FarmEye-AI: Bird Pest Repellent System Based on Edge AI and IoT in Paddy Fields for Smart Agriculture

Muhammad Hidayat Arga Wicaksana[1], Kurniawan Dwi Irianto*[2]
[1,2]Department of Informatics, Universitas Islam Indonesia, Yogyakarta, Indonesia
E-mail: [1]argawicaksana07@gmail.com, *[2]k.d.irianto@uii.ac.id

This study investigates the development of a detection and repellent system for Lonchura birds in paddy fields by assigning object detection inference to the sensor level (in-sensor computing) using a Sony IMX500 intelligent camera module combined with a Raspberry Pi 5 and a motorized pan-tilt mechanism. The applied methodologies include picture dataset compilation and augmentation, transfer learning utilizing an object identification architecture, actuator control implementation, and quantitative evaluation of model performance alongside specimen behavioral response testing. The results demonstrate a precision improvement to 86.4% and a mean Average Precision (mAP) of 87.6% at 0.50; the inference rate is recorded at 25 to 30 frames per second; automatic detection is effective up to 200 cm, along with a response to auditory stimuli for avoidance. The conclusion says that the integrated architecture significantly reduces false detections and delays, hence improving the effectiveness of non-lethal insect management.

***Kata Kunci**: object detection, Lonchura birds, Raspberry Pi 5, pest repellent, IoT.*

I. INTRODUCTION

Rice (*Oryza sativa* L.) is a food that is very important for Indonesia's food security and economic stability [1]. But plant pest organisms often go in the way of making this important good [2]. One of the most harmful hazards is when colonies of sparrows and bondol pests from the genus *Lonchura spp* attack rice plants that are in the milk-ripening stage or rice that has been planted for 70 days [3]. If not dealt with by proactive and precise mitigation techniques, these pests can move about a lot and eat a lot of food in groups, which can cut harvests by up to 50 to 60 percent [4], [1].

Farmers in rice fields continue to rely on mechanical control technologies and direct visual monitoring as first mitigation measures. Conventional instruments, such as scarecrows, nets, and static sound-producing devices, are deemed inefficient because they consume a significant amount of farmers' energy and productive time [5]. Furthermore, a significant shortcoming of this traditional technique is the high level of pest habituation. Bird pests can quickly adapt to patterns of recurrent visual and aural disturbances, so these repellent devices lose their effectiveness and are no longer perceived as a legitimate physical danger [4].

The development of the smart agriculture paradigm based on the Internet of Things (IoT) has currently proven its role in automating various crucial sectors to reduce reliance on manual labor in the fields. The success of this smart architecture can be seen in the implementation of remote agricultural irrigation monitoring systems [6] to real-time water nutrition management and monitoring systems in hydroponic growing media [7]. Adopting a similar automation principle, the design of automatic vermin repellent devices has begun to incorporate IoT technology. This is achieved by utilizing sound actuators, such as sirens or ultrasonic waves, in conjunction with motion sensors (Passive Infrared/PIR) [8], [5]. This innovation offers the advantage of automation, there is a fundamental technical flaw regarding target identification accuracy. The primary limitation of PIR sensors is that they are incapable of detecting the presence of an object solely on the basis of movement signals [8]. The system is highly susceptible to the generation of false alarms (false positives) that are caused by abiotic movements, such as the swaying of rice leaves driven by the wind, due to the sensor's inability to visually validate the shape or type of object. In addition to squandering the power reserves of devices operating in open spaces, the high frequency of these detection errors also results in off-target sound actuation, which ultimately risks accelerating the pest habituation process.

Recognizing the limitations of PIR sensors in identifying object shapes, recent research on pest control systems has shifted toward the use of cameras integrated with Artificial Intelligence (AI) and Computer Vision (CV). This innovative method uses Deep Learning algorithms like You Only Look Once (YOLO) to find and identify avian pests with significantly more accuracy [4], [9]. Although proven to be more accurate, the implementation of these advanced detection models on conventional edge computing devices, specifically Single Board Computers (SBC) like the Raspberry Pi 4, frequently encounters computational bottlenecks. Relying entirely on the Raspberry Pi 4's Central Processing Unit (CPU) for YOLO image processing results in high system latency and extremely low frame rates, while also triggering overheating issues that risk damaging hardware

[4], [9]. Besides these limits on processing performance, most past computer vision experiments still depend a lot on static angled cameras that limit the field of view. This creates a big blind zone for surveillance in the rice field region, which means that the system could fail to respond to pest swarms that migrate outside of the lens range.

These basic requirements show that the current design for pest control systems is not the best way to connect the heavy computational load of AI algorithms with the limited processing power of edge devices for open-space applications. Visual solutions implemented in prior studies still rely on rigid spatial surveillance frameworks and inference processes that are susceptible to latency. However, managing highly mobile wild bird flocks with extensive attack ranges necessitates comprehensive area surveillance and immediate deterrence measures. The incapacity of conventional computing devices to execute algorithms in real-time directly results in delayed system responses, thereby significantly diminishing the overall efficacy of pest prevention.

To get around these problems, this study created an integrated Edge-AI architecture that moves the Deep Learning inference of object detection models, in this case YOLOv11, directly into the sensor hardware. This was done by combining an Intelligent Vision Sensor (Sony IMX500) with a Raspberry Pi 5 microcontroller. This on-sensor computing method can greatly decrease bottlenecks on the main CPU, speed up detection, and make devices use less energy. Also, this smart computing feature works with an automatic area scanning system that uses a servo motor drive to sweep the field of vision smoothly and constantly. This combination of technologies gets rid of the blind spot problems of a static camera, greatly increases the range of field surveillance, and lets the system respond and turn on the audio repellent as soon as pests are found in different parts of the rice fields.

This study seeks to develop and deploy a high-performance, autonomous detection and repellent system for Lonchura spp. birds, addressing the outlined array of challenges. The system that was created is meant to have a very low latency rate, very high visual computing accuracy, and a significantly larger area of surveillance than static vision systems. The goal of this integrated architecture is to produce a reliable precision agriculture (smart farming) technological solution that will lower crop loss rates and help keep national rice production stable.

II. METHODOLOGY

This study employs an experimental-applied methodology to create an Edge AI-driven insect repellant system for the sparrow (*Lonchura spp*). In general, the research stages are: reviewing the literature, collecting and cleaning the data, training the object detection model, and putting the system into use and testing it. This method is based on earlier research that used a Raspberry Pi 4 microcontroller and computer vision technology to find sparrows in real time on farmland [10] [4]. The key parts of this research are as follows:

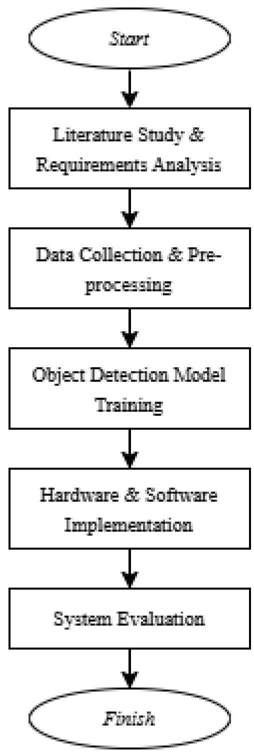

Figure 1. Steps in this research

A. Literature Study and Requirements Analysis

The preliminary phase of this research was a literature review to ascertain the characteristics of the target, specifically sparrow pests (Lonchura spp.), by analyzing assault patterns, activity periods, and the dynamics of flock movements in rice fields [3]. The research was subsequently extended to the domain of computer vision technology to assess the superiority of the YOLOv11 architecture in real-time detection of moving objects, particularly concerning computing efficiency and detection accuracy [11]. After establishing a theoretical framework, a field needs assessment was performed through interviews and observations with rice farmers. This revealed that traditional repellent methods were becoming progressively ineffective due to the birds' capacity to adapt to repetitive disturbance patterns and a significant reliance on human labor. Based on the combination of what we know from research and what we see in the real world, operational specifications for a system that is supposed to work automatically, cover a large area with a pan-tilt electromechanical mechanism, and have an adaptive deterrent method to keep pests from getting used to the device used.

B. Data Collection and Pre-processing

The dependability of a Deep Learning model is significantly influenced by the quality of the dataset employed. The dataset for this study was put together from public sources (Roboflow) and the internet. It focused on pictures of sparrow pests in front of a genuine rice crop. We collected 4,016 photos with 7,513 bounding box annotations for the "Bird_Pest" class in the first stage. Also, background images that did not have any annotations (null) and had things that were not the target, like farmers, scarecrows, and predatory birds, were used. The purpose of these background images was to help the model learn about the environment and cut down on false positive detections. The way the dataset was put together was in line with what Ultralytics suggests. After that, the first set of data was split into three parts: 70% for training, 20% for validation, and 10% for testing [12], It was then stretched to 640x640 pixels to find a compromise between getting details about small objects and the edge device's computing power.

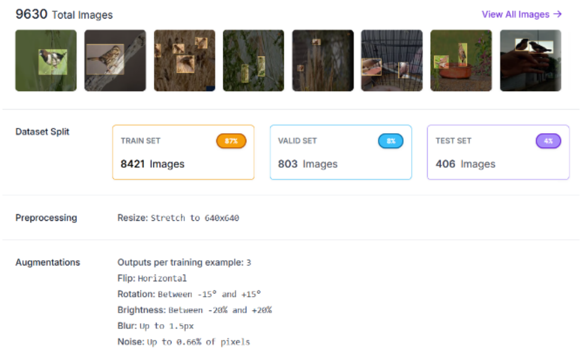

Figure 2. Dataset Distribution After Augmentation

To address extreme outdoor environmental variations and prevent overfitting, the augmentation stage was applied exclusively to the training subset to avoid data leakage [13]. The parameters used to make the picture look better were horizontal flip, rotation (from -15° to +15°), brightness fluctuation (from -20% to +20%), and the addition of blur and noise to make it look like the camera was moving, the light was changing, and the wings were flapping. This artificial multiplication process generated three outputs per training image, resulting in a substantial increase in the total data population to 9,630 images. The final percentage of the dataset changed to about 87% (8,421 photos) for the training set, 8% (803 images) for the validation set, and 4% (406 images) for the testing set [12] because the augmentation only affected the training data. Figure 2 shows how the properties and distribution of the dataset changed after augmentation.

C. *Model Training*

This research evaluates two nano-class object detection architectures: YOLOv8n as the baseline model and YOLOv11n as the proposed model. Training is done on a workstation with a Graphical Processing Unit (GPU) using the transfer learning method from pre-trained weights. To get the most out of the computer and avoid overfitting (when the model only remembers training data and does not identify fresh data), the training method is combined with the Early Stopping protocol and a tolerance threshold of patience = 100. This approach will automatically cease training iterations if the loss function parameters on the validation data do not drop significantly for 100 epochs in a row. Using this tolerance limit has been shown to be particularly helpful at halting the model at the best accuracy point, keeping it from overfitting, and making it better at generalizing without wasting time on unnecessary calculations [14].

D. *Device Implementation*

After training, the AI model is loaded on a Raspberry Pi 5 Single Board Computer that features a Raspberry Pi AI Camera module based on the Sony IMX500 sensor. This architecture uses direct computing on the sensor, or in-sensor computing, which means that the inference process happens at the sensor level instead of the main CPU. This lets the system detect things in real time with very low latency and without causing very high temperatures. The device has a pan-tilt mechanical actuator that is powered by two MG996R servo motors to provide it a wider field of view. The PCA9685 driver module controls the actuator by sending Pulse Width Modulation (PWM) signals through the I2C interface. This makes sure that motor movement instructions run separately from the main CPU [15]. As a last resort, an active speaker based on a USB DAC is used to play predatory recordings and ultrasonic frequencies in a dynamic way (event-triggered). This is a different sound approach that has been shown to stop the habituation process in groups of wild birds [16]. A 5V 10A DC converter module powers the complete hardware instrument. This keeps the electricity stable and stops brownouts when the servo-mechanical actuators take peak current (stall current) at the same time.

E. *System Evaluation*

The goal of the system evaluation phase was to test the software and hardware's reliability in a controlled environment in a way that could be measured. Within the framework of applied IoT architecture, evaluating the time latency (delay) metric is an essential testing parameter to validate the system's robustness and response speed when transmitting instructions between components in an agricultural setting.[17]. The Mean Average Precision (mAP) and Loss Function metrics were used to test how well the AI model worked. Then, the inference rate (Frames Per Second/FPS) of the in-sensor computing architecture was measured to see how it compared to the performance of regular processors in the study [4].

The next step was to use the black-box testing approach to check that the hardware worked properly and that the pan-tilt servo motor moved accurately and the audio playback reaction time was fast. Next, sparrow specimens with a rice field background were used to test the camera's visual skills in stages at distances of 50 cm to 250 cm. This was done to find the greatest limit of detection visibility. A behavioral response test (startle-flight response) of the specimens to bioacoustic exposure was done as a final check to show that the effective radius of the sound wave terror could reach pests beyond the camera's visual detection distance limits. This is in line with the biological deterrence evaluation method used in other studies [18].

III. RESULT AND DISCUSSION

A. *Model Training Performance*

The model training process was conducted to evaluate the effectiveness of the YOLOv11n architecture compared to the previous generation, YOLOv8n. Based on the training results, the use of the Early Stopping protocol stopped the YOLOv8n iteration at the 204th epoch because no significant decrease in the loss function was found in the validation data. In contrast, the YOLOv11n architecture showed better convergence stability and was able to continue training up to a maximum of 350 epochs. These training findings are in line with previous studies confirming that models with superior feature extraction capabilities have longer convergence resilience before experiencing overfitting [16]. A comprehensive comparison of the performance metrics of the two models in this test is presented in Table 1.

Table 1. Model Training Matrix Evaluation Comparison

Matrix Evaluation	**YOLOv8n (Baseline)**	**YOLOv11n (Proposed)**	**Difference**
Precision	83,2%	86,4%	+ 3,2%
Recall	81,7%	81,8%	+ 0,1%
mAP@0.50	86,9%	87,6%	+ 0,7%
mAP@0.50-0.95	56,8%	57,7%	+ 0,9%

Based on Table 1, the YOLOv11n model shows a significant increase in Precision of 3.2%. This higher Precision value is an important indicator in minimizing false positive rates. This ensures that the system has strong discrimination capabilities in distinguishing bird pest targets from distracting objects in the background, such as rice vegetation moving due to wind blowing, thus preventing unnecessary activation of audio speakers [11].

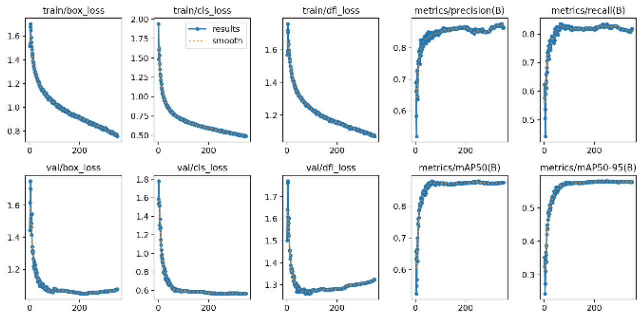

Figure 3. YOLOv11n Model Training Results

Further training characteristics of the YOLOv11n model can be observed in Figure 3. The graph shows a consistent decrease in box loss and classification loss values as the number of epochs increases, which is directly correlated with an increase in the mean Average Precision (mAP) value. The stability of the curve in the final training phase indicates that the model has reached an optimal point in recognizing spatial features of small objects without experiencing symptoms of overfitting [13].

B. *Hardware Functionality Testing and Inference Speed*

After the model was evaluated in software, testing continued by measuring the overall system computational performance on the assembled hardware. The main advantage of the proposed architecture lies in solving the computational bottleneck problem through the use of the Raspberry Pi AI Camera Intelligent Vision Sensor (Sony IMX500) module. The hardware prototype circuit used in this testing can be seen in Figure 4.

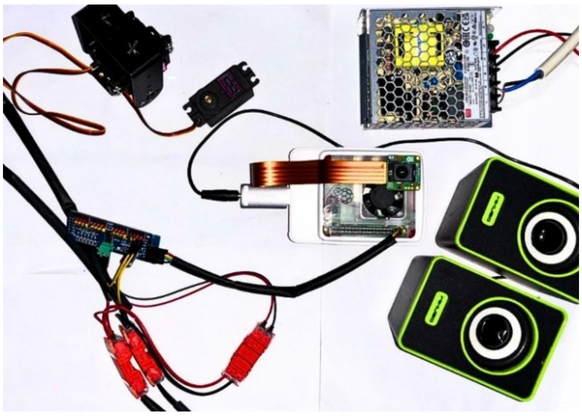

Figure 4. Hardware prototype of this system

Real-time object projection testing shows that in-sensor computation on the Intelligent Vision Sensor module (Sony IMX500) runs stably. The inference rate is recorded consistently between 26 to 30 frames per second (FPS). This result shows a significant performance leap when compared to the previous architecture in the study [4], where YOLO processing on a pure Raspberry Pi only produces 0.39 FPS and only reaches 7 FPS when assisted by the external Google Coral TPU accelerator.

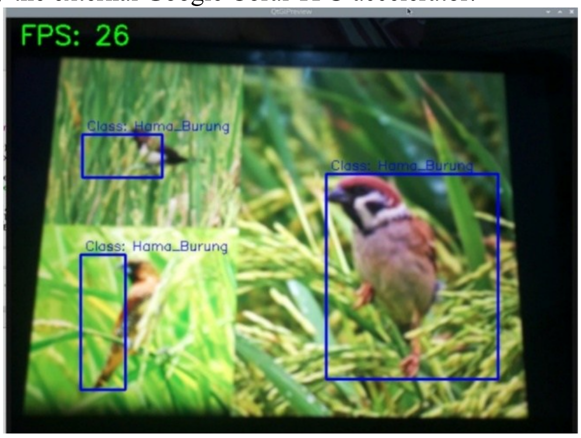

Figure 5. FPS Test Results on Raspberry Pi AI Camera (Sony IMX500)

The high FPS rate ensures the system runs smoothly in executing physical actuators without any delay. Black-box testing was then conducted to validate the audio triggers and mechanical performance of the Pan-Tilt module. The movement mechanism was adaptively designed using a combination of one standard 180-degree servo motor (to maintain the static tilt elevation angle) and one continuous servo motor (for pan area scanning) controlled by the PCA9685 driver.

Based on empirical hardware calibration results, it was found that a continuous servo requires a specific electrical deadband value of 0.35 to achieve precise starting and stopping. Through modulation of a time-based stepping algorithm where the servo is given an additional power (offset) for 0.5 seconds and then returned to the deadband value the system was proven capable of sweeping the corner of the area gradually and turning back automatically. A summary of the testing of these actuator components is presented in Table 2.

Table 2. Functionality Black-box Testing Results

Module	Testing Scenario	Output Observation	Result
Servo Pan-Tilt (MG996R)	*Deadband Calibration (0.35) & Time-Based Scanning*	The continuous servo motor (pan module) successfully scans an area up to 360° stably and stops precisely without any forced vibration (hardware jitter). The standard servo motor (tilt module) also operates validly by locking the elevation angle precisely according to the predetermined parameters (0°, 45°, and 90°)	Valid
Speaker Audio	Positive Detection (Trigger)	Audio plays predator recordings instantly (< 0.1 second latency)	Valid
Speaker Audio	Temporary Occlusion (Cooldown)	Audio stays on steadily covering a 3.0 second pause, then dies	Valid

Based on Table 2, the implementation of deadband calibration (0.35) successfully eliminated analog creep (wild shifts) in the continuous servo motor. This ensures that the scanning movement remains controlled, thus minimizing motion blur artifacts in the camera sensor captures that can disrupt object detection performance [19]. On the other hand, the integration of a 3.0-second cooldown variable in the audio memory circuit proved crucial. This logic prevents noisy flickering (rapid on-off) when the pest hides briefly behind vegetation, ensuring that the audio terror shockwave remains relevant and the speaker components are protected from damage due to over-reactive power cycles.

C. Testing Detection Distance and Bird Behavioral Response

The final evaluation aimed to map the correlation between the optimal viewing distance of the camera lens and the effective range of audio waves. This test was conducted using a specimen of the White-headed Munia (*Lonchura maja*) positioned in a simulation cage. To test the model's discrimination capabilities (occlusion and camouflage handling), the test used an artificial background resembling a rice field. Output parameters were also evaluated based on the specimen's motor reactions (avoidance reflex or startle-flight response) to validate the effectiveness of habituation prevention. Documentation of the distance testing process and observation of the specimen's behavior is shown in Figure 6 and 7.

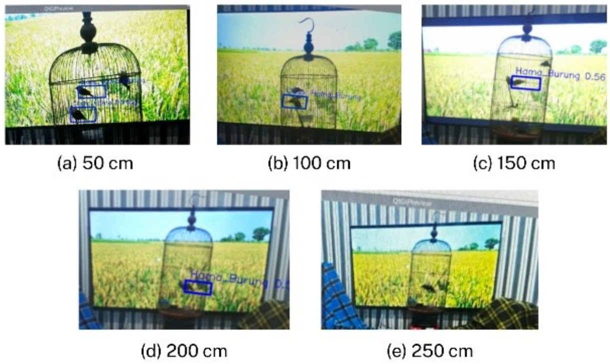

Figure 6. Detection Distance Test Results Based on Metrics

Figure 7. Documentation of Metric Based Detection Distance Testing

Table 3. Recapitulation of Camera Visibility Distance Testing and Specimen Response

Distance (cm)	Detection Status	Audio	Specimen Kinetic Reaction
50	Succeed	Automatically activated	Succeed
100	Succeed	Automatically activated	Succeed
150	Succeed	Automatically activated	Succeed
200	Succeed	Automatically activated	Succeed
250	Failed	Active (Manually Simulated)	Failed

Analysis of the test results in Table 3 confirms that the YOLOv11n algorithm is able to maintain its visual acuity consistently up to a point radius of 200 centimeters, even in conditions where the background blends with the object's color (rice field vegetation camouflage). When the specimen is pulled at a distance of 250 centimeters, the target pixel resolution becomes too small, causing the model to fail automatic identification.

Psychobiological testing complemented previous findings by demonstrating that the effective radius of the loudspeaker significantly exceeded the optical range of the camera; for example, at a distance of 250 cm previously undetectable by the camera, the audio trigger still produced a validated reflex avoidance response. The implementation of dynamic sounds, including simulated predator calls, human voices, and specific event-triggered frequencies, was shown to disrupt the birds' ability to recognize and adapt to disturbance patterns, thus suppressing habituation. These findings reinforce that bioacoustic-based deterrent ecosystems provide a more robust non-lethal deterrent solution than traditional methods such as scarecrows or monotonous sound cannons [18].

IV. CONCLUSION

This research has successfully designed and implemented a highly responsive autonomous bird repellent system through the application of in-sensor computing. This edge computing architecture approach has proven effective in overcoming the processing lag constraints commonly experienced by conventional microcontroller units, allowing for instantaneous and simultaneous repellent detection and actuation. Furthermore, the integration of a continuously moving visual scanning mechanism with dynamic bioacoustic sound shots successfully resolves the problem of surveillance blind spots while preventing pests from adapting to disturbances. These results are significant because they offer a breakthrough in reliable, sustainable, and non-lethal precision agriculture technology to secure the stability of national rice production from the threat of crop losses.

For further development and application, it is recommended that this system be integrated with independent renewable energy sources, such as solar panels, to support continuous device operation in rice fields lacking electrical infrastructure. Further research is also highly recommended to enrich the training dataset class variations so that the model can recognize and repel other types of agricultural pests. Furthermore, direct empirical testing in large-scale rice fields over a full harvest cycle is needed to validate the durability of mechanical components against extreme weather conditions in open spaces.

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