LAF: Find Lost Golf Balls Using a Drone, LoRa, and Computer Vision

1st Sanghyun Park
Big Data
Hallym University
Chuncheon, South Korea
20185126@hallym.ac.kr

2nd Jimin Han
Smart ICT Convergence
Konkuk University
Seoul, South Korea
jiminhan2001@konkuk.ac.kr

3rd Chaerin Yang
Computer Engineering
Kyonggi University
Suwon, South Korea
yylin22@kyonggi.ac.kr

4th Dongik Min
AI and Big Data
Woosong University
Daejeon, South Korea
202110650@wsu.ac.kr

5th Andrew Webb
Computer and Information Technology
Purdue University
Indiana, USA
webb102@purdue.edu

6th Dominic Frederick
Computer and Information Technology
Purdue University
Indiana, USA
will2245@purdue.edu

***Abstract*—Millions of golf balls are annually lost, contributing to environmental pollution. Although solutions to address this problem exist, such as the production of environmentally friendly golf balls, it still carries environmental issues during the production process and demands the consumption of fresh resources and energy. Moreover, a substantial impact on financial decisions is expected when considering an effort to replace all traditional golf balls with environmentally friendly ones. This paper introduces an innovative system designed to reduce the loss of golf balls effectively. The drone, the ultimate output of this study, is equipped with a Raspberry Pi, a camera, and the YOLOv8n model. The coordinates of detected golf balls will be calculated by the Raspberry Pi on the drone transferred to the base station through LoRa communication protocol, and finally uploaded to a server. These data are then presented to the user as markers on a map. The system utilizes a model optimized for golf balls to detect and scan the entire golf course using a drone. It facilitates the retrieval of golf balls by providing the coordinates for their detection, enabling users to recover them easily. This paper focused on systematically locating presently lost golf balls to the maximum extent possible and significantly reducing the prospective incidence of lost golf balls in the future. Finally, the system was tested with a prototype on an outdoor field.**

***Index Terms*—Small-Object Detection, Computer Vision, LoRa, Wireless Communication, TinyML, YOLOv8n, UAV**

I. Introduction

Golfers lose an average of 1.3 golf balls per round [1], and the number of lost golf balls is also approaching nearly 300 million annually [2], in cycle with the gradual increase in the number of golfers [3]. Furthermore, Golf balls which take 100 to 1000 years to decompose can pose environmental challenges. Large amounts of zinc were detected in the process of decaying the golf ball naturally.

Efforts are underway to develop environmentally friendly golf balls [4] as a solution to these issues. The objective of that study was to make golfers use eco-friendly golf balls instead of existing ones. However, replacing the conventional golf balls completely in use seems impractical and leaves the environmental problems caused by those already lost unaddressed. Therefore, the issue of retrieving uncollected golf balls and the multitude that will continue to disappear in the future is a highly significant topic in the context of environmental conservation. This research seeks to explore a novel perspective by identifying golf balls that are currently lost or will be lost. In doing so, it will contribute to the collection of lost or potentially lost golf balls, presenting a novel approach to the golf field. There is currently no method other than individuals physically searching for and collecting golf balls. To confront this challenge, this research proposes a system called '*LAF*'. It finds lost golf balls and provides a list of the coordinates of golf balls for collectors to retrieve them. *LAF* is composed of three main parts: a drone, a base station, and a server.

Figure 1. Drone's view and golf ball detection

The drone, equipped with a Raspberry Pi 4 model B, a camera sensor, and an ESP32 [5], is designed to navigate golf courses and detect lost golf balls. As the drone navigates throughout the entire golf course, photographs of the golf course are captured through the camera attached to the drone. Those are then processed through the YOLOv8 model embedded in the drone's Raspberry Pi attached to the drone, enabling the detection of the presence of golf balls on the golf course. If golf balls are detected, the GPS coordinates of the golf balls are calculated and subsequently stored in the database. All these processes are carried out automatically, obviating the need for human labor. Ultimately, users can access and visualize the locations of golf balls on a table and map through the website.

This study is dedicated to implementing the drone for detecting lost golf balls. This minimizes the requirement for extensive physical exploration, focusing on the coordinates where golf balls exist. As a result, the number of abandoned golf balls left in nature decreases, leading to a reduction in the adverse environmental impact associated with golf balls. Finally, reducing the economic loss incurred through the strayed golf balls, such as the need for repurchase, becomes possible with our system.

II. Literature Review

Biodegradable Golf Ball [4] is one of the solutions that can ultimately contribute to solving environmental pollution caused by lost golf balls. While these golf balls address some environmental concerns associated with traditional golf balls, their production process, particularly the use of corn starch [6], is not entirely environmentally friendly. The production of cornstarch is energy-intensive and its characteristics such as water absorption and biodegradation, critical for making biodegradable products, can lead to further pollution concerns [7]. Additionally, while the application of Polyvinyl Alchohol (PVA) on sustainable materials, such as biodegradable golf balls, enhances sustainability through biodegradability [8], it also raises environmental concerns due to its derivation from oil and petrochemicals [9]. This aspect of the manufacturing process has the potential to undercut the eco-friendliness of the final product.

Contrasting between the system which is to maintain the use of traditional golf balls and biodegradable golf balls, the focus here is on a considerably different approach. Instead of advocating for the complete replacement of traditional golf balls with biodegradable alternatives, this system emphasizes the continued use of existing golf balls. This tactic avoids the environmental challenges accompanied by the production of biodegradable alternatives. By choosing the current system to maintain the use of traditional golf balls, the goal is to balance the environmental considerations with feasible practicality, ensuring that the impact of golf balls on the environment is minimized without needing a drastic change in the current system.

Considering the cost of both traditional and biodegradable golf balls, it's evident that maintaining the use of traditional golf balls offers a practical advantage. Although the end might result as the final product tending to decompose cleanly [10], ingredients used during the production of biodegradable golf balls come with higher production costs, typically around $35.00 for a pack of dozen [11]. This is in contrast to traditional golf balls, which are made from cost-effective materials like hard rubber and durable plastic. The established system of using traditional golf balls remains more economically viable, especially considering the cost differences and the established manufacturing processes for classic golf balls.

YOLO [12] revolutionized object detection by introducing a new approach. Conventional approaches typically involve step-wise processing [13, 14], where each object proposal generated through region proposal undergoes sequential classification. In contrast, YOLO integrates the bounding box and classification problems into a single regression problem, providing a unified approach to address both challenges. This approach enables YOLO to forecast boundary boxes and class probabilities for the entire image in a single pass using a singular neural network, facilitating end-to-end training. This is referred to as single-stage detection, while the conventional method that involves multiple stages is termed multi-stage detection. When YOLO was initially proposed, it demonstrated significantly faster speed compared to traditional multi-stage detection models. However, its accuracy was relatively lower. Nevertheless, *Redmon et al.* [12] team's persistent research and enhancements have led to progressive improvements in both accuracy and speed. In a recent study by *Zhang et al.* [15], YOLO version 4 surpassed the previous state-of-the-art model Faster R-CNN across various metrics.

III. Method

The overview of the overall system architecture and flow is first provided. Following that, the communication structure between each microprocessor within the network part is detailed. The fresnel zone about LoRa, the golf ball dataset, the data augmentation of dataset images, and unit conversion for actual coordinates of the golf ball are described.

A. System Overview

LAF comprises three components: a drone, a base station, and a server. The Raspberry Pi 4 Model B and the ESP32 are attached to the drone. The Raspberry Pi is equipped with a camera and GPS sensor. The drone navigates the golf course, capturing ground images with the camera at intervals of 1 second. Simultaneously, the YOLOv8n model on the Raspberry Pi detects golf balls in the captured images, while the GPS sensor receives the GPS data of the drone. If a golf ball is detected, the actual GPS coordinates of the location of the golf ball are calculated using the relative coordinates of the bounding box of the golf ball box in the image and the GPS coordinates of the drone. After detecting golf balls for a specific duration, the ESP32 embedded in the drone and the ESP32 within the base station initiates LoRa communication when reaching a designated altitude threshold. The ESP32 functions as a data transmitter to the base station, sending the GPS coordinates to the base station. The base station is composed of an ESP32 module and a Raspberry Pi. The Raspberry Pi on the base station receives this information by ESP 32 and forwards it to the cloud server.

B. Internet of Things

Raspberry Pi 4 Model B, which has a quad-core Cortex-A72 processor, is used. The operating system employed is Ubuntu

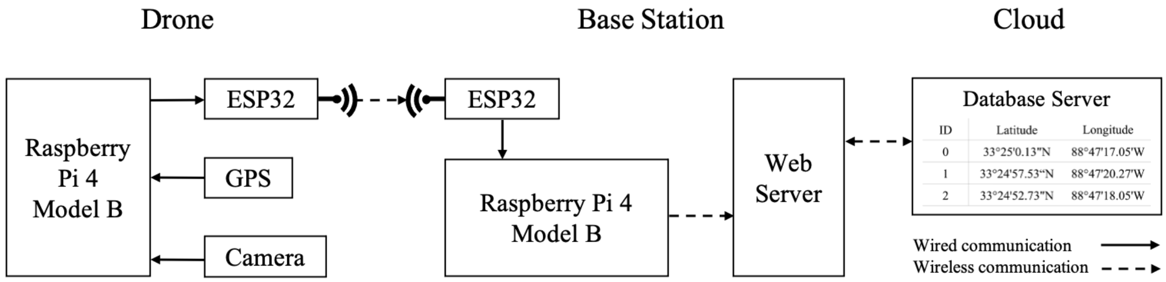

Figure 2. System Overview

LAF is comprised of a Drone, a Base Station, and a Web Server. The Drone detects the golf ball and calculates the GPS coordinates for each golf ball. Subsequently, the ESP32 transmits this data to the base station. This enables users to directly access and review the golf ball's GPS coordinates.

Algorithm 1 Drone operation Algorithm

Input: Drone altitude *alt*; Drone altitude threshold *thr*; Image *img*; Model output *output*; Golf ball GPS coordinate *coord*; Golf ball GPS coordinate list *list*;
Output: Temp file *temp*;
INIT model, camera, GPS, and I2C
while *system is active* **do**
    GET drone GPS data
    if *alt is higher then thr* **then**
        GET *img* from Raspberry Pi Camera
        INPUT *img* to model
        if detected golf ball from *output* **then**
            CALCULATE *coord*
            ADD the *coord* to *list*
            WRITE *list* to *temp*
        end if
    else
        SEND the *temp* to base station
    end if
end while

22.04 Server. The camera utilized is a Lens Board OV5647 Sensor designed for the Raspberry Pi Camera. The Global Positioning System (GPS) sensor employed is the Adafruit Ultimate GPS Breakout, characterized by a sensitivity of -165 dBm, 10 Hz update frequency, 66 channels, a 5V compatible design with a nominal current draw of 20mA, and an internal patch antenna. The camera interfaces with the CSI port using a CSI Cable, commonly in the form of a ribbon cable. The GPS sensor establishes communication through a wired connection to GPIO pins. As the sensors are integrated with the Raspberry Pi via wired communication, the data exchange was executed employing the serial port. Additionally, the incorporation of LoRa communication is deemed essential in this research. The dimensions of a golf course typically span between 5 to 6 kilometers. It is noteworthy that conventional Wi-Fi and LTE(Long Term Evolution) technologies exhibit limitations in providing coverage across such expansive distances. Considering the vast expanse of golf courses spanning several kilometers, this study leverages LoRa network technology. This system can scan the entire golf course without interference of the distance. Furthermore, The ESP32 devices on either terminus engage in mutual communication, affecting data exchange through LoRa transmission [16]. Subsequently, the transfer of data between the Raspberry Pi and the cloud server occurs through the utilization of the HTTP [17] protocol. The storage and retrieval of data are accomplished through the implementation of a RESTful [18] API.

C. Fresnel Zone

LoRa is a physical proprietary radio communication technique that is affected by the Fresnel zone effect. Due to the Fresnel zone effect, when a drone communicates with a base station over longer distances, it requires a higher altitude [19, 20]. Golf courses typically have lengths ranging from 5km to 6km, and the width of the Fresnel zone when the distance between the drone and the base station is 5km can be calculated using the following formula.

$$Radius(mts.) = 17.31 \times \sqrt{\frac{D(in\ km)}{4 \times f(in\ GHz)}} \tag{1}$$

Where $D = 5$ and $f = 0.915$ [21], the Fresnel Radius is 20.23 meters. This implies that for a golf course with a length of 5km, communication would only be possible if the altitude is raised to a maximum of 20 meters, considering the Fresnel zone effect at a distance of 5km between the drone and the base station. To account for the Fresnel zone effect, the drone determines the positions of each golf ball at a low altitude, saves them locally, and intermittently raises the altitude for LoRa communication during the round.

D. Golf ball dataset

To find a lost golf ball with *LAF*, YOLOv8n was retrained with both an open dataset and a custom dataset. The open dataset [23] consists of a total of 2,595 images with 16 classes. It predominantly comprises images captured from broadcast screens and pictures obtained through web crawling. It features golf balls against backgrounds such as the sky, cement roads, and lawns. To eliminate data unrelated to golf balls, 13 classes were dropped. Additionally, for three classes with golf ball images but different class names (e.g., ball, golf, golfball),

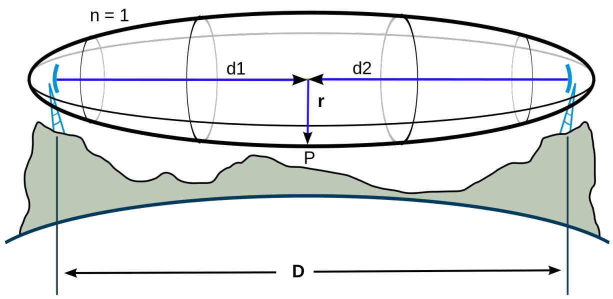

Figure 3. Fresnel zone [22]
When two devices communicate with each other over longer distances, it requires a higher altitude

the class names were modified to ‘golf ball’. The custom dataset was collected by directly capturing and annotating images of golf balls in an environment similar to an actual golf course. It comprises 904 images, shot at a maximum altitude where golf balls are recognizable in the image and considered the maximum safe driving altitude to minimize the risk of collision with people, at 4m. The dataset includes three classes: golf ball, person, and hydrant. Both datasets underwent a resizing process to 512×512 during the dataset creation. The distribution of train, validation, and testing was maintained at a ratio of 7:2:1.

E. YOLO Implementation

Data Augmentation In implementing YOLO for detecting golf balls against the varied green backgrounds of golf courses, data augmentation techniques were essential [24]. These techniques extended the training data range, ensuring powerful model training for a variety of scenarios [25]. Among several augmentation methods, particular emphasis was placed on adjusting HSV (Hue, Saturation, and Value) parameters. The decision to focus on HSV adjustment as the primary augmentation method is supported by observation from *Bhattacharya et al.* [26]. The research highlights the significant impact of HSV adjustment on model performance, seeing a considerable 7% decrease in detection precision for spur defect scenarios when excluded from YOLOv5’s augmentations. Additionally, the study by *Zoph et al.* [27] explored the efficacy of three distinct auto-augmentation strategies: color operations, geometric operations, and bbox-only-operations. It was found that employing color operations solely leads to an enhancement in performance, marked by an increase of 0.8 in mAP score. This finding highlighted the critical role of HSV adjustment in enhancing the ability of the model to accurately identify objects under various lightning and color conditions, a crucial factor in the context of golf ball detection in the middle of the complex visual environment of a golf course [28]. In the HSV color model, the hue component plays a role in differentiating object characteristics based on color [29]. When determining the strategy for adjusting the hue, targeting white golf balls is challenging due to the color white’s absence of hue. As an alternative strategy, the hue of the green background was subtly varied, creating a contrasting backdrop and enhancing the training process. Hue adjustments, implemented as fractional changes, give slight color variations in the overall picture. This method not only changed the grass shades but also diversified visual inputs during training. Saturation and value adjustments were also implemented with hue adjustments to enhance the training dataset. Saturation adjustments are aimed at enhancing color intensity variance, aiding in distinguishing white golf balls from the grassy background. Finally, value adjustments were crucial for adapting to diverse lighting conditions, increasing the model’s adaptability. These moderate yet precise HSV adjustments were integral in enriching the training dataset, enabling the model to efficiently adapt to various environmental conditions, thereby transcending mere performance enhancement.

F. Unit Conversion

The model outputs the relative coordinates of the golf ball on the image, representing the center coordinates of the bounding box, each ranging from 0 to 1. To express these relative coordinates $\mathbf{O} = [x_{pred}, y_{pred}]^T$ as user-understandable geographic coordinates for the golf ball’s position, it is necessary to transform the boundary box coordinate system $\mathbf{O}$ to the Global Positioning System (GPS). The GPS consists of two numerical values: longitude and latitude, with coordinate axes aligned with the azimuthal axes. Therefore, to convert the relative coordinates of an object in the image to GPS, it is essential to align the coordinate axes in the image with the azimuthal axes through vector rotation transformation [30].

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{2}$$

The rotation transformation of a vector is accomplished through the transformation matrix $R(\theta)$.

$$\mathbf{O}' = R(\theta_{img})\mathbf{O} \tag{3}$$

$$= \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \times \begin{bmatrix} x_{pred} \\ y_{pred} \end{bmatrix} \tag{4}$$

$$= \begin{bmatrix} x_{pred}\cos\theta_{img} - y_{pred}\sin\theta_{img} \\ x_{pred}\sin\theta_{img} + y_{pred}\cos\theta_{img} \end{bmatrix} \tag{5}$$

where $\mathbf{O}'$ as rotated coordinates according to the axis of GPS and θ_{img} as cardinal direction of the image.

Conducting a rotational transformation on the coordinates enables obtaining $\mathbf{O}' = [x'_{pred}, y'_{pred}]^T$, transformed to align with the azimuthal axis. Following this, $\mathbf{O}'$ requires conversion to GPS units for comparison with the drone’s GPS. Calculating the actual width and height of the image is possible using the drone’s height from the GPS sensor and the camera’s field of view (FOV) value. For this purpose, the normalized values are first converted to the metric system and then transformed back to the GPS. This ensures that the data is in a comparable state with the drone’s GPS.

$$\mathbf{O}'_{matric} = \mathbf{O}' \odot \max(\mathbf{O}_{matric}) \tag{6}$$

Where $\odot$ as element-wise multiplication. The total length of the horizontal and vertical dimensions in the image can be determined. Multiplying this by the normalized coordinates yields the transformation of the coordinate values into the metric system.

$$\Delta^1_{\text{lat}} = 111,132.954 - 559.822 \cos 2\phi + 1.175 \cos 4\phi \quad (7)$$

$$\Delta^1_{\text{lon}} = \frac{\pi r_e \cos \phi}{180^\circ \sqrt{1 - e^2 \sin^2 \phi}} \quad (8)$$

Where ϕ as the latitude, r_e as the equatorial radius ($r_e = 6,378,137\text{m}$), and e as the eccentricity, with $e^2 = 0.00669437999014$ [31]. Using Equation(7) and Equation(8), it is possible to convert O'_{matric} to GPS units.

$$\mathbf{O'}_{GPS} = \mathbf{O'}_{metric} \oslash \begin{bmatrix} \Delta^1_{\text{lat}} \\ \Delta^1_{\text{lat}} \end{bmatrix} \quad (9)$$

Where $\oslash$ as element-wise division. Subtracting $\mathbf{O'}_{GPS}$ from the drone's GPS coordinates allows us to obtain the final GPS coordinates of the golf ball.

IV. Result

The result of the test on the HSV adjustments to check the influence of Hue, Saturation, and Value on Precision, mAP50, and mAP50-95 are handled. Following that, the result of the experiment of *LAF*'s final prototype in the real world.

A. HSV adjustment test

Before the HSV adjustment augmentations were directly implemented on our dataset, an experiment was conducted based on the hypothesis that altering the HSV of the picture would enhance the efficacy of training the datasets. The experiment comprised four distinct tests. In the experiment, each HSV component was adjusted individually in sequential tests to segregate their effects. Starting with a baseline test with no HSV adjustments, three consecutive tests applied modifications to Hue, Saturation, and Value independently. This methodical approach allowed for a clear assessment of each component's influence on the dataset's training efficacy. As shown in Table I, compared to the initial test when none of the adjustments were given, the Hue adjustment alone marginally improved precision and mAP50-95. When Saturation was adjusted alongside Hue, there was a further increase across all parameters. The final test, which included adjustments to all HSV components, showed a slight decline in precision but improvements in mAP50 and mAP50-95 compared to the initial test. These results indicate that Saturation adjustments were most effective in enhancing mAP50, highlighting its significance in the overall HSV adjustment strategy.

B. Experiments in real world

In a field covered with grass, the *LAF* was tested, resulting in the detection of 22 out of 18 golf balls. The positions of the detected golf balls can be seen on the map through the web page, as shown in Figure 4. However, there was an error where the number of detected golf balls exceeded the actual number.

Table I
HSV ADJUSTMENT TEST RESULT

HSV Configuration	**Precision**	**mAP50**	**mAP50-95**
Hue 0, Sat 0, Val 0	0.8196	0.499	0.2762
Hue 0.015, Sat 0, Val 0	0.8241	0.4949	0.2878
Hue 0.015, Sat 0.5, Val 0	0.8289	0.5002	0.295
Hue 0.015, Sat 0.5, Val 0.3	0.8047	0.5767	0.2959

Test results of incremental adjustments in Hue, Saturation, and Value, measured against Precision, mAP50, and mAP50-95.

Table II
LIST OF GPS COORDINATES

ID	**Time**	**Latitude**	**Longitude**
51	12-14-2023, 20:44:24	40.42600	-86.90995
52	12-14-2023, 20:44:24	40.42604	-86.90982
53	12-14-2023, 20:44:24	40.42603	-86.90981
54	12-14-2023, 20:44:25	40.42604	-86.90980
55	12-14-2023, 20:44:25	40.42603	-86.90980
56	12-14-2023, 20:44:25	40.42603	-86.90982
57	12-14-2023, 20:44:26	40.42603	-86.90983
58	12-14-2023, 20:44:26	40.42603	-86.90985
59	12-14-2023, 20:44:26	40.42602	-86.90984
60	12-14-2023, 20:44:26	40.42601	-86.90984

Experiment results for the GPS coordinates of lost golf balls, including ID, time, latitude, and longitude

The reason for this is as follows: firstly, the deep learning model YOLO used in *LAF* is an object detection model. Object detection models [32], unlike object tracking models [33], cannot inherently determine whether a golf ball has been detected before. Therefore, *LAF* distinguishes each golf ball based on GPS coordinates. However, due to fundamental accuracy issues with the GPS module and errors in the process of unit-converting the coordinates of each golf ball, there were instances where the same golf ball was stored in the database more than once.

V. Conclusions

A. Discussion

As a result of the final test, this system detected 22 out of 18 golf balls. There was a problem that it was recognized as

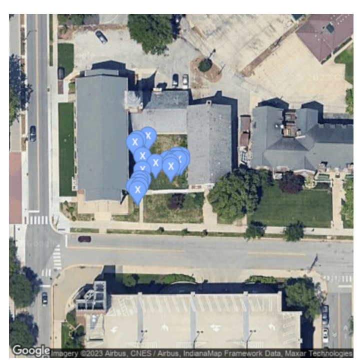

Figure 4. User Interface
The user interface that provides users with the GPS coordinates of the lost golf ball by displaying them as markers on the map

different, even if it was the same golf ball. This is owing to the inaccuracy of the GPS module. Moreover, the YOLO model in this system has undergone an experimental implementation of a custom data loader. An attempt exploring the use of a custom dataloader instead of the conventional method of passing a YAML file when supplying data to the YOLOv8n model. This is undertaken with the aim of fine-tuning the preprocessing, including augmentation, to better fit the custom dataset for the YOLOv8n model. However, the endeavor to use a custom data loader faced challenges as certain parameters of the *build_dataloder()* function provided by YOLOv8 were not yet developed by the YOLO team.

B. Conclusion

This paper presents the system for detecting lost golf balls on a golf course using LoRa communication and drawing up a list of coordinates of golf balls. The drone goes around and scans the entire golf course to detect golf balls. The Raspberry Pi on the drone side was successfully implemented to detect golf balls and calculate the coordinates of golf balls. The Raspberry Pi on the base station side was implemented to receive the coordinates of golf balls and deliver them to the web server on the cloud. The ESP32 attached to the drone and the ESP32 on the base station have established LoRa communication. Also, this system is devised to visualize the locations of golf balls, allowing individuals to easily locate and retrieve them on-site. It has a notable advantage in utilizing existing golf balls without discarding them, making them more environmentally friendly.

C. Future work

Currently, this system is limited to restrictive augmentation. In the future, upon the completion of the development of functions offered by YOLOv8, it will be possible to generate a custom data loader capable of loading and preprocessing data specific to our dataset. With the implementation of this custom dataloader, it should be feasible to directly apply augmentations using Albumentations [34] and custom preprocessing functions tailored to our data. This approach is expected to yield beneficial outcomes for both the model training process and the overall performance.

The current progress is limited to displaying the positions of lost golf balls on a map. Users are required to manually find and retrieve the golf balls by referencing the map. In future research, the plan is to further automate the process by implementing autonomous flight planning to the golf ball locations and creating a retrieval drone for the recovery of the golf balls. This will achieve full automation of the process of finding and retrieving lost golf balls.

Last, in the testing, there is an issue involving the misidentification of a single golf ball as multiple entities. Therefore, future research is needed to replace the less accurate GPS module with an improved version and develop a system capable of recognizing the same golf ball when not precisely matched to each decimal digit.

VI. ACKNOWLEDGEMENT

This research was supported by the Ministry of Science & ICT (MSIT), under the SW University Program (No. 2018-0-00216, No. 2018-0-00213, No. 2021-0-01393, and No. 2018-0-01879), supervised by the Institute for Information & communications technology Planning & evaluation (IITP)

REFERENCES

[1] Dylan Dethier. “Just how ridiculous is it to play 72 holes without changing golf balls?” In: *GOLF* (2019).

[2] Christina Macfarlane. “Golf balls: ’Humanity’s signature litter’”. In: *CNN* (2009).

[3] The R&A. “Golf participation continues to surge worldwide”. In: *The R&A* (2023).

[4] Karine Jarzecki et al. “Max Golf Balls: Biodegradable and Sustainable Golf Balls”. In: (2018).

[5] Marek Babiuch, Petr Foltỳnek, and Pavel Smutnỳ. “Using the ESP32 microcontroller for data processing”. In: *2019 20th International Carpathian Control Conference (ICCC)*. IEEE. 2019, pp. 1–6.

[6] Rahul Sen, Aditya Maan, and Upender Pandel. “Synthesis and Testing of Corn Starch Based Biodegradable Plastic and Composite”. In: *8th International Science, Social Science* (2017).

[7] Neogi Shubhaneel, Dey Apurba, and Chaterjee Pradip Kumar. “Corn starch industry wastewater pollution and treatment processes—A review”. In: *World* 1337.1303.6 (2018), pp. 1324–5.

[8] Zainab Waheed Abdullah and Yu Dong. “Biodegradable and water resistant poly (vinyl) alcohol (PVA)/starch (ST)/glycerol (GL)/halloysite nanotube (HNT) nanocomposite films for sustainable food packaging”. In: *Frontiers in materials* 6 (2019), p. 58.

[9] SK Vineeth, Ravindra V Gadhave, and Pradeep T Gadekar. “Polyvinyl alcohol–cellulose blend wood adhesive modified by citric acid and its effect on physical, thermal, mechanical and performance properties”. In: *Polymer Bulletin* 80.7 (2023), pp. 8013–8030.

[10] Grace Kaufman. *Biodegradable Golf Balls - Complete Information*. https://thegolfmine.com/biodegradable-golf-balls-complete-information/. Accessed: 2024-01-16. 2023.

[11] James Parker. *Are Biodegradable Golf Balls Worth The Cost?* https://biodegradablegolfballs.com/are-biodegradable-golf-balls-worth-the-cost/. Accessed: 2024-01-16. 2021.

[12] Joseph Redmon et al. “You only look once: Unified, real-time object detection”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016, pp. 779–788.

[13] Ross Girshick et al. “Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. June 2014.

[14] Ross Girshick. "Fast R-CNN". In: *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*. Dec. 2015.

[15] Tianxiao Zhang et al. *Efficient Golf Ball Detection and Tracking Based on Convolutional Neural Networks and Kalman Filter*. 2021. arXiv: 2012.09393 [cs.CV].

[16] Jansen C Liando et al. "Known and unknown facts of LoRa: Experiences from a large-scale measurement study". In: *ACM Transactions on Sensor Networks (TOSN)* 15.2 (2019), pp. 1–35.

[17] David Gourley and Brian Totty. *HTTP: the definitive guide*. " O'Reilly Media, Inc.", 2002.

[18] Leonard Richardson and Sam Ruby. *RESTful web services*. " O'Reilly Media, Inc.", 2008.

[19] Mohamed Aref and Axel Sikora. "Free space range measurements with Semtech Lora™ technology". In: *2014 2nd International Symposium on Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems*. 2014, pp. 19–23. DOI: 10.1109/IDAACS-SWS.2014.6954616.

[20] Olakunle Elijah et al. "Factors that Impact LoRa IoT Communication Technology". In: *2019 IEEE 14th Malaysia International Conference on Communication (MICC)*. 2019, pp. 112–117. DOI: 10.1109/MICC48337.2019.9037503.

[21] *Frequency Plans by Country*. Dec. 2023. URL: https://www.thethingsnetwork.org/docs/lorawan/frequencies-by-country/.

[22] Jcmcclurg. *Jcmcclurg, CC BY-SA 3.0 lt;https://creativecommons.org/licenses/by-sa/3.0gt;, via Wikimedia Commons*. Wikimedia Commons. 2012. URL: https://commons.wikimedia.org/wiki/File:FresnelSVG1.svg.

[23] Mrinmoy Bhadra. *GolfBallDetector Dataset*. https://universe.roboflow.com/mrinmoy-bhadra-lojma/golfballdetector. Open Source Dataset. visited on 2023-10-24. Mar. 2023. URL: https://universe.roboflow.com/mrinmoy-bhadra-lojma/golfballdetector.

[24] Agnieszka Mikołajczyk and Michał Grochowski. "Data augmentation for improving deep learning in image classification problem". In: *2018 International Interdisciplinary PhD Workshop (IIPhDW)*. 2018, pp. 117–122. DOI: 10.1109/IIPHDW.2018.8388338.

[25] Connor Shorten and Taghi M Khoshgoftaar. "A survey on image data augmentation for deep learning". In: *Journal of big data* 6.1 (2019), pp. 1–48.

[26] Abhiroop Bhattacharya and Sylvain G Cloutier. "End-to-end deep learning framework for printed circuit board manufacturing defect classification". In: *Scientific reports* 12.1 (2022), p. 12559.

[27] Barret Zoph et al. "Learning data augmentation strategies for object detection". In: *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXVII 16*. Springer. 2020, pp. 566–583.

[28] Winston Chen and Tejas Shah. "Exploring low-light object detection techniques". In: *arXiv preprint arXiv:2107.14382* (2021).

[29] Mengdan Sun et al. "Hue distinctiveness overrides category in determining performance in multiple object tracking". In: *Attention, Perception, & Psychophysics* 80 (2018), pp. 374–386.

[30] Eric W Weisstein. "Rotation matrix". In: *https://mathworld. wolfram. com/* (2003).

[31] Defense Mapping Agency. "Department of Defense World Geodetic System 1984: its definition and relationships with local geodetic systems". In: *Defense Technical Information Center* (1991).

[32] Zhengxia Zou et al. "Object detection in 20 years: A survey". In: *Proceedings of the IEEE* (2023).

[33] Fei Chen et al. "Visual object tracking: A survey". In: *Computer Vision and Image Understanding* 222 (2022), p. 103508.

[34] Alexander Buslaev et al. "Albumentations: fast and flexible image augmentations". In: *Information* 11.2 (2020), p. 125.