Real-Time Monitoring and Identification of Pine Wilt Disease Using YOLOv5 and High-Altitude Platform: A Case Study of Qinba Mountain Area in China

Xing-Rong Fan, Yuhe Deng, Huiting Chen, Hui Wan, and Chaoyuan Jiang

Abstract—**Accurate and large-scale monitoring of pine wilt disease (PWD) remains a critical challenge in forest management due to limited coverage, high operational cost, and insufficient detection reliability in conventional survey methods. To address these limitations, this study develops a real-time intelligent monitoring system that integrates a fixed high-altitude sensing platform with a YOLOv5-based deep learning detector. The system provides continuous panoramic visual acquisition, while an edge-cloud collaborative architecture enables real-time image preprocessing and automatic identification of infected pine trees. A high-resolution dataset collected from the Qinba Mountain region of Chongqing, China, was constructed to train and evaluate multiple YOLOv5 variants. Experimental results demonstrate that the optimal model (YOLOv5x) achieves a mean average precision (mAP) of 68.8% and an overall detection accuracy of 93.78%. Compared with conventional unmanned aerial vehicle (UAV) based monitoring, the proposed system provides larger monitoring coverage (approximately 12 km^2), lower operational cost per 700 km^2 monitoring area (reduced by approximately 76.00%), and improved identification reliability. These results demonstrate that stable high-altitude observation combined with deep learning-based detection offers a scalable and cost-efficient solution for large-area forest epidemic surveillance and intelligent ecological management.**

Index Terms—**Pine wilt disease (PWD), intelligent forest monitoring, high-altitude sensing platform, edge-cloud architecture, large-scale epidemic surveillance**

I. INTRODUCTION

PINE wilt disease (PWD), caused by the pine wood nematode (PWN) and transmitted primarily by *Monochamus* species, is widely recognized as one of the most destructive forest diseases worldwide [1, 2]. Due to its rapid transmission, high mortality rate, and strong environmental adaptability, PWD has caused severe ecological degradation and substantial economic losses in many forest regions. In China, the continuous spread of PWD poses significant challenges to large-scale forest resource protection and ecological stability [3]. Accurate and timely identification of infected pine trees is therefore critical for epidemic control, targeted interventions, and sustainable forest management.

Early studies on PWD monitoring mainly relied on spectral feature extraction [4] and traditional machine learning algorithms [5]. Unmanned aerial vehicle (UAV) based multispectral imagery combined with random forest (RF) or support vector machine (SVM) classifiers has been employed to distinguish infected trees from healthy vegetation [6]. Other studies have fused vegetation indices (VIs) and texture features (TFs) with interpretable learning frameworks to enhance classification robustness [7, 8]. Although these feature-engineering-based approaches have demonstrated some effectiveness, they typically require manual feature design, lack end-to-end object localization capabilities, and are limited in real-time deployment.

With the rapid advancement of deep learning, convolutional neural network (CNN) based object detection models have become the dominant paradigm for forest disease monitoring [9, 10]. In particular, the YOLO series has attracted extensive attention due to its favorable trade-off between detection accuracy and inference speed [11, 12]. Recent studies have incorporated attention mechanisms, adaptive feature fusion modules, and improved intersection over union (IoU) loss functions into YOLO-based architectures to enhance small-target detection and suppress background interference in complex forest environments [13]. Improved YOLOv5 variants have achieved high mean average precision (mAP) values and real-time detection performance on UAV-acquired imagery [14]. These end-to-end frameworks significantly outperform traditional feature-based methods in terms of robustness and automation.

More recently, transformer-based and hybrid CNN-transformer architectures have been introduced to improve global feature modeling and early-stage disease recognition. Fusion networks combining lightweight CNN backbones with vision

Manuscript received: 16 February 2026; revised: 11 March 2026; accepted: 16 March 2026. *(Corresponding author: Xing-Rong Fan.)*

Citation: X.-R. Fan, Y. Deng, H. Chen, H. Wan, and C. Jiang, Real-time monitoring and identification of pine wilt disease using YOLOv5 and high-altitude platform: A case study of Qinba Mountain area in China, *Int. J. Intell. Control Syst.*, 2026, 31(1), 85–91.

Xing-Rong Fan and Yuhe Deng are with Chongqing Key Laboratory of Intelligent Perception and BlockChain Technology, Chongqing Technology and Business University, Chongqing 400067, China (e-mail: fanxingrong@ctbu.edu.cn; dengyuhe@ctbu.edu.cn).

Huiting Chen and Hui Wan are with School of Artificial Intelligence, Chongqing Technology and Business University, Chongqing 400067, China, and also with School of Computer Science and Information Engineering, Chongqing Technology and Business University, Chongqing 400067, China (e-mail: chenhuiting@ctbu.edu.cn; wanhui@ctbu.edu.cn).

Chaoyuan Jiang is with Chongqing Engineering Laboratory for Detection, Control and Integrated System, Chongqing Technology and Business University, Chongqing 400067, China (e-mail: jcy@510link.com).

Digital Object Identifier 10.62678/IJICS202603.10314

transformer (ViT) modules have demonstrated enhanced multi-scale representation capabilities [15–17]. External-attention-based transformer structures have further reduced computational complexity while maintaining competitive detection accuracy [18]. Despite these algorithmic advancements, many transformer-based models require higher computational resources, which may restrict their deployment in large-scale, long-term forest surveillance systems.

Although significant progress has been achieved in detection accuracy, most existing studies are built on UAV-based data acquisition [8, 19, 20]. UAV platforms provide flexible deployment and high-resolution imagery; however, they typically operate in mission-oriented flight modes, resulting in limited coverage per operation, high cumulative labor and energy costs, and discontinuous monitoring. In complex mountainous regions, flight restrictions and weather dependency further constrain operational stability. Moreover, UAV-based monitoring generally requires repeated flight missions to maintain temporal observation, which further increases operational complexity and limits its applicability for persistent large-area surveillance. Consequently, a gap remains between high-performance detection algorithms and scalable, cost-effective monitoring architectures capable of continuous large-area surveillance. Fixed high-altitude sensing platforms provide a promising alternative by enabling persistent observation over wide forest regions without repeated aerial operations, especially in mountainous regions where UAV flights are often restricted by terrain and weather conditions. By utilizing elevated observation points and panoramic imaging devices, such platforms can support long-term monitoring with improved operational stability and reduced monitoring cost per unit area.

To address these limitations, this study proposes a real-time intelligent monitoring system for pine wilt disease trees based on a fixed high-altitude intelligent sensing platform integrated with the YOLOv5 detection framework. The system combines continuous high-altitude visual acquisition, edge artificial intelligence (AI) preprocessing, and deep learning-based object detection to achieve accurate localization and counting of infected trees. Compared with UAV-based systems, the proposed system significantly expands monitoring coverage while reducing operational costs per unit area through persistent infrastructure-based observation rather than repeated aerial missions. A case study conducted in the Qinba Mountain region of Chongqing, China, demonstrates that the system achieves high identification accuracy alongside improved scalability and economic efficiency, providing a practical solution for large-scale forest epidemic monitoring. The main contributions of this work are summarized as follows:

(1) A fixed high-altitude intelligent sensing platform is designed to enable large-area, continuous forest monitoring, overcoming the coverage and operational limitations of UAV-based systems.

(2) A YOLOv5-based real-time detection framework is deployed within an edge-cloud collaborative environment to achieve accurate localization and counting of PWD-infected trees.

(3) Comprehensive comparative experiments validate that the proposed system achieves higher monitoring coverage and lower costs while maintaining competitive detection accuracy, demonstrating its suitability for large-scale forest disease surveillance.

II. Materials and Methods

A. Study Site

The study area is located in the Qinba Mountain region of Chongqing, China (29°56′–30°23′ N, 118°51′–119°52′ E), covering five counties: Chengkou, Wushan, Wuxi, Fengjie, and Yunyang. In 2010, the Qinba Mountain Forestry District was designated as a national key biodiversity conservation area. The region features extensive mountainous terrain and dense pine forest distribution, forming an ecologically sensitive and strategically important forest ecosystem.

Chongqing's total forest area reaches 45,340 km^2, of which pine forests account for 16,383 km^2 (36.13%). Pine resources play a critical role in ecological protection, carbon sequestration, and regional economic sustainability. However, due to the rapid transmission characteristics of pine wilt disease, this region has become one of the most severely affected epidemic zones in southwestern China [14]. Large-area, continuous monitoring is therefore essential for timely detection and epidemic control.

B. System Architecture and Data Acquisition

To enable large-scale automated monitoring, a fixed high-altitude platform (HAP) was deployed in the Qinba Mountain forest region (Fig. 1). The platform integrates panoramic visual acquisition, edge AI preprocessing, and cloud-based deep learning analysis into a unified monitoring system.

The platform integrates a high-resolution pan-tilt-zoom (PTZ) video camera capable of 360° horizontal rotation and long-distance optical zoom for continuous panoramic observation. The camera is typically installed on existing forest fire watchtowers or dedicated monitoring towers positioned at elevated terrain points, providing unobstructed 360° panoramic views of the surrounding forest area. The front-end monitoring devices support image acquisition at resolutions of 720–1080 pixels with a minimum camera resolution of 4 megapixels, ensuring sufficient image quality for detecting small-scale canopy changes associated with pine wilt disease.

The system adopts an edge-AI architecture in which video streams captured by the PTZ cameras are processed by a high-performance edge computing server deployed near the monitoring site. The edge processing unit is equipped with multi-core CPUs, large-capacity memory, and a GPU accelerator (e.g., NVIDIA RTX-series GPU), enabling real-time deep learning inference for video analysis. The processing node supports up to 30 concurrent video streams and achieves an image analysis throughput of approximately 30 frames per second per GPU.

During operation, the PTZ camera performs automated patrol scanning of predefined monitoring sectors using a spatiotemporal scheduling algorithm that avoids conflicts with other monitoring tasks such as forest fire surveillance. Captured video frames are transmitted to the edge AI module,

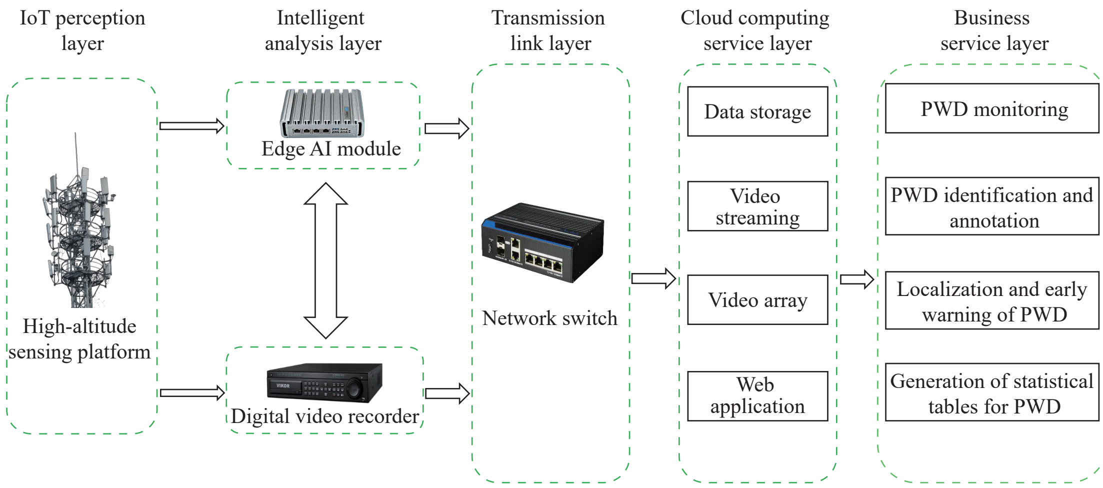

Fig. 1 Monitoring and identification system for pine wilt disease based on high-altitude intelligent sensing platform and a YOLOv5-based object detection model.

where the YOLOv5-based detection framework identifies potential PWD affected trees. Detected targets are further processed using camera parameters (e.g., viewing angle, focal length, and geospatial calibration) to estimate geographic coordinates for accurate tree localization.

The processed detection results and associated images are transmitted to a cloud-based management platform, where monitoring records, spatial distribution maps, and statistical reports of infected trees are generated to support forest disease management and decision-making.

Under the current deployment configuration, a single HAP installation can monitor forest areas within a radius of approximately 3–5 km, providing continuous observation coverage of roughly 10–15 km^2 depending on terrain conditions. This edge-cloud collaborative architecture improves data transmission efficiency, reduces latency, and enables near-real-time epidemic identification. Compared with mission-driven UAV acquisition, the fixed platform ensures stable observation geometry and continuous coverage without repeated take-off and landing operations.

C. Dataset Construction

Dataset collection is a key step in conducting accurate monitoring of pine wilt disease epidemics. First, the camera is rotated via the high-altitude platform to conduct aerial photography in the Qinba Mountain forest area of Chongqing, China, thereby obtaining high-resolution images. Furthermore, the images captured in real time are uploaded to the edge AI high-performance processor for analysis and processing.

A balanced dataset containing both positive and negative samples was constructed to train and evaluate the detection model. A total of 10,000 positive samples were collected, representing red-brown dead or diseased pine trees across different seasons and pine species. To improve model robustness and reduce false positives, 3000 negative samples were included. These consisted of visually similar interference objects, such as discolored shrubs, healthy pine trees, colorful deciduous trees, discolored fir trees, non-pine vegetation, and dead trees unrelated to pine wood nematode infection.

All images were manually annotated using an online labeling tool to generate bounding box annotations for infected trees. The dataset was randomly divided into training (60%), validation (20%), and test (20%) subsets. The training set was used for parameter optimization, the validation set for hyperparameter tuning, and the test set for final performance evaluation. Representative aerial dataset samples are shown in Fig. 2.

D. Detection Model Based on YOLOv5

In this study, we developed a real-time intelligent monitoring system for pine wilt disease based on YOLOv5 and a fixed high-altitude sensing platform (hereinafter referred to as HAP-based monitoring). The object detection framework is based on YOLOv5, an anchor-based one-stage detector implemented in PyTorch. YOLOv5 was selected due to its favorable balance between detection accuracy and real-time inference capability, which is critical for large-area monitoring scenarios.

The network architecture consists of three main components: a cross stage partial-based convolutional backbone for hierarchical feature extraction, a neck that combines a feature pyramid network (FPN) with path aggregation to enhance multi-scale feature fusion, and a head that performs multi-scale bounding box regression and classification. YOLOv5 supports multiple model scales (YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x), which vary in network depth and channel width to balance computational complexity and accuracy.

In this study, multiple variants were evaluated to identify the optimal trade-off between inference speed and detection precision under large-scale deployment conditions. The high-altitude image dataset was normalized and augmented before training. Data augmentation strategies included scaling, flipping, and mosaic augmentation to enhance generalization performance under varying illumination and seasonal conditions. The overall workflow integrating high-altitude acquisition and YOLOv5 detection is illustrated in Fig. 3.

E. Model Training and Evaluation Metrics

Model training was conducted under a unified experimental environment. Hyperparameters such as learning rate, batch

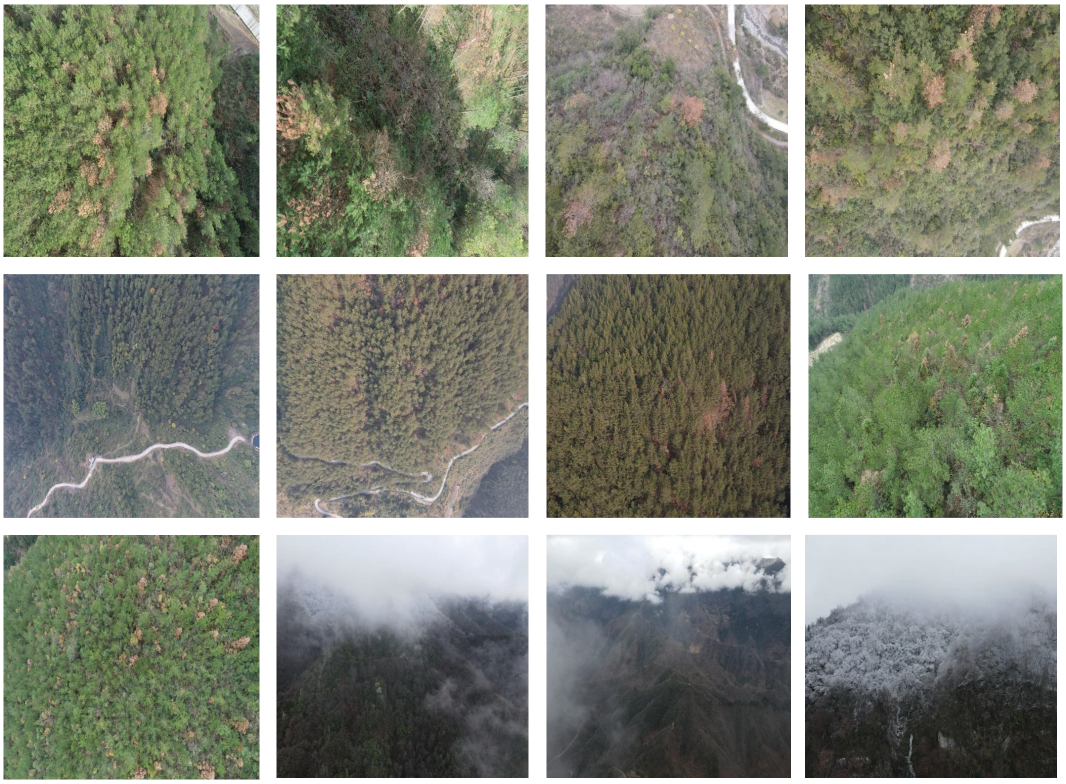

Fig. 2 Representative aerial image samples from the constructed pine wilt disease dataset.

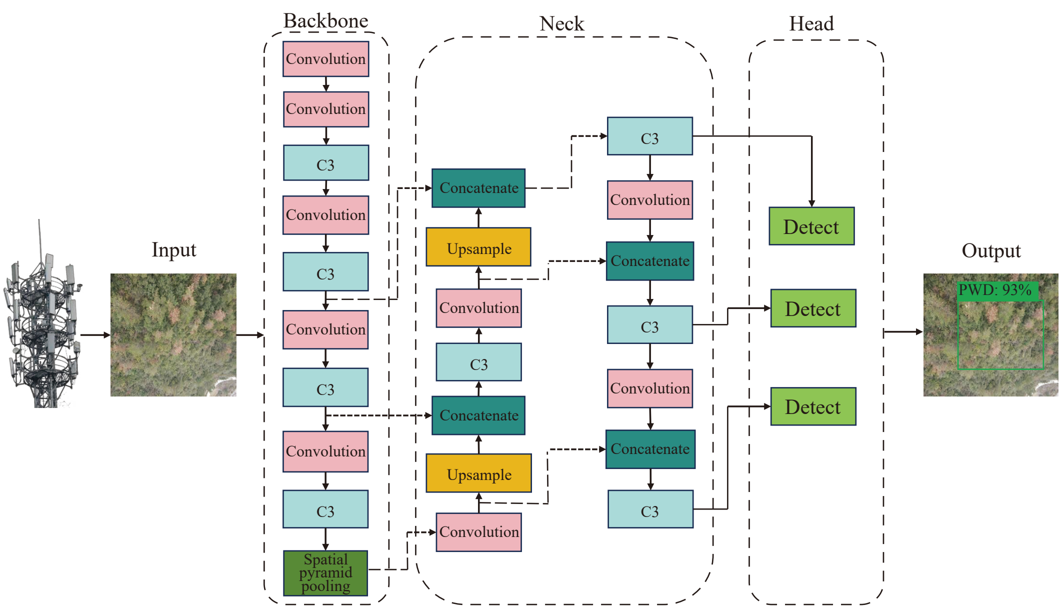

Fig. 3 Overall workflow integrating high-altitude acquisition and YOLOv5 detection.

size, and momentum were optimized through validation experiments to achieve stable convergence. Detection performance was evaluated using standard object detection metrics [8, 19], including mAP, accuracy, and model parameters (Params). In this work, mAP was computed at IoU = 0.5 to quantify localization and classification accuracy.

Model complexity (parameter count) and inference speed were analyzed to assess deployment feasibility within the edge-cloud collaborative system. Besides, all statistical analyses were conducted using Python (SciPy statistical package). By combining detection accuracy with computational efficiency analysis, the evaluation framework ensures that the selected model variant satisfies both precision requirements and real-time monitoring constraints.

III. Results and Discussion

A. Performance Comparison among YOLOv5 Variants

To evaluate the suitability of different model scales for large-area deployment, four variants of YOLOv5 (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) were trained and tested under the same dataset and experimental configuration. The quantitative results are summarized in Table 1.

Table 1 Experimental results of different YOLOv5 variants.

Model	mAP (%)	Accuracy (%)	Params (million)
YOLOv5s	55.4	63.32	7.3
YOLOv5m	63.1	75.38	21.4
YOLOv5l	66.9	84.29	47.0
YOLOv5x	68.8	93.78	87.7

The results indicate a clear trade-off between model capacity and detection performance. As network depth and channel width increase, both mAP and classification accuracy improve steadily. YOLOv5s exhibits the lowest detection performance but has the smallest parameter size, making it computationally efficient for resource-constrained environments. YOLOv5m and YOLOv5l achieve progressively improved performance with moderate parameter growth.

YOLOv5x achieves the highest detection performance, reaching an mAP of 68.8% and an overall accuracy of 93.78%. Although it has the largest parameter size (87.7 million), its superior identification capability makes it more suitable for high-altitude large-area monitoring where detection reliability is prioritized over lightweight deployment. Notably, the achieved accuracy exceeds the 85.00% identification rate reported in representative UAV-based monitoring studies [8, 19], indicating that improved visual representation learning combined with stable observation geometry contributes to enhanced detection robustness.

To further highlight the effectiveness of the proposed system, it is useful to compare the design characteristics of the adopted YOLOv5 architecture with recent state-of-the-art deep learning models for pine wilt disease detection. Compared with recent state-of-the-art methods [14, 15, 18], the proposed system pursues a distinct system-level objective, although its performance is not the highest among these approaches. Rather than increasing architectural complexity through transformer modules, the system adopts a high-capacity YOLOv5x detector integrated with a fixed high-altitude sensing platform. This design emphasizes robust feature learning and stable long-range observation geometry, which are particularly important for detecting infected pine trees under large-scale forest monitoring conditions.

Therefore, while recent transformer-based models mainly aim to improve algorithm-level feature representation, the proposed system demonstrates that combining a mature object detection architecture with a stable observation platform can also achieve competitive detection performance while maintaining practical deployment feasibility.

B. Statistical Significance Analysis

To further validate whether the observed performance differences among YOLOv5 variants are statistically significant, a one-way analysis of variance (ANOVA) test was conducted on the detection accuracy results obtained from repeated experimental runs. The ANOVA results indicate that the performance differences among the four model variants are statistically significant ($p < 0.05$). In particular, the YOLOv5x model demonstrates a statistically significant improvement in detection accuracy compared with the lightweight variants (YOLOv5s and YOLOv5m).

Additionally, pairwise comparisons using a two-sample t-test confirm that the accuracy improvement achieved by YOLOv5x is significant at the 95.00% confidence level. These results suggest that increasing model capacity contributes to more robust feature representation for pine wilt disease tree detection under high-altitude observation conditions.

C. Comparison with Existing UAV Monitoring

To further evaluate system-level effectiveness, the proposed system was compared with conventional UAV-based monitoring. The comparison focuses on three critical dimensions: monitoring coverage, operational cost, and identification accuracy. The results are presented in Table 2.

Table 2 Comparison between UAV-based monitoring system and the proposed HAP-based monitoring system.

System	Area coverage (km^2)	Monitoring cost per 700 km^2 (RMB)	Accuracy (%)
UAV-based monitoring [8, 19]	2–3	~25	85.00
HAP-based monitoring (ours)	12	~6	93.78

In addition to system-level comparison, it is important to consider the deployment scenarios associated with different deep learning detection models. Most recent studies on pine wilt disease detection, including those using improved YOLOv5 models [14] or transformer-based architectures [15, 18], are typically developed and evaluated on UAV-acquired imagery. These approaches benefit from very high spatial resolution and flexible data acquisition, but their practical deployment is often constrained by limited flight duration, battery capacity, and repeated mission requirements.

The results demonstrate that the proposed system substantially improves large-area monitoring scalability. While UAV-based systems typically cover 2–3 km^2 per operation due to flight time limitations and battery constraints, the proposed system achieves continuous coverage of approximately 12 km^2 through panoramic rotation and persistent observation.

From an economic perspective, UAV monitoring requires repeated deployment, manual supervision, and energy consumption, leading to higher cumulative operational costs. In contrast, our system amortizes infrastructure cost over long-term continuous operation. The monitoring cost per 700 km^2 is reduced by approximately 76.00%, highlighting significant improvements in economic sustainability. To further verify the reliability of the system-level comparison, statistical analysis was conducted on repeated monitoring simulations using both UAV-based and HAP-based configurations. The results show that the differences in monitoring coverage and operational cost between the two systems are statistically significant ($p < 0.05$), confirming the advantage of the proposed system for large-area forest surveillance.

Importantly, the proposed system not only expands coverage and reduces cost but also improves detection accuracy. The 93.78% identification rate indicates that stable high-altitude observation combined with deep learning-based detection enhances visual consistency and reduces viewpoint-induced variability, which is common in UAV-based flight missions.

Table 2 therefore highlights a key difference between the proposed system and existing studies. While many recent deep learning models focus primarily on improving algorithmic detection accuracy under UAV imaging conditions, the proposed system emphasizes the integration of a robust detection model with a persistent high-altitude sensing platform. This system-level integration enables simultaneous improvements in monitoring coverage, economic efficiency, and operational stability.

Overall, the experimental results suggest that integrating a fixed high-altitude sensing platform with a high-capacity YOLOv5 detector provides a more scalable and cost-efficient solution for large-scale forest epidemic surveillance. The system bridges the gap between algorithm-level performance and real-world deployment feasibility, aligning with intelligent control system design principles emphasizing reliability, scalability, and operational sustainability.

IV. Conclusions

This study presents a large-area intelligent monitoring system for pine wilt disease based on the integration of a fixed high-altitude sensing platform and a YOLOv5-based deep learning detector. By combining continuous panoramic visual acquisition, edge-cloud collaborative processing, and real-time object detection, the proposed system enables automated localization and counting of infected pine trees in complex mountainous forest environments.

Experimental results demonstrate that among multiple YOLOv5 variants, YOLOv5x achieves the highest detection accuracy, reaching 93.78%, while maintaining stable performance under large-scale deployment conditions. Compared with conventional UAV-based monitoring, the proposed system significantly expands monitoring coverage and reduces operational costs per unit area, while simultaneously improving identification reliability. These results indicate that stable high-altitude observation combined with deep learning-based detection provides a scalable and economically sustainable solution for forest epidemic surveillance.

Beyond algorithm-level improvements, the primary contribution of this work lies in the system-level integration of intelligent sensing, real-time visual detection, and automated statistical analysis within a unified monitoring system. The edge-cloud collaborative framework enhances deployment feasibility and supports long-term continuous operation, addressing the practical limitations of mission-driven UAV monitoring.

Future work will focus on incorporating spatiotemporal epidemic modeling and predictive analytics to enable early warning and dynamic risk assessment of PWD spread. By extending the current visual detection framework toward predictive intelligent control, the system has the potential to support data-driven forest management strategies and large-scale ecological protection efforts.

Acknowledgment

This work was supported by the Science and Technology Research Program of Chongqing Municipal Education Commission (No. KJQN202400802), the Natural Science Startup Foundation of Chongqing Technology and Business University (No. 2056019), and the National College Students' Innovation and Entrepreneurship Training Program (Nos. 202411799008 and S20241179903).

References

[1] Z. Hao, J. Huang, X. Li, H. Sun, and G. Fang, A multi-point aggregation trend of the outbreak of pine wilt disease in China over the past 20 years, *Forest Ecol. Manag.*, 2022, 505, 119890.

[2] N. Mariette, H. Hotte, A. M. Chappé, M. Grosdidier, G. Anthoine, C. Sarniguet, O. Colnard, E. Kersaudy, M. T. Paris, E. Koen et al., Two decades of epidemiological surveillance of the pine wood nematode in France reveal its absence despite suitable conditions for its establishment, *Ann. Forest Sci.*, 2023, 80(1), 21.

[3] M. A. Back, L. Bonifácio, M. L. Inácio, M. Mota, and E. Boa, Pine wilt disease: A global threat to forestry, *Plant Pathol.*, 2024, 73(5), 1026–1041.

[4] L. Cotrozzi, Spectroscopic detection of forest diseases: A review (1970–2020), *J. For. Res.*, 2022, 33(1), 21–38.

[5] S. Zhang, H. Huang, Y. Huang, D. Cheng, and J. Huang, A GA and SVM classification model for pine wilt disease detection using UAV-based hyperspectral imagery, *Appl. Sci.*, 2022, 12(13), 6676.

[6] J. Kuang, L. Yu, Q. Zhou, D. Wu, L. Ren, and Y. Luo, Identification of pine wilt disease-infested stands based on single-and multi-temporal medium-resolution satellite data, *Forests*, 2024, 15(4), 596.

[7] H. Shi, R. Zhang, M. Chen, H. Liu, and L. Chen, Detection of pine wilt disease using an explainable recognition model based on fusion of vegetation indices and texture features from UAV multispectral imagery, *Remote Sens.*, 2026, 18(3), 410.

[8] R. Yu, L. Huo, H. Huang, Y. Yuan, B. Gao, Y. Liu, L. Yu, H. Li, L. Yang, L. Ren et al., Early detection of pine wilt disease tree candidates using time-series of spectral signatures, *Front. Plant Sci.*, 2022, 13, 1000093.

[9] B. Wu, A. Liang, H. Zhang, T. Zhu, Z. Zou, D. Yang, W. Tang, J. Li, and J. Su, Application of conventional UAV-based high-throughput object detection to the early diagnosis of pine wilt disease by deep learning, *Forest Ecol. Manage.*, 2021, 486, 118986.

[10] S. Chen, Q. Yang, J. Zhang, and F. Xu, Detection algorithm for pine wilt disease in complex environments, *Ecol. Inf.*, 2026, 93, 103572.

[11] X. Ye, J. Pan, F. Shao, G. Liu, J. Lin, D. Xu, and J. Liu, Exploring the potential of visual tracking and counting for trees infected with pine wilt disease based on improved YOLOv5 and StrongSORT algorithm, *Comput. Electron. Agric.*, 2024, 218, 108671.

[12] X. Dong, L. Zhang, C. Xu, Q. Miao, J. Yao, F. Liu, H. Liu, Y. Lu, R. Kang, and B. Song, Detection of pine wilt disease infected pine trees using YOLOv5 optimized by attention mechanisms and loss functions, *Ecol. Ind.*, 2024, 168, 112764.

[13] L. Wang, J. Cai, T. Wang, J. Zhao, T. R. Gadekallu, and K. Fang, Detection of pine wilt disease using AAV remote sensing with an improved YOLO model, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sensing*, 2024, 17, 19230–19242.

[14] Z. Du, S. Wu, Q. Wen, X. Zheng, S. Lin, and D. Wu, Pine wilt disease detection algorithm based on improved YOLOv5, *Front. Plant Sci.*, 2024, 15, 1302361.

[15] Z. Chen, H. Lin, D. Bai, J. Qian, H. Zhou, and Y. Gao, PWDViTNet: A lightweight early pine wilt disease detection model based on the fusion of ViT and CNN, *Comput. Electron. Agric.*, 2025, 230, 109910.

[16] Q. Li and W. Chen, Lightweight vision transformer model for pine wilt disease detection using aerial RGB image and adversarial data augmentation, *Smart Agric. Technol.*, 2025, 12, 101167.

[17] J. Wang, L. Jin, F. Wang, H. Zhou, and H. Lin, Hierarchical attention and feature enhancement network for multi-scale small targets in pine wilt disease, *Comput. Electron. Agric.*, 2025, 239, 111037.

[18] S. U. Amin, Y. Jung, M. Fayaz, B. Kim, and S. Seo, Enhancing pine wilt disease detection with synthetic data and external attention-based transformers, *Eng. Appl. Artif. Intell.*, 2025, 159, 111655.

[19] N. Zhang, X. Chai, N. Li, J. Zhang, and T. Sun, Applicability of UAV-based optical imagery and classification algorithms for detecting pine wilt disease at different infection stages, *GISci. Remote Sens.*, 2023, 60(1), 2170479.

[20] D. Ren, M. Li, Z. Hong, L. Liu, J. Huang, H. Sun, S. Ren, P. Sao, W. Wang, and J. Zhang, MASFNet: Multi-level attention and spatial sampling fusion network for pine wilt disease trees detection, *Ecol. Ind.*, 2025, 170, 113073.

Xing-Rong Fan received the BS degree in automation from Chongqing University, Chongqing, China, in 2010, and the PhD degree in pattern recognition and intelligent system from Institute of Automation, Chinese Academy of Sciences, Beijing, China, in 2016. From 2016 to 2018, he was a lecturer in computer science at Chongqing University of Posts and Telecommunications, Chongqing, China. He is currently an associate professor at Chongqing Technology and Business University, Chongqing, China. His current project is “a knowledge-and-data-driven modeling approach and its application”. His research interests include multimodal large language model learning, embodied intelligence, agricultural AI, and spectroscopic AI.

Yuhe Deng is currently pursuing the BE degree in measurement and control technology and instruments at Chongqing Technology and Business University, Chongqing, China. In 2024, she received the municipal first prize in the China Undergraduate Mathematical Contest in Modeling. In 2025, she received the national second prize at the 19th “Challenge Cup” National College Student Curricular Academic Science and Technology Works Competition. In addition, she received the national silver award in the 2nd China College Students New Liberal Arts Practice and Innovation Competition, and the municipal gold award in the 10th China International College Students’ Innovation Competition. Her research interests include computer vision, deep learning, and their applications.

Huiting Chen is currently pursuing the BS degree in artificial intelligence at Chongqing Technology and Business University, Chongqing, China. In 2024, she received the municipal first prize in the China Undergraduate Mathematical Contest in Modeling. In 2025, she received the national second prize at the 19th “Challenge Cup” National College Student Curricular Academic Science and Technology Works Competition. In addition, she received the national silver award in the 2nd China College Students New Liberal Arts Practice and Innovation Competition, and the municipal gold award in the 10th China International College Students’ Innovation Competition. Her research interests include computer vision, deep learning, and their applications.

Hui Wan is currently pursuing the BS degree in artificial intelligence at Chongqing Technology and Business University, Chongqing, China. In 2024, he received the municipal first prize in the China Undergraduate Mathematical Contest in Modeling. In 2025, he received the national second prize at the 19th “Challenge Cup” National College Student Curricular Academic Science and Technology Works Competition, the national silver award in the 2nd China College Students New Liberal Arts Practice and Innovation Competition, and the municipal gold award in the 10th China International College Students’ Innovation Competition. In addition, he earned a bronze medal in the Kaggle Competition “Child Mind Institute—Problematic Internet Use”, achieving a top 5% global ranking. His research interests include deep learning, reinforcement learning, and their applications.

Chaoyuan Jiang received the MS degree in control theory and control engineering from Chongqing University, Chongqing, China, in 2005. Since 1990, he has been working at Chongqing Technology and Business University, China. He is currently the associate dean at Chongqing 2011 Collaborative Innovation Center of Micro/Nano Sensing and Intelligent Ecological Internet of Things, Chongqing Technology and Business University, Chongqing, China. He is a recipient of the Chongqing Outstanding Young and Middle-aged Experts, the Chongqing Talents and Innovation and Entrepreneurship Leading Talent. Additionally, he has served as a member of Engineering Standardization Committee of the China Forestry Engineering Association, the National Technical Committee for Forestry and Grassland Information Standardization, and vice chairman of the Chongqing Internet of Things Industry Association. He has led more than 10 national and provincial/ministerial-level projects, obtained over 70 authorized patents and software copyrights, formulated 2 industry standards, and won the second prize of the Chongqing Science and Technology Progress Award. His research interests include intelligent sensing, sensor networks, measurement and control networks, and their applications.