

A deep learning approach to object detection in quadcopter-based reconnaissance

Morakot Thongprom¹, Manit Inkamchuer², Banjerd Saengchandr³, Rabin Palee⁴,
Viroch Sukontanakarn⁵

¹Department of Information Systems, Faculty of Business Administration and Liberal Arts, Rajamangala University of Technology Lanna, Chiang Mai, Thailand

²Department of Unmanned Aircraft Systems Engineering, College of Integrated Science and Technology, Unmanned Aircraft Systems, Rajamangala University of Technology Lanna, Chiang Mai, Thailand

³Department of Industrial Engineering, Faculty of Engineering, Rajamangala University of Technology Lanna, Chiang Mai, Thailand

⁴Department of Electrical Engineering, Faculty of Engineering, Rajamangala University of Technology Lanna, Chiang Mai, Thailand

⁵Department of Mechatronic Engineering, Faculty of Engineering, Rajamangala University of Technology Isan Khon Kaen Campus, Khon Kaen, Thailand

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ABSTRACT

This paper presents a reconnaissance system utilizing a remote-controlled quadcopter drone, designed to transmit long-range, and real-time video feeds for target object detection. The system enables continuous surveillance and rapid identification of targets in remote or high-risk areas. It employs high-resolution imaging and video capture through a camera mounted on a stabilized gimbal, along with long-range radio frequency communication to ensure high-quality video transmission over extended distances. For object detection and classification, the system integrates the CiRA CORE software, which processes video input from a universal serial bus website camera (USB webcam) quickly and efficiently. Field tests demonstrate the system's effectiveness in dynamic and changing environments, highlighting its strong capability to detect and distinguish targets. The results confirm the feasibility of reliable, real-time target detection from a long-range unmanned aerial surveillance platform.

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Corresponding Author:

Manit Inkamchuer

Department of Unmanned Aircraft Systems Engineering, College of Integrated Science and Technology

Unmanned Aircraft Systems, Rajamangala University of Technology Lanna

128 Huay Kaew road, Muang, Chiang Mai 50300, Thailand

Email: nitagara@rmutl.ac.th

1. INTRODUCTION

A quadcopter is an unmanned aerial vehicle (UAV), commonly known as a "drone," characterized by its use of four rotors, each equipped with a motor and a propeller [1]–[4]. UAVs have become essential tools in modern reconnaissance operations, offering real-time situational awareness and providing accurate and timely intelligence. They are widely deployed in remote or high-risk areas. The development and deployment of drone-based reconnaissance systems capable of transmitting long-range video feeds while simultaneously performing real-time target detection allows critical mission decisions to be made beyond the line of sight. Such systems can be applied to military reconnaissance, border patrol, search-and-rescue missions, natural disaster assessment, and agriculture sector [5]–[7].

Machine vision is a subfield of artificial intelligence (AI) and computer engineering where is dedicated to enabling machines to process and interpret visual data [8]–[10]. It involves the use of cameras,

sensors, and advanced computational algorithms to capture, analyze, and make decisions based on visual input. The goal of machine vision is to replicate or surpass human visual capabilities in various applications, ranging from industrial automation to autonomous systems. One of the critical components within the broader scope of machine vision is object detection. Object detection refers to the task of identifying and locating specific objects of interest within an image or a sequence of video frames. These objects belong to predefined categories such as people, vehicles, animals, or machinery parts. By combining techniques from image processing, pattern recognition, and deep learning, object detection systems can not only recognize objects but also determine their positions within the scene. The technical overview of object detection as a fundamental capability within machine vision. It examines leading detection models and frameworks, highlighting their architectures, operational principles, and the respective advantages and limitations they present in real-world scenarios.

Object detection and recognition using AI in the form of machine vision under the deep learning method can be accomplished by processing input images or videos, either offline or online [11]–[13]. There are various image processing and analysis techniques that can be used to detect and recognize objects or targets of interest. CiRA CORE is another platform that serves as a core technology with relatively low cost. It is a low-code platform that is easy to learn through block-based coding and can be applied to a wide range of tasks.

Importing images and videos for processing with machine vision powered by AI, using various software installed on a computer, is not too difficult. However, the key challenge lies in how to transmit those images and videos from remote or hazardous areas [14], [15]. This research article presents a method for remote image and video transmission using commonly available drones equipped with mobile applications capable of receiving image and video signals via 5G Wi-Fi networks. The received data is then processed on a student-friendly version of the CiRA CORE platform to detect target objects using DeepDetect boxes, where is employed for object detection, enabling real-time detection results [16]. This study is confident that this research presents an application of drones for target surveillance and signal collection for processing through an AI platform with the lowest possible cost while achieving satisfactory results. The experimental process involves simple equipment and can be easily adapted for practical use. Table 1 was summarizing UAV platforms commonly used for deep learning-based applications like object detection, tracking, and reconnaissance.

Table 1. Showing relative UAVs typically used in deep learning research

UAV model	Type	Common uses in deep learning	Camera/payload	Processing unit	Notes
DJI matrice 300 RTK	Industrial drone	Object detection, tracking, mapping	4K camera, thermal camera (Zemuse)	External (Jetson Xavier/Nano)	Heavy payload capacity, customizable
DJI phantom 4 pro	Consumer drone	Object detection, semantic segmentation	20MP 4K Camera	Edge processing module needed	Very common in research datasets
Parrot anafi USA	Compact drone	Surveillance, search and rescue	Thermal + RGB camera combo	External needed (small form)	Lightweight, good zoom features
DJI mavic 2 enterprise	Compact drone	Human detection, reconnaissance	Visual + thermal sensors	Edge module or offloaded	Portable, affordable
skydio 2+	Autonomous drone	Real-time tracking, obstacle avoidance	4K camera with 6 navigation cameras	Built-in AI (NVIDIA TX2)	Designed for AI-driven navigation
Intel falcon 8+	Industrial drone	Infrastructure inspection, object detection	High-res camera (Sony Alpha 7R)	External Jetson units	Precision mapping, reliable
Custom DIY quadcopters	Custom build	Research on novel AI algorithms	Adjustable (GoPro and FLIR)	Jetson Nano/Xavier, RPi + Coral TPU	Flexibility for experimentation

The MJX-20-EIS drone used in this project is the main flying platform for surveillance and monitoring tasks. Compared to the UAVs listed in Table 1, it offers a significantly lower cost, making it suitable for budget-limited projects. The drone connects directly to an Android smartphone running the M RC PRO application, enabling real-time control and live video streaming without additional hardware. Unlike industrial UAVs that require expensive onboard or external processing units, the MJX-20-EIS relies on the smartphone for basic processing and visualization. This low-cost and simple setup makes the MJX-20-EIS an efficient choice for prototyping, education, and small-scale surveillance applications.

2. METHOD

The block diagram in Figure 1 illustrates the overall architecture of the remote drone control and monitoring system, showing the interaction between the user, the drone, and the processing platform. The user operates the system using a radio control controller to maneuver the MJX-20-EIS drone within the

designated target area [17]. The drone is linked to an Android smartphone running the M RC PRO application, which provides real-time flight control and live video transmission. The Android phone acts as an intermediary interface, enabling communication between the drone and the processing system. Video data is captured via a universal serial bus (USB) camera and transmitted to a Windows-based computer running the CiRA CORE platform, where the data is processed and analyzed [18]. The processed visual information is then displayed on a monitor, allowing the user to observe and monitor the target area in real time through an integrated hardware and software framework.

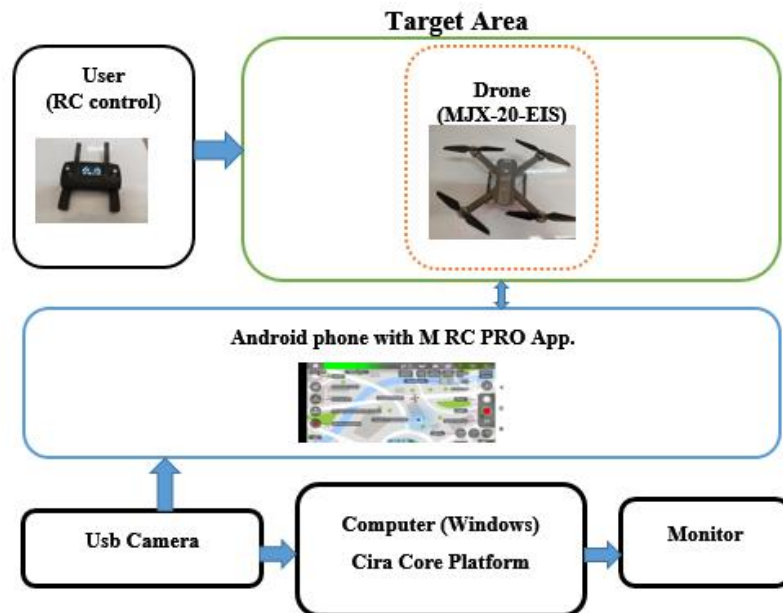


Figure 1. Block diagram of the overall control architecture

2.1. Select hardware

This study selected the MJX B20 drone because it is a low-cost, foldable brushless radio control quadcopter equipped with a 4 K camera capable of capturing high-quality aerial images and videos. The drone features a sturdy gimbal that ensures smooth, vibration-free footage during flight. In addition, electronic image stabilization (EIS) is implemented to effectively compensate for hand jitter and flight-induced vibrations, significantly reducing video shakiness during playback. Table 2 presents the specifications of the MJX B20 radio control drone. Figure 2 illustrates the actual appearance of the drone used in the experiments, including the drone frame and the remote-control device.

Table 2. The specification of radio control drone MJX model

Detail	Value
Maximum rising speed	300 cm/s
Max descent speed	200 cm/s
Maximum speed	40 km/h
Remote control frequency	2.4 GHz
Remote control distance	600 m
Battery	7.6V 3400 mAh
Charging time	330 min
Flying time	22 min
Photo resolution	3840 × 2160
Video resolution	3840 × 2160
App name	M RC Pro
Wi-Fi transfer	5 GHz
Image transfer distance	450 m
Real-time image transfer	720 p at 30 fps
Latency	200-300 ms
Required mobile phone system	Android 4.4 above, iOS 9.0 above



Figure 2. The radio control drone MJX B2 model

2.2. Control system architecture

2.2.1. Workflow of CiRA CORE in deep learning model

The block diagram in Figure 3 illustrates the workflow of a machine learning development process using the CiRA CORE platform with a deep learning approach. This platform supports both object detection and image classification models. The process begins with data input in the form of images or videos, which are then prepared through data labeling that can be performed either manually or automatically. Following labeling, the system advances to node flow design, employing a drag-and-drop interface to create the processing pipeline. The labeled data and the designed workflow are then used for model training via the DeepTrain module, where essential parameters such as the number of epochs, batch size, and learning rate are set, with graphics processing unit (GPU) acceleration supported to enhance training efficiency [19]. After training, the model undergoes testing and evaluation with new data to measure its accuracy and overall performance. Finally, the trained and validated model is deployed for real-world applications.

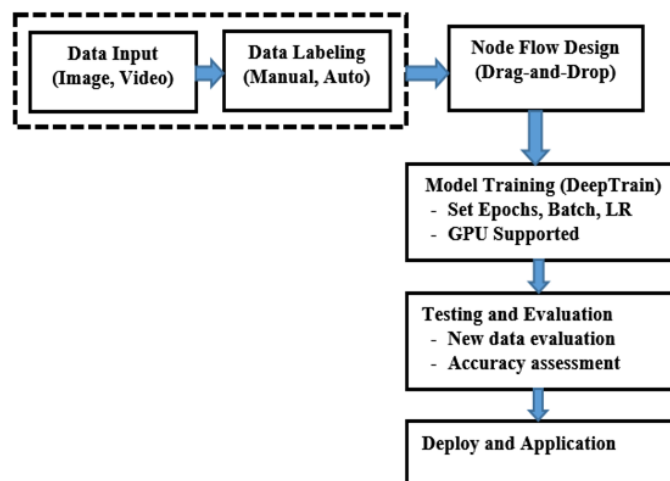


Figure 3. Block diagram of the CiRA CORE in deep learning method

2.3. Proposed architecture of the CiRA CORE platform

The CiRA CORE platform serves as the main implementation tool. The first step involves collecting image data of the target object, which the drone captures through photos or videos in border areas or remote, hazardous locations [20]. These image signals are then transmitted back to a computer for real-time image processing and object detection [21]. Once the target object is identified, the data is used to create training files through the DeepTrain module. The resulting training files are exported and saved into a folder containing three key files: obj.names, test.cfg, and train.weights. Following this, the DeepDetect module is utilized to perform the target object detection by executing the following steps.

2.3.1. DeepTrain

DeepTrain is a core module within the CiRA CORE platform, developed by CiRA Robotics [22], designed to facilitate the training of deep learning models for tasks such as object detection and classification. It offers a user-friendly, low-code environment that simplifies the processes of dataset preparation, data labeling, and AI model training [23]. The workflow of DeepTrain is illustrated in Figure 4.

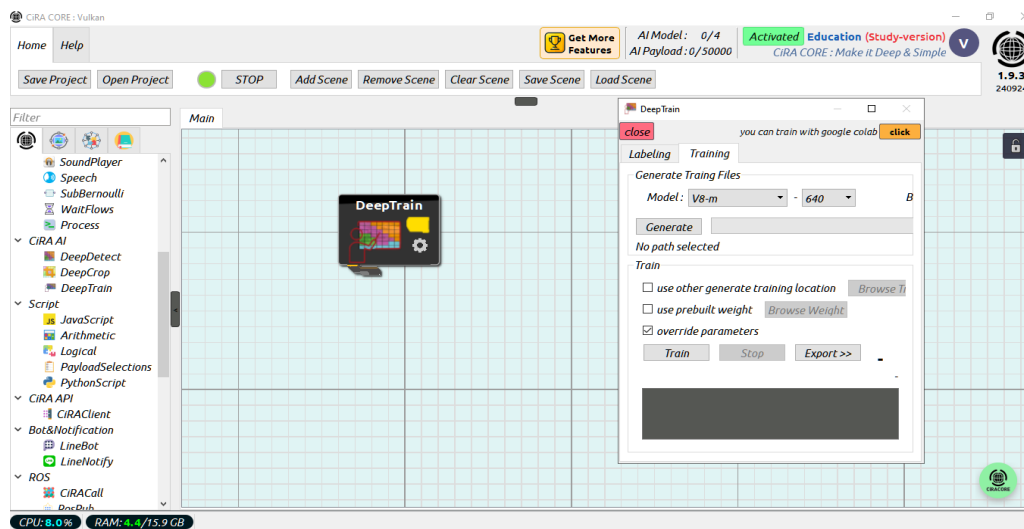


Figure 4. Execution of the DeepTrain module within the CiRA CORE program

2.3.2. DeepDetect

DeepDetect is a component of the CiRA CORE platform, developed by CiRA AMI, designed for object detection tasks within AI applications [24]. It enables users to deploy trained AI models to identify and locate objects in images or video streams. Setting up the DeepDetect box involves selecting a pre-trained AI model. CiRA CORE recommends using data from the 'V8' folder or downloading it online from <https://git.cira-lab.com/cira/cira-pre-trained-weights> [25]. Once the files are downloaded onto your device, click the gear icon on the DeepDetect box. Then, select 'Load Config' and choose the 'V8' folder. Finally, click 'Choose' to activate the pre-trained AI model. Figure 5 shows the process of DeepDetect module setting.

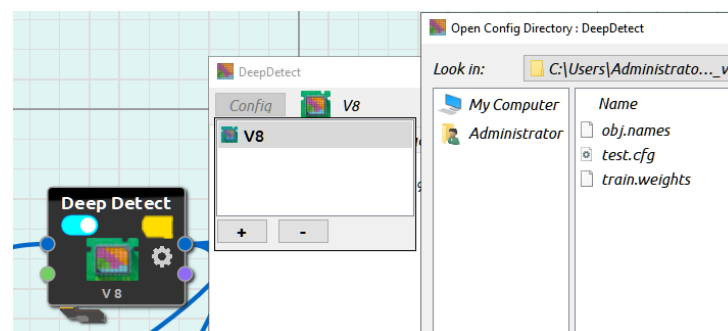


Figure 5. Execution of the DeepDetect module within the CiRA CORE program

2.3.3. Label

Labels in CiRA CORE are versatile elements that facilitate real-time information display and user interaction within AI-driven applications [26]. Figure 6 shows labels displaying outputs from AI models, such as object detection or classification results [27]. For instance, if an AI model detects a "car" or a "motorbike" in a video stream, a label can display the message "Amount Car" (car detected) or "Amount Motorbike" (motorbike detected).

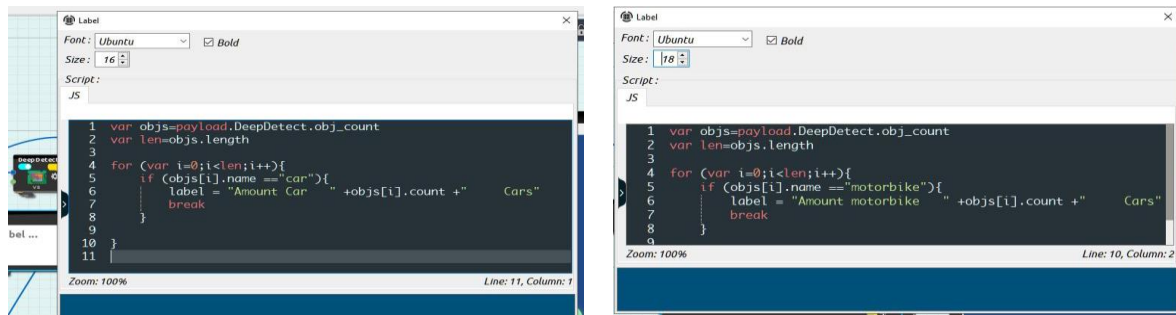


Figure 6. Setting label of target object detection

3. RESULTS AND DISCUSSION

This section presents the results of drone testing for long-distance target navigation. In the first part, a simulation is demonstrated in which object detection is performed through image processing. A video is recorded and used to test the program. In the second part, a live video feed is received from a smartphone application connected to the drone's onboard USB camera. The video is then fed into the program for real-time object detection during patrol missions. The main targets for this surveillance task are cars and motorcycles.

3.1. Simulation result

In the simulation phase, a prerecorded video file was imported into the CiRA CORE program to evaluate the effectiveness of the image-processing and object-detection algorithms. This approach allowed the system to be tested under controlled conditions without the influence of environmental disturbances or communication delays. As illustrated in Figure 7, the system successfully detected and counted the target objects in the video. The object detection process demonstrated stable performance, with clear bounding boxes and accurate classification of cars and motorcycles. These results indicate that the trained model and image-processing pipeline are capable of recognizing the defined target classes effectively. This stable baseline under controlled simulation aligns with previous studies on multi-class vehicle detection using deep learning frameworks, such as you only look once (YOLO) and single shot multibox detector (SSD) variants, which emphasize that minimizing initial communication latency yields high localization accuracy [28]–[30]. Specifically, similar to the findings of evaluating the model in a simulated environment first ensures that the bounding boxes achieve acceptable precision and recall before facing real-world environmental factors [31]. The simulation results confirm that the DeepTrain-generated dataset and trained model are suitable for further deployment in real-time scenarios.

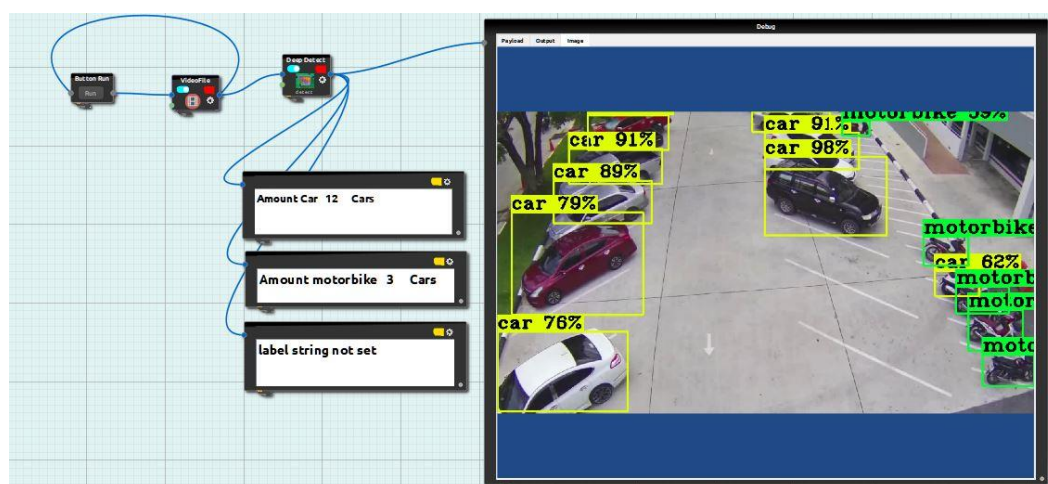


Figure 7. Simulation result of target object detection

3.2. Experiment results

Following the successful simulation, real-world experiments were conducted using a drone equipped with a USB camera. The target dataset, consisting of cars and motorcycles, was first created and trained using

the DeepTrain program. After training, the model was exported and integrated into the CiRA CORE software for real-time processing. The experimental setup involved receiving live video from a mobile phone running the M RC Pro application, which displayed the drone's camera feed. This video stream was captured through a website camera (webcam) and transmitted to the CiRA CORE program for further image processing, as shown in Figure 8.

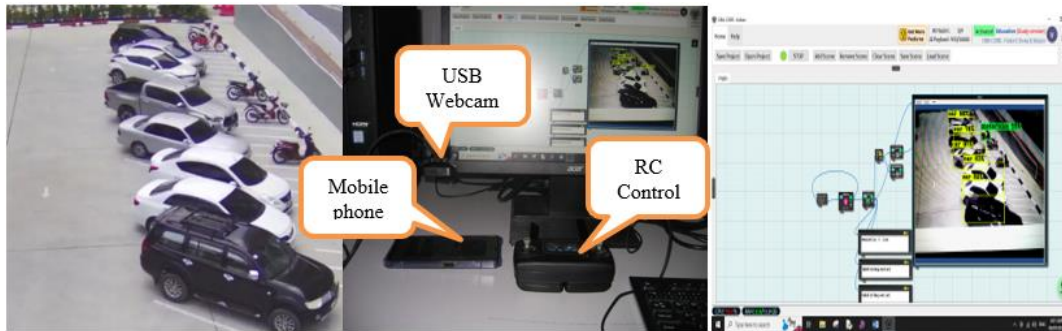


Figure 8. Display on mobile phone of M RC Pro application for drone

The images in Figure 9 show the display interface of the M RC Pro application on a mobile phone used for drone control. The Figure 9(a) presents the control panel with various interactive buttons and features, including options for multi-function buttons, one-key return, takeoff, landing, and camera settings. It also shows a map indicating the location of the drone and the mobile phone, helping the user navigate the target area. Figure 9(b) displays the live video feed captured by the drone's camera, providing a real-time aerial view of the surroundings, including trees, a parking lot, and a person walking. Together, these interfaces enable the user to effectively control the drone and monitor its camera feed simultaneously.



Figure 9. Display on mobile phone of M RC Pro application for drone of (a) application interface with control options and map view and (b) live video feed from the drone's camera shown on the mobile phone

Figure 10 illustrates the drone flight control during the object detection mission. In the experiment, cars and motorcycles were parked within the designated target area. The drone flew over this area to perform surveillance, capturing, and transmitting live images for object detection in real time. Figure 11 illustrates a drone flight control system for target object detection. Figure 11(a) shows real-time detection results displayed in the CiRA CORE program using a webcam video stream, with detected vehicles highlighted on the screen. Figure 11(b) presents the experimental setup and real radio control operation of the drone in target area 1, including a USB webcam, a mobile phone for monitoring, and radio control controller. The results demonstrate that the proposed system can detect a car in real time during drone operation. Despite variations in viewing angle, target distance, and lighting conditions, the detection performance remains stable, confirming the robustness and practicality of the system for real-world patrol missions. Furthermore, while conventional deep learning-based UAV reconnaissance systems often rely on expensive onboard edge-computing hardware (such as NVIDIA Jetson TX2 or Xavier modules) to achieve real-time detection,

our proposed framework demonstrates that a low-cost alternative utilizing a consumer-grade drone (MJX B20) coupled with smartphone video streaming can achieve comparable visual surveillance performance [32]–[34]. This cross-platform approach significantly reduces deployment costs while maintaining acceptable detection stability, validating the architectural concept proposed by recent budget-friendly remote tracking studies [35].



Figure 10. Drone flight control for target object detection



Figure 11. Real-time drone flight control and target object detection system of (a) real-time object detection in the CiRA CORE program and (b) experimental setup and radio control operation in target area 1

4. CONCLUSION

This study presented the design and implementation of a low-cost drone-based remote control and monitoring system integrated with the CiRA CORE platform for real-time target detection. The proposed architecture combines radio control drone, a smartphone-based flight control and video transmission interface, and a Windows-based processing platform to enable deep learning-based visual surveillance without requiring direct onboard computation. Results from both simulation and real-world experiments demonstrate that the trained deep learning model can effectively detect and classify target objects, particularly cars and motorcycles. The simulation phase verified the accuracy and reliability of the DeepTrain-generated dataset and object detection pipeline, while real-flight experiments confirmed the system's ability to process live video streams and perform real-time detection during drone operation. Despite variations in viewing angle, target distance, lighting conditions, and communication latency, the detection performance remained stable, highlighting the robustness and practicality of the proposed system. A key advantage of the system is its use of indirect real-time video acquisition via a mobile phone application, which reduces hardware complexity and cost. Nevertheless, performance can be influenced by factors such as video transmission delay, camera resolution, and environmental conditions. Future work will

focus on improving detection accuracy at longer distances, enhancing robustness under more challenging environments, and integrating onboard processing and autonomous navigation to further reduce latency and extend system capabilities. Overall, the experimental results confirm that the proposed CiRA CORE-based drone surveillance system is well suited for real-world patrol and monitoring missions, particularly in remote or hazardous areas, and can be readily extended to support additional target objects and surveillance applications.

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Morakot Thongprom	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Manit Inkamchuer	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Banjerd Saengchandr	✓	✓		✓	✓		✓	✓	✓	✓			✓	✓
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- C : Conceptualization
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O : Writing - Original Draft
E : Writing - Review & Editing
- Vi : Visualization
Su : Supervision
P : Project administration
Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This research did not involve the use of human participants or animals in the experiments.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS



Morakot Thongprom    is a lecturer in Department of Information Systems at Rajamangala University of Technology Lanna, Chiang Mai, Thailand. He holds a master of science degree in Information Technology. His research interests include system development, the application of information technology, and the integration of artificial intelligence to address various problems. He can be contacted at email: morakot@rmutl.ac.th.



Manit Inkamchuer    is a full-time lecturer in Department of Unmanned Aircraft Systems Engineering at Rajamangala University of Technology Lanna, Chiang Mai, Thailand. He holds a master's degree in Industrial Engineering from Chiang Mai University. He has research interests in unmanned systems, manufacturing processes, automation systems, renewable energy, and robot design. He can be contacted at email: manitinkamchuer@gmail.com.



Banjerd Saengchandr    is an assistant professor at Department of Industrial Engineering at the Rajamangala University of Technology Lanna, Chiang Mai, Thailand. He received D.Eng. in Manufacturing from Asian Institute of Technology. His research interests are manufacturing processes, automation, unmanned system, CFD, renewable energy, and robot design. He can be contacted at email: banjerd@rmutl.ac.th.



Rabin Palee    is a full-time lecturer in charge of the Unmanned Aircraft Systems Engineering Program and assistant professor of Electrical Engineering at Rajamangala University of Technology Lanna, Chiang Mai, Thailand. He holds a master's degree in Information Engineering from University of the Thai Chamber of Commerce. He has research interests in unmanned systems, internet of things, smart farming, artificial intelligence, and embedded system. He can be contacted at email: rabin@rmutl.ac.th.



Viroch Sukontanakarn    is a lecture in Mechatronics Engineering at the Rajamangala University of Technology Isan Khon Kaen Campus, Khon Kaen, Thailand. He received M.Eng. in Electric Power System Management and D.Eng. in Mechatronics from Asian Institute of Technology, in 1998 and 2011, respectively. He has been an associate professor at the field of Mechatronics Engineering at the Rajamangala University of Technology Isan Khon Kaen Campus, Thailand since 2002. His current research interests are power electronics, electrical power systems, microcontrollers, robotics, programmable logic controller, and electric motor drive. He can be contacted at email: viroch.su@rmuti.ac.th.