AI-Based Drowning Detection in UAV-Assisted Coastal Environment

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***Abstract*— With the recent advancements in the aviation industry, UAV (Unmanned Aerial Vehicle) technology is being utilized across various fields. Furthermore, it is evolving into an autonomous driving system powered by AI(Artificial Intelligence) and big data. Leveraging these advantages, the current trend in UAV technology is to deploy these vehicles in public areas that are inaccessible to people, particularly for search and rescue operations. In this study, we propose a UAV-based drowning detection method aimed at rescuing individuals who may be at risk of drowning in summer beaches. To address this issue, we employed YOLOv5(You Only Look Once version 5) as the object detection technology. YOLOv5 is known to have low capacity and fast speed. It is designed and used by implementing the same CSPNet-based backbone as Yolov4 in Pytorch. The simulation results indicate that the proposed model can effectively detect three states: drowning person, swimming individuals and people out of the water. Finally, simulation results show that the learned model achieved a detection accuracy of over 90% on average in sorting three states for several test scenarios.**

Keywords—UAV(Unmanned Aerial Vehicle), YOLOv5(You Only Look Once version 5), AI(Artificial Intelligence), Object Detection, Lifesaving

I. Introduction

Drowning accidents occur consistently at beaches and in valleys every summer, with the number of incidents increasing year after year [1]. In cases of drowning at sea, immediate recognition can be challenging, especially at night or in isolated areas with few witnesses. This delay can result in fatalities due to the critical time lost [2]. Furthermore, safety is compromised by the limited number of rescue personnel available at beaches during summer.

To address this issue, Unmanned Aerial Vehicles (UAVs) can be utilized. UAVs are aircraft that are operated autonomously via remote control, without any personnel on board. Originally, UAVs were developed for military applications, including reconnaissance and combat. However, research into the commercial viability of UAVs has gained momentum since Amazon recently introduced a service known as Amazon Prime Air [3].

Recently, autonomous UAVs have become possible with the advancement of AI (Artificial Intelligence) technology [4]. In addition, the scope of UAV utilization is expanding. In particular, the application of UAVs to the maritime environment is receiving more attention due to the special nature of the environment. This can solve problems that are difficult for people to approach. To this end, various functions such as real-time communication and rescue should be included. For the communication function, the optimal communication method should be selected according to the scope of application of the UAV. For the rescue function, functions such as human identification and rescue equipment delivery are required [5].

In this regard, [6] conducted a study to improve the accuracy of sea surface drowning detection. For this purpose, a method of applying the Attention mechanism to the CNN model was proposed. In this case, EO (Electro-Optica)/IR (Infrared) cameras were used as cameras. Based on the proposed method, the background noise of the EO camera was minimized to improve the detection accuracy when detecting drowning people. However, the background noise of the IR camera had a limitation of increasing.

In [7], a smart drowning prevention and alarm system was developed to prevent drowning. The system was implemented using Arduino nano and uses two sensors, a pulse sensor and an accelerometer, to detect the swimmer's heart rate and tilt pattern. The pulse sensor and the accelerometer serve as a two-way verification process to detect a drowning person, and the air vacuum pump serves as a rapid rescue plan to inflate the life jacket and lift the user to the surface, and the GSM module is used to send a warning message to the rescue team. However, these systems cannot be used for many people and have limitations in that they must be purchased and carried by individuals.

Therefore, in this paper, we intend to use a UAV (Unmanned Aerial Vehicle) to detect drowned people at a beach. Most drowned people occur outside the boundary of a beach that rescue workers cannot check, or in blind spots such as unoperated beaches. To solve this problem, we propose a UAV that can perform search and rescue simultaneously. First, in order to perform a search, we must distinguish between drowned people and non-drowned people. Here, non-drowned people include swimmers and people outside the water. In this study, body structure was used as a feature to distinguish drowned people. In the case of drowned people, only the head and arms are exposed outside the water, and most of the body is underwater. In contrast, non-drowned people have the characteristic of having their upper and lower bodies exposed outside the water. Based on these features, the collected data was labeled to build a learning data set. After building the learning data set, the AI model was trained.

The structure of this paper is as follows. Section 2 describes the system model and presents the learning method and test results of the object detection model. Section 3 then describes the conclusion of this paper and future research plans.

II. System Model

In this section, we propose a UAV-based drowning detection method in a summer coastal environment. The overall structure of the proposed method is shown in Fig.1.

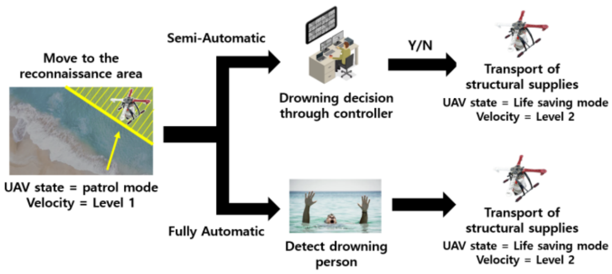

Fig. 1. System configuration of proposed method.

As shown in Fig.1, reconnaissance is divided into two modes. In all modes, due to the limited battery capacity of the UAV, it is assumed that multiple UAVs will conduct search and rescue operations sequentially. Furthermore, the LoRa (Long Range) module is utilized for communication between the UAV and the control center.

The first mode is semi-automatic. Initially, the autonomous UAV navigates to the hazardous area beyond the designated boundary line based on the scheduled reconnaissance time. Upon reaching the dangerous zone, the UAV conducts reconnaissance while following a pre-established autonomous driving path. During this reconnaissance, real-time imaging is captured using the camera mounted on the UAV, and the corresponding data is transmitted to the MCU (Main Control Unit). The MCU then relays the real-time imaging data to the control room. The control room manager analyzes the image data received from the UAV. Once the manager identifies a drowning individual, the UAV can be deployed to deliver rescue supplies to the person in distress.

The second mode is fully automatic. In this mode, the system operates in three distinct step. Similar to the semi-autonomous mode, the UAV navigates to the danger zone beyond the designated boundary and conducts reconnaissance. The reconnaissance data is transmitted to the MCU in real time. The MCU sequentially performs three functions using the transmitted image data. The first function is AI-based drowning detection, utilizing the YOLOv5 object detection AI model. If a drowning person is detected, the second function generates a notification to the control room via LoRa communication. Finally, the UAV promptly moves to the location of the drowning individual and delivers rescue supplies.

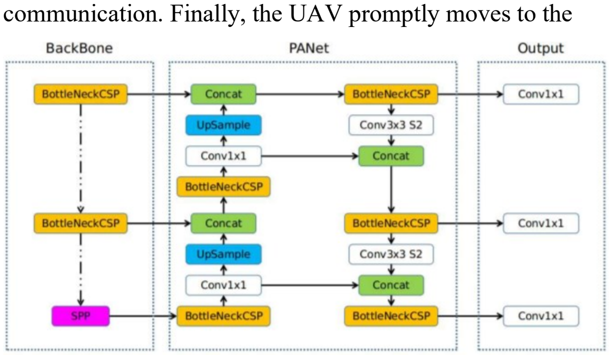

Fig. 2. Architecture of YOLOv5.

III. Object Detction AI Model

In this study, we describe the AI model utilized to perform the aforementioned operations. The UAV environment was also taken into account when selecting the AI model. First, UAVs operate with limited battery resources; therefore, an AI model with low power consumption is essential. Additionally, since the control room must monitor the drowning individual in real time, the object detection processing time needs to be rapid in a streaming environment. Given these considerations, we applied YOLOv5 as the AI model[8]. The architecture of YOLOv5 shows is the Fig. 2.

As you can see in the figure, the Neck part exists together with the Head, and the last Detect Layer is in charge of the Head. The architecture of YOLOv5 is designed to perform object detection with minimal labeling in the most general environment. YOLOv5 is divided into s, m, l, and x models according to performance and time. s is the lightest model (low performance) and has the highest number of frames, and x is the heaviest model (good performance) and has the lowest number of frames. The parameters used to train the model are summarized in Table I.

TABLE I. Simulation Parameter

Parameter	Value
Number of training dataset	2,677
Number of valiedation dataset	765
Number of test dataset	383
Batch Size	32
Epoch	1,000

As shown in Table I, a total of 3,825 image data were collected from Google, Roboflow, and data sharing centers. The training data was divided into 8:2 ratios and used for training and validation. The batch size was set to 32 for model training. The labels of the training data were set to three: out of water, swimming, and drowning. The training results confirmed that objects were detected with an accuracy of approximately 65%. Afterwards, the model whose learning was completed was loaded onto the MCU mounted on the UAV.

IV. Experimental and Results

In this section, we present the experimental setup and scenario for detecting drowning people using a UAV equipped with an AI model, and finally present the experimental results. First, we explain the H/W configuration of this experiment. The UAV, which is the core element of

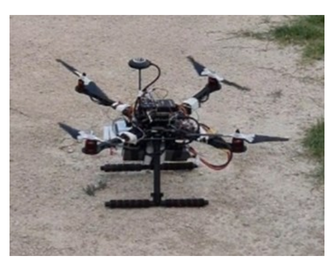

Fig. 3. Product appearance of F450.

Fig. 4. Product appearance of Pixhawk 2.4.8.

the proposed system, uses Pixhawk's F450. The appearance of the F450 is as shown in Fig. 3.

As shown in figure, the diameter of the F450 is 450 mm, the height is 185 mm, and the weight of the main body is about 800 g excluding the battery. Here, the maximum transportable weight including the main body weight of the F450 is 1.6 kg. A +11.1 V 5,200 mAh battery is installed to provide power to the UAV. At this time, the weight of the battery is about 300 g, so the total weight of the manufactured UAV is 1,100 g.

As mentioned earlier, three functions were added to the UAV in this study. The first is autonomous driving, the second is object detection technology, and the third is the rescue product delivery function. For this purpose, two MCUs were installed in the UAV.

First, Pixhawk 2.4.8 was installed to implement the UAV's drive control and autonomous driving functions. The appearance of Pixhawk 2.4.8 is as shown in Fig. 4. Pixhawk 2.4.8 supports the NuttX RTOS(Real-Time Operating Sys.) based on the 32-bit ARM(Acorn RISC Machine) cortexM4 high-performance processor. In addition, it supports bus interfaces such as UART(Universal Asynchronous Receiver/Transmitter), I2C(Inter-Integrated Circuit), SPI(Serial Peripheral Interface), and CAN(Controller Area Network), 14 PWM(Pulse Width Modulation)/ servo outputs, automatic and manual modes, and a micro SD card to store flight log data. In this study, the dronekit-python library was applied for the autonomous driving of the UAV, and MAVlink (Micro Air Vehicle Link) was used for communication.

The second was installed with a Raspberry Pi 4 for object detection and rescue equipment delivery. A camera is connected to the input of the Raspberry Pi to capture the marine environment in real time. The video captured in real

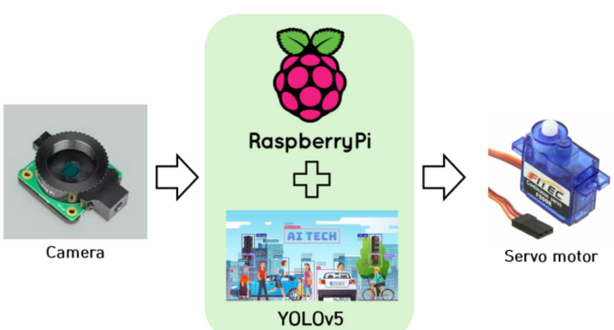

Fig. 5. Operation flow diagram of Raspberry Pi4.

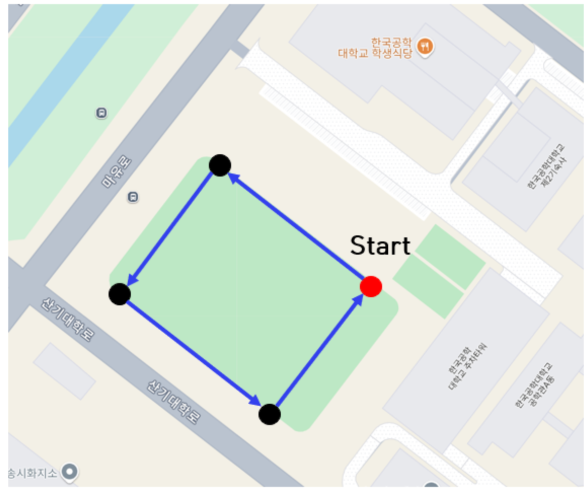

Fig. 6. Experimental scenario.

time is transmitted to the Raspberry Pi to perform object detection. At this time, object detection uses YOLOv5s, which has been trained in advance. If a drowning person is found in the object detection results, the UAV approaches the location of the drowning person. After that, the servo motor is operated to deliver the rescue equipment held by the UAV to the drowning person. The Raspberry Pi's operation flow diagram is shown in Fig. 5.

In this study, HW was configured as above and experiments were conducted based on this. The experimental scenario is as shown in Fig. 6. The experiment was conducted at the Korea University of Engineering and Technology playground, and the procedure was as follows. First, the UAV's autonomous driving mode was changed to ON at the starting point indicated by the red dot. After that, the UAV moved along the preset path indicated by the blue line. At this time, a beach image was placed at a random location along the UAV's moving path. Here, the image was an image that was not used for model learning, and tests were performed for a total of three classes. During the test, if a person who fell into the water was detected, it was confirmed whether the servo motor operated to deliver rescue supplies. Finally, a test was performed to determine whether the UAV returned to the starting point after delivering the rescue supplies.

First, the object detection results can be seen in Fig. 7. As can be seen in the figure, it was confirmed that the swimming person(a) was detected with an accuracy of more than 90%, and the drowning person(b) was detected with an accuracy of more than 90%, and the person outside the water(c) was detected with an accuracy of about 90% too. At this time, in order to analyze the accuracy of object detection in detail, two additional scenarios were tested. In the case of (d), a swimming person and a drowning person are together. In the case of (e), a person outside the water and a drowning person are together. As can be seen from the results, it can be confirmed that objects are detected with an average accuracy of 90% in the two additional scenarios. In addition, in the (a) and (c) scenarios, the drowning person was not detected, so the rescue equipment delivery was not performed, and in the (b), (d) and (e) scenario, the drowning person was detected, and it was confirmed that the rescue equipment was delivered normally.

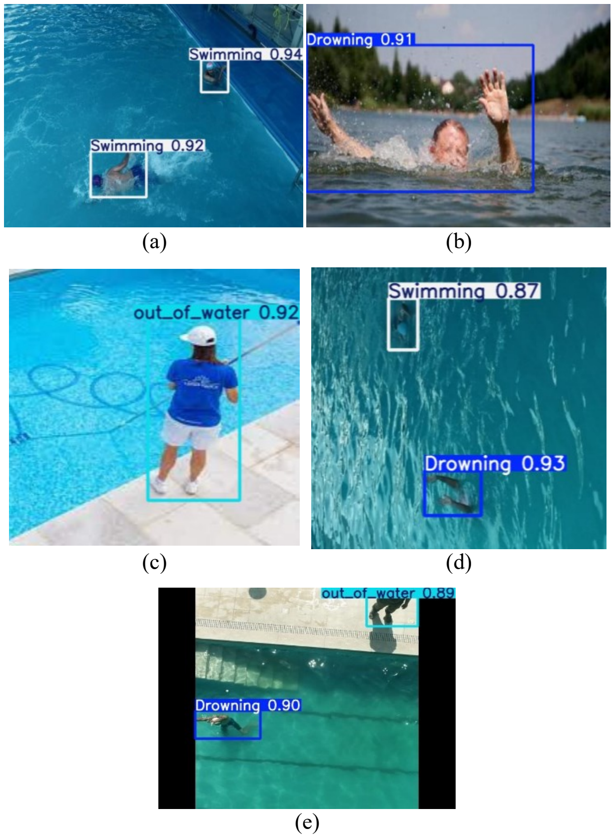

Fig. 7. Object detection results: (a) Swimming, (b) Drowning, (c) Out of water, (d) Both Out of water and Drowning, (e) Both Swimming and Drowning.

However, this study had the following limitations. First, the beach could not be photographed. This is directly related to the issue of portrait rights, and government and local government permission is essential for this. Second, there is a UAV operating license. If there is no drone operating license, the weight and height of the UAV that can be operated are limited. Therefore, in order to verify the validity of this experiment, it is thought that a drone license and government permission for beach photography will be necessary.

V. Conclusion

In this study, we propose a solution to address drowning incidents that occur along the coast. To achieve this, we developed a function to detect individuals in distress and deliver rescue equipment using AI-equipped UAVs. The evaluation of the system's learning performance revealed that it can detect objects with an accuracy of approximately 92%. Based on this, further tests were conducted, it confirmed an average accuracy of around 90%. Notably, a relatively the higher accuracy was observed for individuals outside the water, which can be considered as a result of the different characteristics between two scenarios—those in the water and those on land.

In the future, further experiments in real coastal environments should be conducted to validate the effectiveness of the proposed system in view of the practical application. Additionally, we plan to establish a LoRa-based communication network to facilitate stable communication with the control room and it means that a monitoring program can be implemented within the control room to provide the immediate rescue operation.

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