Artificial Intelligence-Based Detection and Prediction of Giant African Snail (*Lissachatina Fulica*) Infestation in the Galápagos Islands

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Abstract: The Galápagos Archipelago are confronting a significant threat from invasive species, notably *L. fulica*, which disrupts the delicate balance of their natural ecosystem. An innovative solution is proposed, employing mobile application technology and artificial intelligence (AI) to streamline the collection, analysis, and prediction of *L. fulica* movements. The mobile application facilitates efficient recording of *L. fulica* sightings by field teams, including Global Positioning System (GPS) coordinates, type, condition, and quantity. Data collected is transmitted to a cloud-based server for storage and analysis, where machine learning algorithms process time-series data to generate predictive models of *L. fulica* movement patterns. Results underscore the effectiveness of AI in enhancing the efficiency and accuracy of Giant African Snail (GAS) detection and movement estimation, facilitating informed decision-making by administrators and managers. By safeguarding the native flora and fauna of the archipelago, this solution represents a significant stride towards mitigating the impact of invasive species and preserving the unique biodiversity of the Galapagos Islands.

1 INTRODUCTION

The Galápagos Archipelago, renowned for its unparalleled biodiversity and unique ecosystems, faces an ongoing challenge in the form of invasive species that threaten its delicate ecological balance (Khatun, 2018), (Collins et al., 2019). Among these invaders, *Lissachatina fulica*, the giant African snail stands out as a particularly serious threat (Miquel and Herrera, 2014). This mollusk ranks high on the list of the 100 most harmful alien species in the world due to its rapid proliferation and devastating impact on native flora and fauna (Simberloff and Rejmanek, 2020)- Traditional methods of monitoring and controlling *L. fulica* infestations rely heavily on manual data collection processes, which are often labor-intensive, time-consuming, and prone to errors (Elias, 2022). In response to these limitations, there is an urgent need for innovative approaches that leverage technology to enhance the efficiency and effectiveness of pest detection and management efforts.

In this paper, we present a novel solution aimed at automating the detection and prediction of *L. fulica* infestations in the Galápagos Archipelago through the integration of mobile application technology and artificial intelligence (AI). Our proposed system seeks to revolutionize the way *L. fulica* sightings are reported, recorded, and analyzed, thereby facilitating proactive and data-driven decision-making in pest control operations.

Our solution leverages mobile devices and AI algorithms to empower field squads conducting *L.*

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fulica surveillance by enabling real-time data collection and transmission directly from the field. The mobile app streamlines data collection and automatically extracts temperature and humidity data using Google APIs, aiding in pest classification and seasonal analysis. This reduces the workload on field personnel while enhancing data accuracy and timeliness. The centralized server hosted in the cloud receives and analyzes collected data using sophisticated machine learning algorithms to generate predictive models of *L. fulica* movement patterns. These models, based on historical data and environmental variables, allow stakeholders to anticipate and proactively respond to potential outbreaks, minimizing the impact on native ecosystems.

This represents a significant advancement in the field of pest management, offering a scalable and cost-effective approach to monitoring and controlling invasive species in sensitive ecological environments. Through the synergistic integration of mobile technology, machine learning, and deep learning, we aim to empower conservationists and policymakers with the tools and insights needed to safeguard the unique biodiversity of the Galápagos Islands for generations to come.

2 RELATED WORKS

2.1 Plagues and the Galápagos Ecosystem

Pests pose a multifaceted threat by interfering with the normal development of ecosystems, affecting agriculture, public health, ecology, economy and food security (Warner, 2019). This challenge is especially evident in the Galapagos Islands, where invasive species pose a crucial threat to the conservation of the biodiversity of this natural laboratory. The introduction of exotic species can lead to the extinction of endemic species and affect key economic sectors, highlighting the urgency of preventive measures and effective management. The uniqueness of the Galapagos as an evolutionary laboratory underscores the need for international cooperation and continued research to address the emerging dynamics of biological invasions.

One example of this problem is the snail *L. fulica*, whose impact on native biodiversity has been documented. Studies have documented the impact of the snail *L. fulica* on native biodiversity, causing the disappearance of endemic snails in the Hawaiian Islands and economic problems in Nepal due to crop invasion (Budha and Naggs, 2008)(Cowie, 1998). The high reproductive rate of *L. fulica*, with the ability to lay up to 1000 eggs during its life cycle and reach the reproductive stage in six months, contributes to its invasive success (Miquel and Herrera, 2014).

Control strategies for *L. fulica* include methods such as manual removal, trapping, physical barriers and the use of chemicals or predators such as *Euglandina rosea* (Gerlach et al., 2021). However, these methods may have limitations and compromise local biodiversity (Gerlach et al., 2021). The choice of strategies must be carefully considered for effective and sustainable pest management.

2.2 Traditional Human-Based Methods of Pest Surveillance

Historically, pest surveillance and monitoring in ecological environments have relied on manual methods such as visual inspections, trapping, and field surveys. While these approaches have provided valuable insights into pest populations and distributions, they are often labor-intensive, time-consuming, and prone to human error. Moreover, they may lack the scalability and real-time data acquisition capabilities needed to effectively address dynamic pest threats.

Traditional pest surveillance methods, such as visual inspections, trapping and field surveys, have evolved over time (McCallum et al., 2021). Although they provide valuable information on pest population dynamics and distribution, they face significant challenges, such as labor intensity, time required and susceptibility to human error(Awuor et al., 2019). In the Galapagos Islands, visual monitoring, search and egg collection with subsequent incineration, and controlled fire are used to address these challenges (Correoso, 2006). These limitations have led to the exploration of innovations in pest monitoring, with the aim of improving efficiency and providing a sound basis for preventive management and pest control in sensitive environments such as the Galapagos Islands.

2.3 Mobile Applications for Pest Management

The integration of mobile technology into pest management practices has emerged as a promising approach to overcome the limitations of traditional surveillance methods. Several studies have explored the development and deployment of mobile applications for the collection, storage, and analysis of pest-related data. For example, apps such as PestMapper and EDDMapS allow users to report sightings of invasive species and contribute to crowd-sourced monitoring efforts. Similarly, in Kenya, an innovative pest management solution is proposed, focusing on farmers. This solution utilizes mobile devices to process images and leverages crowdsourcing to assist farmers in effectively identifying and controlling pest invasions in their crops (Vanegas et al., 2018). While these applications have demonstrated the potential to enhance data accessibility and community engagement, they often lack advanced features for automated image analysis and predictive modeling.

2.4 Transformer time-series in Pest Detection

Recent advances in transformer-based architectures have paved the way for automated pest detection using prognostic analysis techniques. Researchers have developed algorithms capable of knowing the behavior of an agent and predicting the next destination. The model is trained for the exact coordinates of longitude and latitude to predict, allowing for rapid and accurate identification of invasive species. For example, by knowing the timing of pests, resources could be provided to prevent their increase and subsequent elimination from the environment. However, the application of these techniques to real-world pest management scenarios, particularly in remote or resource-limited environments, remains relatively unexplored due to missing data (Abideen et al., 2021).

In this scenario, the team utilizes the PyTorch framework for their project, and they are tasked with calculating position encoding. To define this mathematically, they first establish the concept of position encoding within the context of neural network architectures. Position encoding is a technique commonly employed in sequence modeling tasks, such as natural language processing and time series analysis, to incorporate positional information into the input embedding. Mathematically, the position encoding function can be defined as follows:

For a given position p in the sequence and dimension d of the embedding, the positional encoding is computed as:

$$PE(2,i) = sin\left(\frac{p}{10000^{\frac{2i}{d}}}\right) \tag{1}$$

$$PE(2,i+1) = cos\left(\frac{p}{10000^{\frac{2i}{d}}}\right) \tag{2}$$

Where i is the dimension index. These sinusoidal functions generate values between -1 and 1 and ensure a unique and repeatable pattern for each position. Also, the model is constructed to accept the following parameters.

- The dimension of the input data, in this case, we use only one input for each of the coordinates for the latitude and longitude.
- The number of features in the transformer model's internal representations (also the size of embeddings). This controls how much a model can remember and process.
- The number of attention heads in the multi-head self-attention mechanism.
- The number of transformer encoder layers. dropout: The dropout probability.

In the training step batched training ensures that the model updates its weights based on the average gradient over several data points, rather than being excessively influenced by any single instance. Also, we can define early stopping to avoid overfitting.Thus, while transformer architectures introduce novel mechanisms and complexities, the foundational principles of training deep learning models in PyTorch remain consistent. (Heaton, 2024)

2.5 Integrated Approaches to Pest Management

A growing body of research advocates for integrated pest management (IPM) strategies that combine multiple techniques and technologies to achieve more effective and sustainable pest control outcomes. These approaches often incorporate elements of biological control, cultural practices, and chemical interventions, supplemented by data-driven decision support systems. By integrating mobile applications, deep learning, and machine learning into existing IPM frameworks, researchers aim to enhance the efficiency, precision, and ecological sustainability of pest management efforts.

3 METHODOLOGY

The methodology employed in this study aimed to develop and implement an automated detection and prediction system for *Lissachatina fulica* infestations in the Galápagos Archipelago.

3.1 In-situ Collection and Perimeter Delimitation for Pest Control

The pest surveillance and management process begins with users reporting snail sightings both inside and outside the Biodiversity and Management Area (ABG). Teams then commence the collection of snails, starting with perimeter delineation or property cleaning, followed by manual collection during the day shift. Weeds are removed, and the area is made debris-free to aid in snail detection. Poison is dispersed to control snail spread before the shift ends.

During the night shift, teams focus on reducing the snail population without live sample collection. They patrol perimeters and interiors, marking snail sightings on maps and collecting them in jars for later analysis. Snails are categorized by age and vitality, then sent to the laboratory as deceased samples. Data from the day's activities, including photos and coordinates, are recorded and organized for analysis.

The final step involves verifying snail eradication through repeated inspections with trained dogs. This thorough process ensures the complete removal of snail infestations from the property. Additionally, a requirement analysis was conducted with input from field personnel, management, and administrative staff to design a system tailored to their needs, including daily report sheets.

In the requirement gathering stage, field personnel identified the need for a database to store detailed information for making informed decisions. Key data fields for each collection of the giant African snail were specified:

- Date and time are mandatory fields, automatically filled or selected.
- Latitude and longitude are automatically filled using the phone's GPS.
- Comments, picture, and substrate are optional fields.

Following this, the system design phase focused on conceptualizing and architecting the solution components. This involved designing a mobile application interface for efficient data collection and developing a cloud-based server infrastructure for storage and processing. Additionally, algorithms for predicting giant African snail movement patterns were developed during this phase.

3.2 Flow of Data Extraction from the Application

The development of the mobile application involved utilizing cross-platform development frameworks such as Flutter or React Native to ensure compatibility with both Android and iOS platforms. Key features including real-time data collection, GPS location tracking, image capture, and offline data storage were integrated into the application. Iterative user testing and feedback sessions were conducted to refine the application's design and functionality based on user preferences and usability considerations.

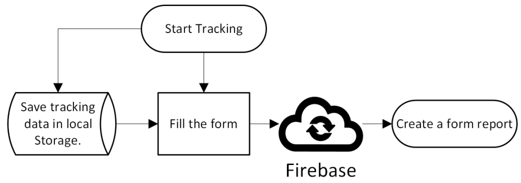

Figure 1: The application collects the tracking, which is stored locally so that when a pest is found, the tracking field in the form can be filled out. When a pest is found (*L. fulica*), it is mandatory to fill in the information on the context in which it was found. You can also add photos of the pest. The form data is stored in the Google Firebase cloud to finally have a report stored in the cloud.

3.3 Dataset

Due to the recent development of the application and the limited availability of data for model training, our team had to find alternative methods to gather data. This led us to utilize an online platform that offers geographical coordinates for shared routes. These coordinates, which include latitude and longitude, are employed to map routes on interactive interfaces and provide accurate information about notable points along the route. Users who contribute routes on Wikiloc can mark their paths using the platform's interactive map and identify significant points along the journey. These points are recorded alongside their corresponding geographical coordinates, enabling other users to precisely follow the route using GPS devices or online mapping tools. In our quest to focus on our specific area of interest, namely the Galapagos Islands, we followed patterns to ensure that the relationships between coordinates were meaningful. We collected data spanning five months and consolidated it, adjusting field titles and retaining only the essential data fields required for training our model. This process resulted in a dataset containing 56,000 entries.

3.4 Application of the K-Means Clustering Model

After conducting the exploratory analysis of the data, they proceeded to find the best k or the number of clusters by analyzing the graph, where they selected k=3. This was chosen because, upon analyzing the data using the elbow method, a clear inflection point was observed at 3, indicating that it is the optimal number for creating the clusters. The final result of the k-means algorithm is a partition of the data into k clusters, where each cluster is represented by its centroid. In this case, there are 3 clusters: the first one with 13,770 geographical positions, the second one with 27,232 geographical positions, and the third one with 15,009 geographical positions. In our case, we selected the first cluster of these clusters for the analysis of the results.

3.5 Predictions with Transformer Time Series

Transformer time series models predict *L. fulica* movement patterns using historical data and environmental variables. The Transformer algorithm operates as follows:

1. **Tokenization of Time Series:** The time series data is converted into a sequence of tokens.
2. **Embedding Tokens:** These tokens are embedded into a higher-dimensional space to capture complex data relationships.
3. **Transformer Blocks Application:** Transformer blocks process the token sequence, capturing long-term dependencies in the data.
4. **Future Value Prediction:** The output of the last transformer block is used to predict future values, typically through a linear layer.

The pseudo-code of the transformer is as simple as the following:

Require: Input lookback time series $\mathbf{X} \in \mathbb{R}^{T \times N}$; input Length T; predicted length S; variates number N; token dimension D; Transformer block number L.

1. $\mathbf{X} = \mathbf{X}^{\mathrm{T}}$.
   $\triangleright \mathbf{X} \in \mathbb{R}^{N \times T}$
2. $\triangleright$ Multi-layer Perceptron works on the last dimension to embed series into variate tokens.
3. $\mathbf{H}^0 = \mathrm{MLP}(\mathbf{X})$
   $\triangleright \mathbf{H}^0 \in \mathbb{R}^{N \times D}$
4. for l in $\{1, \cdots, L\}$:
   - $\triangleright$ Run through Transformer blocks.
   - $\triangleright$ Self-attention layer is applied on variate tokens.

   $$\mathbf{H}^{l-1} = \mathrm{LayerNorm}\left(\mathbf{H}^{l-1} + \text{Self-Attn}\left(\mathbf{H}^{l-1}\right)\right)$$

   $\triangleright \mathbf{H}^{l-1} \in \mathbb{R}^{N \times D}$

   - $\triangleright$ Feed-forward network is utilized for series representations, broadcasting to each token.

   $$\mathbf{H}^{l} = \mathrm{LayerNorm}\left(\mathbf{H}^{l-1} + \text{Feed-Forward}\left(\mathbf{H}^{l-1}\right)\right)$$

   $\triangleright \mathbf{H}^{l} \in \mathbb{R}^{N \times D}$

   - $\triangleright$ LayerNorm is adopted on series representations to reduce variates discrepancies.
5. End for

$\hat{\mathbf{Y}} = \mathrm{MLP}\left(\mathbf{H}^L\right)$ $\triangleright$ Project tokens back to predicted series, $\hat{\mathbf{Y}} \in \mathbb{R}^{N \times S}$ (Liu et al., 2023)

Algorithm 1: Transformer Architecture.

3.5.1 Time Series Analysis and Model Deployment

In addition to the implementation of the Transformer algorithm, additional activities were performed to ensure the effectiveness and successful deployment of the predictive model. This involved the use of time series analysis techniques to incorporate time dependencies and seasonality into the predictive model.

Next, integration and deployment activities were carried out to implement the developed model into a cohesive system. This included integration of the mobile application with cloud-based server infrastructure to enable seamless data transmission and storage. Implementation of computer vision and machine learning models on the server enabled real-time processing of data collected from the mobile application. Extensive end-to-end testing was performed to ensure the reliability, scalability, and security of the integrated system.

3.5.2 Performance Evaluation and Validation

The final phase of this research involved thorough evaluation and validation studies to gauge the effectiveness and practicality of the implemented system in real-world scenarios. Through rigorous trials and validation exercises, feedback was gathered from end-users and stakeholders to identify areas for improvement and assess the system's impact on key pest management outcomes, including detection efficiency, response time, and resource allocation.

Controlled experiments and carefully constructed case studies were conducted to compare the performance of the automated detection and prediction system with alternative methods. These efforts provided further validation, confirming the usefulness and effectiveness of the developed solution through empirical examination and comparative analysis.

4 RESULTS AND DISCUSSION

The implementation of the automated detection and prediction system yielded promising results in effectively addressing *L. fulica* infestations in the Galápagos Archipelago.

4.1 Mobile Application Performance

The developed mobile application demonstrated strong performance in facilitating real-time data collection and transmission from field staff to cloud-based servers . Field testing indicated that the app's easy-to-use interface and intuitive design significantly improved the efficiency and accuracy of *L. fulica* surveillance efforts. Additionally, the addition of features such as GPS location tracking and offline data storage ensured seamless operation in remote and resource-constrained environments. Here we have two of the main tabs of the User Experience of the application. The incorporation of these user-centric design elements contributes to the application's success in optimizing data collection processes and enhancing surveillance efforts.

4.2 Machine Learning Model

As previously noted, a clustering approach was employed to initialize the training process for the transformers. Please refer to Fig. 2 for visual representation.

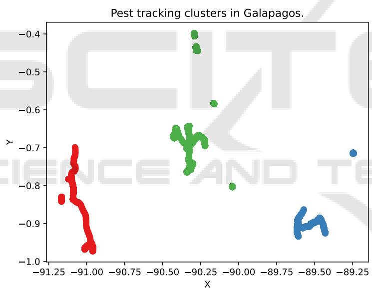

Figure 2: This image represents the different clusters given the position of the pests found. They are the key to improving the number of correct positions, as they prevent the transformer model from better modeling the phenomenon in a specific area.

The machine learning models deployed for predicting *L. fulica* movement patterns demonstrated considerable predictive accuracy and robustness. Time-series analysis techniques effectively captured temporal dependencies and seasonal variations in *L. fulica* populations, enabling the generation of reliable predictive models. These models provided valuable insights for proactive pest management strategies, allowing stakeholders to anticipate and preemptively respond to potential *L. fulica* outbreaks. The model produced these predictions with remarkable accuracy as is shown in Fig 3.; the error rate in longitude (x) and latitude (y) inside the geographic system was only 0.001. Every spot on the picture represents a place where the model predicted there would be pests, which is quite similar to what was observed. This high degree of accuracy highlights how well the predictive model predicts the existence of pests, offering insightful information for preventive pest management plans and facilitating prompt responses to stop possible outbreaks.

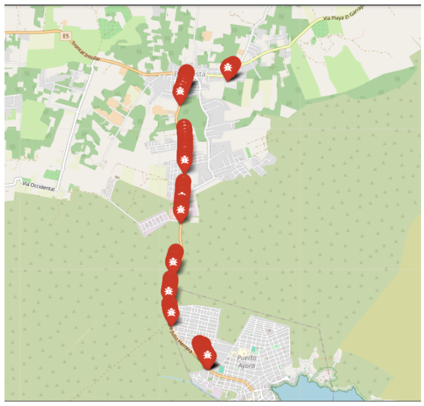

Figure 3: This image represents 112 predicted points where plagues were indeed found in the first days of the 16th month, with an error of 0.001 in the geographic system in both x (longitude) and y (latitude).

4.3 Real and Prediction Positions with Transformer Model

For a better understanding of the effectiveness of the employed model, Fig. 4 illustrates the relationship between actual x coordinates (X-axis) and predicted coordinates using a Transformer model (Y-axis). Actual coordinates are depicted as blue dots, while the blue line represents the trend predicted by the model. It is evident that the model accurately predicts the actual x coordinates, as most blue dots cluster closely around the blue line, indicating precise model predictions. However, some points deviate from the blue line, suggesting that the model predictions have a few problems in all cases, indicating room for improvement through parameter optimization.

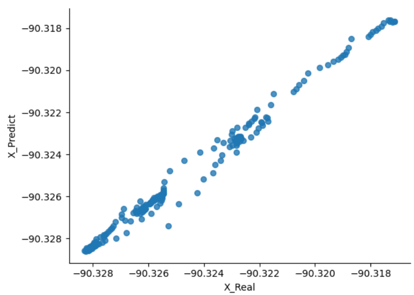

Figure 4: Relationship between the actual X coordinates and the coordinates predicted with our model.

Similarly, Fig. 5 illustrates the relationship between actual y-values and predicted y-values. The model performs better for y-values compared to x-values, indicating its stronger predictive capability for this coordinate. However, discrepancies between actual and predicted values still exist, suggesting the need for adjustments or modifications to enhance the model's accuracy, particularly for x-values. With

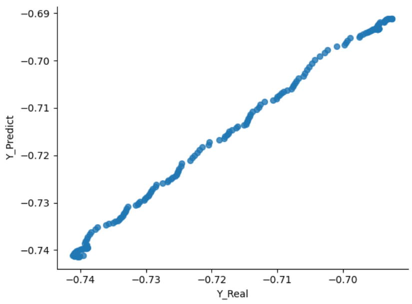

Figure 5: Relationship between the actual y coordinates and the coordinates predicted with our model.

a precision of 0.001 in geographic coordinates, the study distinguished between correctly predicted (1) and incorrectly predicted (0) x and y coordinates in the Fig 6. Notably, the predominant distribution within class 1 suggests the accuracy of both the training process and the resulting outcomes. This distribution underscores the effectiveness of the model in accurately predicting geographic coordinates, thereby instilling confidence in its overall performance and reliability.

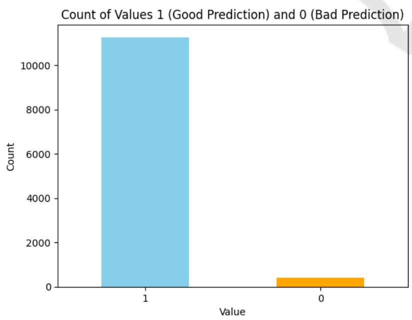

Figure 6: This bar chart represents the total positions from month 16 to month 24 which are the test positions in graph 1 are the correct positions and 0 are the incorrect coordinates which were predicted with a value of 0.001 in geographic coordinates.

4.4 Integration and Deployment

The integration of mobile application, computer vision, and machine learning components into a cohesive system facilitated seamless data transmission, processing, and storage. End-to-end testing confirmed the reliability, scalability, and security of the integrated system, ensuring its suitability for operational deployment in real-world scenarios. Additionally, user feedback and validation studies highlighted the system's practical utility and ease of adoption by field personnel and stakeholders.

Table 1: Metrics obtained from the three methods.

	RMSE	
Model	**X**	**Y**
Prophet	0.6734	0.1393
LSTM	0.0599	0.0121
Transformer	0.0118	0.0111

4.5 Comparison with Traditional Methods

Comparing the automated detection system with traditional methods showed significant improvements in efficiency, response time, and resource allocation. The automated system excelled in accuracy, speed, and scalability, mitigating the impact of *L. fulica* infestations in the Galápagos Archipelago.

The section analyzes LSTM, Prophet, and Transformer models with 56,000 data points. While Prophet is specialized for time series with strong seasonal patterns, LSTM and Transformer models are more versatile.

Results show that the proposed model consistently outperforms others, as shown in Table 1.

4.6 Discussion

The results demonstrate the effectiveness of integrating mobile technology, computer vision, and machine learning into pest management practices to achieve more sustainable and efficient outcomes. By leveraging real-time data collection, automated image analysis, and predictive modeling capabilities, the developed system empowers stakeholders with timely and actionable insights for proactive pest control strategies. Moreover, the scalability and adaptability of the system enable its potential application in other ecological settings facing similar pest management challenges.

In predictions of destinations, the team uses root mean square error (RMSE).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

Where:

- n is the total number of observations.
- y_i are the observed values.
- $\hat{y}_i$ are the predicted values.

5 CONCLUSIONS

In conclusion, this study introduces an innovative solution for detecting and predicting *L. fulica* infestations in the Galápagos Archipelago using mobile app technology and AI. By combining real-time data collection, automated image analysis, and predictive modeling, our system offers a scalable and efficient approach to pest management in sensitive ecosystems. This research demonstrates improved surveillance efficiency and accuracy, enabling rapid reporting and proactive response to potential outbreaks. This integration of mobile tech and AI provides actionable insights for targeted control measures, contributing to the preservation of the Galápagos' ecological integrity.

6 FUTURE WORK

Moving forward, further research is necessary to refine the solution, validate predictive models, and integrate additional data sources. Ongoing collaboration with local stakeholders is crucial for successful implementation and sustainability. Additionally, computer vision technology will enhance efficiency by accurately classifying *L. fulica* specimens from field images, reducing manual workload and expediting data collection.

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