© 2025 IJNRD | Volume 10, Issue 4 April 2025 | ISSN: 2456-4184 | IJNRD.ORG

IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Real-Time Vehicle Detection from UAV Aerial Images

B.JAGADEESH,D.JAGADEESH,K.VENKATA SAI,I. PAVAN

Under the guidance of Mrs P SRAVANI RAJESWARI assistant professor

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.

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:

The rapid advancement of Unmanned Aerial Vehicles (UAVs) has opened new possibilities for real-time monitoring and detection, particularly in vehicle detection from aerial imagery. This project presents a high-performance, real-time vehicle detection model based on YOLOv5, specifically designed for UAV-captured images using the VisDrone2019 dataset, which includes annotations for cars, vans, trucks, and buses. The model introduces key enhancements, including an additional prediction head to improve the detection of smaller objects and a Bidirectional Feature Pyramid Network (BiFPN) for efficient feature fusion across scales. Soft Non-Maximum Suppression (Soft-NMS) is also integrated to reduce false negatives in dense environments. Together, these improvements enable highly accurate vehicle detection, making the model suitable for applications such as traffic monitoring, urban planning, and emergency response.

This project focuses on the development and deployment of a real-time vehicle detection model using UAV-acquired aerial images, addressing the needs of traffic management, urban planning, and emergency response. The scope includes:

1. Data Collection and Processing: Utilization of the VisDrone2019 dataset, which includes various vehicle types such as cars, vans, trucks, and buses.

2. Model Architecture Enhancements: Integration of an additional prediction head for improved small-scale vehicle detection, alongside a Bidirectional Feature Pyramid Network (BiFPN) to enhance feature fusion and scale-invariance.

3. Advanced Detection Techniques: Implementation of Soft Non-Maximum Suppression (Soft-NMS) for better detection accuracy in high-density vehicle scenes.

4. Real-Time Detection Capabilities: Optimization for real-time processing on UAV platforms, enabling quick response in real-world applications.

5. Applications: Designed for use in traffic surveillance, city infrastructure monitoring, disaster response, and other real-time observation needs that benefit from accurate vehicle detection at various scales and in complex environments.

This project contributes to advancements in UAV-based monitoring by addressing key detection challenges and providing a scalable, adaptable solution for urban and critical area surveillance.

The rapid advancement of Unmanned Aerial Vehicles (UAVs) has opened new possibilities for real-time monitoring and detection, particularly in vehicle detection from aerial imagery. This project presents a high-performance, real-time vehicle detection model based on YOLOv5, specifically designed for UAV-captured images using the VisDrone2019 dataset, which includes annotations for cars, vans, trucks, and buses. The model introduces key enhancements, including an additional prediction head to improve the detection of smaller objects and a Bidirectional Feature Pyramid Network (BiFPN) for efficient feature fusion across scales. Soft Non-Maximum Suppression (Soft-NMS) is also integrated to reduce false negatives in dense environments. Together, these improvements enable highly accurate vehicle detection, making the model suitable for applications such as traffic monitoring, urban planning, and emergency response.

With the growing adoption of UAV technology for surveillance and monitoring, real-time vehicle detection from aerial images has become essential for applications in traffic management, urban planning, and emergency response. Traditional vehicle detection models often struggle with small-scale objects, densely populated urban settings, and complex visual backgrounds, which reduces detection accuracy and limits practical use in high-stakes scenarios.

EXISTING MODEL :

Current vehicle detection systems for aerial images, while effective for general object detection, face limitations in accurately identifying small-scale objects in complex urban environments from high altitudes. These systems typically use single-scale feature extraction methods, which may miss critical details needed for detecting smaller or closely aligned vehicles. Non-Maximum Suppression (NMS) is commonly applied for overlapping detections, yet it can lead to missed detections when vehicles are closely grouped. Additionally, many existing models are computationally intensive, making real-time processing difficult on UAV platforms. These limitations highlight the need for enhanced multi-scale feature handling and improved overlap filtering for practical, high-accuracy real-time applications.

DISADVANTAGES :

1. Limited Small-Scale Detection: Existing systems often struggle to accurately detect small-scale vehicles from high-altitude UAV images, leading to missed detections in dense, urban areas.

2. Inefficient Feature Fusion: Traditional models lack effective multi-scale feature fusion, which reduces detection accuracy across varied object sizes in complex environments.

3. Missed Detections in Dense Areas: Standard Non-Maximum Suppression (NMS) can suppress true positive detections when vehicles are closely aligned.

4. High Computational Cost: Many current models are computationally intensive, making real-time processing difficult on lightweight UAV platforms, impacting response time

5. Reduced Real-Time Performance: The need for extensive processing resources limits the practicality of existing systems for real-time applications on UAVs

PROPOSED SYSTEM :

The proposed system leverages the YOLOv5 model, widely recognized for its speed and accuracy in object detection tasks, to enhance real-time vehicle detection from UAV-acquired aerial images. YOLOv5 serves as the base model due to its lightweight architecture, which enables rapid processing on UAV platforms. To address the challenge of detecting small-scale vehicles, an additional prediction head is integrated into YOLOv5, improving detection for smaller objects often missed in high-altitude imagery. Additionally, a Bidirectional Feature Pyramid Network (BiFPN) is introduced, enabling multi-scale feature fusion and enhancing detection accuracy across diverse object sizes. For handling densely packed vehicles, Soft Non-Maximum Suppression (Soft-NMS) is employed, effectively reducing false negatives by retaining closely aligned detections. This system is optimized for real-time processing, making it ideal for applications in traffic monitoring, urban planning, and emergency response. Combining YOLOv5 with these architectural enhancements creates a scalable, high-performance solution for real-world UAV surveillance applications.

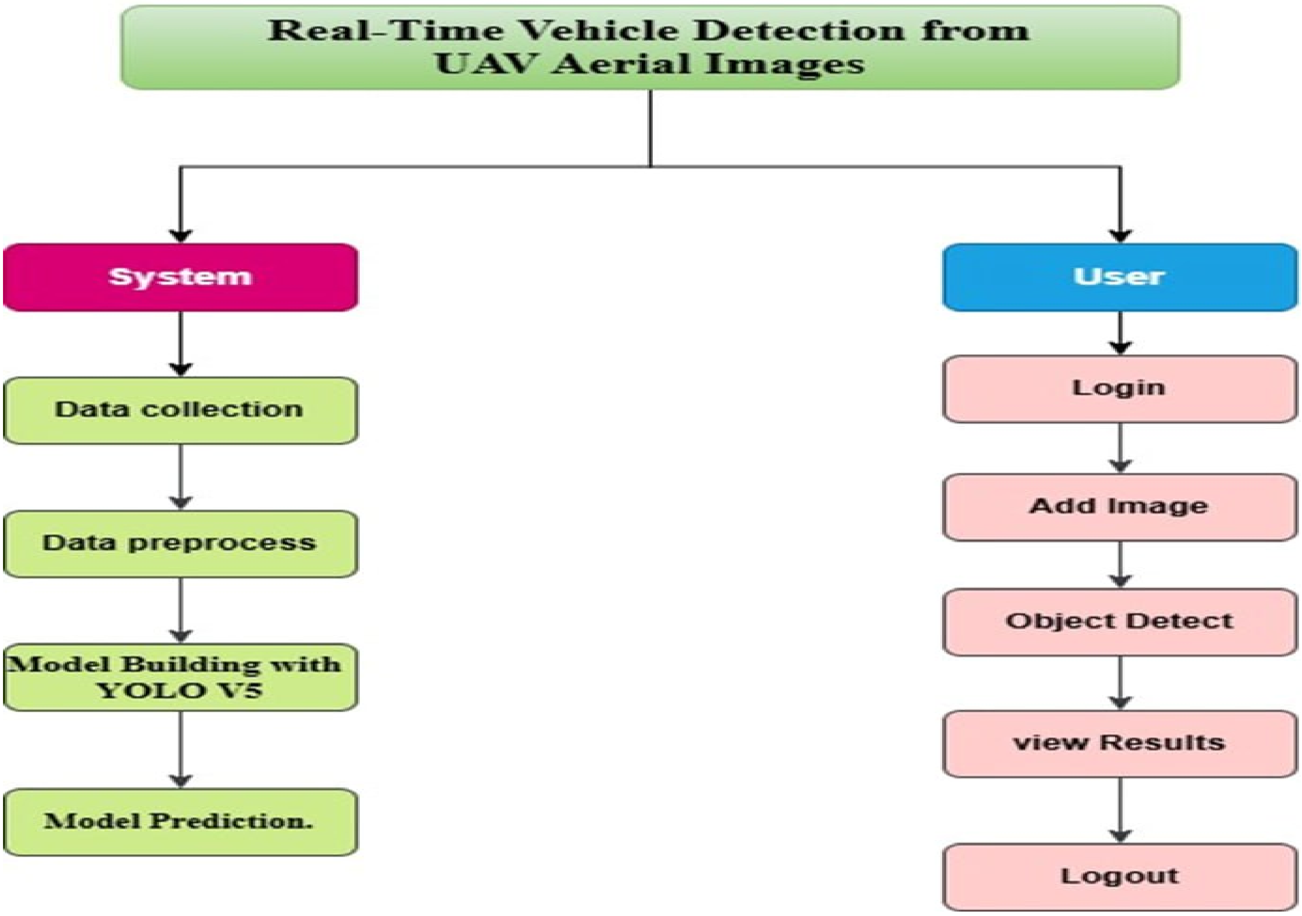
ADVANTAGES :

1) High Detection Speed and Accuracy: Leveraging YOLOv5 as the base model ensures rapid and accurate vehicle detection, suitable for real-time processing on UAV platforms.
2) Improved Small-Scale Detection: The addition of a specialized prediction head enhances YOLOv5's ability to detect small-scale vehicles, increasing accuracy in high-altitude imagery.
3) Enhanced Multi-Scale Feature Fusion: The integration of a Bidirectional Feature Pyramid Network (BiFPN) improves YOLOv5's performance across

varied object sizes by fusing features from multiple scales, resulting in more reliable detection in complex environments.

4) Reduced False Negatives in Dense Areas: Soft Non-Maximum Suppression (Soft-NMS) minimizes missed detections in dense areas by effectively handling closely aligned vehicles, reducing the chance of suppressing true positives.
5) Resource-Efficient Real-Time Processing: YOLOv5's efficient architecture, combined with these enhancements, allows for real-time performance even on resource-limited UAV systems.
6) Versatile Application in Real-World Scenarios: The proposed system's accuracy and efficiency make it well-suited for diverse applications, including traffic surveillance, urban planning, and emergency response, where immediate insights are essential

Block diagram of proposed system :



FUNCTIONAL AND NON-FUNCTIONAL NEEDS :

These are the requirements that the end user specifically demands as basic facilities that the system should offer. All these functionalities need to be necessarily incorporated into the system as a part of the contract.

1. Dataset Preparation

Function: The system processes and splits the VisDrone2019 dataset into training and testing sets for vehicle detection.

Features:

- Organizes data into train/test splits (typically 70-80% training, 20-30% testing)
- Processes data to ensure it is suitable for YOLOv5 training.

2. Pre-processing

Function: Standardizes images to match YOLOv5 requirements and improves the model's ability to generalize.

Features:

- Resizes images to a fixed dimension.
- Normalizes pixel values (scaling between 0 and 1 or -1 to 1).
- Applies augmentation techniques like rotation, flipping, and scaling to enhance model robustness

3. Training

- Function: Trains the YOLOv5 model with modifications for improved performance, especially for small object detection.

Features:

- Use of transfer learning with pre-trained weights.
- Additional prediction head for detecting small objects.

Integration of Bidirectional Feature Pyramid Network (BiFPN) or better feature fusion.

4. Evaluation

Function: Evaluates the trained model's performance on a testing dataset.

Features:

- Measures accuracy, precision, recall, and F1-score for vehicle detection.
- Applies Soft-NMS to resolve overlapping bounding boxes.

5. User Registration

Function: Allows users to create an account for personalized access.

Features:

- Collects user data (name, email, password).
- Saves and tracks user analysis results.

6. User Login

Function: Provides secure user access to their account.

Features:

- Validates user credentials.
- Ensures user data privacy and security.

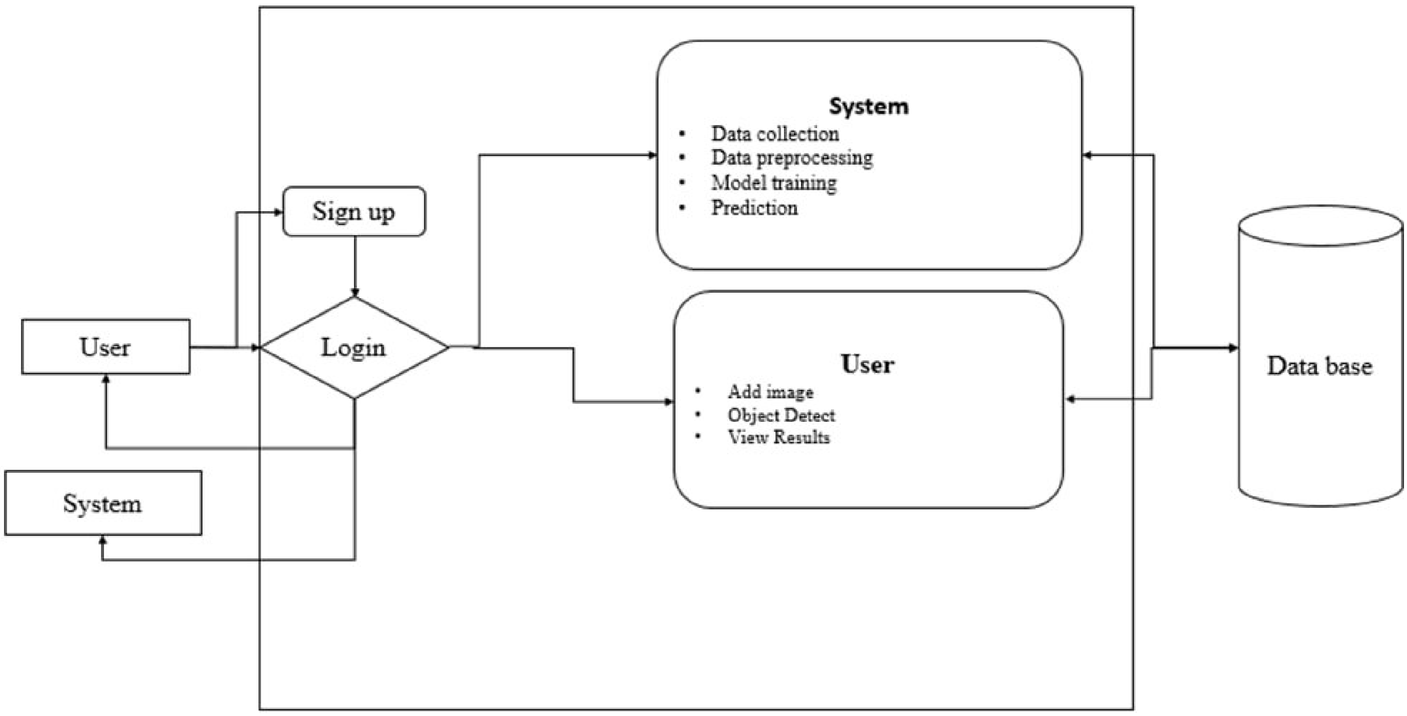
7. Upload Image

Function: Enables users to upload aerial images for analysis.

Features:

- Supports various image formats.
- Pre-processes the uploaded images for object detection.

ARCHITECTURE :

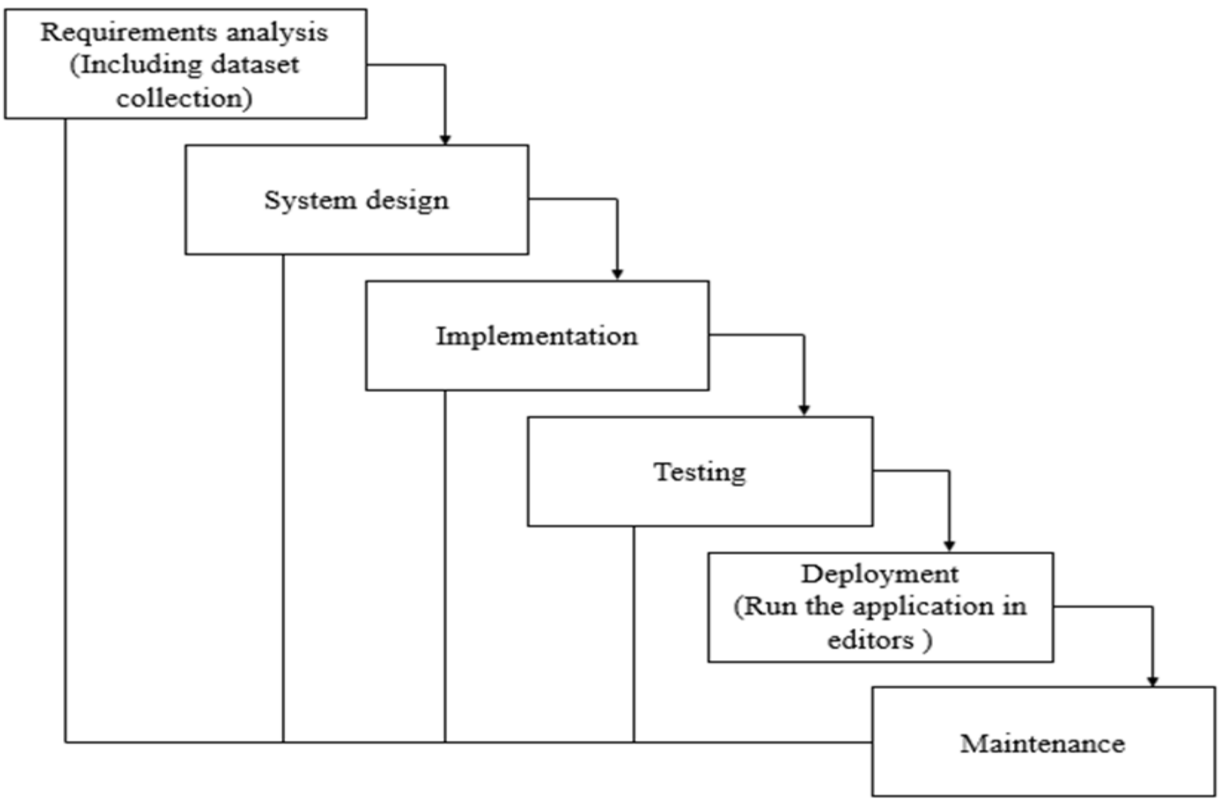


Flowchart Of Application Interface

SOFTWARE DEVELOPMENT LIFE CYCLE – SDLC:

In our project we use waterfall model as our software development cycle because of its step-by-step procedure while implementing.

The SDLC typically consists of six stages: requirement analysis, design, development and testing, implementation, documentation, and evaluation.13 Each phase in the SDLC encompasses a certain set of activities and tasks, providing a systematic structure and reusable framework to define the various steps involved in the development of a system.



Classical Overview Of Waterfall Model

USE CASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis.

Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

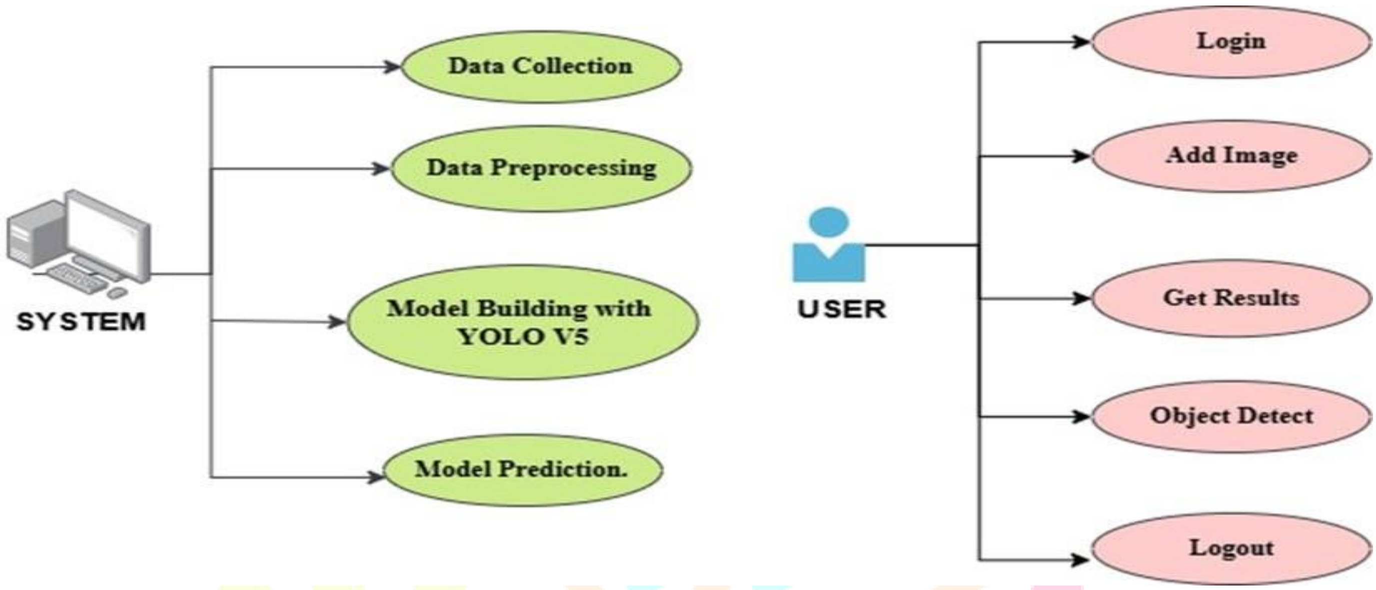


diagram for application interaction

IMPLEMENTATION AND RESULTS :

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modelling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control

- User Registration

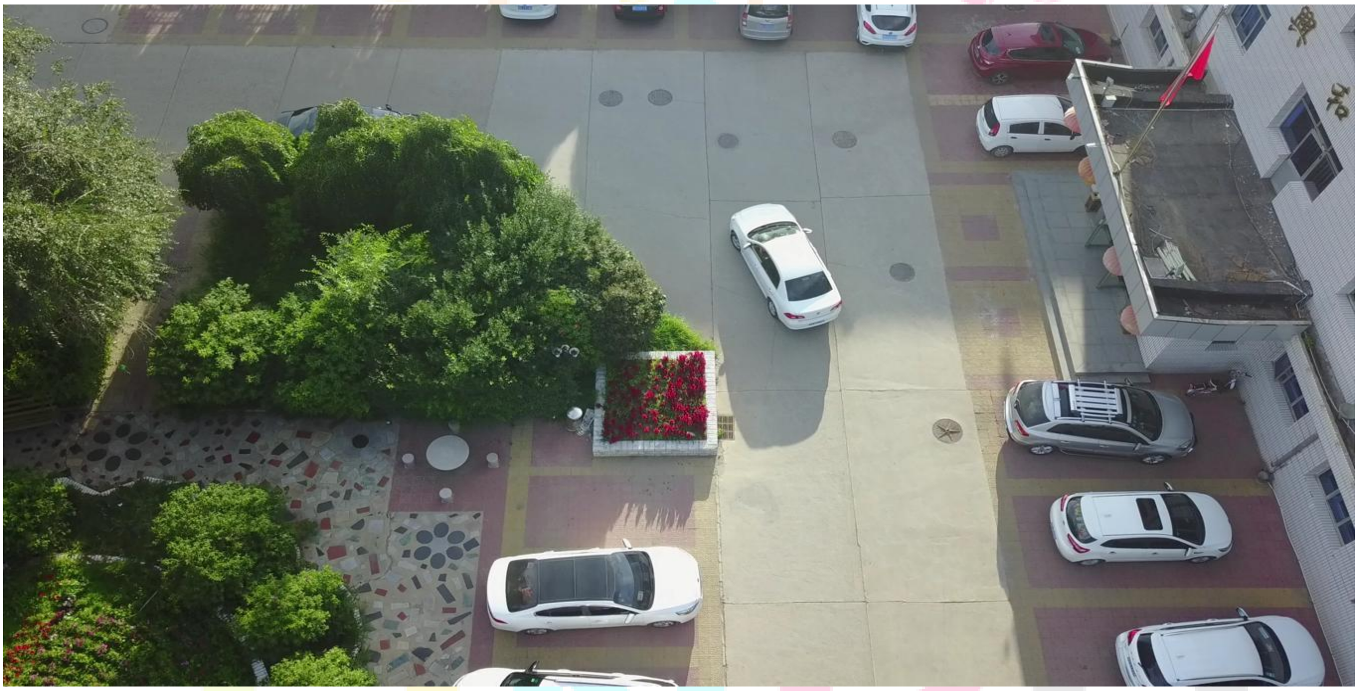
Users can create an account by providing basic details such as name, email, and password. Registration enables personalized access and allows users to save and track analysis results within their profile.

•User Login

Registered users log in with their credentials to securely access system features and personal data. Login validation ensures user data privacy and secure access.

• Upload Image

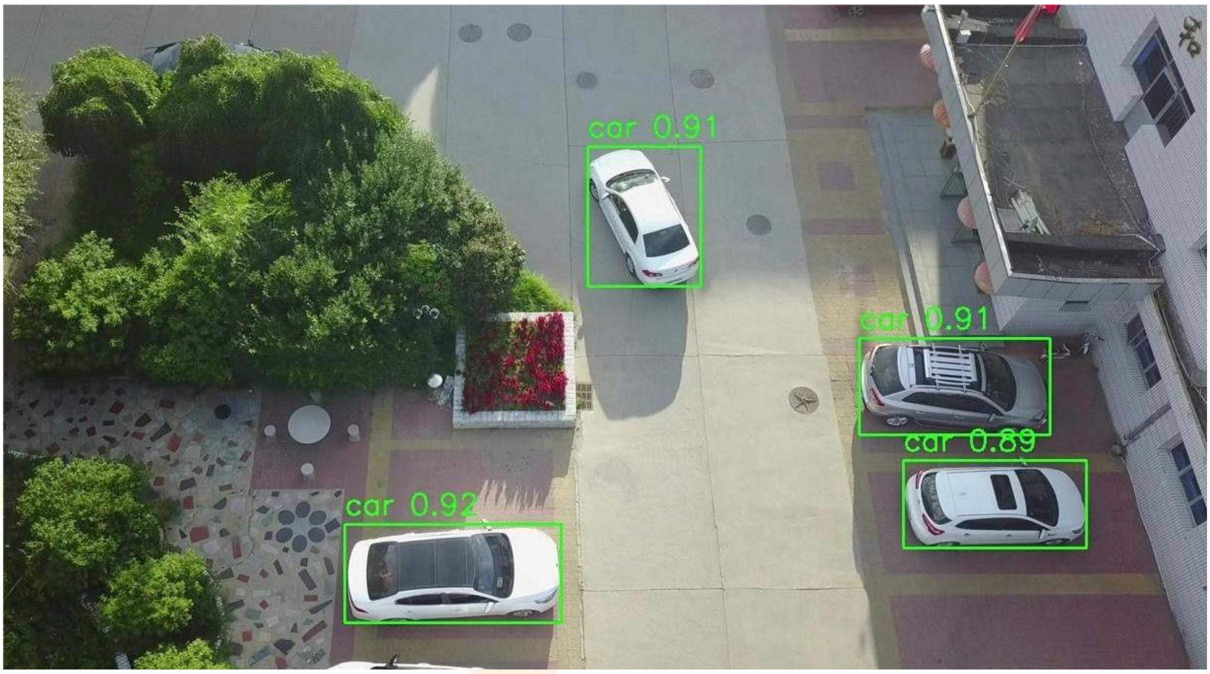
Users can upload UAV-acquired aerial images via a web or mobile interface. The system accepts various image formats, and uploaded images are pre-processed and prepared for vehicle detection.



- View Results

Users receive detection results, including identified vehicle types, bounding boxes, and confidence scores. Results are presented visually and intuitively, allowing easy interpretation and immediate insights for applications such as traffic analysis and urban planning.

.



REFERENCES

1. Liu, Z., & Wang, H. (2024). "Real-time Pedestrian Detection for UAVs in Urban Environments Using YOLOv5." Journal of UAV Applications, 15(1), 102-110.

2. Zhang, X., & Li, Y. (2023). "Enhanced Vehicle Detection in Aerial Imagery Using Multi-scale Feature Fusion and YOLOv5." Aerial Imaging and Computer Vision Journal, 18(2), 145-152.

3. Chen, L., & Liu, Y. (2023). "UAV-based Vehicle Detection in Traffic Surveillance with Deep Learning Models." Journal of Traffic Monitoring and Control, 10(4), 175-183.

4. Wang, M., & Zhang, W. (2023). "Advanced Vehicle Detection in Aerial Images Using YOLOv5 with Soft-NMS and BiFPN." International Journal of Remote Sensing and UAV Technologies, 22(3), 199-208.

5. Kim, J., & Park, T. (2023). "Efficient Traffic Flow Monitoring from UAVs Using Deep Learning." UAV Systems in Urban Planning, 9(2), 88-95.