Advanced Avian Wildlife Management (AAWM) System through Deep Learning based UAV Swarm and Sonic Deterrents for Airport Safety

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Abstract

Birdstrikes pose significant challenges to both airplane and passenger safety. This study introduces an innovative advanced avian wildlife management system (AAWM) utilizing UAV swarms and deep learning-based models for wildlife detection in airport's vicinity. UAV swarms detect birds through onboard depth cameras and deep-learning models. Faster R-CNN and YOLOv9 models were trained and evaluated with IOU threshold values of 0.3 and 0.5. The Faster R-CNN model demonstrated best performance, achieving accuracies of 94.34% and 86.13% respectively. Upon accurate bird detection, the UAV swarm employs a sonic deterrent with frequencies ranging from 20KHz to 25KHz, effectively dispersing birds without causing harm. This integrated approach enhances airplane and bird safety in airport environments.

1. Introduction

Bird strikes pose a serious safety concern in aviation due to collisions between birds and aircraft during critical flight phases. Bird strikes can cause engine damage, windshield obstruction, and structural impairments, posing risks to passenger safety. Aviation authorities globally employ wildlife management programs and deterrent methods like noise, visual aids, physical barriers, and chemicals to mitigate bird strikes, but challenges persist. An Advanced Avian Wildlife Management System (AAWM) proposes innovative solutions such as UAV swarms with deep learning-based bird detection and sonic deterrents to enhance airspace protection effectively without harming birds or disrupting airport operations Fig:[1].

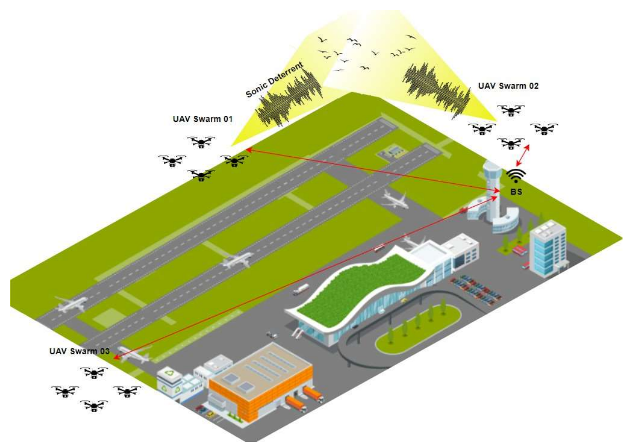

Figure 1. Proposed System Model for Advanced Avian Wildlife Management System.

2. Proposed System Overview Analysis

The proposed system integrates UAV swarms equipped with advanced depth cameras and deep learning models and sonic deterrents to address the challenge of detecting and managing wildlife near airports, thus enhancing safety for aircraft and wildlife birds. Deep learning models like Faster R-CNN and YOLOv9 enable real-time bird detection by recognizing and localizing objects efficiently. After detection, a sonic deterrent, foil membrane transducer, like the one used in Polaroid ultra-sonic range modules generates a high frequency of 20-25 kHz to scare the birds away. The UAV swarms are monitored from a control tower base station. This integrated system promises increased effectiveness in mitigating bird-related hazards, enhancing aviation safety, and supporting wildlife conservation efforts with humane bird management methods.

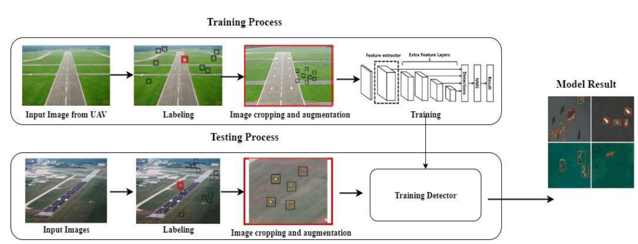

Figure 2. Flowchart of the proposed AAWM system based on the deep-learning method for bird detection.

2.1. System Model

Fig:[2] illustrates the proposed approach for bird identification, comprising four distinct phases. Initially, aerial images of birds are acquired using an Unmanned Aerial Vehicle (UAV). Subsequently, a labeling procedure is conducted to establish that a single bird corresponds to a 40 × 40 pixel box. The third phase involves image preprocessing techniques such as cropping and augmentation to generate numerous sub-images from the aerial photographs. The final stage focuses on training the deep-learning models by extracting features from the hidden layers. Ultimately, the efficiency of each learning model in bird detection is assessed through a rigorous testing process.

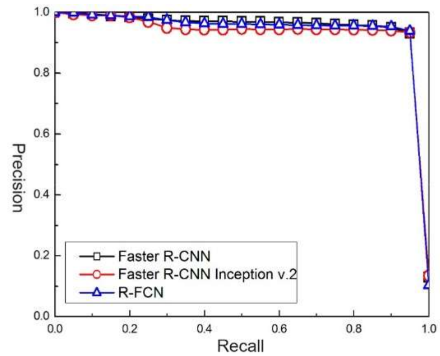

Figure 3. Precision-recall plot for Faster R-CNN model at IOU = 0.3.

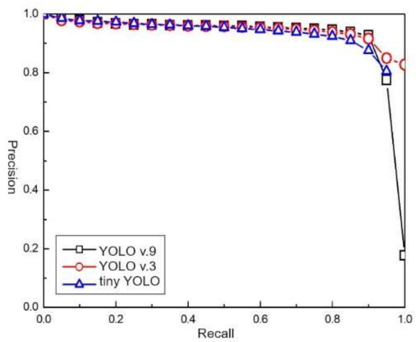

Figure 4. Precision-recall plot for YOLO model with IOU = 0.3.

2.2. Faster R-CNN Model and YOLOv9 Model

In Faster R-CNN, Region Proposal Network (RPN) initially predicts anchor box coordinates (x_a, y_a, w_a, h_a) and an object score using convolutional features, generating region proposals [1]. These proposals undergo Region of Interest (ROI) pooling to extract fixed-size feature maps (Pi) from corresponding regions [2]. A classification head uses SoftMax activation to predict class probabilities, while a regression head refines bounding box coordinates ($\Delta x'$, $\Delta y'$, $\Delta w'$, $\Delta h'$) for improved localization accuracy. Training involves a combined loss function comprising classification loss (computed using SoftMax cross- entropy) and regression loss (computed using smooth L1 loss).

$$ClassificationLoss = -\sum_i \sum_c 1(yi = c)\, log(pi, c) \quad (1)$$

$$RegressionLoss = \sum_i smooth_{L1}\,(\Delta_i - \Delta_i) \quad (2)$$

YOLO simplifies object detection into a single regression task by dividing the input image into an $S\times S$ grid. It directly predicts bounding boxes and class probabilities from grid cells, enabling fast processing suitable for real-time applications. Each grid cell in YOLO anticipates multiple bounding boxes (typically B) with associated confidence scores and class probabilities. Predictions include coordinates for bounding box centers *(x,y)* and dimensions *(w,h)*, computed using sigmoid and exponential functions for accurate localization. Confidence scores are determined based on objectness probability and the inter- section over union (IoU) metric, ensuring precise detection [3].

2.3. Sonic Deterrent

Foil membrane transducers, similar to those found in Polaroid ultrasonic range modules, are capable of emitting sonic deterrents at frequencies of 20–25+ kHz [4], falling within the ultrasonic range. The foil membrane vibrates in response to specific electrical inputs, thus, producing ultrasonic sounds effective in repelling birds.

3. Results Analysis

This study mainly compared two object detection models, Faster R-CNN and YOLOv9, using a diverse dataset of bird species. Other models such as R-FCN, YOLOv2 and Tiny YOLO were also trained. Intersection of union (IOU) is used as an indicator to determine whether or not an object is accurately identified. The Faster R-CNN model employed a ResNet-50 and achieved an impressive accuracy of 94.34% (at IOU=0.3). In contrast, YOLOv9 utilized a lighter backbone network with 07 convolutional layers and smaller filter sizes with Adam optimizer, achieving an accuracy of approximately 84.74% (at IOU=0.3) with a loss value of 0.35. This study highlights the trade-offs between accuracy and real-time performance. Over- all Faster R-CNN model performance was exceptional. After the successful detection of birds, onboard sonic deterrent Foil membrane transducers emit a frequency range of 20KHz to 25KHz, which is known to be aversive to birds but harmless to humans, therefore scaring the birds.

4. Conclusion and Future Work

This study presents a novel AAWM system that uses UAV swarms, deep learning models, sonics deterrents, to identify and disperse wildlife birds near airports. Results showed that faster R-CNN model achieved good accuracy of 94.34% and 81.13% at IOU=0.3 and 0.5 respectively. Once bird presence is accurately detected, the UAV swarm uses a sonic deterrent to repel birds without harming them. Furthermore, enhancing the proposed system's efficiency and practical implementation are the foremost KPIs.

5. Acknowledgement

This research was supported by the MSIT (Ministry of Science and ICT), Korea , under the ITRC (Information Technology Research Center) support program (IITP-2024-RS-2023- 00259061) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation). This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ICAN(ICT Challenge and Advanced Network of HRD) program(IITP-2024-RS-2022-00156394) supervised by the IITP(Institute of Information & Communications Technology Planning & Evaluation)

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