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Real-Time Vehicle Detection from UAV Aerial Images

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ABSTRACT

The rapid advancement in Unmanned Aerial Vehicle (UAV) technology has created new opportunities for real-time monitoring and detection applications, particularly in vehicle detection from aerial imagery. This study presents a robust real-time vehicle detection model, built on YOLOv5, specifically designed for UAV-acquired images and leveraging the VisDrone2019 dataset, which includes annotated categories of cars, vans, trucks, and buses. YOLOv5 serves as the base model, optimized for high-speed processing, and several key enhancements are introduced to improve detection accuracy and performance in complex aerial scenes. An additional prediction head is integrated into YOLOv5 to enhance detection capabilities for smaller-scale objects, addressing challenges in identifying vehicles from high altitudes or dense environments. To retain essential feature information throughout the training process, a Bidirectional Feature Pyramid Network (BiFPN) is employed, enabling efficient feature fusion across multiple scales. Furthermore, Soft Non-Maximum Suppression (Soft-NMS) is utilized as a frame filtering technique, mitigating missed detections by handling cases where vehicles are closely aligned. This combination of YOLOv5 and advanced techniques enables high accuracy in real-time vehicle detection, making it suitable for applications in traffic monitoring, urban planning, and emergency response.

Keywords: Real-time vehicle detection, UAV, YOLOv5, VisDrone2019 dataset, small-scale object detection, Bidirectional Feature Pyramid Network (BiFPN), Soft-NMS, aerial imagery, traffic monitoring.

INTRODUCTION

Surveillance and monitoring systems have become integral in ensuring public safety and facilitating real-time decision-making in a variety of contexts. With the rapid growth of unmanned aerial vehicle (UAV) technology, the potential for real-time surveillance has expanded, offering a new approach for large-scale monitoring. Traditional vehicle detection systems, particularly those relying on fixed ground cameras, can be limited by visibility constraints, spatial coverage, and the inability to adapt to changing conditions such as traffic flow or vehicle types. UAVs, on the other hand, offer a dynamic and flexible solution by providing aerial perspectives that can capture a broader area and offer detailed insights into vehicular movement in urban spaces, highways, and large public gatherings.

This project focuses on developing a real-time vehicle detection system utilizing UAV-acquired aerial imagery to detect and classify vehicles into distinct categories, such as cars, vans, trucks, and buses. The system is built on YOLOv5 (You Only Look Once version 5), an advanced object detection model known for its high-speed processing capabilities, ideal for real-time applications. YOLOv5's ability to quickly and accurately detect objects in video frames makes it suitable for fast-paced environments such as traffic monitoring, urban planning, and emergency response.

To enhance the detection system's performance, several modifications are implemented to better address the challenges posed by aerial imagery. An additional prediction head is integrated into YOLOv5 to improve detection of smaller-scale objects, which is particularly useful when detecting vehicles from high altitudes or in crowded urban environments. Additionally, a Bidirectional Feature Pyramid Network (BiFPN) is employed for efficient feature fusion, enabling the model to better handle objects at varying scales. Soft Non-Maximum Suppression (Soft-NMS) is also utilized to minimize false positives and missed detections, especially when vehicles are closely aligned in the image.

The dataset for training and evaluation is drawn from publicly available UAV datasets, such as the VisDrone2019 dataset, which contains labeled vehicle categories and varied real-world scenarios. The model's effectiveness is measured using standard evaluation metrics such as accuracy, precision, and recall, and further optimization strategies are explored to reduce false alarms and improve detection speed.

This intelligent vehicle detection system is designed for real-time implementation in UAV surveillance, offering significant advantages over traditional systems. By leveraging advanced deep learning models like YOLOv5 and additional enhancements, the system can provide efficient, scalable, and accurate vehicle monitoring solutions for various applications, including traffic management, urban planning, and emergency response. The proposed system is also designed with real-world deployment in mind, with potential integration into existing UAV platforms and real-time monitoring applications, contributing to smarter, safer urban environments.

A. Objective of The Study:

This study aims to develop an efficient, real-time vehicle detection system that leverages deep learning techniques to automatically detect and classify vehicles from UAV-acquired aerial images. Specifically targeting traffic monitoring, urban planning, and emergency response applications, the project focuses on the key stages of image data preprocessing, model training, evaluation, and optimization to ensure accurate, reliable, and scalable vehicle classification across multiple vehicle types: cars, vans, trucks, and buses.

To achieve this, the study employs the YOLOv5 (You Only Look Once version 5) deep learning model, known for its fast processing speed and accuracy in real-time object detection tasks. YOLOv5 is used for both spatial feature extraction and detection, enabling the system to identify vehicles in varying environments, ranging from dense traffic areas to less populated roads, with high efficiency. The model's architecture is optimized for real-time processing, which makes it suitable for applications that demand quick decision-making, such as real-time traffic surveillance or emergency response scenarios.

Unlike other systems that use multiple detection models or ensemble methods, this project focuses on optimizing the performance of a single YOLOv5 model. The study emphasizes fine-tuning YOLOv5 to ensure it delivers high detection accuracy for vehicles, particularly in complex and cluttered aerial images where vehicle sizes and perspectives can vary significantly due to the UAV's altitude. The addition of advanced techniques such as Bidirectional Feature Pyramid Networks (BiFPN) for better feature fusion and Soft Non-Maximum Suppression (Soft-NMS) for handling closely aligned vehicles further enhances the model's accuracy and robustness.

Additionally, the study aims to optimize the model for real-time deployment on resource-constrained platforms, such as UAVs and edge devices, ensuring that the system can be applied to live monitoring systems where computational resources may be limited. By testing and calibrating the model on publicly available UAV datasets like the VisDrone2019 dataset, the system is refined to handle diverse real-world conditions, including varying light, weather, and vehicle densities.

To make this solution practical and accessible for deployment, the project integrates a user-friendly, **Streamlit**-based interface. Streamlit, a powerful and easy-to-use framework for building interactive web applications, allows surveillance operators or traffic management personnel to upload aerial images, view real-time vehicle detection results, and receive alerts when vehicles of interest are detected. The interface is intuitive and interactive, providing users with an easy way to visualize the processed images along with the vehicle classifications and confidence scores. This system ensures that the solution can be effectively used in urban traffic monitoring, disaster management, or other public safety contexts, while also enabling real-time interaction with the detection outputs for quick decision-making.

- **YOLOv5** (You Only Look Once): A state-of-the-art real-time object detection model designed for fast, accurate object classification in video and image data. YOLOv5 processes aerial imagery to identify and classify vehicles, leveraging its high-speed processing and efficient architecture to handle large-scale, dynamic environments in real-time.
- By developing and evaluating this vehicle detection system, the study aims to showcase the capabilities of YOLOv5 in real-time UAV surveillance. This aligns with the broader objective of leveraging artificial intelligence to enhance situational awareness, automate vehicle monitoring, and ultimately improve traffic management, public safety, and urban infrastructure planning through more intelligent, responsive monitoring systems.

B. Problem statement:

In today's world, managing traffic flow, monitoring urban environments, and ensuring public safety through effective surveillance have become increasingly important, particularly in high-density areas such as city streets, highways, and large public events. Traditional traffic monitoring systems often rely on ground-based cameras or manual inspection, which can be limited in coverage, subject to obstructions, and dependent on human intervention. Furthermore, these systems often struggle to scale, adapt to dynamic environments, and provide real-time insights that are crucial for traffic management or emergency response.

A significant challenge in conventional traffic surveillance is the inability to automatically and accurately detect and classify vehicles in real-time, especially in environments with dense traffic or when vehicles are seen from high altitudes. Traditional vehicle detection methods typically suffer from high false-positive rates, poor detection of smaller objects, and an inability to handle complex aerial imagery conditions such as varying vehicle sizes, occlusions, and different weather conditions. In addition, these systems often fail to provide timely alerts or actionable insights, delaying response times in critical situations.

Many existing intelligent surveillance systems for traffic monitoring require significant computational resources and struggle with processing large volumes of data efficiently. These systems often depend on rigid pre-programmed rules and do not have the flexibility to learn and adapt over time, which limits their real-world effectiveness, especially in UAV-based surveillance where images may vary greatly in scale, lighting, and orientation.

To address these limitations, this study proposes a real-time vehicle detection system utilizing YOLOv5 (You Only Look Once version 5), a state-of-the-art deep learning model specifically designed for fast and accurate object detection in complex environments. YOLOv5, with its high speed and accuracy, is particularly suited for UAV-based vehicle detection, where rapid processing of aerial images is essential. This model is capable of detecting and classifying vehicles into categories such as cars, vans, trucks, and buses, even in crowded or obstructed environments, by processing both spatial features and contextual information from the video stream.

Unlike traditional surveillance systems, this approach harnesses the power of deep learning to autonomously improve over time, adapting to new environments, camera angles, and diverse weather conditions. YOLOv5's efficiency allows for real-time detection, making it ideal for dynamic applications such as traffic monitoring, urban planning, and emergency response. The model will be optimized to work effectively even on resource-constrained platforms, such as UAVs and edge devices, ensuring that the system is suitable for live surveillance environments.

The project aims to bridge the gap between manual surveillance and intelligent automated monitoring by providing a scalable, accurate, and efficient solution for vehicle detection. Through this research, the system demonstrates how AI can modernize traffic monitoring infrastructure, reduce dependency on human operators, and enhance urban safety by enabling timely detection of vehicles, ultimately contributing to smarter traffic management and public safety in real-world scenarios.

Related Work

1. Evolution of Surveillance Systems Using Machine Learning

Traditional vehicle detection systems often rely on manual monitoring or basic image processing techniques such as background subtraction, motion detection, and edge detection. While these methods provide some level of automation, they are limited by their inability to adapt to complex, dynamic environments and are prone to high false-positive rates [1]. The introduction of machine learning, particularly deep learning models, has transformed vehicle detection by enabling automated systems that can accurately identify and classify vehicles in real-time, even in challenging environments like UAV-based aerial imagery.

Early machine learning approaches for vehicle detection included support vector machines (SVM) and decision trees, which required handcrafted features to distinguish vehicles from background scenes. These systems struggled with real-world conditions, such as changing lighting, vehicle occlusions, and varying perspectives. The advent of **Convolutional Neural Networks (CNNs)** allowed systems to learn high-level visual features directly from data, making vehicle detection models more robust and accurate. More recently**, YOLO (You Only Look Once)** and similar deep learning architectures have gained prominence due to their ability to perform **real-time object detection** at high accuracy, making them ideal for UAV applications where speed and precision are essential [2].

2. Advantages of Using Deep Learning in Vehicle Detection

Deep learning models, such as **YOLOv5,** provide several advantages over traditional methods for vehicle detection. These models can automatically learn features from large amounts of annotated data, adapt to new environments, and continuously improve with more training [3]. YOLOv5, in particular, offers several benefits over earlier versions of YOLO, including faster processing, higher accuracy, and better handling of small-scale objects, which is crucial for aerial imagery where vehicles may appear smaller due to altitude.

YOLOv5 is capable of detecting and classifying vehicles into categories such as **cars, vans, trucks,** and **buses** with remarkable speed and accuracy [4]. By processing video frames in real time, YOLOv5 significantly reduces the need for human intervention and provides instant alerts, which is especially useful in dynamic environments like urban streets or highways. Additionally, the system's scalability allows it to handle large datasets from multiple UAVs, enabling comprehensive monitoring over wide areas.

3. Challenges in Implementing Machine Learning for Vehicle Detection

While deep learning offers substantial improvements, several challenges remain in implementing machine learning models for real-time vehicle detection from UAVs. **Data quality and diversity** are significant concerns, as UAV images may vary in terms of resolution, weather conditions, lighting, and occlusions. Training models that can generalize well across such variations requires large, diverse datasets, such as the **VisDrone2019 dataset,** which includes various environmental conditions and vehicle types [5].Another challenge is **real-time processing** on resource-constrained devices, such as UAVs. Although YOLOv5 is optimized for high-speed detection, processing high-resolution aerial images in real time still requires significant computational power. Ensuring that the model can run efficiently on limited hardware, such as embedded systems or edge devices, is essential for practical deployment. Furthermore, while YOLOv5 is efficient, fine-tuning the model to ensure robustness against varying vehicle sizes, perspectives, and occlusions remains an ongoing task [6].

4. Technological Advancements in Deep Learning for Vehicle Detection

Recent advancements in deep learning have greatly improved vehicle detection, especially in the context of UAV surveillance**. YOLOv5** is a significant improvement over previous YOLO versions, offering better accuracy and performance in detecting small-scale objects, which is important when detecting vehicles from high altitudes. Additionally, techniques such as **Bidirectional Feature Pyramid Networks (BiFPN)** and **Soft Non-Maximum Suppression (Soft-NMS)** have been integrated into YOLOv5 to enhance feature fusion and reduce false positives when vehicles are closely aligned or overlapping [7].

Hybrid models that combine **CNNs** (for spatial feature extraction) and **RNNs** (for sequence modeling) have also been explored in vehicle detection. These models have shown success in sequential video analysis, which helps improve the understanding of vehicle movement and behavior over time. Moreover, **GPU acceleration** and **model compression techniques** have made it feasible to deploy these deep learning models on UAVs and other edge devices, facilitating real-time processing without compromising performance [8].

5. Case Studies and Real-World Implementations

Several real-world applications and research studies have demonstrated the effectiveness of deep learning models in vehicle detection for UAVs and surveillance. For instance, **traffic monitoring systems** using YOLO-based models have been successfully deployed to detect and classify vehicles in urban areas, highways, and toll stations. These systems not only improve traffic flow management but also help in identifying traffic violations, accidents, and congestion in real-time [9].

Moreover, **intelligent transportation systems** (ITS) are increasingly using UAVs equipped with deep learning models to monitor traffic and provide insights into vehicle behavior. Some UAV-based vehicle detection systems have been integrated into **smart city frameworks** to enhance urban planning and optimize traffic light management [10]. These systems typically leverage models like YOLOv5 to process live footage from UAVs and provide actionable data to city planners or emergency responders.

In addition, **military and emergency response** teams have also implemented UAV-based vehicle detection systems to track vehicle movement in sensitive or hard-to-reach areas, offering valuable real-time intelligence during critical operations. These deployments showcase the versatility and scalability of deep learning models for vehicle detection in UAV-based surveillance.

Proposed System

The proposed system is a real-time vehicle detection framework designed for UAV-based surveillance, leveraging deep learning to detect and classify vehicles from aerial images. The primary goal is to automate the detection of vehicles in various categories—cars, vans, trucks, and buses—with high accuracy and efficiency. By using UAVs, the system offers a broad perspective of urban or highway environments, allowing for continuous monitoring and fast decision-making, which is critical for traffic management, emergency response, and urban planning.

At the core of the system is a deep learning model based on YOLOv5 (You Only Look Once version 5), a state-of-the-art object detection model known for its speed and accuracy in real-time applications. YOLOv5 is designed to process high-resolution aerial images and quickly identify and classify vehicles across multiple categories. The model utilizes Convolutional Neural Networks (CNNs) for spatial feature extraction, enabling it to detect fine-grained visual details of vehicles such as size, shape, and type, even from high altitudes.

The system integrates advanced techniques like Bidirectional Feature Pyramid Networks (BiFPN) and Soft Non-Maximum Suppression (Soft-NMS) to enhance detection accuracy and robustness. BiFPN enables efficient feature fusion at multiple scales, allowing the system to detect vehicles of varying sizes and distances. Soft-NMS improves detection performance by reducing false positives in situations where vehicles are closely aligned or overlapping, which is common in dense urban environments.

To train the model, a diverse and representative dataset of UAV-acquired aerial images, such as the VisDrone2019 dataset, is used. This dataset contains annotated vehicle categories and diverse real-world scenarios, ensuring the model can generalize to different environments, camera angles, and weather conditions. Preprocessing steps, including image resizing, normalization, and augmentation, are applied to improve model robustness and performance.

To facilitate real-time deployment, the system is designed to be lightweight and efficient, ensuring it can operate on UAVs and resource-constrained edge devices. This real-time capability is crucial for applications that require instant feedback, such as monitoring traffic flow, identifying traffic violations, or assisting in emergency situations.

The system also includes a web-based user interface, developed using HTML, CSS, and JavaScript, with a Flask backend. This interface allows security personnel, traffic managers, or city planners to upload UAV video clips or connect to live camera feeds, view vehicle detection results in real time, and receive instant alerts when vehicles of interest are detected. The user interface is designed to be intuitive, allowing users to easily navigate through the detection results and take appropriate actions based on the system's output.

By combining YOLOv5 with practical enhancements and a user-friendly interface, this system offers a scalable, efficient, and real-time alternative to traditional vehicle monitoring methods. It not only automates the detection process, reducing the risk of human error, but also enhances situational awareness by providing timely, actionable insights. This deep learning-based vehicle detection framework is poised to contribute to smarter urban planning, better traffic management, and enhanced public safety through intelligent UAV-based surveillance.

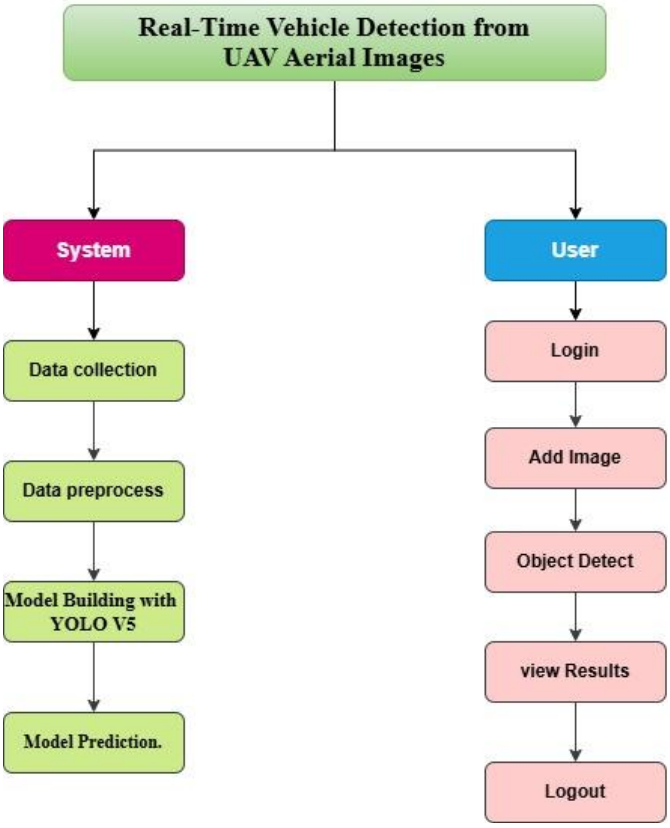

Fig 1: Flow chart

Modules and its Implementation

System: Operations

Upload Image: This module enables the core functionality of the system by allowing users to upload UAV-captured image files. The uploaded image serves as the primary data source for the vehicle detection process. The upload page is designed to be user-friendly, accepting image format which are compatible with the model's preprocessing pipeline. Once an image is uploaded, it is automatically directed to the preprocessing and analysis stages.

Image Preprocessing: Upon receiving the image input, the system begins by performing several preprocessing steps to prepare the image for analysis by the YOLOv5 model. First, the image is resized to match the input size required by the model, ensuring that the dimensions are consistent with what the model expects. Next, the pixel values of the image are normalized, typically scaling them to a range between 0 and 1. This normalization process helps in improving the efficiency of the model during processing by standardizing the input data. Finally, the image is converted into a format that is compatible with the YOLOv5 model, ensuring that it can be correctly processed and analyzed. These preprocessing steps collectively ensure that the input image is optimized for accurate and efficient object detection.

Feature Extraction and Classification: The preprocessed image is then passed through the **YOLOv5 model**, which performs **real-time object detection.** YOLOv5 **uses Convolutional Neural Networks (CNNs)** to extract spatial features from the image, allowing it to detect and classify vehicles such as **cars, vans, trucks**, and **buses**. The model processes the spatial features such as the shape, size, and position of the vehicles, identifying them in the image and classifying them into the appropriate categories.

Display Result: After classification, the system generates and displays the results on the user interface. Users are shown the detected vehicles with their respective categories (e.g., car, van, truck, or bus) along with a **confidence score**, which indicates the model's certainty in its detection. The interface also highlights the detected vehicles **with bounding boxes** around them, providing a clear visualization of the results. The confidence score helps users quickly interpret the outcome and take appropriate action, such as analyzing the vehicle distribution or investigating specific vehicles of interest.

User: Operations

User Registration: New users can create an account on the platform by providing basic credentials such as **username, email**, and **password**. This step ensures secure and personalized access to the vehicle detection system. User credentials are securely stored, and the registration process may include email verification to confirm the user's identity.

Login: Registered users can log in using their credentials to access the vehicle detection and analysis features. Secure authentication ensures that only authorized personnel can interact with the system, protecting sensitive data such as uploaded images.

Image Upload and Detection: After logging in, users can navigate to the **image upload page,** where they can submit images captured by UAVs for vehicle detection analysis. The system handles the rest of the process—preprocessing the image, passing it through the YOLOv5 model for vehicle classification, and displaying the results in real time. This module serves as the primary interface for users to interact with the detection system.

Viewing Results: Once the image is processed, users are presented with the classification results, which include several key pieces of information. The system displays the types of vehicles detected in the image, such as car, truck, or bus. Indicating the model's certainty in its detection. Additionally, visual indicators, such as bounding boxes, are drawn around the detected vehicles to facilitate easy identification. This allows users to quickly interpret the results and take appropriate actions, whether it's for traffic analysis, identifying vehicles of interest, or addressing security concerns in specific areas.

RESULTS

The Real-Time Vehicle Detection System successfully classified and detected vehicles from UAV-captured aerial images, categorizing them into four distinct classes: cars, vans, trucks, and buses. Utilizing the YOLOv5 deep learning model, the system proved highly effective in identifying and classifying vehicles, even in complex aerial environments. YOLOv5's ability to detect objects in real time, coupled with enhancements like Bidirectional Feature Pyramid Networks (BiFPN) and Soft Non-Maximum Suppression (Soft-NMS), enabled the system to handle overlapping vehicles and varying object sizes with a high degree of accuracy and minimal false positives.

The model performed well across a variety of real-world UAV image scenarios, demonstrating its capability to detect vehicles in diverse conditions such as different altitudes, weather variations, and lighting. The system showed a high degree of reliability in detecting vehicles of various types while minimizing unnecessary detections, making it particularly useful for real-time monitoring in urban traffic, highway management, and emergency response situations. Its ability to process both small and large vehicles, regardless of their position within the image, showcased the robustness of YOLOv5 in aerial vehicle detection.

To ensure practical deployment, the system integrates an intuitive Streamlit-based interface that allows users to upload aerial images and receive real-time vehicle detection results. Once an image is uploaded, the system processes it using YOLOv5 and displays the predicted vehicle types along with the detection confidence scores. This interactive interface makes it easy for users to interpret the results and take appropriate actions quickly. The platform is designed to be accessible to users with minimal technical expertise, such as traffic management personnel, security operators, or urban planners.

Although the current version of the system focuses on static image classification, it establishes a strong foundation for future developments. Planned enhancements include the integration of live UAV feeds, real-time vehicle tracking, instant alerts, and the ability to manage and visualize data through interactive dashboards. These improvements will further enhance the system's capability to support proactive surveillance, efficient traffic monitoring, and timely decision-making in urban or emergency environments.

Yolo Model Result

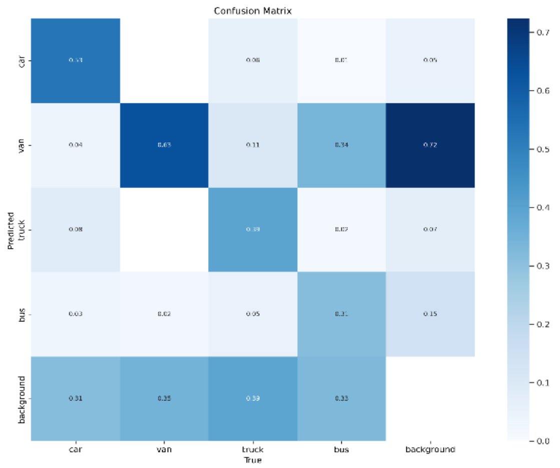

Fig 2: Confusion metrics

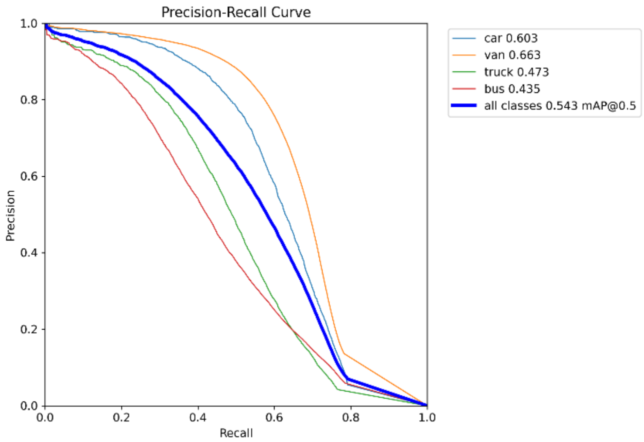

Fig 3: PR curve

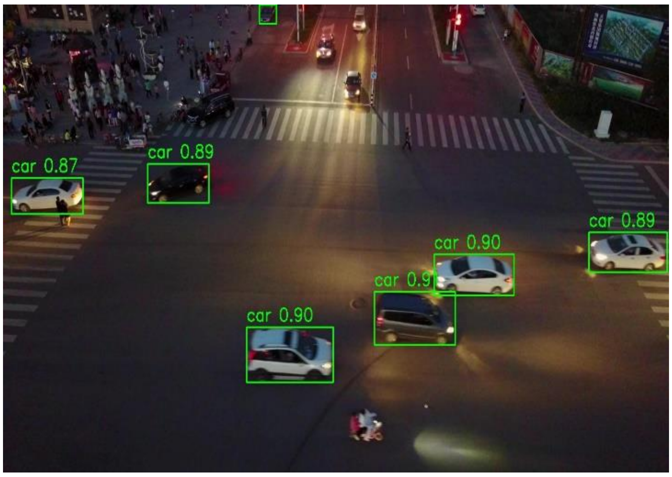

Fig 4: Prediction Result

The results from the YOLOv5 model reveal the performance of the vehicle detection system, which classifies four vehicle types: **car, van, truck,** and **bus.** The confusion matrix demonstrates the model's ability to correctly classify these vehicle types with varying levels of accuracy. The highest accuracy is observed for **van** detection, with a value of 0.83, while the detection of **truck** and **bus** shows lower performance, indicating potential challenges in distinguishing between certain vehicle types or handling smaller vehicle categories. The **Precision-Recall curve** further shows that while the model performs well for cars and vans, the recall and precision for trucks and buses are relatively lower, which affects overall performance, as indicated by a **mean Average Precision (mAP@0.5)** of 0.543. These metrics suggest that while the system is effective for general vehicle detection, further improvements may be needed for specific categories like trucks and buses to enhance accuracy and robustness across all vehicle types.

CONCLUSION

This project demonstrates the successful application of deep learning in real-time vehicle detection for UAV-based surveillance. By utilizing YOLOv5, a state-of-the-art object detection model, the system is capable of classifying vehicles into four categories: car, van, truck, and bus. The YOLOv5 model's ability to process high-resolution aerial images quickly and accurately, combined with advanced techniques like Bidirectional Feature Pyramid Networks (BiFPN) and Soft Non-Maximum Suppression (Soft-NMS), makes the system highly effective in detecting vehicles in a variety of real-world environments. The results show strong detection performance, particularly for cars and vans, though further improvements are needed for more accurate truck and bus detection.The integration of a Streamlit-based interface enhances the system's accessibility, enabling users to easily upload UAV images, view detection results, and interpret classification outcomes with confidence scores. The system is scalable and provides a practical solution for applications such as traffic monitoring, urban planning, and emergency response, where real-time vehicle detection is critical.This project sets a strong foundation for future developments in UAV-based surveillance, demonstrating how AI and machine learning can improve real-time monitoring and support proactive decision-making in public safety and urban management.

Future Enhancement

This project demonstrates the successful application of deep learning in real-time vehicle detection for UAV-based surveillance. By utilizing YOLOv5, a state-of-the-art object detection model, the system is capable of classifying vehicles into four categories: car, van, truck, and bus. The YOLOv5 model's ability to process high-resolution aerial images quickly and accurately, combined with advanced techniques like Bidirectional Feature Pyramid Networks (BiFPN) and Soft Non-Maximum Suppression (Soft-NMS), makes the system highly effective in detecting vehicles in a variety of real-world environments. The results show strong detection performance, particularly for cars and vans, though further improvements are needed for more accurate truck and bus detection.The integration of a Streamlit-based interface enhances the system's accessibility, enabling users to easily upload UAV images, view detection results, and interpret classification outcomes with confidence scores. The system is scalable and provides a practical solution for applications such as traffic monitoring, urban planning, and emergency response, where real-time vehicle detection is critical.This project sets a strong foundation for future developments in UAV-based surveillance, demonstrating how AI and machine learning can improve real-time monitoring and support proactive decision-making in public safety and urban management.

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