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Proposal Real-Time Corridor Monitoring System Based on Deep Learning Algorithm

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ABSTRACT

e nanosized-based carrier systems which comprise solid lipid matrix combined with liquid lipids and surfactants. Urban Air Mobility (UAM) has emerged as a next-generation transportation solution to address urbanization and traffic congestion challenges. This study proposes a secondary surveillance system based on a monocular camera to support the safe operation of UAM. The system aims to mitigate unexpected issues such as GNSS signal disruptions and 5G network failures and enhance flight safety by detecting unidentified aerial objects. The YOLOv8 object detection model was utilized to achieve high accuracy and real-time detection performance. YOLOv8 leverages an advanced backbone network and an enhanced pyramid structure to effectively detect objects of various scales, maintaining high detection performance even in complex environments and for fast-moving objects. Furthermore, its diverse versions, ranging from lightweight to high-performance models, enable a balance between efficiency and accuracy. In this study, drones were used as experimental targets, and experiments conducted within a 20m range confirmed detection rates exceeding 80%. YOLOv8's real-time processing capability and high detection rate highlight its potential as a key technology for UAM surveillance systems.

Keywords: *Edge Computing, Yolo, Deep Learning, Corridor Monitoring, Object Detecting*

1. INTRODUCTION

The global concentration of population in metropolitan areas is accelerating in conjunction with industrialization and the relocation of financial systems to urban centers. This is resulting in a notable increase in congestion within transportation networks, with existing surface transportation systems becoming increasingly unable to meet the demand. This phenomenon is particularly prevalent in large urban areas, such as metropolitan regions, and is accompanied by a rise in social costs. This has resulted in the necessity for the development of novel transportation systems, with urban air mobility (UAM) representing the next generation of transportation solutions to address these issues. Urban air mobility (UAM) has the potential to alleviate traffic congestion and increase efficiency through the establishment of a three-dimensional aerial network that extends beyond the two-dimensional ground transportation network.

In South Korea, a number of government agencies and research institutes, including the Ministry of Land, Infrastructure, and Transport, are engaged in the promotion of the introduction and operation of UAMs. In addition, theoretical and technical preparations are underway based on specific plans, such as the K-UAM Operation Concept [1], which have been developed to facilitate the introduction of UAMs. However, the commercialization of UAMs requires the implementation of systematic aircraft management and advanced surveillance systems, particularly the development of a novel traffic management system that differs from the existing Air Traffic Management System (ATM). Technologies such as the Global Navigation Satellite System (GNSS), 5G networks, and low-power radar are indispensable for the communication and surveillance of UAMs, which are utilized for communication, navigation, and aircraft monitoring. However, these systems are susceptible to unforeseen disruptions, such as those affecting the Global Navigation Satellite System (GNSS) or 5G networks, which can present a considerable risk to the safety of flight operations.

The necessity for supplementary surveillance systems to safeguard against such disruptions has been underscored. In particular, the implementation of a secondary surveillance system utilizing edge computing [2] is of significant importance in order to prevent the potential loss of data or the occurrence of positioning errors as a result of GNSS and 5G network failures. In contrast to conventional centralized surveillance systems, edge computing-based systems are capable of performing surveillance functions with reliability even in the event of network instability or failure. This is achieved by processing aircraft detection and surveillance information directly on edge devices. Edge device-based surveillance systems play a pivotal role in enhancing the overall reliability of the system by enabling each device to operate autonomously.

Technologies that may be employed for surveillance and detection in UAM systems include radar, lidar, and cameras. Radar employs electromagnetic radiation to ascertain the direction and distance of objects, yet it is challenging to discern the specific object type. Lidar employs lasers to facilitate precise detection; however, it is a costly technology with a limited range. In contrast, camera sensors are relatively inexpensive and well-suited for wide-area surveillance, rendering them an optimal alternative for the continuous monitoring of UAM flight paths and the detection of objects. Cameras facilitate cost-effective, wide-ranging object detection and can be integrated with recently developed deep learning models to achieve high accuracy and performance.

In light of the aforementioned considerations, this study proposes the implementation of a secondary surveillance system that employs a camera-based detection system for the monitoring of aircraft in UAM corridors.

2. SYSTEM ARCHITECTURES

The objective of this paper is to present a secondary surveillance system that is capable of detecting and identifying flying objects in a corridor environment. This system employs a monocular camera, as illustrated in Figure 1. The efficacy of the method for detecting and identifying flying objects in the corridor will be evaluated using the YOLOv8 object detection model. In this manner, our objective is to address issues such as GNSS disruption and 5G network communication breakdowns within the corridor, as well as to address concerns that could potentially compromise the safety of flight operations by detecting unidentified flying objects, including TODs.

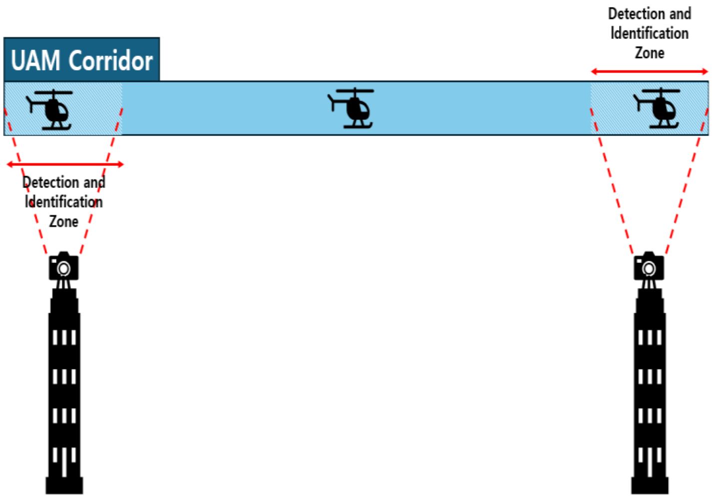

Fig. 1 UAM Corridor

The detection and surveillance of aerial vehicles such as unmanned aerial vehicles (UAVs) using cameras necessitates a considerable degree of real-time processing power. In particular, high-performance object detection algorithms that can rapidly and accurately identify objects are crucial for ensuring the high-speed mobility of UAMs and their safe operation in diverse environments. In the secondary surveillance system proposed in this study, the detection of moving objects in real time is of paramount importance. Furthermore, it is essential to detect and recognize objects without interruption on the screen and to distinguish unidentified airplanes in real time. To fulfill these requirements, this study employed the object detection model YOLOv8 (You Only Look Once version 8), which is regarded as the most sophisticated and optimized model in the domain of object detection. YOLOv8 represents an advancement over the algorithms of the existing YOLO series [3], offering enhanced accuracy and efficiency, particularly in the context of real-time object detection and classification.

A real-time corridor surveillance system must be capable of rapidly and accurately identifying objects in motion within the airspace. The identification and confirmation of these objects must be conducted via a screen capable of processing real-time video without interruption. Accordingly, a recognition rate of at least 80% is essential for accurately detecting small objects moving at high speeds in the air and at a distance without delay. To test the efficacy of the proposed methodology in an environment analogous to the aforementioned scenario, the object was selected as a drone. Figure 2 below depicts the potential configuration of an object detection experiment utilizing a drone.

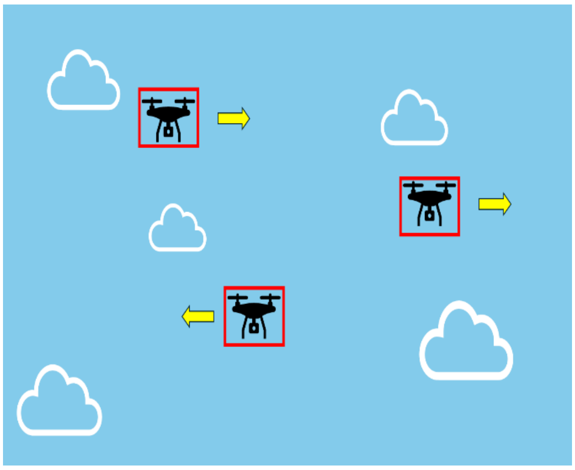

Fig. 2 Predictive Image

UAM detection algorithms

In order to detect UAMs, it is essential to utilize an object detection algorithm that can be processed in real time. YOLO v8 is a model that optimizes performance by incorporating the latest artificial intelligence (AI) computation technology in the domain of object detection. It is a deep learning algorithm model based on CNN (Convolutional Neural Networks) [4], which provides enhanced accuracy and efficiency in comparison to previous YOLO v3, v5 [5], and v7 [6], and exhibits superior FPS performance in comparison to existing models, demonstrating an exemplary capacity to detect and classify objects in real time. Figure 3 illustrates the architectural structure of YOLOv8.

YOLOv8 employs an advanced backbone network and an enhanced feature pyramid structure [7] to effectively detect objects of varying scales. The model demonstrates robust performance even when processing high-resolution images, maintaining high accuracy, particularly for small objects and complex backgrounds. Furthermore, YOLOv8 optimizes the processing speed of the model through parallel processing and optimized computation, thereby ensuring suitability for real-time applications. YOLOv8 is available in different versions, allowing users to select a model that aligns with their specific requirements, ranging from lightweight to high-performance. The lightweight models facilitate accelerated processing speeds, whereas the high-performance models exhibit enhanced accuracy. This flexibility enables the deployment of YOLOv8 in a diverse array of applications.

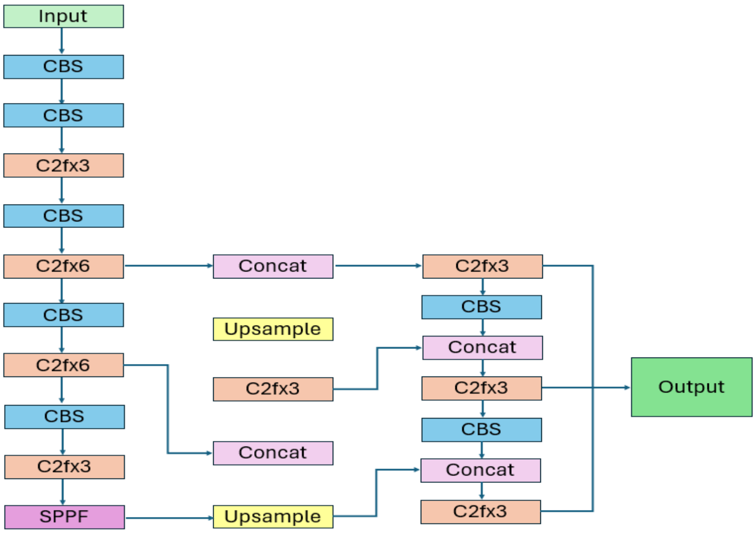

Fig. 3 YOLOv8 Structure

Algorithm Train

The YOLOv8 system provides a default pre-trained COCO dataset comprising five models. The datasets are designated as n, s, m, l, and x, in order of decreasing size. As the model size decreases, the computational efficiency of operations within the CNN-based block increases, allowing for a reduction in computational load and faster computation. In particular, the

YOLOv8 n-model, which is the smallest model, exhibits a rapid computation speed for real-time object detection, due to its minimal memory and computational resource consumption, which is a consequence of the reduced number of parameters. In this study, the n-model was utilized for algorithm training due to its suitability for real-time object detection and image processing. Table 1 illustrates the mean average precision (mAP) [8] and CPU ONNX of the COCO dataset provided by YOLO

Table. 1 COCO Dataset

Model	mAP	CPU ONNX
v8n	37.3	80.4
v8s	44.9	128.4
v8m	50.2	234.7
v8l	52.9	375.2
v8x	53.9	479.1

For the purposes of this experiment, drones were selected as a single class, 2,000 images of drones were collected, and a custom dataset of approximately 10,000 images was created using Roboflow's auto-labeling feature and geometric shape transformations. Subsequently, a dataset comprising approximately 20,000 images was procured from Roboflow's open and custom datasets, which were collectively designated as the single class "drone." Thereafter, the algorithm was subjected to training.

Table. 2 Simulation Setting

Category	Setting
GPU	RTX 3060 ti
DATA Set	22,517
Pytorch	2.0.1
Cuda	12.6
Batch	32
Epoch	20
learning Rate	0.01

The training was conducted on an RTX 3060 Ti GPU in an environment with the batch size and epoch set to 32 and 20, respectively. Figure 4 illustrates the outcomes of the datasets utilized for training. It is evident that all models are capable of recognizing the drone. Figure 5 depicts the mAP [9] results, which are a graph of the mAP values over 20 training runs. The mAP50 metric enables the assessment of the model's accuracy in detecting and evaluating objects. The value of mAP50 can be employed to assess the accuracy and performance of the model, the efficacy with which the trained model detects and classifies disparate objects, and the degree of correspondence between the predicted and actual locations of the objects. As illustrated in the mAP graph, the recognition rate reaches a value exceeding 90% following eight training runs.

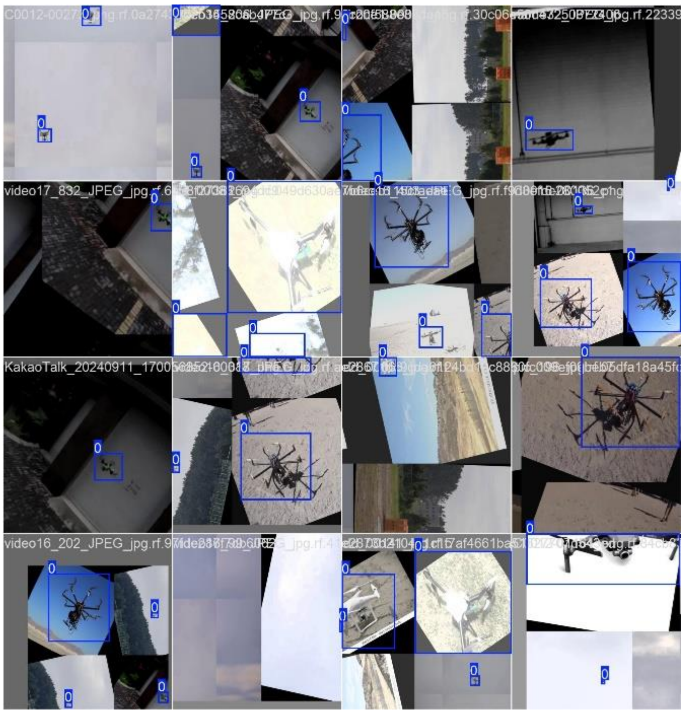

Fig. 4 Experimental Dataset

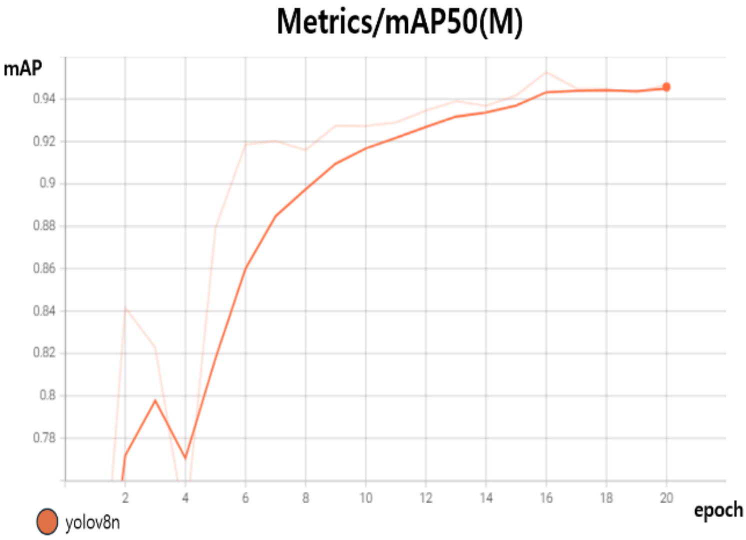

Fig. 5 mAP Results

3. SYSTEM TEST

UAM aircraft are designed for vertical takeoff and landing in order to minimize the space required for takeoff and landing. They have at least four rotor blades and are divided into three main flight modes: multirotor, lift-and-cruise, and tiltrotor.

UAM airframes are classified into three categories: passenger, cargo, and special-purpose. Many global airframe developers are focusing their efforts on developing 5-6-seater airframes, though some are also exploring the potential of smaller UAM airframes, such as 2-seaters and 3-seaters, depending on the intended application. In order to test the aforementioned hypotheses, an experiment was conducted using the most similar drone. The maximum identification distance was determined to be 20 meters. The distance from the camera lens to the corridor was determined to be 20 meters, excluding the height of the camera from the ground. Figure 6 illustrates the distance between the camera and the drone.

A laptop was used to connect the camera sensor and stream the video in real time, allowing for the assessment of the V8N model's capacity to accurately detect drones using the trained PT file and achieve a recognition rate exceeding 80%. Furthermore, the system was tested to ascertain its capacity for recognizing multiple objects simultaneously, utilizing two drones. This experiment assumes the presence of airplanes traversing the UAJM corridor at consistent intervals.

Fig. 6 Distance from the camera to the drone

The results demonstrate that the system exhibits robust performance in object detection and recognition, with an impressive recognition rate of 80%. Figure 7 illustrates the recognition rates of 0.83 and 0.85, respectively.

Figure 8 depicts the live streaming screen on the laptop. It can be observed that the detection of objects on the live streaming screen is conducted without any interruption to the video feed, and the performance is commensurate with that expected of a real-time image processing system.

Fig. 7 System test Recognition rate

Fig. 8 Live streaming

4. CONCLUSIONS

This paper proposes the implementation of a secondary surveillance system utilizing monocular cameras to address the issues of GNSS disturbance and 5G network communication failure in the corridor, as well as to detect unidentified flying objects, such as TOD, which present a potential hazard to the safety of flight operations. The system employs an object detection model to identify and detect UAM airplanes when monitoring a specified section of the corridor using a monocular camera. As there is currently no UAM airplane in existence, a drone analogous to the one that is to be developed was employed to traverse the corridor and gauge the drone's performance in flight. The resulting measurements demonstrated a high degree of stability, with a recognition rate exceeding 80%. At this time, the drone was measured after assuming the maximum identification distance of 20 meters. However, future research will entail measuring the size of Hanser University's Taean Airfield after assuming the maximum identification distance of 100 meters. It is anticipated that the Cesna will be identified as a larger object than the drone, which should result in a higher recognition rate. Furthermore, the identification of the aircraft's registration number will enhance the system's security and stability. Moreover, experiments will be conducted in a variety of environmental conditions with the aim of further enhancing the system's resilience to external influences.

5. ACKNOWLEDGMENTS

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