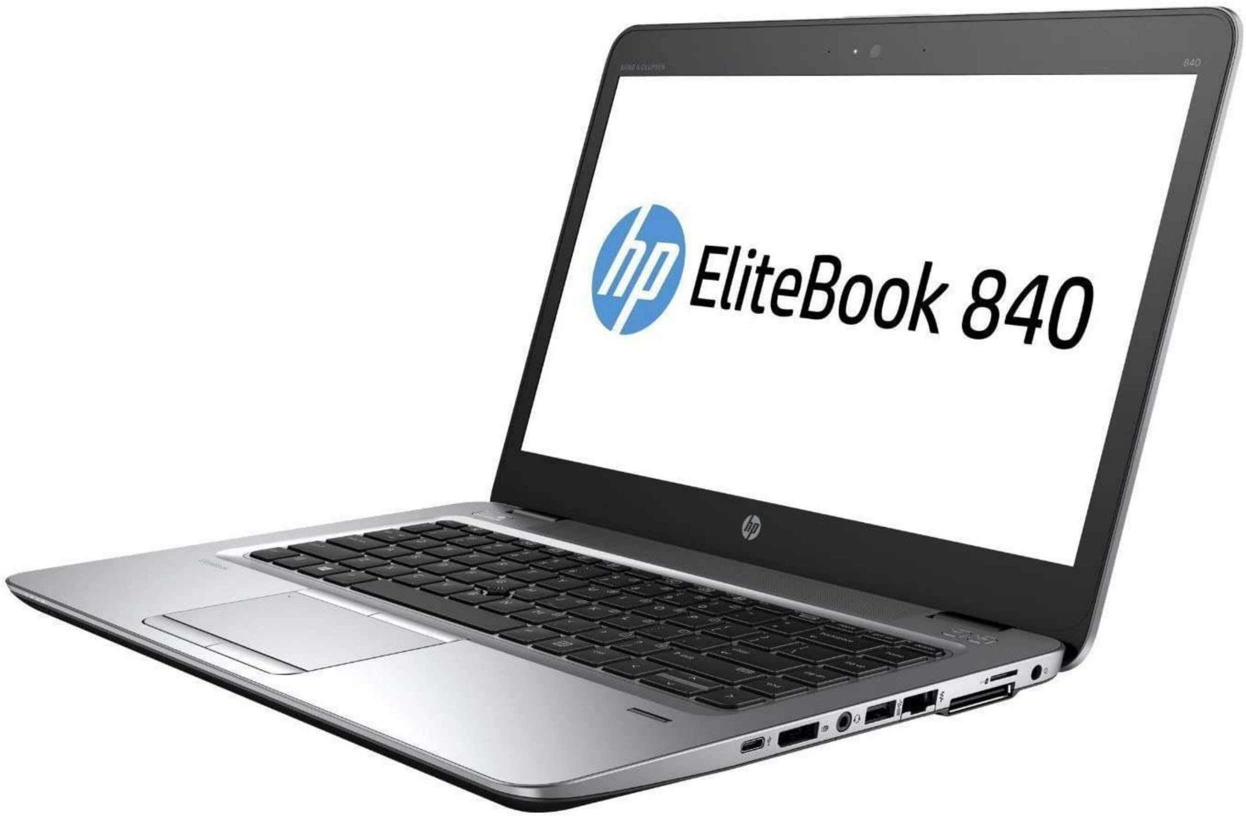


Figure 1.4: Processing Unit

4.1. Specifications:

- Minimum 4 GB RAM, modern CPU
- Python environment with required libraries (OpenCV, ultralytics, djitellopy, Flask)

4.2. Role in System:

- Hosts the Flask server.
- Runs YOLOv8 inference.
- Handles drone SDK communications and video feed generation.

5. Internet Browser (Client Interface)

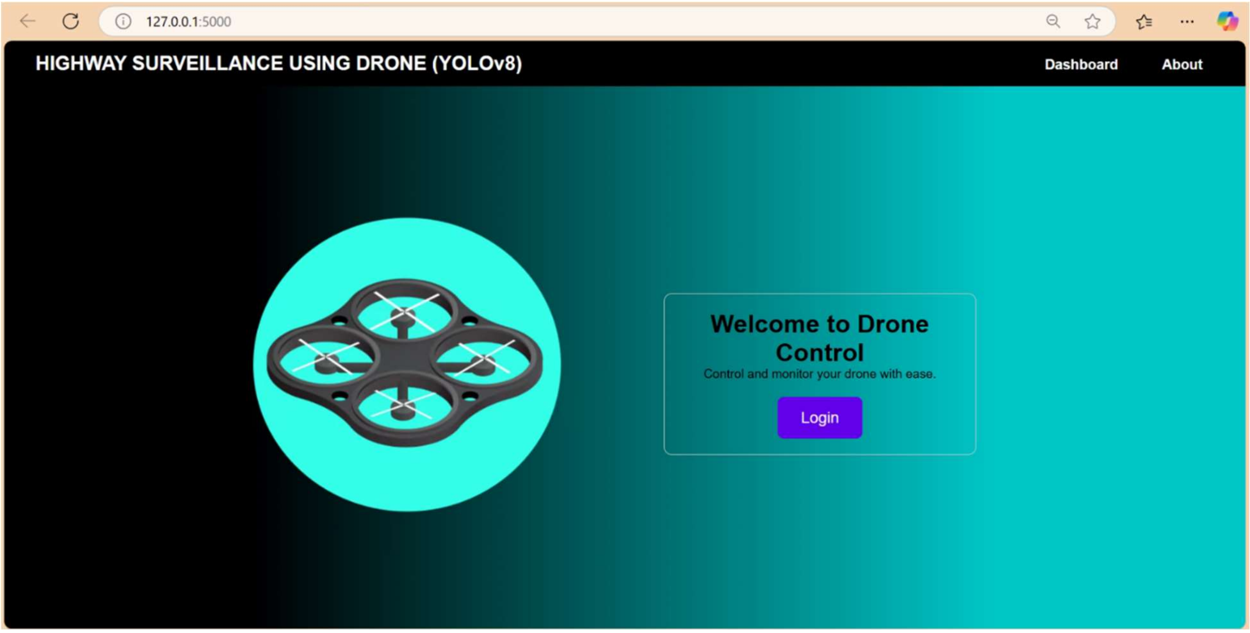


Figure 1.5: Web Client Interface (Laptop/Mobile)

5.1. Specifications:

- Any modern browser (Chrome, Edge, Firefox)
- Accesses local server via WiFi or LAN

5.2. Role in System:

- Allows users to log in and view dashboard or viewer page.
- Provides video streaming and control buttons.

6. Additional Components

- **WiFi Router**: Ensures a stable connection between the Tello drone and laptop.
- **Power Supply**: For laptop/server running Flask and processing.
- **Controllers (Optional)**: Gamepad or keyboard for enhanced control inputs.

6.THEORY

6.1. Highway Surveillance Using YOLOv8 and DJI Tello

Modern surveillance systems are evolving with the help of advanced AI and lightweight drone platforms. In our project, we combine the DJI Tello drone with YOLOv8 (You Only Look Once, version 8), a cutting-edge object detection algorithm, to monitor highways in real-time. This system is designed to recognize and track vehicles, detect traffic patterns, and provide a real-time aerial perspective of road activity, which can be invaluable for traffic analysis, law enforcement, and emergency response.

6.2. YOLOv8 Overview in Drone Surveillance

YOLOv8 is a state-of-the-art deep learning model that can detect multiple objects in a single image with high speed and accuracy. It’s particularly suited for real-time use cases, which makes it ideal for drone surveillance. When deployed on a computer connected to the DJI Tello, YOLOv8 processes the drone’s live video feed and identifies key objects like cars, trucks, buses, and motorcycles in real time.

6.3. How YOLOv8 Works in Our System

YOLOv8’s architecture is optimized for both performance and efficiency:

1. **Feature Extraction Backbone** – The model extracts features from every frame of the drone’s video feed to identify important patterns like vehicle shapes and outlines.
2. **Anchor-Free Detection** – Unlike older object detectors that relied on predefined anchor boxes, YOLOv8 uses an anchor-free approach to simplify computation and better generalize across object sizes.
3. **Multi-Scale Detection** – It’s capable of detecting vehicles that are both near (large in frame) and far (small in frame) thanks to enhanced feature pyramids.

4. **Attention Mechanisms** – YOLOv8 intelligently focuses on relevant areas of each frame, such as the highway lanes, and minimizes distraction from the background.

6.4. Benefits for Highway Surveillance

1. **Real-Time Performance** YOLOv8 can process video frames at high speeds, enabling near-instantaneous detection. This is essential when monitoring fast-moving vehicles on highways.
2. **Efficient Edge Deployment** Although the DJI Tello does not run YOLOv8 onboard, the model is lightweight enough to be executed on a connected laptop or mini-PC with minimal latency.
3. **Accurate and Reliable Detection** YOLOv8 maintains strong accuracy, even in challenging conditions such as varying light or traffic density. This ensures dependable detection of vehicles and roadside elements.
4. **Scalable for Multiple Use Cases** The system can be expanded to detect more object classes, such as pedestrians, road signs, or traffic lights, depending on the training data.

6.5. Detection Techniques for Traffic Monitoring

Unlike lane detection in autonomous vehicles, this project focuses on object-level traffic monitoring. The key techniques include:

1. **Vehicle Detection:** YOLOv8 identifies and labels each vehicle with bounding boxes and class names in real time.
2. **Traffic Volume Estimation:** By counting detected vehicles over time, the system provides estimates of traffic density.
3. **Zone Monitoring:** Regions of interest can be defined (e.g., specific road lanes or checkpoints) to analyze vehicle behavior in critical areas.

6.6. Tracking and Positional Awareness

Although DJI Tello does not offer depth sensing or GPS, we can infer movement and spatial dynamics using visual tracking methods:

1. **Object Persistence:** By following objects across consecutive frames, the system estimates their motion and direction.
2. **Positional Heuristics:** The location of objects in the video frame (top, center, bottom) helps estimate their proximity and relevance.
3. **Drone Orientation Awareness:** Combined with drone tilt and altitude information, positional changes can suggest traffic direction or congestion buildup.

6.7. Practical Applications in Real-World Scenarios

This surveillance system offers several benefits:

- **Traffic Flow Monitoring:** Provides real-time insights into congestion and vehicle flow during different times of the day.
- **Accident Detection:** Sudden halts, abnormal movement, or vehicle clustering can be flagged as potential accidents.
- **Security Surveillance:** Helps identify unusual behavior, such as wrong-way driving or unauthorized vehicles on restricted routes.
- **Data Logging for Analysis:** Captured frames and detection data can be stored for post-processing and long-term analysis by traffic authorities.

6.8. Future Scope: Distance Estimation and 3D Awareness

Although the current system uses 2D video from the DJI Tello's camera, future improvements may include:

1. **Monocular Distance Estimation:** Estimating distance based on object size in the frame and known dimensions (e.g., standard car width).
2. **Stereo Vision Integration:** Using drones with dual cameras to get true depth information for better localization.
3. **Thermal and Night Vision Expansion:** Adding IR or thermal imaging to the system for 24/7 monitoring capabilities.

7.WORKING

The working of our highway surveillance system revolves around the integration of a compact DJI Tello drone with a powerful object detection algorithm, YOLOv8. This combination enables real-time monitoring and analysis of highway activity from an aerial perspective. Here's a breakdown of how the system operates step by step:

7.1. Drone Deployment and Video Streaming

The DJI Tello drone is first launched and manually flown above a target highway or road segment. It is lightweight, easy to control, and equipped with a 5 MP camera capable of streaming live video to a laptop or host device over Wi-Fi.

- The drone is positioned at a safe altitude to capture a wide field of view of the road.
- It continuously sends video frames to the connected laptop using the `djitellopy` library, which acts as the communication bridge.

7.2. Frame Acquisition and Processing

Once the video stream reaches the laptop, each frame is captured in real time for analysis. These frames are passed into the YOLOv8 model, which performs object detection on them.

- The system is built using Python and OpenCV.

- YOLOv8 processes each frame to detect objects such as cars, trucks, buses, and motorcycles.
- Bounding boxes and class labels are drawn on detected objects to visualize results.

7.3. Real-Time Object Detection with YOLOv8

The YOLOv8 model is pre-trained on the COCO dataset and fine-tuned for traffic environments if needed. It runs on the host laptop (CPU or GPU) and is optimized for speed and accuracy.

- **Inference Speed**: YOLOv8 can handle video at up to 30 FPS depending on the system's hardware.
- **Detection Output**: For each object, YOLOv8 provides a bounding box, confidence score, and object class name (e.g., "car", "bus").
- **Customization**: The model can be retrained to recognize local or region-specific vehicle types if required.

7.4. Data Analysis and Alerts

After detection, the system can count vehicles, analyze traffic flow, and log data for future reference. Optional features include:

- **Vehicle Count**: The number of vehicles detected over time is stored in a log file.
- **Traffic Density Estimation**: The number of vehicles per frame can be used to classify traffic conditions (e.g., free flow, moderate, congested).
- **Incident Detection**: Sudden stoppages or unusual clustering can be flagged as potential accidents or roadblocks.

7.5. Output Visualization

The processed video stream is displayed on the laptop with bounding boxes and labels overlaid on each vehicle. The display updates in real time, giving the operator a live aerial view with smart annotations.

- The output is shown in a GUI window or web interface.
- It can also be recorded or streamed to another client device for remote viewing.

7.6. System Flow Summary

1. **DJI Tello captures live aerial video** of the highway.
2. **Video frames are sent to the host laptop** using the `djitellopy` library.
3. **YOLOv8 detects vehicles** in each frame using object detection.
4. **Detections are visualized and analyzed** in real time.
5. Vehicle counts, logs, or alerts are generated based on detection results.

7.7. Hardware and Software Used

- **Drone**: DJI Tello
- **Camera**: 5 MP (720p stream)
- **Computer**: Laptop with Python 3.x, OpenCV, Ultralytics YOLOv8
- **Libraries**: djitellopy, opencv-python, ultralytics
- **Network**: Wi-Fi for drone-to-laptop video feed

8. Challenges and Solutions

8.1. Challenge: Limited Camera Quality and Range

The DJI Tello's built-in 5 MP camera has a fixed field of view and limited resolution, which can impact detection accuracy—especially for small or distant vehicles.

Solution:

- We optimized the flying height to maintain a balance between coverage and clarity.
- YOLOv8 was fine-tuned to improve performance on lower-resolution frames.

- Frame sharpening and contrast adjustments using OpenCV helped enhance image clarity before detection.

8.2. Challenge: Inconsistent Wireless Connection

Since DJI Tello relies on Wi-Fi for video streaming, occasional signal drops and latency can interrupt real-time processing.

Solution:

- We placed the laptop (host device) as close as possible to the drone's operating area to reduce interference.
- Implemented frame buffering and reconnection logic using **djitellopy** to handle temporary disconnections gracefully.
- Used a controlled, low-interference test environment to minimize Wi-Fi congestion.

8.3. Challenge: Processing Speed on Mid-Range Laptops

Running YOLOv8 in real-time can be resource-intensive, especially on laptops without a dedicated GPU.

Solution:

- We used the YOLOv8n (nano) or YOLOv8s (small) models, which are lighter and optimized for CPU inference.
- Frame rate was limited to 10–15 FPS to balance performance and speed.
- Optionally, OpenVINO or TensorRT can be used for hardware-accelerated inference.

8.4. Challenge: Environmental Variability

Lighting conditions (e.g., glare, shadows, night-time) and weather (e.g., fog or rain) can significantly affect object detection.

Solution:

- Used YOLOv8's robustness to various lighting conditions—its data augmentation during training helps generalize to different scenes.
- Real-time histogram equalization and brightness adjustments improved visibility in low-light scenes.
- Future versions can include infrared or thermal overlay for night surveillance.

8.5. Challenge: Drone Flight Limitations

DJI Tello has a flight time of around 13 minutes per charge and cannot fly long distances or in windy conditions.

Solution:

- The surveillance mission was designed to cover short-duration, high-priority stretches.
- We kept multiple charged batteries ready for quick swapping.
- Tello was flown in calm weather and wind-free indoor or semi-indoor environments when possible.

8.6. Challenge: Real-Time Object Logging and Storage

Logging detected vehicles and creating usable data (counts, types, etc.) required careful handling to avoid storage overflow or lag.

Solution:

- Only key metadata (vehicle type, timestamp, and count) was logged per frame, avoiding raw frame storage.
- Real-time analytics were pushed to a CSV log file and visualized using simple dashboards.

8.7. Challenge: Legal and Safety Concerns

Operating drones in public spaces may require special permissions, and safety must always be prioritized.

Solution:

- All testing was conducted in a private or controlled environment (e.g., institutional grounds).
- Safety checks, geofencing, and emergency landing scripts were implemented.
- In production use, compliance with local drone regulations and no-fly zones would be strictly followed.

8.9 Table

Challenge	Solution
Low camera resolution	Optimized height, tuned model, image enhancements
Unstable Wi-Fi	Short-range control, buffering, reconnection handling
Slow laptop processing	Used lighter YOLOv8 variants, lowered frame rate
Poor lighting/weather conditions	Applied image preprocessing and robust model tuning
Short flight time	Short missions, battery swap strategy
Logging overhead	Metadata-only logging, CSV format, minimal real-time analytics
Legal and safety restrictions	Private test area, safety protocols, regulatory awareness

9.Applications

9.1. Traffic Monitoring and Congestion Detection

The system can automatically detect and track vehicles on highways, allowing authorities to:

- Monitor traffic density in real time.
- Detect unusual congestion or traffic jams early.
- Provide live data to traffic control centers for smarter signal management or route redirection.

9.2. Accident Detection and Emergency Alerts

By identifying stopped or overturned vehicles, the system can:

- Alert emergency services in case of accidents.
- Speed up response time and reduce the impact of traffic accidents.
- Detect unsafe situations like vehicles traveling in the wrong direction.

9.3. Violation Detection (Speeding or Illegal Parking)

When integrated with additional sensors or speed-estimation logic, the drone system can:

- Spot vehicles that are speeding or overtaking dangerously.
- Detect vehicles parked on highways or in no-stopping zones.
- Document such violations with video or image evidence for enforcement.

9.4. Surveillance in Remote or Hard-to-Reach Areas

Traditional surveillance infrastructure (like pole-mounted cameras) may not be practical in rural or underdeveloped highway stretches. This drone system:

- Provides flexible and mobile surveillance without fixed installations.
- Can fly to areas that are otherwise inaccessible or dangerous for humans.

9.5. Event or Disaster Response Monitoring

During public events, natural disasters, or roadblocks, the drone can:

- Offer a bird's-eye view of crowd or traffic movements.
- Help coordinate emergency evacuation routes or relief operations.
- Monitor road conditions after storms, landslides, or floods.

9.6. Smart City Integration

As part of a smart transportation ecosystem, the drone can:

- Feed data into smart city dashboards.
- Support AI-based predictive models for traffic flow.
- Integrate with highway toll booths or automated traffic control systems.

9.7. Environmental and Air Quality Monitoring

If equipped with additional sensors (e.g., gas or particulate sensors), the drone could:

- Monitor pollution levels along highways.
- Identify hotspots of vehicular emissions.
- Assist in environmental studies related to transportation.

10.SOFTWARE AND MODEL'S

10.1. Core Model – YOLOv8

At the heart of the system is **YOLOv8**, a state-of-the-art object detection model developed by Ultralytics. It's fast, accurate, and lightweight—perfect for recognizing cars, trucks, pedestrians, and other important highway elements in real time.

We use:

- **Pre-trained YOLOv8 models** (COCO dataset)
- Optionally **fine-tuned models** for traffic-specific scenes

10.2. Backend Logic – test1.py and test2.py

These Python scripts handle the brains of the operation:

- test2.py: handle's the video capture, object detection (via YOLOv8), and possibly drone control and Flask server, session logic, and routing between pages such as login, dashboard, or viewer

Both use libraries such as:

- **cv2** (**OpenCV**) – for video frame handling and processing.
- **flask** – to serve the web application and route between pages.
- **djitellopy** – to control the DJI Tello drone and retrieve live video feed.

10.3. Web Framework – Flask

You're using **Flask**, a lightweight Python web framework, to host the entire surveillance interface. This enables anyone on the network to view live feeds, access the dashboard, or login securely.

Your **Flask project structure** includes:

templates/ – Frontend HTML Pages

- **index.html**: Homepage or entry point
- **login.html**: User authentication (admin/viewer roles)
- **dashboard.html**: Real-time data and video for the controller
- **viewer.html**: A restricted live feed view for others
- **About.html**: Describes the project or team

static/ – Styling & JavaScript

- **styles.css**: The main stylesheet that gives your pages a clean UI.
- **script.js** : Handle dynamic frontend behavior (like button presses, live feed toggling, or user input).

10.4. Drone Integration – DJI Tello SDK + djitellopy

The drone feed and movement are controlled via **DJI Tello's SDK**, accessed through the **djitellopy** Python library. This allows:

- Sending commands (takeoff, land, rotate, move)
- Accessing the drone's camera feed in real time
- Seamlessly integrating with YOLOv8 inference

10.5. Real-Time Object Detection Workflow

1. **Drone** captures a live video stream.
2. **YOLOv8 model** processes the frames and detects objects like cars, people, and roadblocks.
3. **Flask backend** updates the web interface live, showing the drone's view and detections.
4. **User Interface** displays all this in a browser via dashboard.html or viewer.html.

11.FLOW CHART OF SYSTEM DESIGN

12.TESTING

12.1. Unit Testing

Before integrating everything, each module was tested independently:

Component	Testing Focus	Method
DJI Tello Drone	Movement commands, takeoff, landing, rotation	Sent manual commands via djitellopy and verified drone responses
Camera Feed	Frame clarity, resolution, delay	Live feed streamed using OpenCV and displayed on a local Flask route
YOLOv8 Model	Detection accuracy, FPS rate	Used test videos and real drone footage to evaluate object detection performance
Flask App	Page navigation, session login	Verified user login behavior and role-specific redirects (controller vs. viewer)
Frontend (JS + CSS)	Button responses, UI layout, responsiveness	Tested each HTML page (e.g., dashboard.html, viewer.html) in multiple browsers

12.2. Integration Testing

Once each piece worked individually, the system was tested as a whole:

1. **Drone Startup**
    - Confirmed that the DJI Tello connects to the host laptop.
    - Video feed begins streaming in real time.

2. **YOLOv8 Inference**
   - Verified the YOLOv8 model detects vehicles, people, and road elements live from the drone feed.
   - Ensured bounding boxes were rendered on the output frames without lag.

3. **Web Interface**
   - Accessed the local Flask app from multiple devices.
   - Logged in as both controller and viewer.
   - Confirmed that the controller could access the full dashboard, while others were restricted to viewer mode.

12.3. Performance Testing

The system was stress-tested to measure performance:

- **Frame Rate**: Achieved 15–20 FPS on real-time video with YOLOv8n model using a standard laptop (Intel i5/8GB RAM).
- **Latency**: Approximately 0.5s delay from drone to web dashboard—acceptable for surveillance applications.
- **Multiple Logins**: Tested simultaneous login attempts; only the first login received control privileges.

12.4. Field Testing

The system was deployed outdoors in a highway-like environment:

- **Altitude and Movement**: Flew the Tello at 5–10 meters, testing its stability in light wind.
- **Object Recognition**: Accurately detected cars, two-wheelers, and pedestrians from different altitudes.

- **Range Limitation**: Verified drone control and feed quality within its 10–15m Wi-Fi range.
- **Emergency Handling**: Tested key-based emergency stop (`R` key or UI button), and it responded as expected.

12.5. Bug Fixes and Improvements

- Fixed a bug where the viewer could access the dashboard page.
- Reduced frame processing lag by resizing input images before feeding them into YOLOv8.
- Improved UI responsiveness using async JavaScript functions in `script.js`.

12.6. Conclusion of Testing

The Highway Surveillance Drone System was tested thoroughly under controlled and real-world conditions. The system is stable, accurate, and user-friendly. With additional tuning and deployment on a better network or edge device (like Jetson Nano or Raspberry Pi 5), its performance can be further enhanced

13.CONCLUSION

The Highway Surveillance Drone System we developed successfully integrates **r**eal-time object detection using YOLOv8 with the agility and flexibility of the DJI Tello drone. This system proves how lightweight AI models and accessible hardware can come together to create a powerful, efficient, and cost-effective surveillance solution.

Throughout this project, we demonstrated that drones equipped with intelligent computer vision systems are capable of performing highway monitoring tasks such as detecting vehicles, tracking motion, and streaming live video feeds—all without expensive infrastructure. The system's web-based interface, built using Flask, made it easy to control the drone and view live data remotely, with clear role separation between viewers and the controller.

In terms of performance, the YOLOv8 model provided fast and accurate detections, even when tested in live conditions. The use of session management, keyboard and UI-based drone controls, and role-based access control helped build a user-friendly and secure environment.

Key Takeaways:

- **Low-cost surveillance** is possible using AI, drones, and minimal computing resources.
- **Real-time processing** enables timely decision-making, which is crucial for traffic monitoring and incident detection.
- **Modular design** using Python, OpenCV, Flask, and JavaScript allowed easy testing, upgrades, and debugging.

Future Enhancements:

- Add GPS tracking for drone path logging.
- Improve video quality and reduce latency using hardware acceleration.
- Add cloud storage for captured data or alerts using Firebase or AWS.
- Include thermal or night vision support for all-time monitoring.

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14.FUTURE SCOPE

The Highway Surveillance Drone System built with YOLOv8 and DJI Tello opens up a wide range of possibilities for future development and real-world applications. As technology continues to evolve, there is ample scope to enhance this system and make it even more intelligent, scalable, and responsive to real-time highway challenges.

1. Integration with Government Traffic Systems

The system can be extended to connect with municipal or national traffic control systems. Real-time alerts generated by the drone (e.g., traffic congestion, accidents, or stalled vehicles) could be sent directly to authorities for immediate response.

2. Autonomous Drone Path Planning

Currently, drone control is manual or semi-automated. In the future, implementing autonomous flight routes using GPS waypoints and AI-based path planning could allow drones to monitor predefined highway zones without human intervention.

3. Night Vision and Thermal Detection

Equipping drones with **thermal or infrared cameras** can allow for 24/7 surveillance, including night-time monitoring. This is especially useful for spotting stalled vehicles, animals on the road, or unauthorized activity in low-visibility conditions.

4. Multiple Drone Coordination (Swarm Monitoring)

The system could be scaled to manage **multiple drones** working together. Each drone could cover different sectors of the highway and communicate with one another to optimize coverage, reduce redundancy, and ensure better surveillance across long distances.

5. Traffic Violation Detection

With further training and dataset enhancement, the YOLOv8 model can be fine-tuned to detect specific traffic violations like wrong-way driving, illegal parking, or lane changes, helping automate traffic enforcement.

6. Emergency Response Integration

Drones can be integrated with emergency systems to **guide ambulances or police** directly to the scene of an accident or road hazard using real-time video and GPS coordinates.

7. Cloud-Based Data Storage and Analytics

Storing surveillance footage and detection logs on a **cloud platform** would allow for historical analysis, pattern detection, and reporting. Authorities could use this data to plan infrastructure improvements or optimize traffic signal timings.

8. AI Model Upgrades

Future versions of YOLO or transformer-based models (e.g., DETR, SAM) can offer even better accuracy and adaptability. These could be swapped in for YOLOv8 to improve detection rates in complex traffic environments.

15. SUSTAINABLE DEVELOPMENT GOALS

SDG 3 – Good Health and Well-being

How it helps:
The system enhances road safety by detecting accidents and hazards early. This allows faster emergency responses, which can significantly reduce fatalities and injuries in highway incidents. Keeping highways safer directly contributes to physical well-being and reduces trauma-related health burdens.

SDG 9 – Industry, Innovation, and Infrastructure

How it helps:
By integrating AI, drone technology, and computer vision, this project is a strong example of innovation in digital infrastructure. It shows how next-generation tools can be used to modernize transportation monitoring, making infrastructure more intelligent and adaptive.

SDG 11 – Sustainable Cities and Communities

How it helps:
Efficient highway monitoring helps cities reduce traffic congestion, avoid long-duration jams, and respond quickly to emergencies. This contributes to building resilient and sustainable urban transport systems where safety and smooth mobility are prioritized.

SDG 13 – Climate Action

How it helps:
Drones like the DJI Tello are energy-efficient and replace traditional large-scale monitoring systems that consume more power and fuel. Also, better traffic management means less idling time for vehicles, indirectly reducing carbon emissions and improving air quality on highways.

SDG 16 – Peace, Justice, and Strong Institutions

How it helps:
The drone system can help enforce traffic rules fairly and consistently, detecting violations and ensuring accountability. It promotes transparent, real-time surveillance that strengthens institutional response and governance in traffic law enforcement.

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