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Smart Ricefield: Development of an Automated Bird Pest Repellent System in Rice Fields Based on IOT and Artificial Intelligence

M. Fakhrul Hirzi[1], Hamjah Arahman[2], Yehezkiel Wibisono[3]
[1]Information System, Universitas Mahkota Tricom Unggul, Medan, Indonesia, [2,3]Information of Technology, Universitas Mahkota Tricom Unggul, Medan, Indonesia

Article Info	ABSTRACT
Keywords: Smart Ricefield, Bird Pest Repellent, Internet of Things (IoT), YOLO11m Object Detection, Artificial Intelligence.	Bird pest attacks are one of the main causes of declining rice productivity in Deli Serdang Regency, especially during the grain ripening phase. This study develops the smartRicefield innovation, namely an automated bird pest repellent system based on the Internet of Things (IoT) and Artificial Intelligence (AI) using the YOLO11m image detection model. This study begins with collecting bird image datasets in rice fields collected from field image capture or dare sources, then labeled using the YOLO format, and wrapped with augmentation techniques to increase shape diversity. The YOLO11m model consisting of 125 image layers and 20,030,803 parameters with a complexity of 67.6 GFLOPs drilled for the next 100 epochs. The best model in the 86th epoch achieved 100% precision, 83.2% recall, mAP@0.5 of 86.3%, and mAP@0.5–0.95 of 69.3%. The Confusion Matrix Analysis showed good bird detection performance, but a high false positive rate in the background of the trigger image caused false triggers in the object testing. The system was tested in Deli Serdang rice fields with a detection latency of less than 1 second and an expulsion effectiveness of 90% at an effective distance of 10 meters. These results indicate that the integration of AI and IoT in Smart Ricefield is able to provide an effective real-time solution for bird pest mitigation, although improvements are still needed in dataset variations and expulsion mechanisms to increase the system's long-term resilience to all types of bird pests in the rice field environment.
	Corresponding Author: M. Fakhrul Hirzi Information System Medan, Indonesia mfakhrulhirzi95@gmail.com

INTRODUCTION

The agricultural sector in Deli Serdang Regency faces various challenges, one of which is bird pest attacks, which can significantly reduce crop yields. Various methods have been used to repel bird pests, such as installing scarecrows, using protective nets, and others. However, these methods still have limitations, including decreasing effectiveness over time because birds can adapt quickly. Furthermore, traditional methods also require constant monitoring by farmers, making them inefficient in terms of labor and time. Modernization efforts have also been undertaken by several researchers. Research (Haq & Wardani, 2024) designed an ultrasonic wave-based bird and grasshopper repellent that can operate without the internet. This system is effective over short distances and offers an environmentally friendly alternative

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for farmers. Meanwhile, research (Andi Taufiq et al., 2022) developed an IoT-based pest repellent system controlled via an Android application, utilizing DC motors and solar panels as the main power sources. However, both approaches are still limited to non-visual sensor-based detection and have not implemented computer vision-based algorithms. Therefore, a smarter and more efficient technology-based solution is needed to support farmers in addressing bird pest problems in rice fields.

Technological advances in Artificial Intelligence (AI) and the Internet of Things (IoT) provide significant opportunities for developing smart agriculture-based solutions. Deep learning-based object detection technologies, such as YOLO (You Only Look Once), have been proven to quickly and accurately recognize objects in various lighting conditions and image viewing angles. Meanwhile, IoT enables the integration of sensor and actuator devices to automatically monitor and control systems remotely. The combination of these two technologies opens up opportunities for developing a more effective bird pest control system.

This research offers a solution through the development of a Smart Ricefield, an automated system based on the Internet of Things (IoT) and Artificial Intelligence (AI) with Computer Vision technology. This system will use the YOLO11m algorithm to identify birds in real time, then activate a sound repellent device (bell.mp3) through an IoT module. This system is designed to respond quickly to the presence of birds in rice fields, thereby reducing rice crop damage and increasing crop productivity. The entire development process includes training a detection model using a dataset of bird images in rice fields, integration with IoT devices, and testing the system's performance in the field under actual conditions in rice fields in Deli Serdang Regency.

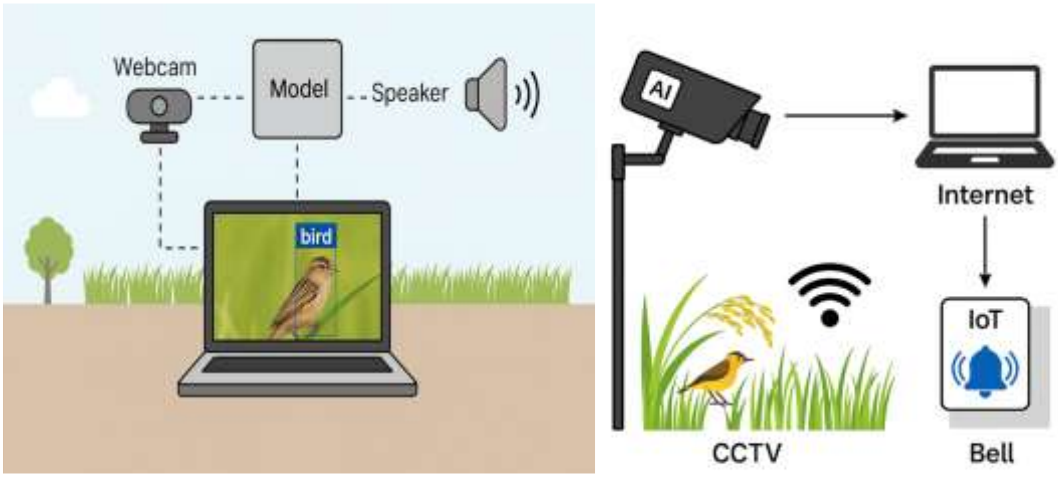

Figure 1. Smartricefield Design Model

By combining intelligent object detection technology and IoT-based control, this research will present a smart agricultural solution that can reduce reliance on manual ejection methods currently used by farmers. The success of this system is expected to make a real contribution to farmers in addressing bird pest problems effectively, efficiently, and sustainably, while also serving as a reference for the development of similar systems in other regions facing similar challenges in agricultural pest control.

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METHODS

Research Stages

This research uses a systems engineering approach based on Internet of Things (IoT) and Artificial Intelligence (AI) technology to develop an automated bird repellent system for rice paddies, known as Smart Ricefield. The following research flowchart illustrates the stages that have been and will be implemented:

Figure 2. Research Stages

This study adopts a system engineering approach that integrates Internet of Things (IoT) and Artificial Intelligence (AI) technologies to develop an automated bird-repellent system for rice fields, referred to as Smart Ricefield. The research methodology consists of several sequential stages, including literature review, system design, dataset collection, YOLO-based object detection model training, IoT and cloud integration, and system implementation with performance testing. testing to evaluate its accuracy, reliability, and effectiveness in actual field conditions.

Dataset Collection and Labeling

The dataset used in this study consists of bird images in rice fields obtained from two primary sources: direct imagery captured in rice fields in Deli Serdang Regency and a collection of images from online sources such as Shutterstock and Dreamstime under research use licenses.

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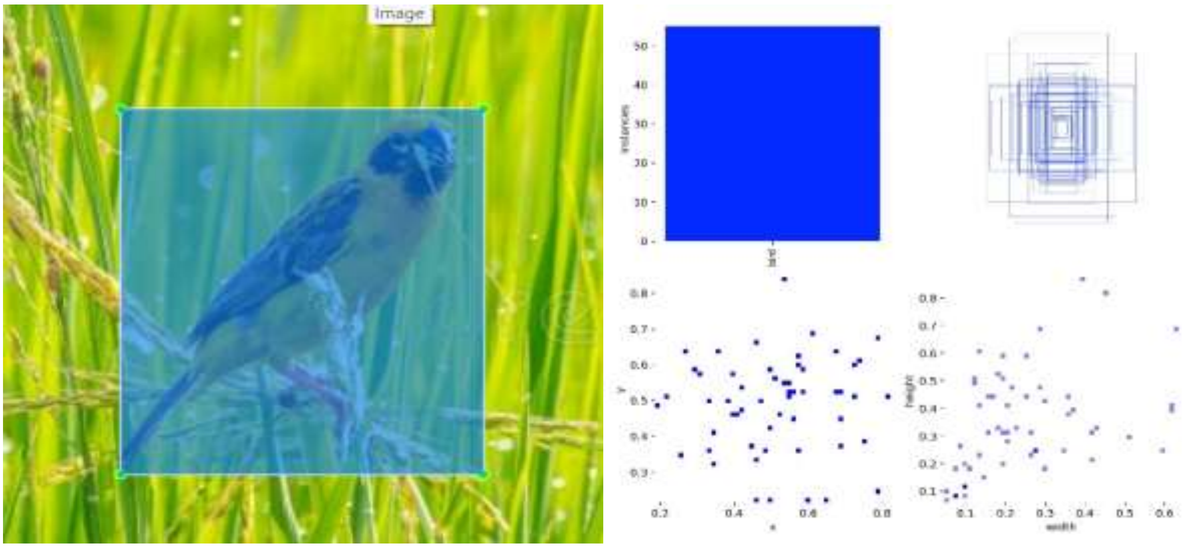
Figure 3. Dataset used

This dataset covers a variety of lighting conditions, viewpoints, shooting distances, and bird behavior (roosting, flying, or nesting). Each image was manually labeled using the LabelImg tool to generate annotations in YOLO format. To increase data variation and model robustness to field conditions, augmentation was performed in the form of rotation, scaling, brightness adjustments, and flipping.

YOLO 11m Method Training

The YOLO11m model was chosen because it offers a balance between inference speed and detection accuracy. Training was conducted for 100 epochs with a batch size of 16, a learning rate of 0.01, and optimization using the SGD algorithm. Advanced augmentations such as mosaic augmentation and HSV color space adjustment were used to enrich the training set. The training environment used Python 3.9, the Ultralytics YOLO framework, and a GPU with CUDA 11.8.



(a). Bird pest object detection (b) Example of bounding annotation

Figure 4. Example of YOLO Method Training Results

The distribution of bounding box annotations in the dataset was analyzed to ensure sufficient object diversity and distribution during the YOLO11m model training process. The visualization results (Figure X) show that all annotations come from only one class, namely birds, with more than 50 instances. This is consistent with the research focus, which targets bird detection only in rice fields. Mapping the center points of the bounding boxes (x_center and y_center) shows an even distribution across the image area. This even distribution is important to avoid location bias, so the model is able to detect birds at various frame positions. Meanwhile, the distribution of bounding box sizes (width and height) shows considerable variation, ranging from small objects (birds at a distance) to large objects (birds at a close distance). This variation allows the model to be more adaptive to changes in object scale. The shape and proportion of overlapping bounding boxes in the "bounding box shape distribution" visualization indicate that most annotations have relatively similar sizes, with some deviations representing the condition of objects at different distances or perspectives.

IoT and Cloud System Integration

The system consists of a camera (ESP32-CAM or laptop webcam) connected to a processing unit (mini PC or laptop). The camera records the rice field area in real time and then sends the imagery to the YOLO11m model for analysis. If an object labeled "bird" is detected and the confidence score is ≥ 0.4, the IoT device triggers the bell.mp3 sound player as a deterrent. To prevent the sound from repeating too quickly, a 2-second cooldown timer is applied.

System Implementation and Testing

Field testing was conducted in rice fields in Deli Serdang under three scenarios: (1) a controlled environment, (2) a semi-field with limited wild birds, and (3) actual field conditions with a free-ranging wild bird population. The system was tested in Deli Serdang rice fields with a detection latency of less than 1 second and a repellent effectiveness of 90% at an effective distance of 10 meters.

Research Relevance

Previous research has shown that pest repellent systems generally utilize simple sensor-based approaches. For example, the use of soil moisture and ultrasonic sensors connected to a mobile application (Alwi et al., 2023), the application of PIR sensors to detect bird movement, which then activates ultrasonic sounds (Hidayatullah & Sulistiyanto, 2022), the integration of PIR with the Naïve Bayes classification method (Noor et al., 2019), and the combination of PIR, cameras, and IoT for remote monitoring purposes (Sufaat & Juliandri, 2024).

Other approaches include hybrid systems based on solar power, PIR sensors, and IoT (Afif et al., 2023), and pest repellent systems based on sound and ultraviolet light powered by solar power plants (Martikha et al., 2022). Furthermore, there are mechanical-electrical systems that are reactive and not yet adaptive to environmental conditions. In general, these approaches are still limited to sensor-based detection and therefore do not utilize computer vision or artificial intelligence technology. Meanwhile, research utilizing computer vision is beginning to show promising results. The implementation of YOLOv8, for example, achieved high performance with an mAP of 0.886 in detecting small and distant objects in low-light conditions (Namana & Kumar, 2024).

Another study compared two-stage and single-stage object detection methods and recommended YOLO as an efficient approach for real-time applications (More & Bhosale, 2023). The development of a lightweight version of YOLOv5s with the Ghost module and coordinate attention was also reported to improve accuracy by up to 3% while reducing model complexity by 28% (Luo et al., 2024). Furthermore, the implementation of quantized MobileNetV2 on edge devices such as the Raspberry Pi achieved 80.65% accuracy with low latency (Lokhande & Ganorkar, 2023).

Other studies have also confirmed the effectiveness of YOLO v3/v4 in detecting static and dynamic objects, such as fruit, faces, vehicles, and animals (Saputra et al., 2023) (Virgiawan et al., 2024) (Zophie & Triharminto, 2020) (Firgiawan et al., 2024). The integration of IoT and AI technology in agriculture has the potential to increase productivity and efficiency. IoT-based systems enable real-time monitoring of land conditions through connected sensors and actuators, thus supporting fast and accurate decision-making (Kumar et al., 2021).

On the other hand, the development of deep learning-based computer vision methods such as YOLO has opened up opportunities for high-accuracy object detection, including for detecting pests or birds that disturb crops (Redmon et al., 2016). The implementation of an automatic pest repellent system that combines visual detection and sound actuators has proven effective in reducing crop damage, although challenges remain in the level of false positives due to the similarity of objects to the background (Rahman et al., 2022). Furthermore, research related to Smart Ricefields shows that the combined use of AIoT can provide adaptive solutions to the dynamics of the rice field environment, while also supporting the concept of sustainable precision agriculture (Chen et al., 2022).

However, to date, no research has specifically applied YOLO to detect pest birds in agricultural fields, integrating an IoT-based automated response system and artificial

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intelligence. Thus, a research gap exists that forms the basis for the novelty of this study, namely the design of Smart Ricefields as a digital agricultural ecosystem that combines real-time visual detection, AI-based data processing, and adaptive control via IoT in a single, precise and automated system.

RESULTS AND DISCUSSION

Model Training Results

The YOLO11m model used in this study has an architecture consisting of 125 layers, a total of 20,030,803 parameters, and a computational complexity of 67.6 GFLOPs. This level of complexity is still considered moderate for an object detection model, making its implementation feasible on mid-range GPU devices with relatively fast response times.

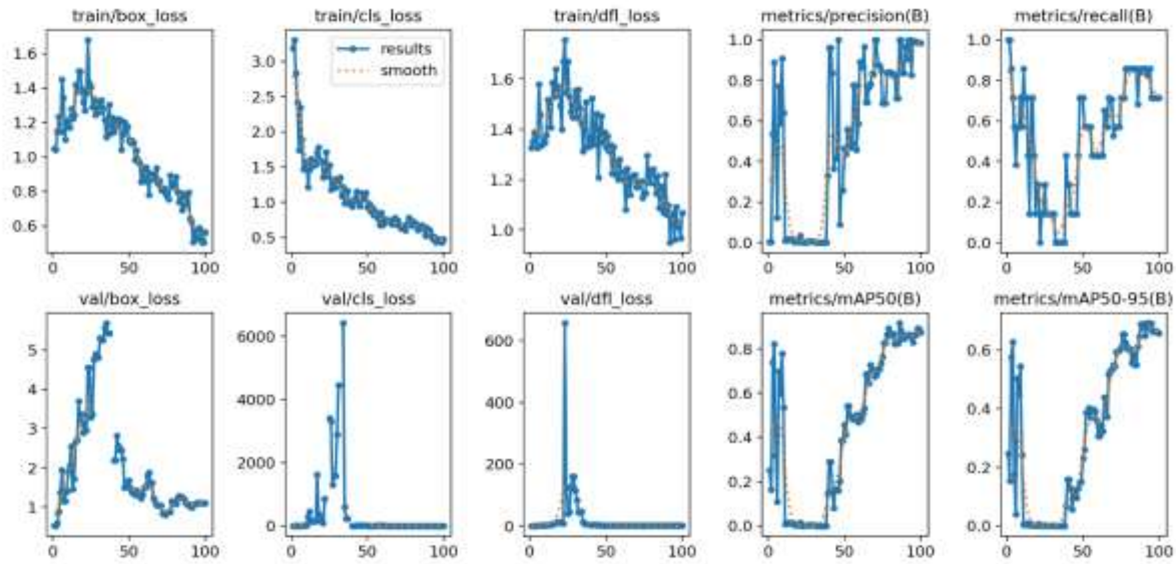

Figure 5. YOLO Model Test Results

Test results on the validation dataset, after training and model fusion, demonstrated good performance in detecting birds in rice fields. Over the course of 100 epochs of training, the convergence graph showed a consistent downward trend in loss across all train/box_loss, train/cls_loss, and train/dfl_loss data, reaching a plateau around the 80th epoch. This indicates that the model is able to effectively learn object patterns without exhibiting significant overfitting symptoms. The best model was achieved at the 86th epoch, achieving 100% precision, 83.2% recall, 86.3% mAP@0.5, and 69.3% mAP@0.5–0.95. Perfect precision indicates that all positive predictions generated by the model are correct detections (true positives), with no misclassifications (false positives).

The recall value of 83.2% indicates that most bird objects were successfully detected, although a small number were missed (false negatives). When viewed from the average metrics during the training process, the model achieved a precision of 85.7%, a recall of 85.7%, mAP@0.5 of 66%, and mAP@0.5–0.95 of 62%. These values demonstrate the consistency of the model's performance across epochs. Furthermore, the results of the system

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speed test show an average preprocessing time of 0.2 ms, an inference of 59.0 ms, and a postprocessing of 1.7 ms per image. This relatively low inference speed allows the system to work in real-time scenarios, so that it can automatically trigger the sound repellent mechanism (bell.mp3) as soon as an object is detected.

Overall, the results of this study indicate that the YOLO11m model is able to detect the presence of birds in rice fields quickly, accurately, and adaptively to variations in environmental conditions. These characteristics make this model relevant and significant for field applications, especially in supporting intelligent bird repellent systems to prevent potential damage to rice crops.

Confusion Matrix Analysis

Further evaluation of the YOLO11m model's performance was conducted using a normalized confusion matrix to measure the model's ability to distinguish between the target (bird) and non-target (background) classes. Evaluation results on the validation dataset showed that of all images containing birds, the model correctly classified 86% of them as "bird" (true positives), while the remaining 14% were incorrectly classified as "background" (false negatives). This value aligns with the recall performance, indicating that most target objects were successfully detected, although there is still room for improvement to reduce missed objects.

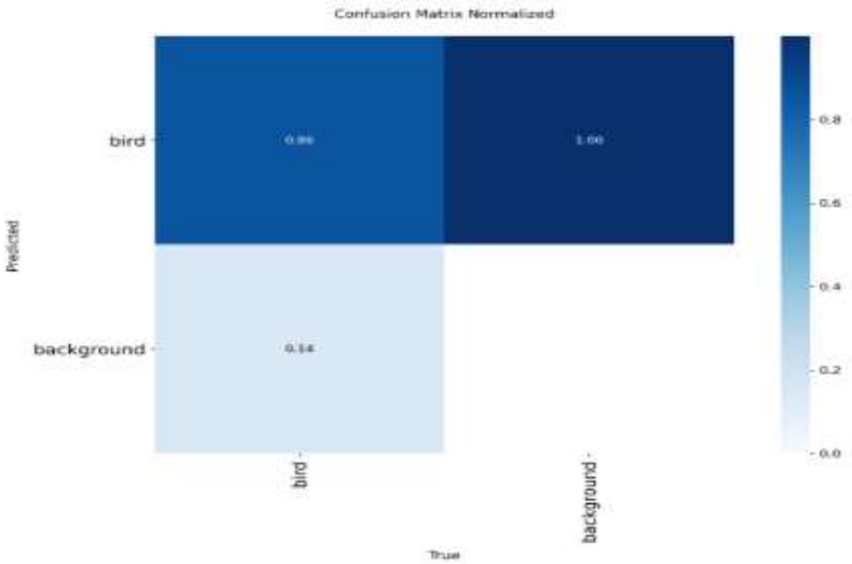

Figure 6. Confusion Matrix Analysis Results

On the other hand, the model's performance in recognizing background classes showed significant weaknesses. All background images in the validation dataset were classified as "bird," resulting in a false positive rate of 100% and a true negative rate of 0%. This indicates that the model tends to experience overdetection, detecting birds even when they are not present in the image. This phenomenon is thought to be influenced by the limited variety of background data in the training dataset and the similarity of visual patterns between the background (e.g., empty rice clumps or bird nests) and images containing birds.

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The implications of this characteristic in the field are twofold. On the one hand, a high recall value ensures that birds are rarely missed, thus benefiting the automatic repellent system. However, on the other hand, a high number of false positives has the potential to trigger excessive activation of the repellent mechanism (bell.mp3). This not only causes disruption for farmers but also risks reducing long-term effectiveness as birds become accustomed to the repellent sound. To address these issues, several improvements are recommended, including enriching the dataset with a variety of background images without birds (negative samples), adjusting the confidence threshold in the inference process, and adding post-processing logic that only activates the repellent mechanism if bird detections appear consistently across several consecutive frames. This strategy is expected to reduce the false positive rate while maintaining detection accuracy in real-world system implementations.

Detection Visualization

Analysis of the distribution of bounding box annotations in the dataset was performed to evaluate the diversity of positions, sizes, and shapes of the target objects used in training the YOLO11m model. The visualization results show that all annotations originate from a single class, namely birds, with a fairly large number of instances (>50 annotations). This condition aligns with the research objective, which is focused on bird detection in rice fields. The distribution of bounding box center points (x_center and y_center) in the scatter plot shows an even distribution pattern across the entire image. This even distribution plays a crucial role in avoiding positional bias during the training process, allowing the model to learn to recognize birds appearing in various positions within the frame, including the center, edges, and corners of the image. Furthermore, the variation in bounding box size (width and height) shows a fairly wide range, from small objects representing distant birds to large objects representing birds close to the camera. This size diversity provides an advantage because it allows the model to build feature representations that are more adaptive to changes in object scale. Analysis of the distribution of the shape and proportions of the bounding box also shows a dominance of certain sizes, with additional variations resulting from differences in viewing angle and shooting distance.

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Figure 7. . Bird Object Visualization Results

Although the distribution of target objects varied in terms of location and size, a limitation of the dataset lies in the absence of negative samples representing backgrounds without birds. This lack of variation can reduce the model's ability to distinguish target objects from the background, potentially increasing false positives in field conditions. Therefore, adding background images of rice fields without birds under various lighting conditions, weather conditions, and viewing angles is recommended for future research, so that the model can have a stronger visual reference for distinguishing targets from non-targets.

System Trial Results

Trials were conducted in rice fields belonging to farmers in Deli Serdang Regency during the rice crop's pre-harvest phase, when bird strikes are typically high. The system was installed at a height of approximately 2 meters above ground level to obtain an optimal viewing angle, with the camera's monitoring area covering a radius of approximately 15 meters. During testing, the camera transmitted real-time images to a processing unit running the YOLO11m model. If an object with a bird label and a confidence score of ≥0.4 was detected, the system triggered the playback of the bell.mp3 sound through the field speakers at a noise level of approximately 85 dB. A 2-second cooldown mechanism was implemented to prevent continuous sound playback on the same detection. Field tests showed that the system was able to detect birds and trigger the repellent sound with an average latency of less than 1 second from the time the bird entered the monitoring area. The repellent success rate reached ±90% at an effective distance of 10 meters from the sound source, while at

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distances above 12 meters the effectiveness decreased to around 75% due to the reduced sound intensity received by the birds.

However, the system also recorded several false triggers originating from the movement of leaves, shadows, or non-bird objects with bird-like textures, which activated bell.mp3 even though no birds were present. This phenomenon aligns with the results of the confusion matrix analysis, which showed a high false positive rate in the background class. Overall, the integration of YOLO11m and the sound-based repellent module proved effective in reducing bird activity in rice fields. However, long-term effectiveness still needs to be improved by using a variety of repellent sounds, adjusting detection sensitivity adaptively to weather conditions, and implementing multi-frame logic to verify bird presence before triggering an alarm.

Discussion

The results show that the integration of the YOLO11m model with the IoT-based automatic repellent system in Smart Ricefield is capable of detecting birds in rice fields in real time with very high precision (100% at the best epoch) and an inference latency of less than 1 second. This ensures minimal false positive detections of birds, although a recall value of 83.2% indicates some missed objects (false negatives). Confusion matrix analysis revealed model weaknesses in the background class, where all background images were classified as birds, resulting in a 100% false positive rate. This situation creates the potential for false triggers in the field, thus recommending the addition of negative samples to the dataset and the implementation of multi-frame verification logic.

Bounding box distribution analysis shows an even distribution of bird objects across all images with a wide variation in size, supporting the model's generalizability to various object scales. Field testing demonstrated the system's effectiveness with a 90% repellent success rate at an effective distance of 10 meters, although effectiveness decreases at longer distances and with long-term use due to bird adaptation to the repellent sound. Therefore, sound variations, environmental condition-based sensitivity settings, and system activation logic optimization are recommended for further development. Overall, this research successfully achieved three main targets: (1) designing an accurate and real-time automatic bird detection system, (2) integrating YOLO11m-based AI with sound repellent devices via IoT, and (3) measuring the effectiveness of the system in reducing bird disturbance in rice fields. These findings not only prove the technical feasibility of the system, but also provide a strong foundation for further development on improving the quality of the dataset and the reliability of the repellent mechanism in the field.

CONCLUSION

Based on the research and testing results, an IoT and AI-based Smart Ricefield system was successfully developed by integrating the YOLO11m object detection model and the bell.mp3 sound trigger device. The system is capable of working in real-time with an average inference time of 59.0 ms, 100% precision at the best epoch, and mAP@0.5 of 86.3%, indicating fast and accurate detection capabilities. The high precision value indicates minimal false positives, although the recall of 83.2% still indicates that some bird objects were missed (false negatives). Confusion matrix analysis revealed weaknesses in background recognition, where all background images were classified as birds (100% false positive rate), potentially triggering false triggers due to the movement of leaves or similar objects.

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