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衛星物聯網-智慧鳥類監測與驅趕系統
Smart Bird Monitoring and Selective Deterrence System Based on Satellite IoT

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***Abstract*—This study presents the development of Sanxia Avian Lens, an integrated edge-AI and satellite-IoT system for campus-scale ecological monitoring and selective bird deterrence around Mind Lake at National Taipei University. The proposed system combines camera-based bird detection, edge artificial intelligence, non-terrestrial network (NTN) satellite communication, cloud gateway integration, and web-based visualization to support real-time observation of avian activity in an outdoor campus environment. A Raspberry Pi-based edge device is deployed to capture image data and perform bird species detection locally, reducing the need for continuous high-bandwidth transmission while enabling faster on-site decision-making. Detected bird information is then transmitted through a satellite communication module and the CeresGate cloud gateway via an NTN satellite link, which allows data delivery even in environments where conventional terrestrial networks may be unstable or unavailable. Based on the supported satellite communication architecture, the NTN component can be understood as a flexible satellite-IoT solution that may involve GEO-based wide-area coverage or LEO-based 5G NTN connectivity depending on the adopted Hestia module or gateway model. The transmitted data are forwarded to an MQTT broker, stored in a PostgreSQL database, and rendered on Sanxia Avian Lens, a two-dimensional and three-dimensional visualization website designed to display detection records, ecological information, and monitoring results in an accessible format. These results confirm the feasibility of combining edge-AI, satellite-IoT communication, MQTT-based data transmission, and web visualization for ecological monitoring and selective deterrence in academic campus environments.**

Keywords: Bird Monitoring, YOLO26n, Edge Computing, Satellite IoT, Non-terrestrial Networks (NTN), Selective Deterrence, Autonomous Mobile Robot, MQTT

I. Introduction

Environmental monitoring and wildlife management have become important issues in urban settings. University campuses are suitable study sites because they combine ponds, vegetation, open spaces, and human activity within a compact environment. The Mind Lake area of National Taipei University (NTPU) contains diverse bird activity and provides an appropriate field site for campus-scale bird monitoring and management.

However, bird monitoring and selective pest-bird management remain challenging. Manual observation is labor-intensive and incomplete over long periods, while repeated human deterrence may be inefficient and may accidentally harm birds. Conventional deterrence methods can also become less effective due to habituation, and unstable terrestrial network coverage may limit real-time data transmission and remote visualization.

To address these issues, this study proposes an integrated edge-AI and satellite-IoT system for automated bird monitoring and selective deterrence at Mind Lake. The main contributions are as follows:

1) A YOLO26n-based model is developed for real-time bird detection under campus field conditions.
2) A dual-threshold strategy is used to separate ecological logging from high-confidence deterrence activation.
3) A mobile deterrence subsystem provides event-driven and non-continuous deterrence.
4) A satellite-IoT pipeline is constructed using the Hestia NTN module, CeresGate gateway, MQTT broker, and PostgreSQL database.
5) The Sanxia Avian Lens platform visualizes bird events, weather information, map markers, and 3D campus scenes.

The remainder of this paper is organized as follows. Section II reviews related work, Section III presents the system architecture, Section IV describes the experiments and results, Section V discusses limitations and future work, and Section VI concludes the study.

II. Related Work

A. Real-Time Object Detection

YOLO, proposed by Redmon et al. [1], reformulated object detection as a single-stage regression task, enabling real-time prediction of bounding boxes and classes in one forward pass. This study adopts YOLO26 [2] because its efficient inference, NMS-free end-to-end design, and lightweight detection head are suitable for embedded bird-detection scenarios.

The evaluation follows common object detection conventions from MS COCO [3] and Pascal VOC [4]. Since this study reports mAP@0.5, the fixed IoU threshold used in Pascal VOC is especially relevant.

B. Edge Computing and Embedded Inference

Shi et al. [5] described edge computing as moving computation closer to data sources to reduce latency and improve responsiveness. This is useful for ecological monitoring because transmitting every image frame to a remote server would increase bandwidth usage and delay deterrence responses.

In this study, edge-side inference allows the Raspberry Pi to process visual data locally and transmit only compact event-level results. Lightweight models such as YOLO26 are therefore suitable for balancing detection accuracy, computation, memory, power, and communication limits.

C. Data Augmentation and Model Generalization

Shorten and Khoshgoftaar [6] showed that data augmentation improves model generalization by increasing training diversity. This is important for campus bird recognition because outdoor images may contain lighting changes, occlusion, blur, viewpoint variation, and seasonal background differences.

Therefore, this study applies augmentation methods such as orientation correction, contrast adjustment, and Gaussian noise injection to improve robustness under practical Mind Lake field conditions.

D. Bird Deterrence and Habituation

Bird deterrence must avoid excessive or predictable activation because birds may habituate to repeated stimuli. Avery and Werner [7] emphasized the importance of novelty, placement, and controlled use, while Blackwell et al. [8] showed that nonlethal deterrence can influence bird behavior under suitable conditions.

These studies support the event-driven deterrence design used in this project. The proposed dual-threshold strategy records low-confidence detections for ecological logging but activates deterrence only for high-confidence target detections, reducing unnecessary disturbance and delaying habituation.

E. Satellite Communication and Non-Terrestrial Networks

Kodheli et al. [9] highlighted the role of satellite communication in wide-area connectivity and space-based data collection, especially where terrestrial networks are unavailable or unstable. The 3GPP TR 38.811 report [10] further provides the study framework for NR support of non-terrestrial networks.

In this project, the Hestia NTN module and CeresGate gateway transmit compact bird-detection events through a satellite link. By combining edge inference with satellite-IoT communication, the system avoids sending large image streams and forwards lightweight results to the MQTT broker and PostgreSQL database.

F. Campus Bird Species Reference

Local ecological references help define target species and interpret monitoring results. The *Field Guide to Birds of NTPU* [11] provides campus-specific bird information and supports the selection of Mind Lake species used in the detection model and visualization platform.

III. Methodology

A. System Overview

The proposed system enables autonomous bird detection, selective deterrence, and real-time remote data transmission in areas with limited or unreliable terrestrial networks. As shown in Fig. 1, the architecture consists of three layers: the edge layer, the NTN satellite link, and the cloud visualization layer.

B. Operational Scope and Deployment Conditions

The current prototype shown in Figs. 2a and 2b is evaluated around Mind Lake under sunny and dry campus conditions. This scope is selected because clear weather provides better bird visibility, camera quality, rover mobility, and satellite message transmission stability. The web platform also displays weather information to support environmental interpretation.

Rainy or adverse-weather deployment is not included in this evaluation, as moisture may affect camera visibility, wheel traction, exposed electronics, and rover movement. Therefore, this work focuses on validating the core pipeline, including bird detection, selective deterrence, satellite transmission, database logging, and Sanxia Avian Lens visualization. Weather-resistant deployment is left for future work.

C. Hardware Platform

Table I lists the principal hardware components used in the current prototype. The hardware design combines an edge-AI controller, satellite communication module, mobile rover chassis, motor-driving circuit, obstacle sensing, power regulation, and protective enclosure materials.

D. Software Platform

Table II lists the software stack used across the edge, communication, database, backend, and visualization layers. The system is designed as an IoT ecosystem that bridges hardware-level sensing and actuation with a web-based two-dimensional and three-dimensional visualization dashboard.

The integration layer uses a Python bridge with `paho-mqtt` to subscribe to the `birds/events` topic and `psycopg2` to write decoded event payloads into PostgreSQL. The frontend uses React Three Fiber and Drei to render the Omni Scope 3D scene, while material conversion logic converts imported textures into lighting-responsive `MeshStandardMaterial` objects. The platform also supports English and Traditional Chinese localization. For 2D visualization, backend detection counts are converted into density markers and fly-away indicators for deterrence events.

E. Edge AI: Bird Recognition Model

1) Dataset Construction: The YOLO26n recognition model focuses on bird species observed around Mind Lake, where the prototype is deployed. The dataset includes 11 target classes: Eurasian Tree Sparrow, Red Turtle Dove, Common Kingfisher, Black-crowned Night Heron, Common Moorhen, White-breasted Waterhen, Rock Pigeon, Muscovy Duck, Mallard, Domestic Duck, and Domestic Goose [11].

Field images were collected around Mind Lake, and Roboflow images were added for classes with fewer samples. Approximately 20,000 annotated images were prepared for training and validation. This focused dataset improves deployment relevance and aligns the model with the actual operating environment of the mobile deterrence system.

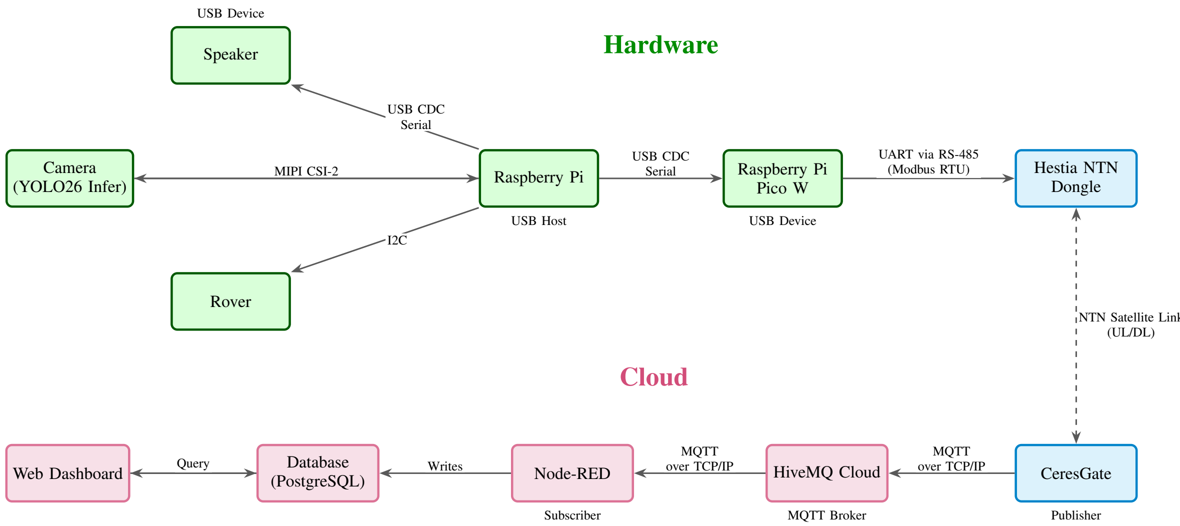


Fig. 1: System architecture of the proposed edge-AI and satellite-IoT bird monitoring system. The hardware layer performs local image inference and device communication, while the cloud layer stores and visualizes event-level detection data into the web dashboard. The dashed line represents the NTN satellite uplink and downlink between the Hestia NTN dongle and CeresGate.

TABLE I: Hardware Platform Components

Component	**Model / Spec**	**Purpose**
Single-board computer	Raspberry Pi 4 & 5	Main edge controller for camera input, YOLO inference, event generation, and local subsystem coordination.
Microcontroller	Raspberry Pi Pico W & 2 W	Low-level device coordination and communication support for field-deployed sensing modules.
Camera	Raspberry Pi Camera v3 & AI Camera	Image acquisition for bird recognition in the Mind Lake area.
Satellite module	Hestia A1 NTN Dongle	Satellite uplink for transmitting event data when terrestrial network coverage is unavailable or unstable.
Ultrasonic sensor	HC-SR04	Obstacle-distance sensing for rover movement safety.
Drive motors	Four 12 V gear motors, 400 rpm	Rover propulsion for mobile deterrence movement.
Motor control	Two BTS7960 motor drivers; PCA9685 16-channel PWM driver	High-current bidirectional motor control and PWM signal distribution.
Signal isolation and prototyping	Four-channel PC817 optocoupler module, 170-hole breadboard, 1 kΩ resistors, jumper wires	Signal isolation, circuit prototyping, and wiring integration.
Power system	LiPo battery, LM2596 step-down converter, rocker switch, 16/18 AWG red and black wires	Field power supply, voltage regulation, and manual power control.
Mechanical structure	Motor mounting brackets, robot wheels, brass hex couplings, M3 screws, M3*80 mm isolation columns	Rover chassis assembly, motor mounting, and structural support.
Protective materials	Corrugated plastic, black heating tube, acrylic box, 3 mm acrylic sheet	Electrical insulation, component protection, and prototype enclosure fabrication.

2) Image Preprocessing and Data Augmentation: Image preprocessing and data augmentation were applied to improve model generalization under real field conditions around Mind Lake, where images may suffer from blur, low quality, and insufficient lighting. Three augmentation methods were used during training.

Low-resolution blur. This augmentation simulates detail loss caused by distant objects, low-resolution cameras, or image resizing. It is performed by downsampling and then upsampling the image:

$$I' = U_s(D_s(I)) \tag{1}$$

where I is the original image, $D_s(\cdot)$ is downsampling, and $U_s(\cdot)$ restores the image size. This helps the model handle blurred or pixelated bird images.

Low-quality image simulation. This method simulates degradation caused by compression or unstable camera quality:

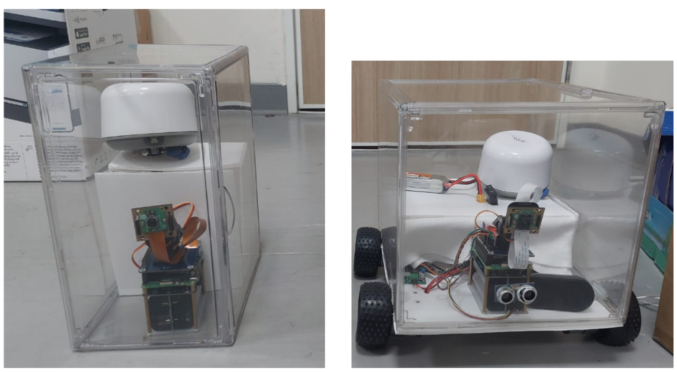
$$I' = Q_q(I) \tag{2}$$

where $Q_q(\cdot)$ represents quality degradation and q controls the degradation level. It helps the model recognize birds in unclear or compressed images.

Low-light effect. This augmentation simulates darker

TABLE II: Software Platforms

Category	**Technology**	**Purpose**
Edge OS	RPi OS Lite	Lightweight Linux distribution running on field-deployed Raspberry Pi devices.
Edge firmware	MicroPython	Low-level firmware for Raspberry Pi Pico W / Pico 2 W devices and sensor-side communication logic.
AI framework	Ultralytics YOLO26n	Lightweight real-time bird species recognition on the edge device.
Protocols	MQTT, Modbus RTU (RS-485)	MQTT for bird-event transmission; Modbus RTU over RS-485 for hardware-level communication where required.
Satellite gateway	CeresGate	Bridge that converts satellite NTN messages into standard MQTT payloads and forwards them to the cloud-side message system.
MQTT broker	HiveMQ Cloud	Central cloud-based message broker routing JSON payloads from field devices to the database bridge and backend services.
Flow automation / Data pipeline	Node-RED	MQTT data processing, JSON transformation, data routing, and forwarding of event records to the database.
Database	PostgreSQL	Relational storage for bird events, detection results, locations, weather-related records, and system data.
Database management	DBeaver	Database inspection, query execution, schema checking, and event data management during development and testing.
Deployment	Docker	Containerized deployment of backend, database, Node-RED, and MQTT-related services to improve portability and maintainability.
Backend	Python Flask	RESTful API layer providing endpoints while also serving backend logic for the web system.
Frontend UI	HTML/CSS/JavaScript, Bootstrap 5, Chart.js	Dashboard layer for event tables, statistics, community information, and general user interaction.
Frontend 3D	React, Three.js, React Three Fiber	Interactive Omni Scope engine for rendering the campus scene and UAV/rover-related visualization.
3D asset pipeline	Blender	Modeling and optimization of the NTPU campus three-dimensional scene exported as `.glb` assets.



(a) Fixed Point (b) Mobile

Fig. 2: Proposed Models

(a) Original (b) Augmented

Fig. 3: Effect of the preprocessing and data augmentation pipeline on a representative Mind Lake bird image.

outdoor conditions caused by shadows, cloudy weather, or weak sunlight:

$$I' = \alpha I \tag{3}$$

where α is a brightness reduction factor with $0 < \alpha < 1$. This improves detection robustness under low-light conditions.

This step enhanced the amount of dataset from 20.000 original images to 80.000 original annotated and augmented images.

3) Model Training: YOLO26n was selected for its lightweight architecture and suitability for edge-side. Fig. 4 shows training pipeline before deployment on the Raspberry Pi 5. Transfer learning from COCO-pretrained weights was conducted for 50 epochs. As shown in Fig. 5, the training losses decreased consistently, and the validation box and DFL losses followed a similar downward trend. Although the validation classification loss showed moderate fluctuation, the overall evaluation metrics remained stable. The final model achieved a precision of approximately 0.956, a recall of approximately 0.925, and an mAP@0.5 of 0.959. These results indicate that the trained detector provides reliable performance for campus bird detection under the evaluated conditions.

F. Dual-Threshold Inference Strategy

A single fixed confidence threshold cannot simultaneously optimize ecological data completeness and deterrence precision. This study therefore adopts a dual-threshold strategy. The lower threshold is used for ecological logging, while the higher threshold is used only for deterrence activation. The decision flow is shown in Fig. 6

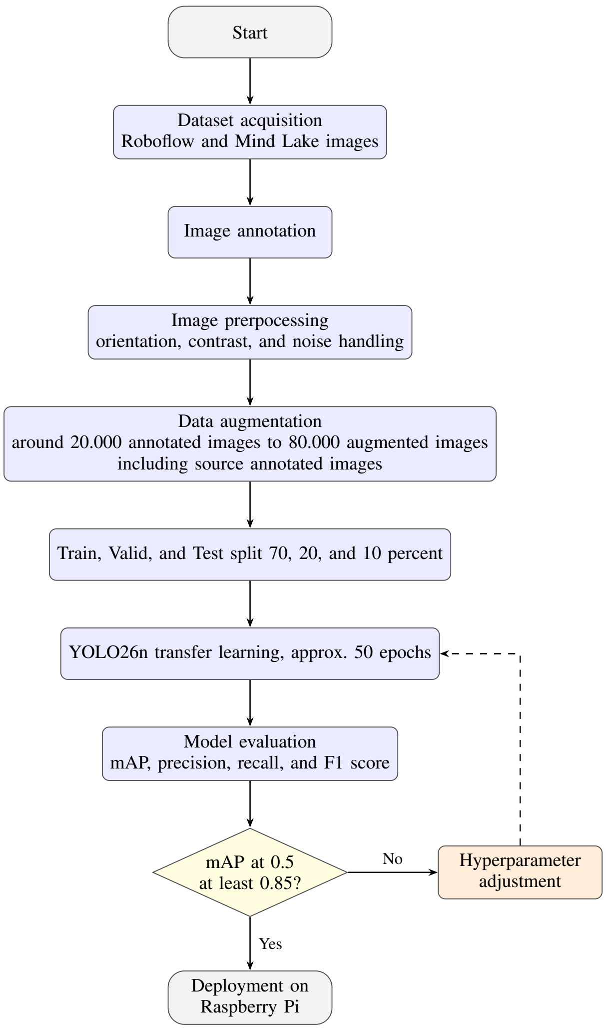


Fig. 4: Model training and deployment workflow. If the validation mAP at 0.5 does not meet the target threshold, the model is adjusted and retrained before deployment.

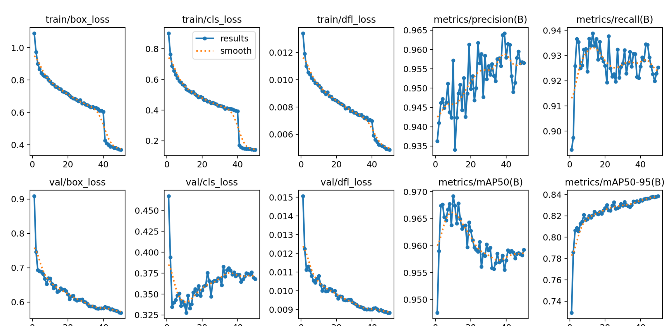


Fig. 5: YOLO26n training convergence over 50 epochs. Training losses generally decrease, validation losses show an overall downward trend, and the final model reaches approximately 0.959 mAP@0.5.

G. Satellite Transmission System

Fig. 7 shows The satellite link serves as the primary communication channel between edge devices and the cloud database when terrestrial network access is unavailable. After local inference is performed on the Raspberry Pi, each confirmed detection event is first organized as a structured JSON payload. The payload contains essential event fields such as device identifier, timestamp, detected class identifier, confidence score, location information, and deterrence status. To satisfy the transmission constraints of the NTN channel, this JSON payload is compacted and converted into a hexadecimal payload before being sent through the Hestia NTN dongle.

The encoded hex payload is transmitted through the NTN satellite link and received by the CeresGate cloud gateway. CeresGate then forwards the satellite message to the MQTT broker, allowing the cloud-side system to receive satellite-originated field events using a standard publish-subscribe communication model. Once validated, the architecture can scale to additional field devices by extending MQTT topic subscriptions and backend database handling.

TABLE III: Evaluation Metrics

Metric	**Description**
Model Performance	
mAP@0.5	Mean AP at IoU threshold 0.5
mAP@0.5 to 0.95	Mean AP across IoU 0.5 to 0.95
Precision	True positive fraction of predictions
Recall	True positive fraction of ground truth
F1 score	Harmonic mean of precision and recall
Species-level average precision	Species-level recognition performance

H. Backend and Visualization Platform

The Node-RED backend subscribes to MQTT event messages forwarded from CeresGate. Since the satellite message arrives as a hexadecimal payload, Node-RED decodes it back into JSON, validates the fields, and stores structured records in PostgreSQL, including timestamp, species id, confidence score, and event type.

The backend also provides RESTful endpoints for event retrieval, location data, weather information, and dashboard integration. Sanxia Avian Lens uses these records to display event tables, species statistics, weather context, detection markers, and deterrence indicators through two-dimensional and three-dimensional campus visualization.

IV. Experiments and Results

Field evaluations were conducted over five weeks around Mind Lake at National Taipei University. The current evaluation focuses on sunny and dry conditions because they provide stable image capture, safer rover movement, and more reliable field operation. Rainy-weather deployment is not included in the present quantitative evaluation.

A. Evaluation Metrics

Performance is assessed in model recognition quality, Table III summarizes all metrics used in the current evaluation.

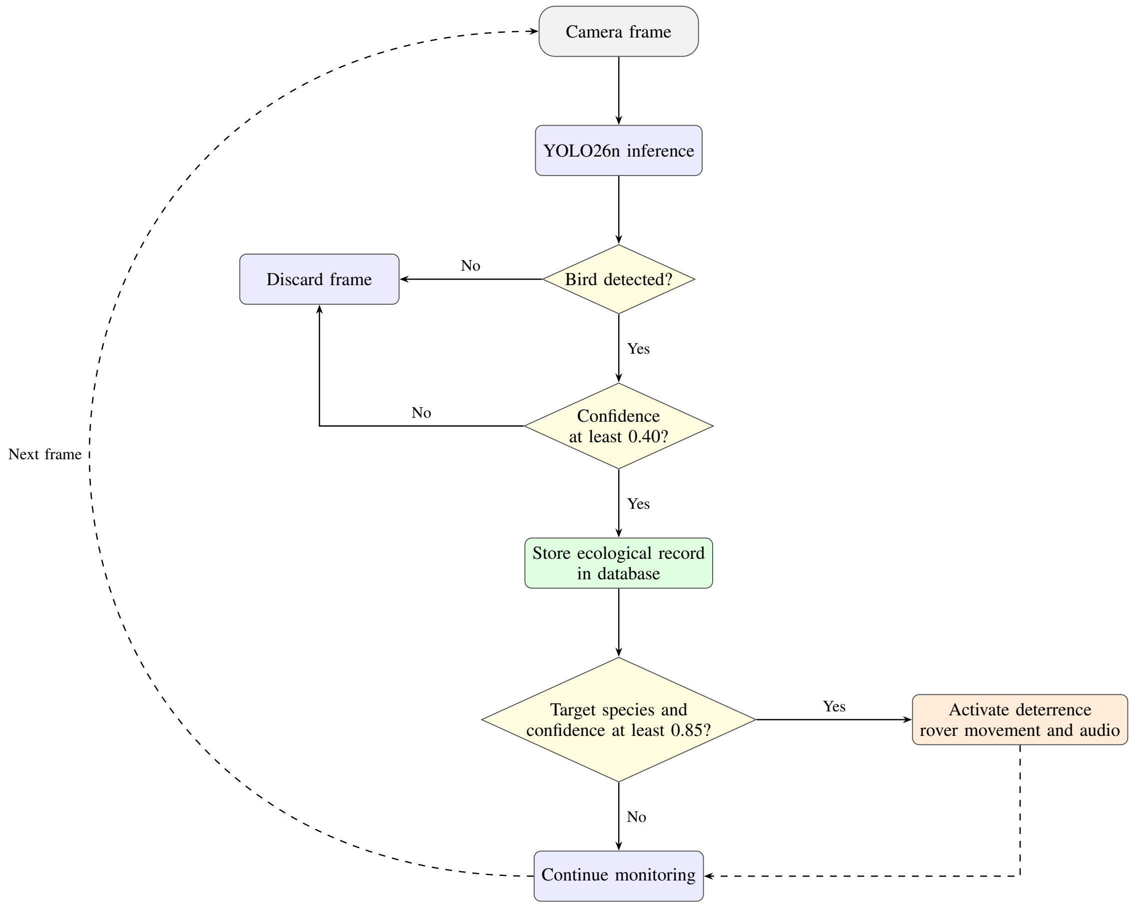


Fig. 6: Dual-threshold inference decision flow. The lower confidence threshold preserves ecological observations, while the higher confidence threshold activates deterrence only when the target species is detected with sufficient certainty.

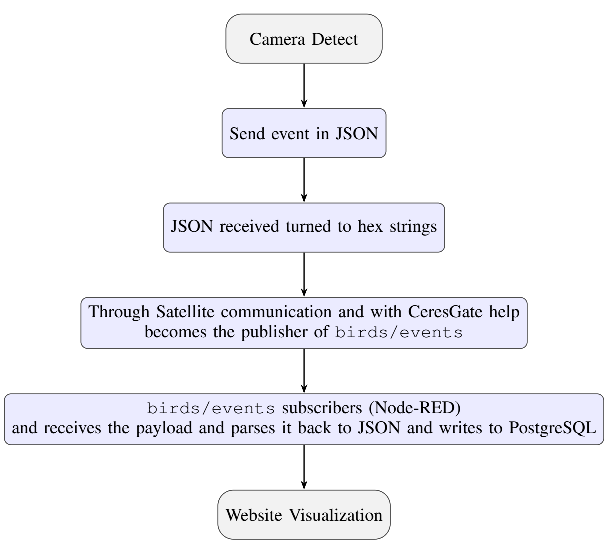


Fig. 7: Satellite communication pipeline.

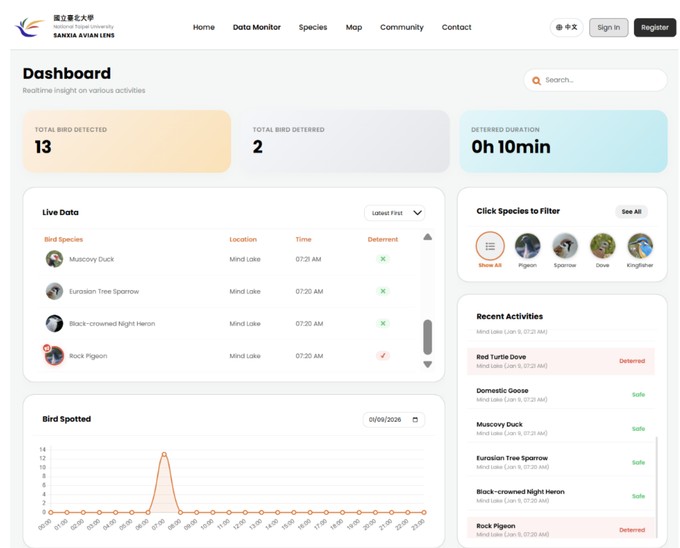
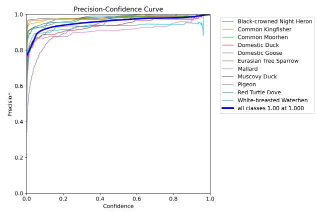


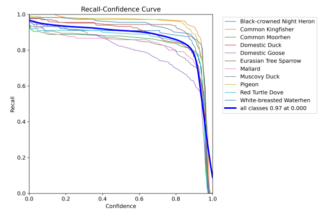
Fig. 8: Sanxia Avian Lens web-based visualization dashboard displaying real-time bird event logs and a spatiotemporal campus map.

B. Bird Recognition Performance

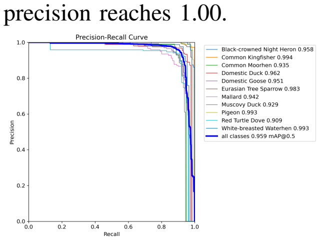
The confidence-based evaluation curves support the threshold design of the proposed system. Fig. 9a shows



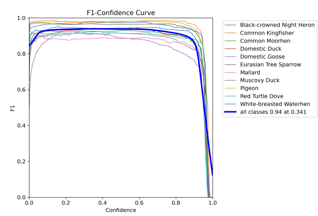
(a) Precision versus confidence threshold. At threshold 1, precision reaches 1.00.



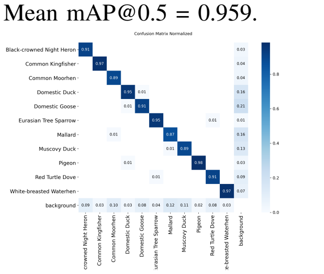
(b) Recall versus confidence threshold. At threshold 0.0, recall reaches 0.97.



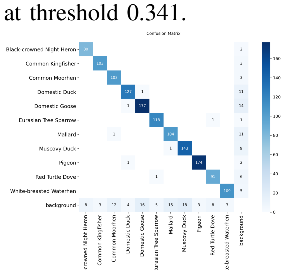
(c) Precision-recall curves for all 11 evaluated Mind Lake species. Mean mAP@0.5 = 0.959.



(d) F1 score versus confidence. Peak mean F1 of 0.94 is achieved at threshold 0.341.



(e) Normalized confusion matrix.



(f) Confusion matrix.

Fig. 9: Evaluation Metrics.

that precision increases as the confidence threshold becomes stricter, reaching approximately 1.00 near a threshold of 1.00. In contrast, Fig. 9b shows that recall is highest at low thresholds, reaching approximately 0.97 at a threshold of 0.000, and decreases as the threshold increases. This indicates a trade-off between detection reliability and detection coverage.

Based on this trade-off, the system adopts a dual-threshold strategy. A lower threshold is used for ecological logging to record more bird appearances, while a higher threshold is used for deterrence activation to avoid unnecessary responses caused by uncertain detections.

The precision-recall curve in Fig. 9c shows strong overall performance across the 11 Mind Lake bird species, with an all-class mAP@0.5 of 0.959. Species such as Common Kingfisher, Pigeon, White-breasted Waterhen, and Eurasian Tree Sparrow achieve high AP values, while Red Turtle Dove, Muscovy Duck, Common Moorhen, and Mallard remain more challenging under field conditions.

As shown in Fig. 9d, the all-class F1 score reaches approximately 0.94 at a confidence threshold of 0.341. Therefore, this value is suitable for general event logging, while a higher threshold such as 0.85 can be used for high-confidence deterrence activation.

The normalized confusion matrix in Fig. 9e and the confusion matrix in Fig. 9f show that most predictions are concentrated along the diagonal, indicating good species-level classification. Overall, the results confirm that YOLO26n performs reliably for campus-scale bird monitoring, while careful threshold selection remains important for deterrence applications.

C. Satellite, Backend, and Website

The satellite transmission experiment verifies the end-to-end delivery of bird-detection events from the Raspberry Pi to the Sanxia Avian Lens website. Because NTN satellite communication has limited payload capacity, the system uses compact JSON keys such as `t`, `ts`, and `c` instead of longer names such as `event_type`, `timestamp`, and `confidence`.

Each event is generated as compact JSON, encoded into a hexadecimal payload, transmitted through the Hestia NTN dongle, and received by CeresGate. The message is then forwarded to the MQTT broker, decoded by Node-RED, parsed, and stored in PostgreSQL. The website retrieves these records through RESTful API endpoints for visualization.

The event schema contains three common fields: `t`, `id`, and `ts`. The field `t` represents the event type, where `0` is detection, `1` is target-state change, and `2` is repellent action. The field `id` is a unique 12-character hexadecimal identifier, while `ts` stores the Unix timestamp.

For example, a pigeon detection event is represented as:


```
{"t":0,"id":"a1b2c3d4e5f6","ts":1717850000,"b":8,"c":0.88}
```


Here, `b=8` represents pigeon and `c=0.88` represents the detection confidence. Before transmission, the JSON string is encoded into hexadecimal format, shown below in shortened form:


```
7b2274223a302c226964223a226131623263...
...336434653566636222c227473223a313731...
...373835303030302c2262223a382c2263223a302e38387d
```


After reception, Node-RED decodes the payload back into JSON, validates the fields, and writes the parsed data into PostgreSQL. This confirms the complete data path from edge-side detection to satellite transmission, cloud storage, RESTful API retrieval, and web-based visualization.

V. Discussion

A. Detection Capability and Threshold Design

The YOLO26n model is designed for lightweight inference on the Raspberry Pi platform and delivers real-time performance sufficient for prompt deterrence activation. The dual-threshold design operationally decouples ecological data collection from active pest management. The lower threshold maximizes long-term behavioral records, while the higher threshold ensures that deterrence stimuli are delivered only under high certainty, reducing unnecessary disruption to non-target species.

B. Satellite Communication Trade-Offs

The NTN satellite link introduces bandwidth and latency constraints not present in terrestrial IoT systems. Future work should establish quantitative relationships between SINR, RSRP, latency, and transmission success rate across different weather conditions and field locations, providing an empirical basis for adaptive retransmission strategies.

C. Deterrence Effectiveness and Habituation Mitigation

Consistent with findings by Avery and Werner [7] and Blackwell et al. [8], a static always-on deterrent may lose effectiveness through habituation. The event-driven activation mechanism confines deterrence stimuli to confirmed detection windows, reducing stimulus frequency and delaying the onset of habituation. Extended longitudinal field measurements would allow habituation curves to be quantified and optimal activation intervals to be determined.

D. Limitations

Four principal limitations are acknowledged. First, the current prototype has been evaluated only under sunny and dry Mind Lake conditions and has not yet been validated as an all-weather system. Second, the absence of GPS prevents real-time trajectory logging; the current campus map primarily visualizes predefined event locations and detection markers. Third, ground-based deterrence cannot reach birds perched at elevation, such as tree canopies or rooftops, limiting coverage to low-altitude targets.

VI. Limitations and Future Work

GPS integration. Adding a GPS module would enable dynamic positioning and trajectory logging, displaying bird event locations and rover paths on the visualization map in real time.

Aerial deterrence platform. Developing a quadrotor that simulates raptor flight behavior would extend deterrence coverage to elevated locations inaccessible to the ground rover, substantially increasing efficacy against perched birds.

Expanded species recognition. Enlarging the training dataset to cover additional species and using active learning to prioritize underrepresented classes would improve generalization across broader campus and regional ecosystems.

Weather-resistant deployment. Future hardware revisions should include waterproof enclosures, improved wheel traction, and protected electrical connectors so that the system can be evaluated under rainy and adverse-weather conditions.

VII. Conclusion

This study presented a smart bird monitoring and selective deterrence system for the Mind Lake area of National Taipei University, integrating edge-AI inference, NTN satellite-IoT communication, and a mobile deterrence rover. The system addresses limitations in manual observation, repeated deterrence, and communication reliability in network-limited environments.

The YOLO26n model was trained using approximately 80,000 augmented and annotated images and achieved an overall mAP@0.5 of 0.959 across 11 bird classes, with pigeon detection reaching an AP of 0.993. A dual-threshold strategy supports ecological logging and high-confidence deterrence activation, balancing data completeness with reduced false deterrence.

Compact JSON events are converted into hexadecimal payloads and transmitted through the Hestia NTN module and CeresGate gateway. The data is forwarded through MQTT, decoded by Node-RED, stored in PostgreSQL, and retrieved through RESTful APIs for Sanxia Avian Lens visualization.

Overall, the system demonstrates the feasibility of combining edge AI, satellite-IoT transmission, and web visualization for campus-scale bird monitoring. Future work will focus on GPS trajectory logging, aerial deterrence, weather-resistant hardware, and expanded species recognition.

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