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# Aircraft Detection and Registration Number Recognition System with YOLO and OCR

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**ABSTRACT**

Recently, large airports are promoting a smart airport business that introduces robots and IoT using artificial intelligence and big data, which are major technologies in the fourth industrial era. Various artificial intelligence technologies are applied not only to customer convenience but also to airport security and control, and in particular, video monitoring and analysis technologies such as missing children are introduced through intelligent CCTV. In this paper, we propose a system for recognizing aircraft detection and registration number (tail number) taking off and landing on the runway using YOLO, a deep learning object detection model, and character recognition technology (OCR). It acquires aircraft data through cameras installed on the ground and learns it with the fastest YOLO model among deep learning object detection models to automatically detect aircraft in the airport and its registration number area. And the registration number recognized the result detected by YOLO using the OCR algorithm through the image preprocessing process. This study conducted data acquisition and real-time detection tests at Taean Airfield (RKTA) at Hanseo University in Korea, and real-time aircraft detection was more than 90% and registration number recognition was more than 80%. Through this system, information on the direction, location, model, and registration number of the aircraft can be acquired, confirming its utility as an automatic ground monitoring system for small airports in the future.

***Keywords:*** *Deep Learning, Aircraft Detection, YOLO, Optical Character Recognition (OCR)*

## 1. INTRODUCTION

Currently, large airports are equipped with airport congestion and surveillance systems due to the latest navigation safety equipment such as airport surface detection equipment (ASDE), Synthetic Aperture Radar (SAR), and Automated Radar Terminal (ARTS). In addition, large airports in developed countries have been actively researching and developing to develop the aviation industry using the technologies of the 4th Industrial Revolution, and are developing and piloting systems that introduce advanced AI technologies to reduce safety accidents in airports. Various state-of-the-art IT technologies, such as automatic immigration and deep learning object detection technology, and strengthening visitor identification through multiple authentication methods, are being developed to prevent safety accidents in hot spots and identify tracking routes at airports defined by ICAO[12]. In addition, Incheon International Airport has been conducting research since May this year to establish a future air control system using AR in collaboration with the Ministry of National Defense. However, in military and small airports, it is difficult to operate equipment due to manpower and maintenance costs to apply high-performance radar equipment and systems built at large airports. However, small airports have a high risk of safety accidents and high traffic volume as flight training is mainly conducted. Therefore, this paper conducted a study on object detection and identification code recognition through deep learning to establish a navigation safety monitoring system applicable to military and small airports.

## 2. PRIOR RESEARCH

### *2.1. Object Detection Based on Deep Learning*

Computer vision has various applications and uses, one of which is object detection. Object detection should address the problem of predicting the location of objects and the problem of identifying detected objects, and deep learning-based object detection models are divided into two-step or one-step detection methods depending on how two problems are performed. The two-step method locates candidate objects through Region Proposal algorithms such as Selective Search[1] in the first step, and classifies the classes of candidate objects in each position in the second step. Starting with Region Proposal with Convolutional Neural Network (R-CNN) [2], Fast R-CNN [3], Fast R-CNN [4], Region-based Fully Convolutional Networks

(R-FCN) [5], and Mask R-CNN [6] are two typical methods. Second, the one-step method is to simultaneously perform localization and classification problems, typically single shot multiBox detector (SSD) [7], You Only Look Once (YOLO) [8], and RetinaNet [9]. In general, a one-step method has a faster processing speed than a two-step method but a lower accuracy, and on the contrary, two steps have a higher accuracy than a single step but a slower processing speed. Among the one-step model, YOLO divides the image into a constant grid, creates a boundary box for each grid, calculates the class probability, and performs classification and localization. The original author of YOLO has steadily developed into YOLO v2-3 since the release of version 1. However, as the original author stopped developing further, v4 and v5 were each published by different developers. YOLO v4 was developed on the basis of YOLO v3, changing backbone to CSPDarkNet53 based on CSPNet to increase detection speed, applying SPP (Spatial Pyramid Pooling) and Path Aggregation Network (PAN) to Neck, and Bag of Freebies, Bag of Specials [10]. Among them, in this paper, YOLOv4 was used to recognize small objects such as aircraft identification code areas while maintaining real-time processing speed, and Figure 1 shows the performance indicators of YOLOv4.

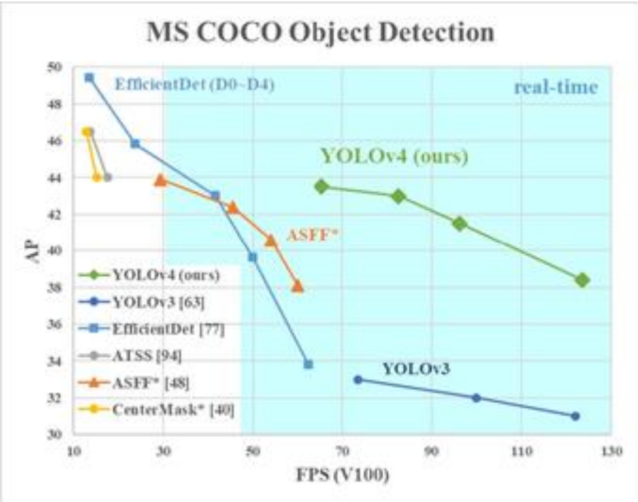



**Fig. 1 Comparison of the proposed YOLOv4 and other object detectors.**

### *2.2. Character Detection and Recognition*

To recognize the aircraft identification code, we first detect the identification code area and then apply OCR (Optical Character Recognition) technology that converts the characters in the image into digital characters. In the past, character recognition was conducted through image processing, such as feature extraction and template matching through preprocessing, but recently, character recognition has become possible more quickly and accurately through deep learning. Starting with Tesseract OCR, Easy-OCR, and RNN, various models with high performance such as Attention[15] and TRBA (TPS ResNet-BiLSTM-Attn)[11] continue to be announced. Character recognition using OCR technology is already common in geodesic and PDFs, and a system that provides necessary information to users such as blind people by reading signs, signboards, and information boards in natural backgrounds is also being actively studied. In order to accurately recognize characters, you need to detect the character area well. There is no difficulty in detecting and recognizing characters in clean backgrounds such as documents, but in natural backgrounds, the character recognition rate is significantly reduced due to background noise. To this end, after detecting the character region, only that part applies OCR techniques or improves the character recognition rate of natural backgrounds through various learning data and powerful algorithms. Presented by NAVER's CLOVA AI team, CRAFT [13] performs well in character area detection and array detection in natural backgrounds, while TRBA (TPS ResNet-BiLSTM-Attn) [11] also performs well in character recognition in natural backgrounds. Recently, many studies have been conducted to detect objects in transportation and recognize identification numbers. Through the recognition of license plates using deep learning technology, smart parking control systems and road monitoring systems have already been developed to the commercialization stage, and recently, a study has been published to identify nationalities through identification numbers such as warships and ferries at sea through video information[14]. In this way, the nationality and flight information of the aircraft can be known through the recognition of the identification number of the aircraft, and the technology can be applied to the traffic safety monitoring system of small and medium-sized aircraft such as drones, UAM, and PAV in the future.

### *YOLO learning for aircraft object detection and classification*

We intend to build an aircraft-only detection model based on deep learning for use as an aircraft safety accident monitoring and control system. YOLO v4 is a supervised learning that requires image data for learning and an answer file indicating the class and object location of the object in the image. YOLO is pretrained with COCO dataset, but if there is no object to be detected in the dataset, data should be collected by crawling or other methods and customized learning should be performed after preprocessing. The more data to be learned, the better the object detection accuracy, so an automatic collection program creation development or data augmentation process is required. In this paper, aircraft images were automatically collected through real-time images, and large amounts of data were constructed through data augmentation to improve the accuracy of the detection model.

### *Configuring the Aircraft Dataset*

Many deep learning-based object detection models, including YOLO, are mostly learned with COCO datasets. COCO dataset consists of 80 classes, including Airplane. However, other classes such as car, bird, etc. are not related to aircraft detection and cannot be classified. Therefore, in this paper, we intend to construct a dataset by taking pictures of aircraft to build a detection model that detects aircraft and classifies models. An IP camera was installed at the Taean Airfield (RKTA) of Hanseo University in Korea to film aircraft taking off and landing through real-time images, and to reduce the computational process, it was filmed with monochrome. The camera used was equipped with 1920 x 1080 pixels (Full-HD) resolution and RTSP support. In order to automatically acquire data, a program was developed to take pictures when the aircraft entered the camera frame using the 'Airplane' class pretrained in YOLO v4. As a result, approximately 7500 images of the four aircraft models were collected and all of the images were labeled as shown in Figure 2.

However, the 'Cessna' class, which is widely used for flight education, accounted for 80% of the total data, and the learning imbalance between classes was expected due to the large gap in data volume with other classes, so data augmentation was carried out for classes with less data. Data augmentation is a method of creating a new image by transforming the original data through image processing and image synthesis of a small amount of data. The image processing method is a stochastic application of several filters to images such as Gaussian blur & Nosie, Rotation, Brightness, and Histogram equalization, and has the advantage of being augmented without significant changes in the labeled coordinate file. The image synthesis method is a method of properly mixing two images, Cut-Mix and Puzzle-Mix, and creating a new image, resulting in a big change in the labeled coordinate file. As illustrated in Fig. 3, this paper generated 264,130 data using the image processing methods, such as 360° rotation, histogram equalization, etc., and the overall data structure is as illustrated in Table 1. The image to which Rotation is applied must also move the bounding box coordinates by the degree of rotation.

**Fig. 2 Aircraft data for 4 classes**

(1st quadrant: Citation, 2nd quadrant: Kingair, 3rd quadrant: Cessna, 4th quadrant: Seminole)

**Fig. 3 Result of Data Augmatation (L : Rotation, R : Histogram Eqalization)**

| **Table 1:**Train Dataset Table | | | | | |
|---|---|---|---|---|---|
| Aircraft type | Class Index | Data ratio | Aircraft type | Class Index | Data ratio |
| Cessna | 1 | 95% | Seminole | 2 | 2% |
| Kingair | 3 | 1% | Citation | 4 | 2% |

***Learning an Aircraft Detection Model Using YOLOv4***

The prepared aircraft data set is trained using YOLOv4. To detect a small identification code area on the aircraft, we trained the original image at 1920 x 1080 resolution. The equipment used for learning was GPU: RTX 3060 and CPU: intel i7, and the total learning time took 46 hours. A total of 228,960 training data and 35,170 validation data are presented in Figure 4. The model achieves an overall accuracy of 87% across all classes, and the accuracy for each class is shown in Table 2. Through this, it was confirmed that the more data there is, the better the learning is and the higher the accuracy is. Afterwards, the weights learned through the camera that collected the data were tested in real-time images, showing nearly 100% accuracy for Cessna, high accuracy for other objects that lacked data, and near real-time detection speed at 25 FPS.

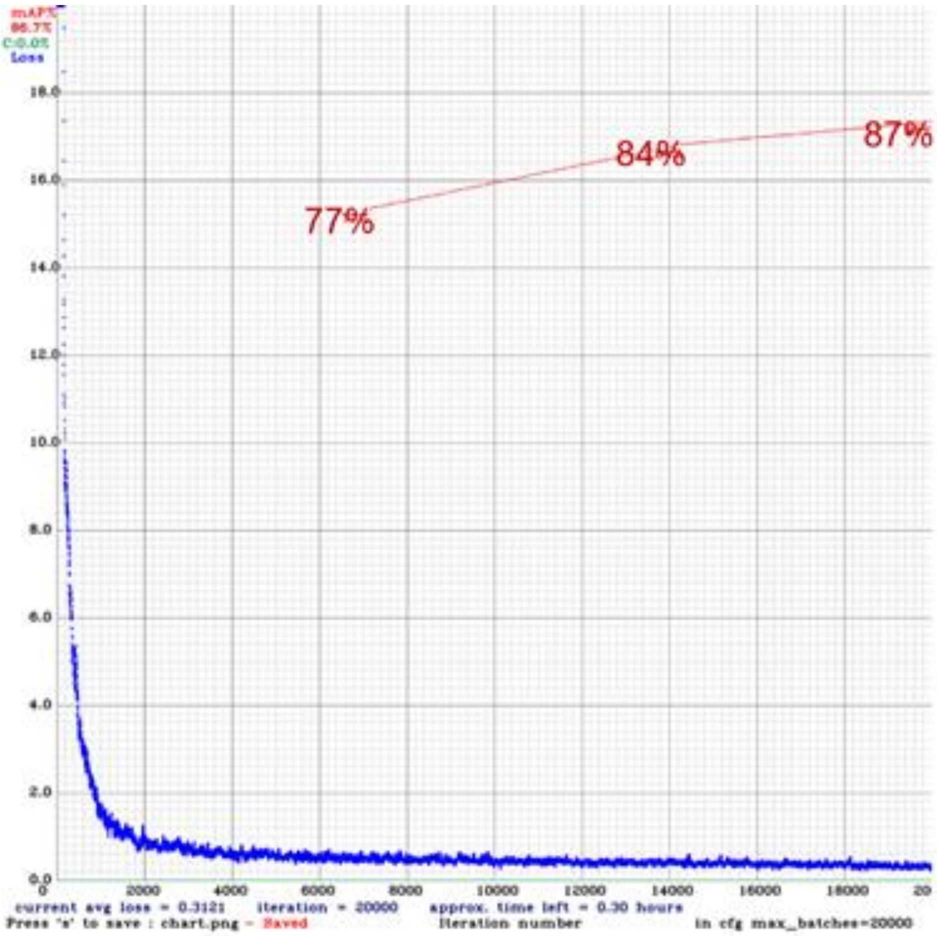



**Fig. 4 Train Result Char**

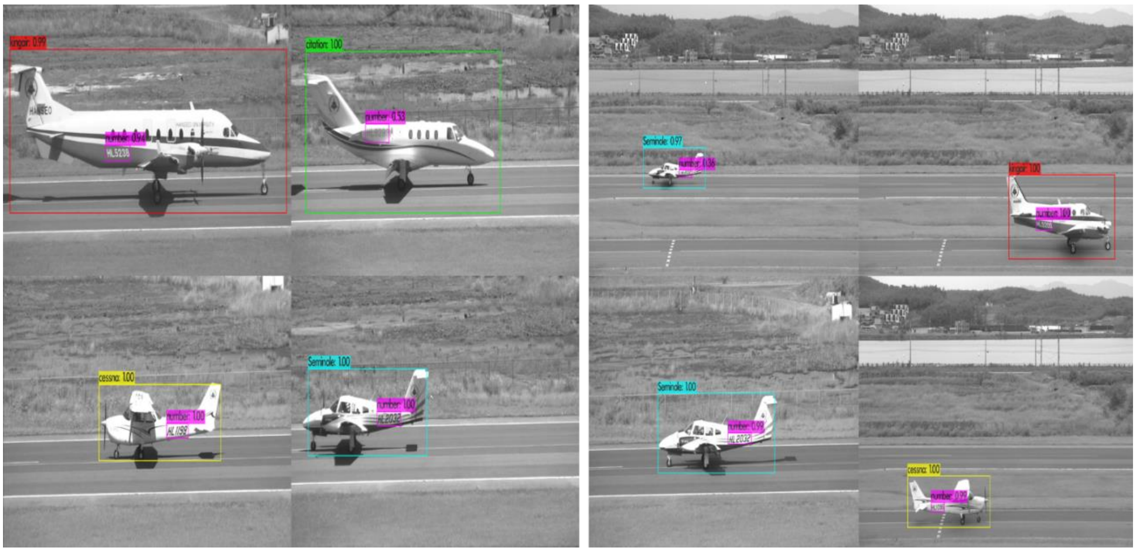


**Fig. 5 Detection result**

| **Table 2.** Train Result Table | | | | |
|---|---|---|---|---|
| Index | Class | map | Test | Fps |
| 0 | Number | 83.38% | RTSP | 25 |
| 1 | Cessna | 99.92% | | |
| 2 | Seminole | 94.09% | | |
| 3 | Kingair | 83.01% | | |
| 4 | Citation | 73.03% | | |

***Recognition of aircraft registration number***

Table 2's [Index 0:number] is an aircraft identification code area that has been classified and labelled to improve the accuracy of character recognition. In previous studies, after aircraft detection progressed without detection of the identification code region, identification code characters were recognized using the corresponding detection results. In this case, there was a problem of misunderstanding or unrecognition due to pictures or lines on the surface of the aircraft. To solve this problem, an algorithm that detects a license plate in a license plate recognition system and performs character recognition by cropping the corresponding area was applied to designate and learn the aircraft identification code area as a class. Although the aircraft identification code area is not in the form of a square border like a license plate, YOLO learning has detected the aircraft's identification code area with high accuracy.

***4.1 Identification Code Area Detection***

To recognize the aircraft identification code, the area was first detected through YOLO v4. During the aircraft-only Dataset labeling process, ground truth coordinates were designated as the number class for the aircraft identification code area. As a result of learning, the identification code area was recognized with high accuracy, and the corresponding part was cropped and used in the character recognition stage.

Image preprocessing is performed to make it easier for computers to recognize aircraft identification code characters in images cut into character areas. Image processing filters, which are widely used in the image preprocessing process that makes good use of character characteristics, are carried out through various stages such as gray scale, Gaussian blur, and threshold. Since we already shoot with monochrome, we preprocess and apply OCR algorithms by applying only Gaussian blur, Threshold and Contours filters. It showed better performance to go through the preprocessing process than to put the original image directly into the OCR algorithm as an input.

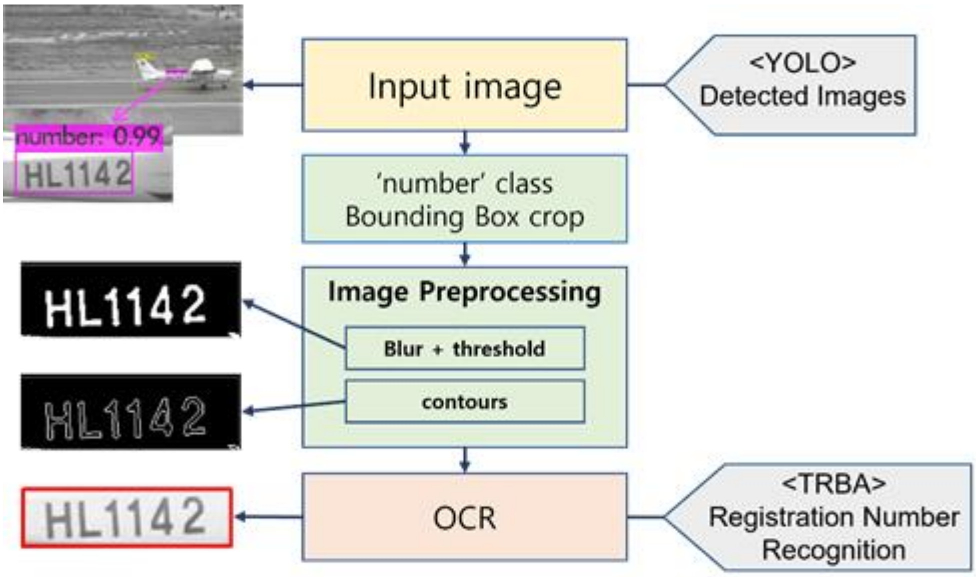
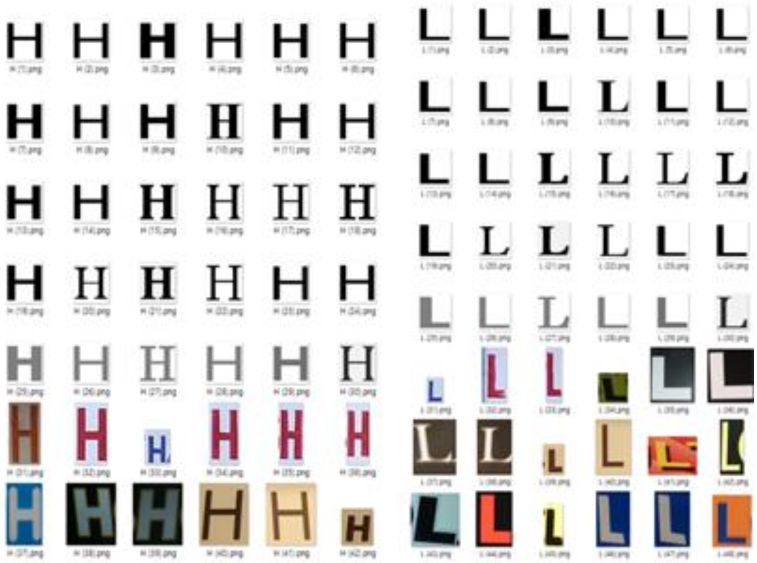


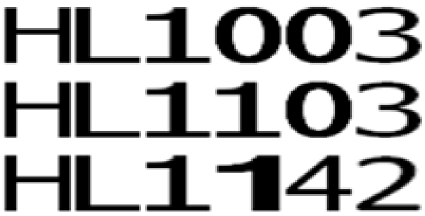

**Fig. 6 registration number recognition stage**

### *4.2. Identification Code Recognition Algorithm*

Among the various character recognition programs, we applied a deep learning-based TRBA (TPS-ResNet-BiLSTM-Attn) network developed by Naver Clova AI team. TRBA provides pre-trained weights. However, since the aircraft identification code is smaller than the aircraft and does not have various forms such as signs and advertisements, but has a certain ratio and size, we intend to create artificial data similar to the aircraft identification code and apply it to learning[16],[17]. Learning was conducted with artificial data of the aircraft identification code, and the pretrained model and the custom model were compared. Figure 7 shows (a) the alphabet used for the aircraft artificial data, (b) the generated artificial data, and (c) the image of the actual aircraft identification number. Table 3 is the result of comparing the recognition rate of TRBA's pretrained and custom model. The predictivity of the model learned with artificial data is higher, and it can be seen that the performance is improved.



**Alphabetical data used in aircraft artificial data**




**Artificial data generated**


**Image of the identification number of the actual aircraft**

**Fig. 7 Aircraft registration number**

**Table 3.** Comparison of TRBA's pretrained and custom model recognition rates

| | Input data | Predicted Labels | Confidence Score |
|---|---|---|---|
| Pretrained model | HL1198 / HL1103 | hli193 / hl1003 | 0.1896 / 0.8965 |
| Custom model | HL2032 / HL1142 | hl2032 / hl1142 | 0.7633 / 0.7148 |

***Proposed system test***

Hanseo University Taean Airfield (RKTA) tested the system proposed in this paper through real-time images. The configuration of the proposed system is shown in Figure 8. It receives real-time images through the camera and automatically detects aircraft entering the camera frame through the custom YOLO model with the aircraft dataset. At this time, the aircraft model and the aircraft identification number area are detected and only the corresponding area is cut. The identification code area is input to the OCR algorithm to output the identification code image as text. The experiment was conducted by installing a 1920 x 1080 pixels (Full-HD) resolution camera with weights learned through GPU: RTX 3060, CPU: intel i7, and as shown in Figure 9, when the aircraft enters the camera frame (L) and identification code information (R).

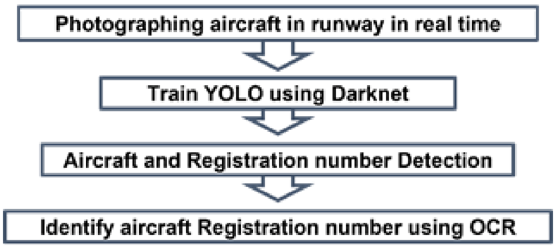



**Fig. 8 System Configuration**


**Fig. 9 Real-time registraion number recognition log file (L: camera image, R : registration number log.txt)**

## 3. CONCLUSIONS

This study creates and learns aircraft datasets to construct aircraft-specific detection models suitable for small airports, and proposes a system for recognizing aircraft identification codes to know the information of the aircraft. A two-step algorithm is implemented to detect and classify aircraft that are taking off and landing at high speed on the ground and to recognize the identification symbol, which is a small object on the aircraft. Considering the characteristics of detection objects and algorithms for each stage, an accurate aircraft detection and identification code recognition model was implemented through image preprocessing and data augmentation. YOLO v4, a real-time detector, was used to keep up with the fast speed of the aircraft, and the model was re-learned with a dataset suitable for the Taean Airfield (RKTA) of Hanseo University, which conducted the experiment, to improve accuracy. In addition, various image processing processes and deep learning character recognition model TRBA were used to recognize smaller identification codes than aircraft, showing better recognition rates than in previous studies. However, there is an error in the identification code area, such as recognizing the number 1 after the Korean aircraft's unique number HL as i, so the artificial identification code dataset will also be reinforced to improve performance. We also want to modify the program so that we can display country information about the alphabet before the identification code, such as HL (Korea) and N (United States).

This study automatically detects aircraft, identifies aircraft type, direction of movement, and identification number recognition to know aircraft possession country and various information. It can be applied not only to aircraft at small airports but also to monitor and control future vehicles such as UAM, PAV, marine transportation, and drones. In addition, it is thought that it can be applied as a system for preventing safety accidents by installing it in hot-spots in airports with a high risk of accidents. In the future, in addition to providing information through aircraft classification and identification codes, a more user-friendly platform can be built by connecting with map services. In addition, the first study to learn by creating an aircraft identification code artificial dataset to detect and recognize aircraft identification codes can lead the development of various systems by building aircraft data and artificial identification code dataset DB in the future.

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