An IoT Solar Bird Repellent with Image Processing

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Rice (Oryza sativa) is one of the most widely cultivated crops globally, with about 90% of total production coming from Asia (Fukagawa & Ziska, 2019; Schneider & Asch, 2020). The Philippines ranks eighth among Southeast Asian rice producers (FAOSTAT, 2020). However, ensuring future food security remains one of the greatest challenges facing farmers today. Rapid population growth, climate change, farmland fragmentation and degradation, pest infestation, lack of stakeholder integration, uneven urbanization, and political instability threaten sustainable food production (Maja & Ayano, 2021; Sahoo et al., 2025; Godde et al., 2021; Çakmakçı et al., 2023). Over the next 35 years, global food output must increase by at least 60% to meet the demands of the growing population (DA Communications Group, 2022; Isakova, 2022).

Rice farmers encounter numerous challenges, including insufficient irrigation systems, labor shortages, lack of postharvest facilities, limited capital, fluctuating rice prices, high input costs, and persistent pest and disease infestations (Cao et al., 2023; Gamage et al., 2024). Among these issues, birds have become one of the most damaging pests. Many species, such as pigeons, doves, parakeets, munias, sparrows, and weaver birds, feed on grains and fruits and can cause severe crop losses. Birds begin consuming rice grains from the ripening stage until harvest, leading to unfilled panicles and yield reduction. Large flocks can destroy crops, damage storage facilities, and contaminate nearby areas. A significant number of farmers experienced crop loss due to bird attacks (Micaelo et al., 2023; Zhong et al., 2025; Anderson et al., 2013).

In Sariaya, Quezon, Philippines, farmers identified Maya birds (Passer montanus) as one of the primary rice-eating pests. These birds cause substantial crop damage during the ripening stage of rice. Farmers have traditionally employed various deterrent methods such as installing nets, building scarecrows, or using clappers to produce noise across the fields. However, these conventional methods are no longer effective because birds have quickly adapted to them. Several studies have confirmed that traditional scarecrows provide only short-term relief and lose their deterrent power over time.

As technology evolves, researchers have explored the development of more effective, technology-based bird deterrents. Devices incorporating sensors such as Passive Infrared (PIR) sensors, Piezo ultrasonic sensors, cameras, and microcontrollers like Arduino Uno and Raspberry Pi have been developed to detect and repel birds automatically. Some systems use wind power, infrared imaging, RFID, Wi-Fi, and LoRa technologies to trigger high-frequency sounds or visual cues that deter birds. Electronic bird-repellent systems using acoustic and visual stimuli effectively frightened and confused birds (Chen et al., 2024; Amenyedzi et al., 2025), prompting them to relocate to quieter areas. These technologies have even been applied in airports to prevent bird congregation near runways and reduce the risk of aircraft collisions.

Technological advancement has also transformed the agricultural industry by enhancing automation and efficiency. Sensors, actuators, and microcontrollers now play an integral role in monitoring and controlling agricultural processes. Studies highlight that the application of technology in agriculture accelerates harvesting, minimizes manual labor, and improves productivity (Aijaz et al., 2025; Sanyaolu & Sadowski, 2024; Getahun et al., 2024; Vărzaru, 2025; Nautiyal et al., 2025). In recent years, research has expanded to include the observation of bird behavior and attacks in both wind farms and rice fields (Villegas-Patraca et al., 2012; Yordanov et al., 2025; Tesfahunegny et al., 2020; Marques et al., 2021). Hasanudin et al. (2020) noted that the use of actuator and sensor-based systems for environmental monitoring is steadily increasing, offering opportunities to develop innovative pest-control solutions.

Despite global progress in agricultural technology, limited research in the Philippines focuses on developing bird-repellent systems for rice fields. This study focuses on developing an IoT-based solar bird-repellent system integrated with image processing technology to help farmers protect their rice fields without harming birds. The system employs a camera to capture real-time images, allowing its recognition module to identify bird species and trigger a speaker that emits specific sound frequencies to drive them away. Designed primarily to counter rice-eating species such as the Eurasian Tree Sparrow (Passer montanus), locally known as Maya, and the Mayang Paking, the system addresses a major agricultural challenge in the Philippines, where these birds cause significant crop losses by attacking in flocks during the rice-ripening stage. The Maya is characterized by its chestnut crown, black chin and throat, white cheek patches, and brown-black wings, while the Mayang Paking features a reddish-brown body, silvery-blue bill, and black head, both species known for feeding on grains and gathering in large groups, exacerbating crop destruction (Animalia, 2023). Utilizing components such as a Raspberry Pi, camera module, tweeter speaker, and photovoltaic panels, the project aims to create a sustainable and efficient prototype that enables farmers to safeguard their crops through an innovative, eco-friendly approach.

Theoretical Framework

The Threat of Birds to Rice Production

In the Philippines, the Eurasian Tree Sparrow (Passer montanus), locally known as the Maya, is one of the most common rice-eating birds found in paddy fields. These birds feed on rice grains from the ripening stage until harvest, often causing unfilled panicles and substantial grain loss. Flocks of sparrows can knock grains off stalks, depleting yields significantly. Studies have shown that birds can affect up to 75% of local rice production in some regions (Angkaew et al., 2023; Htay et al., 2022). Birds have become one of the primary pest concerns for farmers worldwide, not only damaging crops but also contaminating fields and residential areas with their droppings, which pose health risks. Among the most problematic species are crows, which damage both agricultural and residential areas.

To mitigate bird attacks, farmers have historically relied on traditional deterrent methods such as scarecrows, hawk kites, colored lights, lasers, flashing devices, and chemical repellents. However, these methods have proven increasingly ineffective as birds quickly adapt to them. Scarecrows, often constructed from bamboo and old clothing, were once common in Sariaya, Quezon, but their effectiveness has declined over time. Farmers in the region continue to rely on manual deterrence techniques, as no advanced technological bird repellers are yet in use.

Despite technological advancements, bird pest management remains time-consuming and costly. Developing effective systems requires resources that are often unavailable to small-scale farmers. Kendall et al. (2022) emphasized that in many developing countries, farmers still rely on outdated and inefficient manual deterrence methods, despite the availability of emerging electronic solutions.

Emergence of Electronic and Sensor-Based Bird Repellents

Advances in agricultural technology have enabled the development of electronic bird-repellent systems. These devices typically incorporate microcontrollers, sensors, cameras, solar panels, and sound emitters to deter birds using high-frequency noise. Arowolo et al. (2022) explain that birds can detect ultrasonic frequencies around 29 kHz, beyond the human hearing range of up to 20 kHz. Ultrasonic sounds above 20 Hz can irritate birds, prompting them to leave the area.

Researchers have discovered that specific predator calls, particularly those of falcons (Buteolagopus), are especially effective in frightening pest birds. Baral et al. (2019) and Uzma et al. (2021) found that the falcon's sound produced the strongest repelling effect against crows, especially when played in 60-second bursts followed by 360-second pauses. These studies emphasized that the frequency, volume, and duration of the sound are critical in determining a repellent's effectiveness. Importantly, these systems are designed to be environmentally friendly, humane, and cost-efficient compared to chemical deterrents or netting systems.

Technological Innovations in Bird Repellent Systems

Recent developments in the field have focused on automation and intelligent systems that detect, identify, and repel birds in real time. Singh et al. (2021) developed a modified scarecrow equipped with a Passive

Infrared (PIR) sensor and a flapping mechanism. When birds entered the field, the system detected their presence, moved its arms, and activated a buzzer to scare them away. Similarly, Murthi et al. (2021) proposed a design incorporating an LCD, infrared (IR) sensors, a relay, and ultrasound generators powered by solar panels, laying the groundwork for sustainable, autonomous deterrent systems.

Machine learning and image processing have further advanced bird detection systems. Arowolo et al. (2022) developed a bird-detection model using a convolutional neural network (CNN) running on a Raspberry Pi 4. Equipped with a 0.3-megapixel camera and solar-charged lithium batteries, the system could detect birds within 10–15 meters and automatically trigger varying sound frequencies to prevent bird habituation. Similarly, Priya et al. (2020) designed a system that used a 360-degree rotating camera and a piezo ultrasonic sensor to detect birds and emit a 60 kHz ultrasonic signal powered by Python-based OpenCV image processing.

Machine learning allows devices to analyze visual data, recognize bird species, and adapt deterrence mechanisms accordingly. According to Brown (2021), machine learning enables computers to learn from data, such as numbers, images, or text—without explicit programming, forming the foundation of artificial intelligence applications like image-based bird detection.

IoT and Connectivity in Agricultural Pest Management

The integration of the Internet of Things (IoT) into agriculture has revolutionized pest management. IoT-based systems connect sensors, cameras, and actuators to enable real-time monitoring and automation. Modern agriculture now utilizes technologies such as GPS, drones, moisture sensors, and robotics to enhance productivity and sustainability

(Mishra et al., 2020.

In one innovative project, Golla and Gullipalli (2020) collaborated with the Bioseco company to develop a LoRa- and Wi-Fi–based bird monitoring and deterrence system. The design featured an Arduino Uno, LoRa transceiver, piezoelectric buzzer, and LED indicators. Data collected from sensors were transmitted via the ESP8266 Wi-Fi module to both a web interface and mobile application, allowing users to monitor and control the system remotely. The system successfully detected and tracked birds up to 500 meters away, demonstrating the potential of IoT and LoRa technology in long-distance agricultural monitoring.

Research Framework

Data

According to Hamed et al. (2021), since species differ in their sensitivity to various sound frequencies, data on sound limits for different pest birds were used during the application of sonic waves to control birds in this experiment, as indicated in Table 1.

Table 1

Species-specific sensitivities to frequencies, peak sensitivity, and range of sensitivities.

Species	Lower Limit (HZ)	Most Sensitive (kHz)	Upper Limit (kHz)
Dove (Spilopelia senegalensis)	50	1.8-2.4	11.5
Crow (Corvus cornix)	300	1-2	8
Pigeon (Columba livia)	20	1-2	10
House Sparrow (Passer domesticus)	675		11.5

According to Levitt et al. (2022), the birds were disturbed at frequencies ranging from 28 kHz to 60 kHz. Accordingly, Dmello et al.

(2025), a locally built solar-powered electronic device, successfully produced ultrasonic waves that were amplified, broadcast at a sufficiently loud volume, and automatically varied in frequency between 15 kHz and 25 kHz.

During the testing stage of the developed system, the researchers discovered that the frequency and predator sounds were not effective in driving away the Maya. Based on related literature and previous studies, the most effective sounds for repelling birds are predator sounds, such as those of a falcon. These types of sounds have been successfully used to drive away crows and pigeons. Therefore, during sound testing, it was found that the sounds of guns, missiles, and cannons are effective in driving away the Maya.

To prevent the birds from becoming accustomed to the system, it emits five random sounds. Testing showed that when the sounds are startling, the birds fly away, which is why gunshot, cannon, and missile sounds were chosen. The system can identify birds at a distance of approximately 60–70 meters, while the emitted sound can reach approximately 100–120 meters. When a bird is detected, the system emits a sound, and the bird can react from 100–120 meters away. However, at this distance, the birds respond slowly and may require multiple sound emissions before leaving. When the interval alert mode is activated, the speaker emits a sound every five minutes to maintain the deterrent effect.

Design

The study employed a developmental research design to conduct this study. This approach was used to identify solutions to the stated problems, justify findings, and fulfill the study's objectives. Similarly, a quantitative design was utilized through computational, statistical, and mathematical tools to gather, present and analyze the survey results. It is conclusive in nature, as it aims to quantify the problem and determine its prevalence by producing findings that can be generalized to a larger population.

Respondents

The respondents of the study consisted of rice farmers and IT experts, all selected through random sampling. This method ensured that each member of the population had an equal chance of being included in the sample. A total of ten (10) rice farmers from a selected barangay and five (5) IT experts participated in the study. The chosen barangay was selected as the site for the system testing.

Instrument

A structured questionnaire was used as the primary data collection instrument. The questionnaire consisted of thirty-three (33) closed-ended questions, each designed to gather specific information relevant to the study's objectives. A 5-point Likert scale was applied, allowing respondents to express their level of agreement or disagreement with the given statements. This format facilitated quantitative analysis and ensured consistent responses across participants.

Statistical Treatment

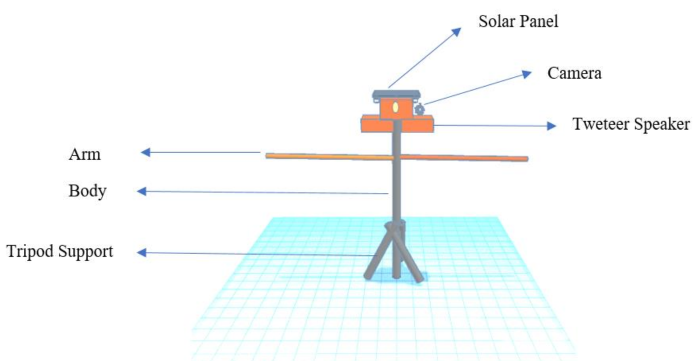
To analyze and interpret the collected data, the study employed appropriate statistical procedures. The total scores on the Likert scale were computed by multiplying the frequency of each response by its corresponding scale value. The mean score was then calculated by dividing the total score by the total number of respondents. The Likert scale is a widely used method for gathering quantitative data, as it allows for clear interpretation and easy presentation of results through tables, charts, and graphs. The 5-point Likert scale, in particular, provides a balanced measure of opinions, capturing both positive and negative sentiments as well as neutral responses, thus offering a clear understanding of the respondents' true perceptions.

Experimental Design

Figure 1 illustrates the preliminary model on which the system was developed.

Figure 1

An illustration of experimental design



Tinkercad was used to create this 3D representation, providing a visual framework for the proposed design. This model remains open to modification based on potential enhancements and suggestions received after its presentation. The purpose of creating this initial design is to visualize and refine how the final system might look and function in future iterations.

Agile Methodology

The Agile methodology is a project management approach that divides a project into multiple phases, emphasizing continuous collaboration, iteration, and improvement. It follows an iterative process, meaning each cycle enhances the previous one through evaluation and refinement. This ongoing focus on quality and adaptability ensures that the final product is both efficient and effective.

Figure 2

Agile methodology framework

Procedures of Different Phases

Planning. Planning is the initial stage in developing a functional and reliable system. The group first discussed the feasibility of creating the proposed system and identified roles and responsibilities among members. Specific tasks, such as data gathering and manuscript preparation, were assigned to ensure an organized workflow and a smooth development process.

Analyze. After planning, the next step was to analyze the collected data and materials. The researchers carefully examined whether the data were accurate, relevant, and suitable for the development of the system. This phase ensured that only valid and useful information would inform the design and functionality of the project.

Design. Following the analysis, the design phase began, where the conceptual framework of the system took shape. A simple, user-friendly layout was prioritized without compromising functionality. Software tools were utilized to create a 3D model that served as the visual and structural foundation for constructing the device.

Develop. During development, the physical assembly of the device was carried out. Each component was connected carefully to prevent short circuits or hardware malfunctions. This phase required precision and an understanding of how each part interacts with the others to ensure the system operated as intended.

Testing. The testing phase involved evaluating the system's functionality to identify and correct any bugs or defects. The team conducted a thorough assessment to confirm that the system performed efficiently. Any issues discovered were promptly fixed before moving to the deployment stage, ensuring that the device met the desired performance standards.

Deployment. Once testing was successfully completed, the system was deployed in an actual working environment. This phase marked the transition from development to real-world application. The deployment process also provided valuable insights into system performance, functionality, and usability.

Feedback. After deployment, feedback was gathered from users and evaluators. Both positive and negative comments were carefully considered to identify areas for improvement. This feedback loop is an essential component of the Agile methodology, allowing the system to evolve through continuous enhancement and refinement based on real-world experiences.

Technical Framework

Materials

The materials used in developing the IoT-based solar bird-repellent system with image processing include the following:

Software

Table 2

List of software

Name	Description
Python	It is used to code image recognition.
VS Code	It is used to code Python Language.
OpenCV Library	It is used for camera logic.
Tensorflow	It is used for the deep learning of image recognition.
Google Colab	It is used to train machine learning.
Anaconda Software	It is a virtual environment so that the libraries in the computer are not damaged while coding object detection.
Geany IDE	After the code is deployed in the Raspberry Pi, it is used to code Python.

Table 2 presents the software materials used for the system's detection module, specifying the programming languages and tools employed to train the machine learning model.

Hardware

Table 3 provides a comprehensive overview of the hardware components utilized in the development of the system, detailing each material's functional role in the project. Each hardware element has been carefully selected to ensure compatibility, efficiency, and reliability in performing its designated tasks.

Table 3

List of hardware materials

Name	Description
Raspberry Pi 3b+	This is the central hardware component of the system. It will process the images received from the camera.
CCTV Bullet Camera	The camera serves as the system's human eye and accepts the current situation of recording the entire video.
Solar Charger Controller	Charge controllers, also referred to as charge regulators, control voltage and/or current to keep batteries from overcharging. It regulates the voltage and current from the solar panels to the battery.
LDR Sensor Module	The LDR sensor module detects light intensity. It is connected to the board's AO and DO-designated analog and digital output pins. The LDR's resistance falls off in direct proportion to the brightness of the light when there is light.
OD Gel Battery	Gel batteries serves as the storage of power.
Solar Panel	It is used to convert light from the sun into electricity to load the battery. PV modules can also be utilized in battery-less systems.
Horn Tweeter Speaker	A tweeter speaker is used to produce high frequencies to the limit of our human hearing range.
Amplifier	The amplifier serves as the controller of the volume of the sound.
Round Metal Tubes	In this project, a round metal tube is used to make a scarecrow structure.
USB Flash drive	It serves as the storage of data.

Modeling

Figure 3 illustrates the connections between the hardware components. The 18V solar panel charges the battery through a charge controller, which prevents overcharging. The DC converter then steps down the battery voltage to 5V before supplying power to the Raspberry Pi. The

CCTV Bullet Camera is connected directly to the microcomputer for monitoring purposes. Additionally, the photoresistor is connected to the battery and functions as a switch, enabling the automatic shutdown of the amplifier and speaker at night and their automatic activation in the morning.

Figure 3

Diagram of block hardware

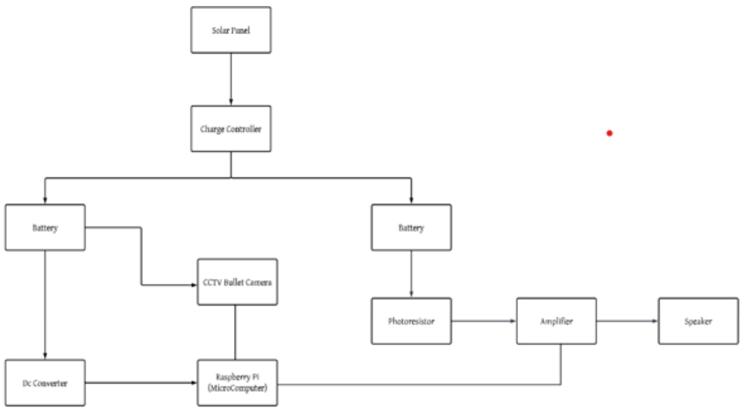


Figure 4

Circuit diagram of the developed system

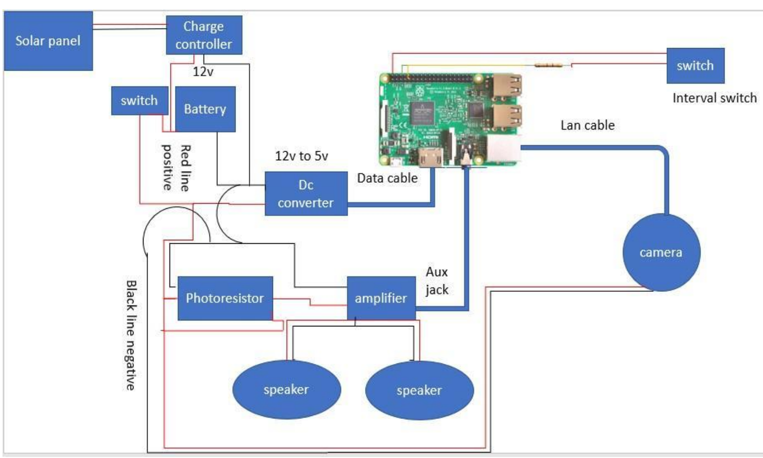


Figure 4 illustrates the connections for the audio amplifier, interval switch, camera, DC converter, and Raspberry Pi (RPI) and serves as a reference for wiring the hardware components. The solar panel connects to the solar charge controller, which in turn connects to the battery, with the positive wire routed through a switch. The negative terminal of the battery is directly connected to the DC converter, camera, and amplifier. The output of the DC converter is connected to the power input of the RPI.

The RPI connects to the camera via a LAN cable and to the amplifier via a jack cable, while the speaker is connected directly to the amplifier. Additionally, the 5V positive output of the RPI is connected to the interval switch, and the GPIO 17 pin, along with the negative terminal, is connected to the output of the interval switch through a resistor. This setup ensures proper power distribution and communication between all hardware components, enabling the system to operate efficiently.

Table 4

Interval Switch Mode of Raspberry Pi

2	5v positive	Red
6	negative	Black
11	GPIO 17	Green

Figure 5

Color-coded graphic of the Raspberry Pi GPIO

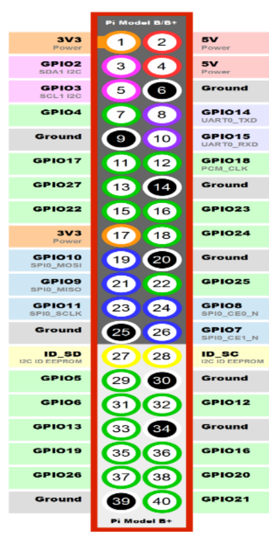


Figure 5 presents a color-coded graphic of the Raspberry Pi GPIO, showing the pin numbers, GPIO numbers, and pin types. This diagram serves as a convenient reference for wiring and identifying the proper connections on the Raspberry Pi.

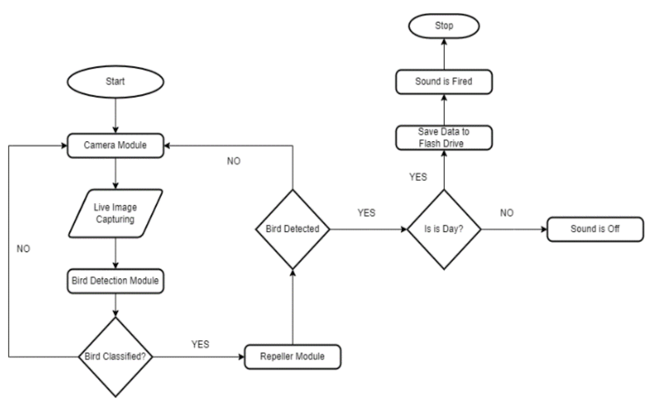
The term "GPIO" refers to the pins used to connect the Raspberry Pi board to external input and output devices. A GPIO (general-purpose input/output) port can handle both incoming and outgoing digital signals. The Model B+ has a 40-pin GPIO layout, similar to the previous model. On the Model B+ board, there are 9 fixed ground pins (0V), 2 fixed 3.3V pins, and 2 fixed 5V pins. The 5V pins receive a direct supply from the mains adapter and can be used to power other 5V devices in addition to the Raspberry Pi. The 3.3V pins are used to test LEDs and provide a stable 3.3V supply for external components.

System Design

Figure 6 presents the system process in a flowchart. The camera module serves as the system's “eye,” capturing the current scene. The camera takes an image every 30 seconds, which is then processed by the bird detection module to determine whether a bird is present. After processing, the image is automatically deleted.

Figure 6

Flowchart of the system camera detection mode



If a bird is detected, the repeller module is activated, the data is saved to a flash drive, and the speaker emits a sound. The speaker operates during the daytime and automatically turns off at night. If no bird is detected in a captured image, the image is deleted automatically, the speaker remains silent, and the bird detection module proceeds to process the next captured image.

Figure 7 illustrates the interval mode process in a flowchart. When the interval mode is active, the camera is turned off, and the speaker emits sound every five minutes. The speaker operates during the daytime and automatically turns off at night.

Figure 7

Flowchart of the system interval alert mode

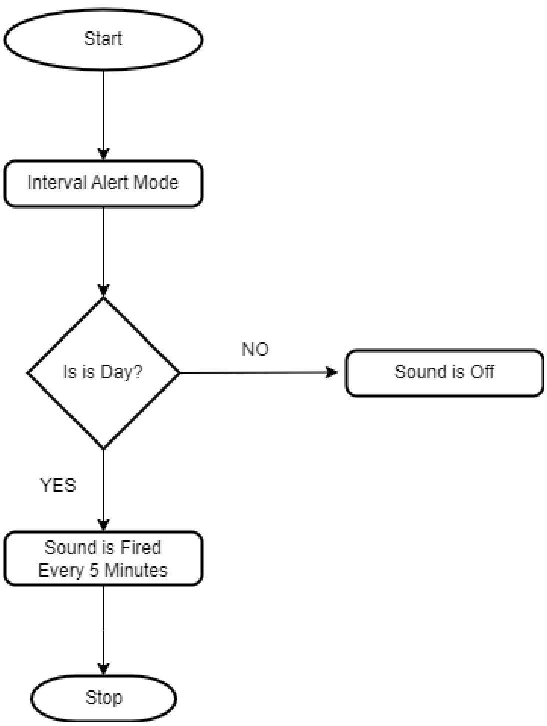


Figure 8

System architecture

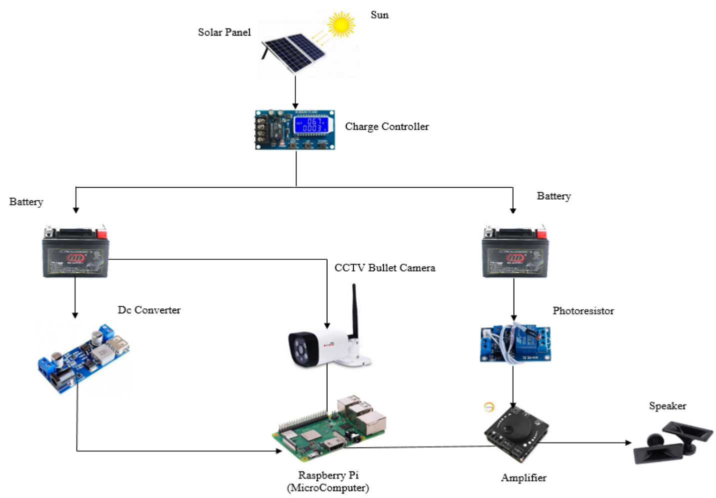


Figure 8 shows that the bird-repellent system comprises a single-board computer, camera, and speaker. Both the speaker and camera are connected to the Raspberry Pi to enable communication, allowing the exchange of data. The camera captures images and sends information to the Raspberry Pi, while the speaker produces loud sounds to scare away birds. The Raspberry Pi serves as the system's central processor, analyzing images from the camera and sending signals to the speaker to activate the deterrent sounds.

The system is powered by gel batteries, which are charged via solar panels, with the charging current regulated by a charge controller. A photoresistor is incorporated to automate the system, turning off the amplifier and speaker at night and switching them on in the morning. This integration ensures that the system operates efficiently while conserving power during periods of inactivity.

Figure 9

System structure

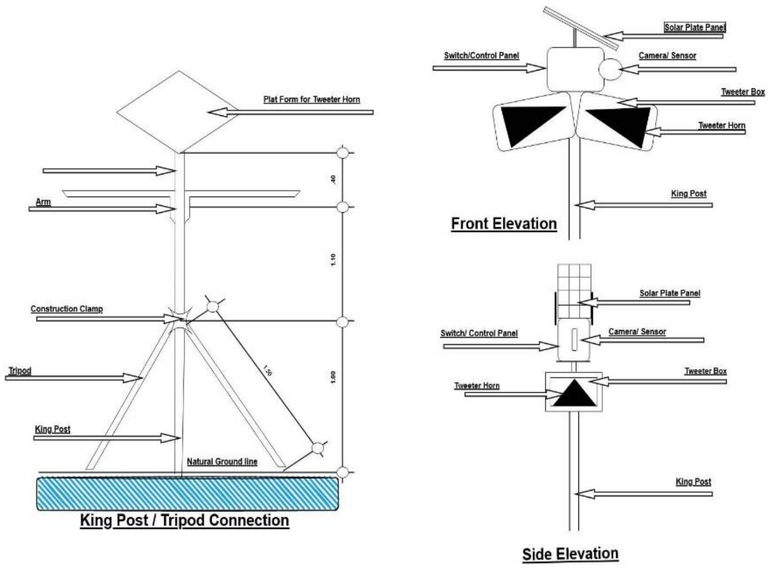


Figure 9 illustrates the assembly of the system, providing a clear guide for researchers to implement and understand the connections between each component. Multiple views of the system are presented to facilitate analysis of its physical layout once constructed. Additionally, each part of the system is labeled, making it easier to identify components and comprehend their placement within the overall setup.

Figure 10

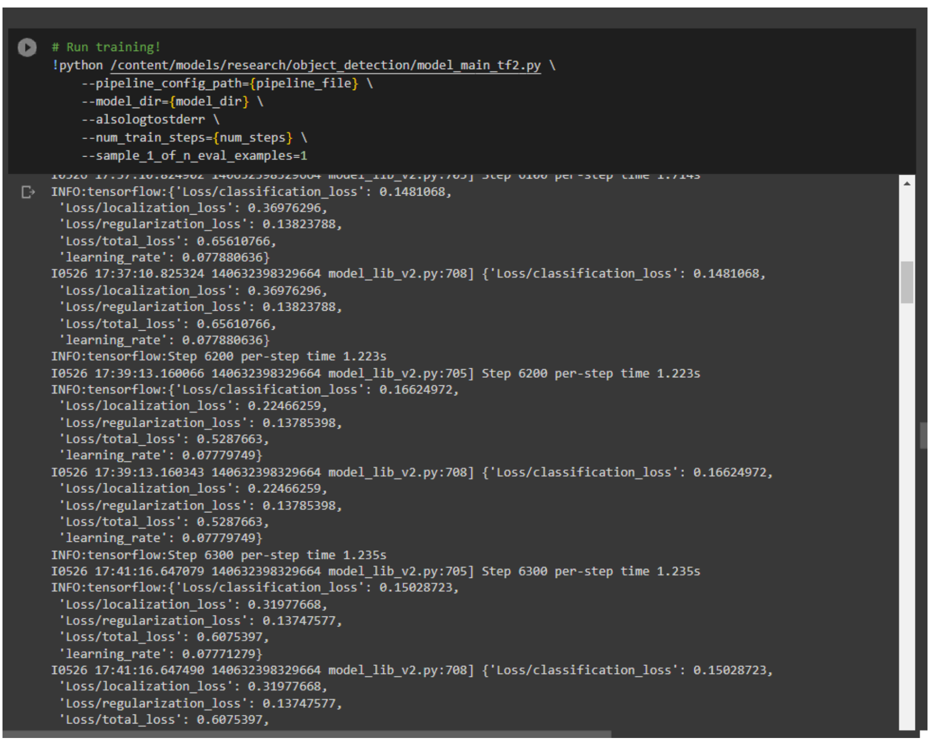
Labelling of birds

Figure 10 illustrates the process of bird labeling in an image. In machine learning, data labeling involves identifying unlabeled data, such as images, text files, or videos, and adding one or more informative labels. This provides context, allowing a machine learning model to learn from the data and make accurate predictions or classifications.

Figure 11 shows an example of the system's detection model during training. The TensorFlow Lite Model Maker library simplifies the training of a TensorFlow Lite model using a custom dataset. By leveraging transfer learning, both the training time and the amount of data required for effective model training are significantly reduced.

Figure 11

Train custom TFLite detection model



```
# Run training!
!python /content/models/research/object_detection/model_main_tf2.py \
    --pipeline_config_path={pipeline_file} \
    --model_dir={model_dir} \
    --alsologtostderr \
    --num_train_steps={num_steps} \
    --sample_1_of_n_eval_examples=1
```

```
INFO:tensorflow:{'Loss/classification_loss': 0.1481068,
 'Loss/localization_loss': 0.36976296,
 'Loss/regularization_loss': 0.13823788,
 'Loss/total_loss': 0.65610766,
 'learning_rate': 0.077880636}
I0526 17:37:10.825324 140632398329664 model_lib_v2.py:708] {'Loss/classification_loss': 0.1481068,
 'Loss/localization_loss': 0.36976296,
 'Loss/regularization_loss': 0.13823788,
 'Loss/total_loss': 0.65610766,
 'learning_rate': 0.077880636}
INFO:tensorflow:Step 6200 per-step time 1.223s
I0526 17:39:13.160066 140632398329664 model_lib_v2.py:705] Step 6200 per-step time 1.223s
INFO:tensorflow:{'Loss/classification_loss': 0.16624972,
 'Loss/localization_loss': 0.22466259,
 'Loss/regularization_loss': 0.13785398,
 'Loss/total_loss': 0.5287663,
 'learning_rate': 0.07779749}
I0526 17:39:13.160343 140632398329664 model_lib_v2.py:708] {'Loss/classification_loss': 0.16624972,
 'Loss/localization_loss': 0.22466259,
 'Loss/regularization_loss': 0.13785398,
 'Loss/total_loss': 0.5287663,
 'learning_rate': 0.07779749}
INFO:tensorflow:Step 6300 per-step time 1.235s
I0526 17:41:16.647079 140632398329664 model_lib_v2.py:705] Step 6300 per-step time 1.235s
INFO:tensorflow:{'Loss/classification_loss': 0.15028723,
 'Loss/localization_loss': 0.31977668,
 'Loss/regularization_loss': 0.13747577,
 'Loss/total_loss': 0.6075397,
 'learning_rate': 0.07771279}
I0526 17:41:16.647490 140632398329664 model_lib_v2.py:708] {'Loss/classification_loss': 0.15028723,
 'Loss/localization_loss': 0.31977668,
 'Loss/regularization_loss': 0.13747577,
 'Loss/total_loss': 0.6075397,
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Figure 12

Graph of downward trend in Tensorboard

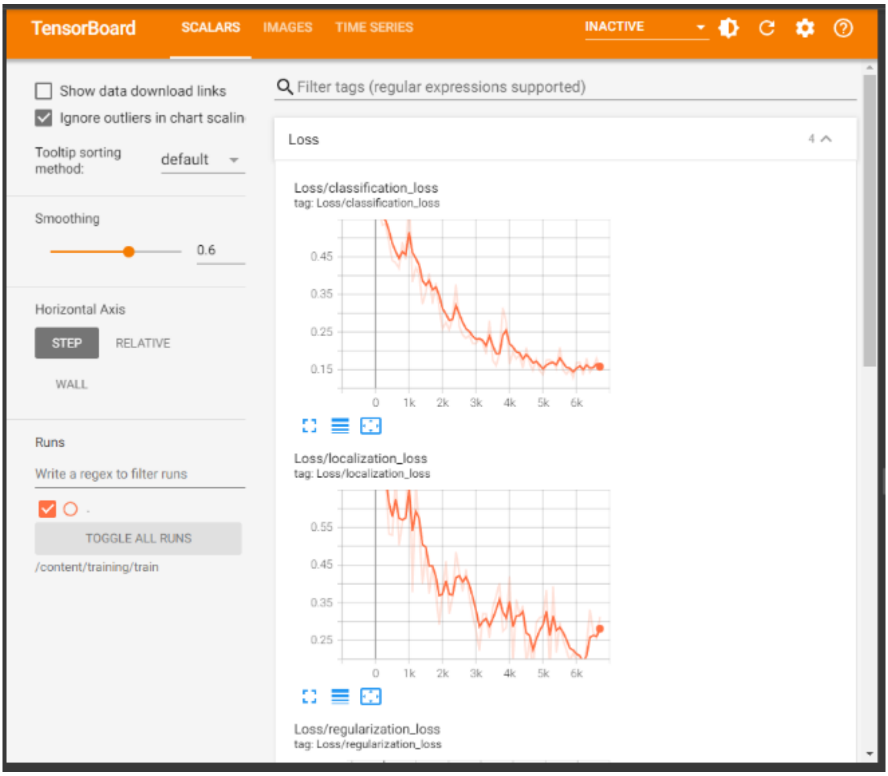


Figure 12 shows TensorBoard, a tool that provides essential measurements and visualizations during the machine learning workflow. TensorBoard's extensive built-in functionality allows users to quickly understand the behavior of their model. It can monitor various metrics, including accuracy, root mean squared error, and log loss.

The model is then converted to TensorFlow Lite, which enables faster detection and is fully compatible with the Raspberry Pi. This conversion ensures efficient deployment of the trained model on the system's hardware while maintaining performance.

Figure 13

Testing TensorFlow lite model

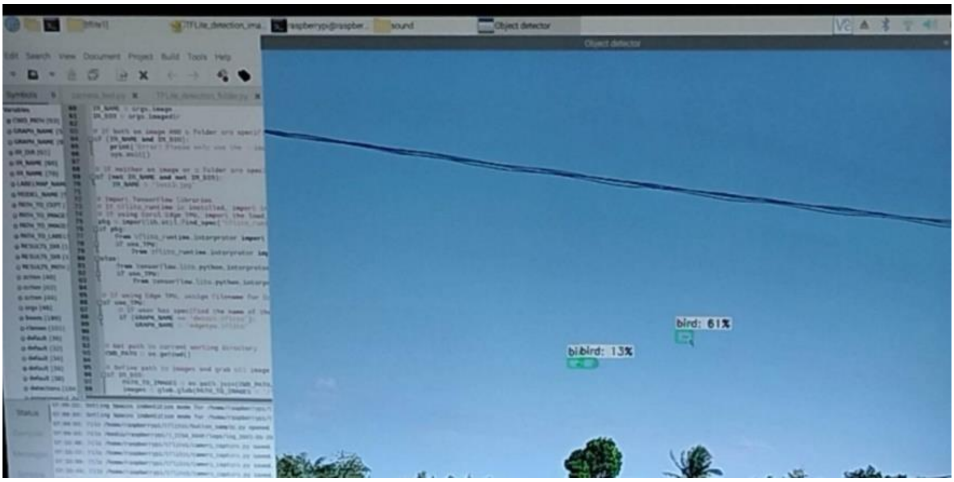
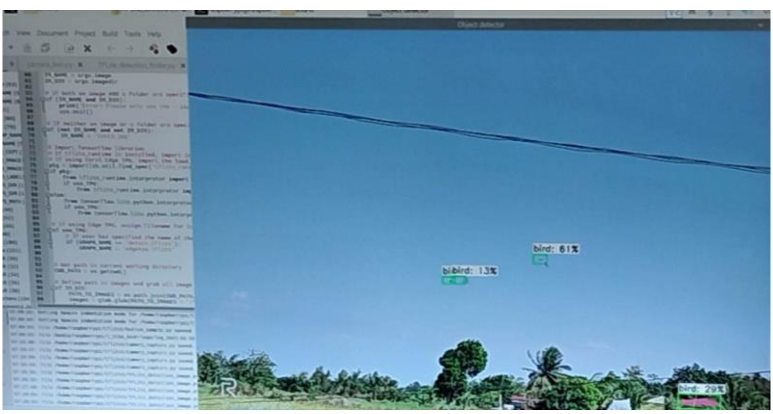


Figure 13 illustrates the testing of the model. The results of bird detection show accuracy rates of 61% and 13%, respectively. The detection module was able to identify the bird even when it appeared as a small dot; however, the success rate in such cases was only 13%.

Figure 14

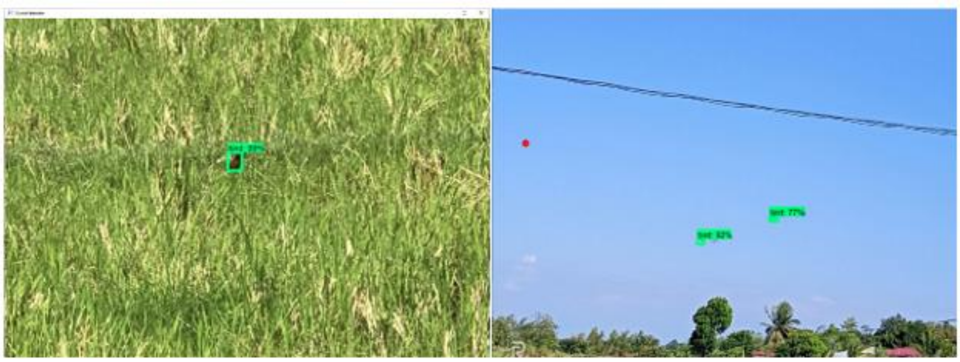
Image processing



As illustrated in Figure 14, the system captures an image, and the detection module identifies whether a bird is present; if so, the speaker emits a sound. During testing, the researchers found that the detection module could reliably identify birds only within a distance of 60–70 meters from the system. When birds are farther away, the likelihood of detection decreases. The camera has a 2MP HD resolution, which limits image clarity, particularly for distant birds.

Figure 15

Result of image processing



The image processing function of the system utilized TensorFlow and Google Colab. TensorFlow was primarily used for training and inference of deep neural networks. With TensorFlow, best practices for performance monitoring and model retraining were implemented to ensure the detection module remained accurate and efficient.

The image demonstrates that the image processing function is operational. The detection module successfully identified the bird in the image, achieving confidence levels of 99%, 92%, and 77% for different detections.

Figure 16

The developed system

The IoT solar bird repellent with image processing is more reliable for driving away birds in rice fields than traditional scarecrows. The developed system effectively deters birds and can serve as a practical alternative to conventional methods. It reduces the effort required to manage birds, as they no longer need to travel back and forth across the fields to scare them away manually.

The researchers conducted extensive sound testing to observe the reactions of the sparrow (Maya). Various sounds, including frequencies, predator sounds, and startling sounds, were tested in a controlled environment. While the Maya showed signs of panic when exposed to frequency and predator sounds in this controlled setting, these sounds were ineffective in a real-world environment, such as a rice field. In open paddy fields, the sound dispersed before reaching the birds, resulting in little to no reaction. Among the tested sounds, the Maya responded most effectively to the sounds of guns, cannons, and missiles.

Figure 17

Testing the sound with Maya in a Cage

Observations also showed that the birds remained calm while inside the cage under normal conditions. However, when the system emitted gunshot, cannon, or missile sounds, the birds became visibly agitated, jumping, restless, and attempting to escape the cage. Based on these observations, the researchers concluded that the Maya are strongly affected by and react to these specific startling sounds.

Cattle are subjected to a variety of stressors, including thermal and chronic stress. For dairy cows, reducing stress is particularly important, as maximizing milk yield is a top priority. The metabolic and psychological strain on high-yielding cows can lead to decreased milk production and milk with lower protein and fat content. One significant source of stress is noise. Abrupt or loud noises can negatively affect milk production, making it essential to raise cattle in a quiet environment. Exposure to noise at 80 dB has been shown to reduce feed intake, increase agitation, and elevate heart rates in cows (Table 5). Additionally, noise can disrupt reproductive function, affecting the estrus cycle and conception rates.

Table 5

Impact of the noise of varying intensity on cattle

Noise Volume [dB]	The Effects of Noise
80 dB	Excessive anxiety, increased heart rate, reduction in feed intake
90-95 dB	Anxiety, frequent bowel movements, muscle tension, increased heart rate, reduction in rumen contractions food retention
≥100 dB	Morphological and biochemical changes in the blood (increase in blood glucose levels, development of leukocytosis)

Table 6 presents the materials, tools, and equipment used in the project, along with their respective prices and total cost. Conducting a cost–benefit analysis helps decision-makers make informed judgments about the system’s economic feasibility and allocate resources effectively. The study found that developing the IoT-based solar bird-repellent system required a higher initial investment compared to a traditional scarecrow, which is inexpensive since its materials are locally sourced. However, traditional scarecrows have become less effective because birds easily adapt to their static presence. In contrast, the proposed system, though costly at first, offers a long-term and sustainable solution through its durable components such as the Raspberry Pi, camera, solar panel, and battery, which can last for several years with minimal maintenance. Furthermore, it reduces farmers’ labor and time, as it automatically detects and repels birds without the need for manual intervention. Therefore, despite its higher cost, the system proves to be a more efficient, durable, and cost-effective investment for modern rice farming in the long run.

Table 6

Cost and benefit Analysis

	Description	Quantity	Price
1	1 ¼ Pipe (Post)	1	980
2	2 meters Pipe (Arm)	1	185
4	ABC Silicon Sealant Clear	1	280
5	Adjuster PC	1	15
6	Angle Bar 3/16	1	320
8	Black Screw	132	140
9	Bosny Spray Paint	2	340
10	BreadBoard	1	59
11	Clamp	3	270
12	Cutting Disc (HardiFlex)	1	250
13	Cutting Disc (Metal)	2	160
14	Double Sided Tape	1	19
15	Double Wire	1	22
16	Epoxy Primer Gray	1	270
17	Flat Bar	1 1/2	320
18	Glue Gun	1	200
19	Glue Stick	9	38
20	Hardi Sanepa 10x10 ft.	1	435
21	Heatsink	1	15
22	Jumper Wire	1	19
24	Light Control Switch	1	83
26	Manpower		2,000
27	Memory Card 16GB	1	400
29	Mini Amplifier	1	347
30	MOSFET	1	35
31	Nut and Bolt	4	40
32	OD Battery	1	550
33	Paint Brush	1	35
35	Regulator	1	15
36	Relay Module	1	39

	Description	Quantity	Price
37	Resistor	2	10
39	Shipping Fee		141
40	Socket	6	60
41	Solar Charger Controller	1	230
42	Solar Panel	1	669
43	Soldering Iron	1	160
44	Soldering Lead	1	60
46	Switch	2	96
47	Terminal	4	20
48	Thinner	1	45
49	Tweeter Speaker	2	1,300
50	Welding Rod	1	150
51	Wire	1	44
52	USB 32GB	1	500
53	Ethernet Cable	1	150
54	Raspberry Pi	1	4,000
55	Google Collab	1	600
56	CCTV Rover	1	3,000
	Total Amount		**19,116**

Despite the higher cost, the bird-repellent system represents a worthwhile investment for farmers. The system is durable, with components designed to last several years. For instance, the Raspberry Pi can last 7 to 10 years, the camera and battery up to 5 years, and the solar panel up to 25 years. This longevity makes the system a sustainable and cost-effective solution over time, providing reliable bird control for paddy fields.

Evaluation of the System

Table 7 shows that the system received an overall mean score of 4.1 from IT experts and farmers, with a verbal interpretation of "Excellent."

Among the quality attributes, Functional Suitability scored the highest with a mean of 4.47 ("Very Excellent"), indicating that the system functions correctly and meets farmers' expectations.

Table 7

Overall mean score

ISO 25010 Characteristics	Mean Score	Interpretation
Functional Suitability	4.47	Very Excellent
Reliability	3.55	Excellent
Performance Efficiency	4.33	Excellent
Usability	4.36	Very Excellent
Security	3.92	Excellent
Compatibility	2.7	Poor
Maintainability	3.26	Neither/Nor Excellent
Portability	4.23	Very Excellent
Overall Mean Score	**4.1**	**Excellent**

The system was also found to be reliable in driving away birds and accessing recorded data, with a mean score of 3.55 ("Excellent"), showing general satisfaction with its dependability. Performance Efficiency achieved a mean score of 4.33 ("Very Excellent"), reflecting that the system performed well during demonstrations. For Usability, the system received a mean score of 4.36 ("Very Excellent"), suggesting that farmers found it easy to operate and that the camera and sound effectively deterred birds even from a distance. Security scored 3.92 ("Excellent"), indicating satisfaction with the system's originality and protective features.

In contrast, the system did not meet the Compatibility requirement, scoring 2.7 ("Poor"), indicating that farmers were dissatisfied with its ability to exchange information. Similarly, Maintainability scored 3.26 ("Neither/Nor Excellent"), suggesting uncertainty among farmers regarding whether system components could be reused or easily adapted to future changes.

Finally, the system met the Portability requirement with a mean score of 4.23 (“Very Excellent”), showing that farmers were satisfied with its ease of installation and its ability to replace traditional scarecrows in rice fields.

Conclusion

Based on the evaluation by IT experts and farmers, the overall functionality of the system is working effectively. Respondents agreed that the system performs its intended functions well, although compatibility with other systems remains limited. Overall, the system received an “Excellent” rating across the ISO 25010 characteristics. Therefore, the researchers concluded that the system is reliable for driving away birds in the rice fields.

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