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CURRENT METHODS OF CONTROLLING PEST BIRDS IN AGRICULTURAL CROPS

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Abstract: In addition to weeds, pathogens and pests in animals, birds also pose a threat to the productivity of agricultural crops. Farmers face a significant and potentially costly problem when they lose crops to birds. Correctly identifying bird species and the damage they can cause is essential in creating an effective management plan. Currently, different methods of bird removal are used, from traditional ones to methods that use the latest artificial intelligence techniques. The most used methods of combating hooting are divided into: visual, auditory, chemical, exclusion, habitat modification, and deterrence. This paper presents a review of the most current methods and techniques of bird deterrence for the protection of agricultural crops.
Keywords: birds, control, techniques, methods, removal

1. INTRODUCTION

Around the world, invasive birds affect economies, natural resources, and human safety (Klug et. al, 2023). However, not all bird species are considered harmful to agricultural crops. Many bird species have an important role to play in maintaining ecological balance. These have an essential role in seed dispersal, seed pollination, pest control (insects and various animal species) and even in preventing the incidence of diseases (Graviola et. al, 2024; Pejchar et. al, 2002; Wenny and. al, 2016; Whelan and. al, 2015). To be designated as a pest bird, it must affect social, economic or conservation resources or values (Valerience et. al, 2025).

It is difficult to obtain accurate estimates of damage to birds, and this is mainly for four main reasons. First, birds are responsible for many types of damage, such as the destruction of a variety of crops; competition with native birds; the spread of parasites and diseases; a danger to human safety at airports; and a real social problem in urban areas. Second, bird damage varies greatly in time and place, and the causes of these variations are often unknown. Third, the damage is caused by many species of birds. Finally, damage estimation methods that are credible are often crop–specific or have not been fully developed (Dhital P.R., 2025; Sausse C. et. al, 2021).

These reasons make managing damage to birds and evaluating the effectiveness of methods used to reduce damage difficult. Damage mitigation strategies that work in one place or time or for a specific species may not work in another context. In addition, it is necessary to manage the damage caused by pests of native birds, as well as to ensure control measures that do not endanger their populations. Many of these pests are protected native species (Varriano S. et. al, 2025).

The first step in managing pest birds and their damage is to identify the birds and establish a cost–effective management plan (Bomford M. and SinclairR., 2002).

2. RESEARCH METHODS

There are many examples of eradication campaigns that outline the circumstances and techniques that are necessary to combat pest birds successfully.

These methods can be divided into six main groups. Visual techniques use a visual stimulus to activate a trigger in the bird. Auditory techniques stimulate a trigger in the bird. Chemical methods use chemical agents to kill or create discomfort for birds. Birds are excluded by putting a physical barrier in their way. Habitat modification is when a farmer alters what birds like about that environment, causing them to look elsewhere. Removal methods involve forcibly removing birds from their natural environment, either by trapping or killing (Micaelo et. al, 2023).

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

Visual deterrent techniques

One of the oldest approaches to deterrence is the use of visuals. Basically, they are dangerous objects placed in certain places to scare away birds. Scarecrows and life–size models of natural predators, such as foxes, cats, and owls, are examples of visual deterrents. Also as visual deterrents can be used: reflective tapes, kites and balloons, radio–controlled aircraft or unmanned aerial vehicles (drones).

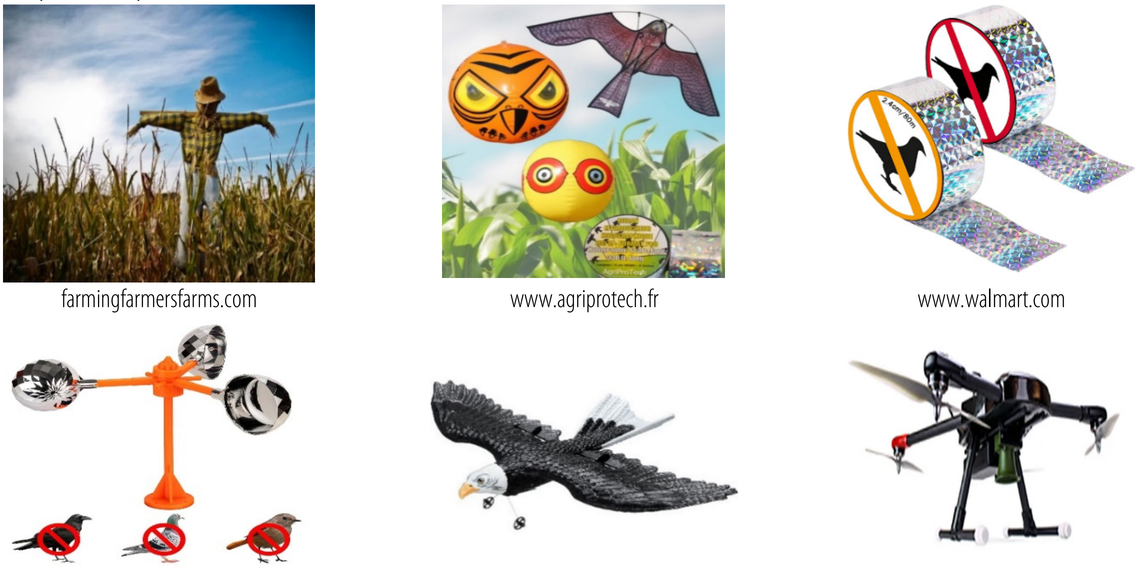

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Figure 1. Visual deterrent techniques

These methods have the advantage that they are affordable and can be easily obtained and installed. However, it should be borne in mind that birds are very intelligent pests and quickly get used to this type of visual deterrence. In addition, when plastics and other materials used in visual deterrents deteriorate, they can scatter the landscape (Pruteanu et. al, 2023).

Auditory deterrent techniques

Auditory deterrent methods include frightening stimuli, such as high–intensity sounds transmitted by sonic devices, such as bird alarms, distress calls, ultrasonic sounds, and predators; or loud noises of weapons, cannons, firecrackers or modified missiles. Because loud noises elicit a fear response from birds, as well as their natural instinct to avoid dangers, auditory methods have been shown to be effective. Most hearing deterrents also have visual elements. (Mohamed et. al, 2020).

The most used auditory deterrent techniques are: rifles, pyrotechnic missiles, flares (light rockets), gas cannons, AV alarms, sounds that imitate predators, ultrasound and infrasound (Mohamed et. al, 2020; Pruteanu et. al, 2023).

However, these methods require a lot of work, and the birds are afraid of the noise transmitted by explosions and sound scaring devices. If they are not changed regularly, birds can get used to them.

Chemical deterrent techniques

They have been used since ancient times, and birds do not tend to get used to them. The most used chemical detangling techniques are tactile repellents, sticky substances, gels, baking soda or disorienting substances such as Avitrol that irritate and disturb birds, making them run away from their location. Some people also use chemical sprays that are harmful to the touch, smell, and taste of birds. These are not the best, as they can also contaminate the surroundings.

Most of these substances do not trap birds, but frighten them or cause them to be disoriented, agitated or hyperactive (tc.canada.ca; Conover, M.R., 1984).

Physical deterrent techniques

Physical deterrence includes tools such as nets, foam, and spikes (long, thin rods with spikes) that prevent birds from finding shelter or food. In most studies that evaluated physical and auditory deterrence methods, physical deterrence was as effective or more effective than auditory deterrence in preventing crop damage. When using physical deterrents such as nets and spikes, the most important considerations are cost, installation time, and risk of physical contamination. For example, it is possible for a small vineyard to install the nets to protect the grapes, but for larger fields, this can be extremely expensive or time–consuming (Wang Z. 2020).

Habitat Modification Deterrent Techniques

The removal or alteration of the natural features of a site is called habitat modification. This involves removing ponds, planting in places without flowers, planting crops that do not attract birds, such as tall grass, eliminating possible nesting areas, using barrier techniques, and even using chemicals used in the birds' natural foods. Allowing grass to grow longer may prevent some birds, such as geese and starlings, from foraging near crops, as these birds prefer to feed in short grass (Olympians, E. M. et. al, 2022; Marateo, J. et. al, 2015).

In addition to these techniques, which are sometimes inefficient and costly both in terms of economic and labor factors, in recent decades, with the advancement of technology, various smart devices for detecting and combating harmful birds have been developed and tested that have proven to be very effective (Chika O. et. al, 2018).

These devices are based on convolutional neural networks (CNNs) and using datasets such as: D–CNN (deep convolutional neural network); ImageNet, BirdNET, NABirds (contain bases for species identification); Faster R–CNN (a machine learning algorithm); YOLO (real–time detection and machine learning algorithm through image segmentation) (Pruteanu A. et al 2024).

3. RESULTS

Mohond Ruzaimi and collaborators have developed an affordable, non–lethal mechanical bird repellent that reduces bird litter on outdoor surfaces and vehicles by 50% through the use of sound and light (fig.2).

(a) (b)

Figure 2. Product of bird-repellent machine (a) Final product (b) Product hanging on tree

The device has a 3D printed body made of ABS and PLA for strength and environmental friendliness, which includes LED lights, doorbells and PIR sensors. These parts are activated when birds move; This causes a sensory overload of the birds, which keeps them safe. Installation in the field demonstrated the effectiveness of the device: it reduced bird droppings by more than 50% in two days. This inventive solution improves public health and cleanliness by reducing exposure to harmful bird droppings (Mohd Ruzaimi, et al., 2005).

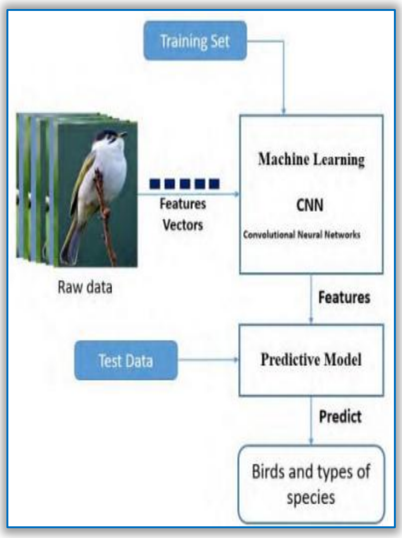
Various studies have shown that the use of artificial intelligence can have a positive impact on pest bird control. Machine learning devices can estimate the reaction of birds by recognizing posture, behavior, through the sounds emitted, they also provide a classification of species thus providing imported data for both farmers and ornithologists (Gavali, P. 2020).

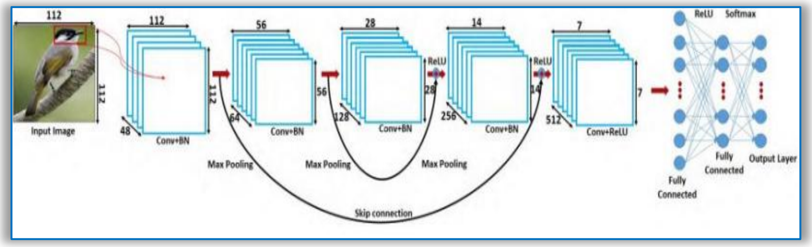
A method using a convolutional neural network (CNN) is shown in figure 3 (Huang and Basanta, 2019). This model classifies birds in their natural habitats by extracting bird information from previously captured or real–time images.

THE ANTI–ADAPTATION PEST BIRD REJECTION (AHBR) method using Q–learning concepts allows the detection of the pest bird trying to adapt in the culture by learning the threat means. This method of repelling pest birds from crops shows the optimal threat sound model that makes adaptation difficult by determining the pest birds' reaction based on the LaS (Long–term and short–

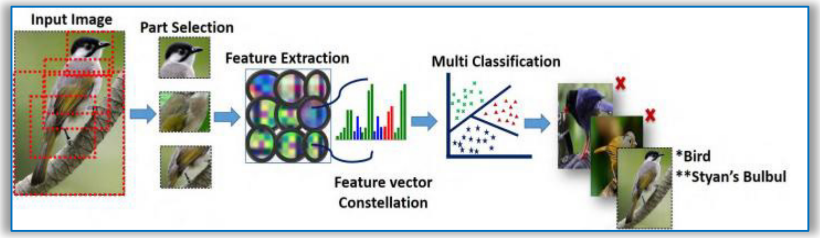
ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

term) policy and rewarding according to the determined reaction using the RL (Reinforcement Learning) policy. LaS allows to find out the actual reaction of the bird to the sound of a threat, and RL measures the variable threat level of long–term and short–term sounds. The AHBR method has as an element RL, which helps to learn the pest bird, the environment, which includes: the agent (pest bird detection device), the environment (the detection range of the bird), action, reward and situation (indicates the presence of the bird in the environment). The situations can be repeated when there is an invasion of harmful birds. The agent is activated according to the reward. The action is to play threatening sounds to repel harmful birds. Based on the updated reward, the AHBR method can select the sound that the bird feels is the most threatening, and this order is repeated. (Lee et. al, 2021).





CNN architecture for detecting bird images



Feature extraction paradigm for bird images

Input raw data and feature illustration for a classifier

Figure 3. Artificial intelligence model of detecting harmful birds (Huang and Basanta, 2019)

Another deep learning method called WILD BIRD BEHAVIOR CLASSIFICATION (WBBC) (Lee et. al, 2019), based on Faster R–CNN algorithm, which helps in real–time detection of birds. This algorithm is composed of three modules. The first module in the WBBC algorithm is frame separation, the module that processes the video data for real–time operation. It has a linear structure and uses Faster R–CNN for bird recognition. If the resolution is high, the video data is larger than the processing level and the processing cannot process more than one frame per second, thus causing a real–time bird detection problem. If the resolution is low then accurate detection becomes impossible. Therefore, if the resolution is higher, it is possible to accurately detect the bird. The WBBC algorithm defines three resolution modes (224p, 480p, 720p).

The second module, the training module, is a basic learning module comprising a wild bird dataset using Faster R–CNN. The purpose of this module is to build a pre–trained data model for wild bird classification by collecting common features of birds. Two factors, such as the variety of appearance (beak, color, size) depending on the habitat and species and the appearance of the birds depending on their mobility, can determine a overfitting problem in deep learning. Thus, the problem of bird diversity can be solved using Faster RCNN of deep learning. The behavior was manually divided into two datasets Staying and Flying birds by image analysis. The orchard is a complicated environment, consisting of trees, branches, leaves and other objects, so a deep training model, a VGG–16 network, was used. The third detection module has the role of detecting the birds that enter through the frame separation module, then reads the weight and makes bird classification.

In the following figure 4, there are briefly described the network structures of four comparative SR (Super–Resolution) methods of bird detection namely: VDSR (Kim and al., 2015), FSRCNN (Dong and al., 2016), DRRN (Tai and al., 2017) and Faster R–CNN (Ren and al, 2017).

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

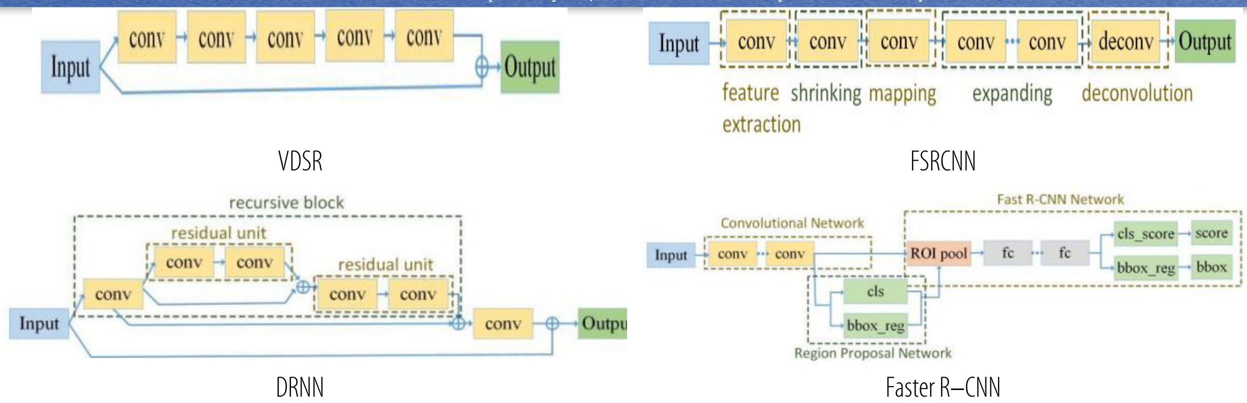


Figure 4. Network structures of four comparative SR (Super–Resolution) methods (Li and al., 2017)

Figure 4 illustrates four models deep learning via simplified network structures with only 6 convolutional layers, where the activation functions.

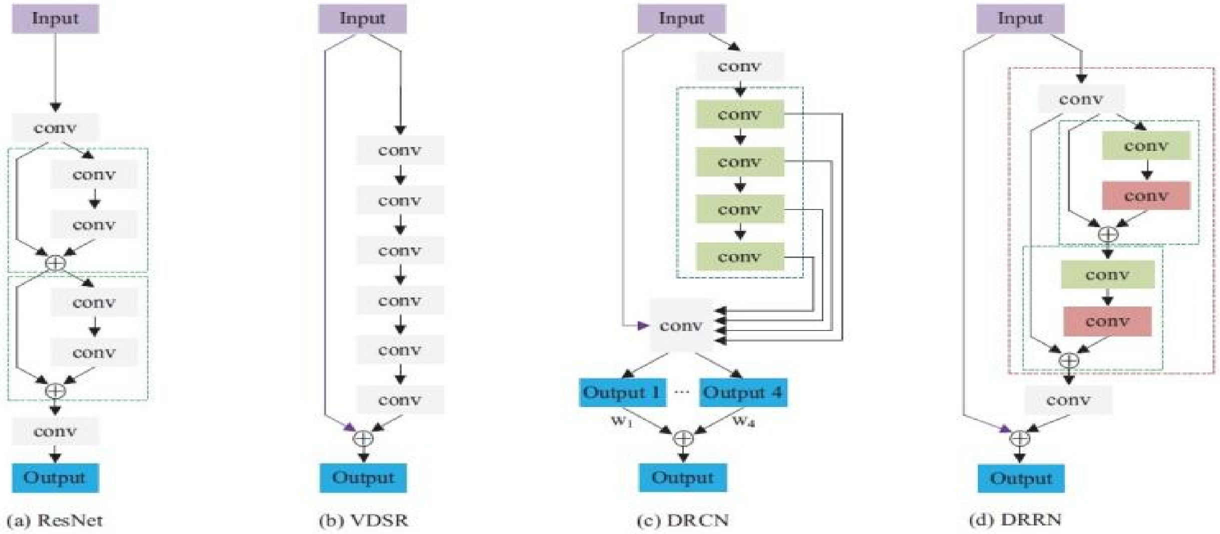


Figure 5. Comparative deep learning models (Tai et. et. al., 2017)

ResNet, figure 5 (a), is a framework residual learning model that aims to facilitate the training of deep networks. Based on the easy optimization of a residual mapping, the authors let the layers match explicitly, i.e. stacked layers. Dashed green box means a residual unit (Tai et. al., 2017; He et al, 2017).

VDSR, figure 5 (b), is also a residual learning model, but which uses the input image ILR and the output image HR. This model uses 20 weight layers in the residual branch (3x3 for each layer), resulting in a larger receptive field (41 × 41 vs. 13 × 13). The purple line refers to global identity mapping. The use of the model on a large scale characterizes it as a robust model for images with different scales (Tai et. et. al., 2017; Kim et. et. al., 2015).

DRCN, figure 5 (c), is a three part model: embedding network (Output 1), net inference (output 4) and net reconstruction (output). In this model, the authors introduce a recursive layer in the network, thus avoiding the increase of the model parameters. The dotted blue box indicates a recursive layer, including the convolutional layers (in light green) having the same weights (Tai et. et. al., 2017; Kim et. et. al., 2016).

DRRN, figure 5 (d), is a model that follows global residual learning in the identity branch and recursive learning in the residual branch, in which several residual units are stacked. The dotted red box refers to a recursive block consisting of two residual units. In recursive block, the corresponding convolutional layers in the residual units (in light green or light red) have the same weights (Tai et. et. al., 2017).

In all four cases shown in figure 4, the outputs are monitored and represented with light blue color and ⊕ indicates the addition of the smart element.

Table 1 shows the quantitative results of three sets of tests at scale factor 3, having three structures: Peak Signal–to–Noise Ratio (PSNR), Structural Similarity (SSIMs) , Information Fidelity Criterion (IFCs) for four methods: Super–Resolution Convolutional Neural Network (SRCNN), Very Deep Super–Resolution (VDSR), (Random forests) RFL, Deep Recursive Residual Network (DRRN), (Tai et. et. al., 2017).

Table 1. Benchmark results of four methods (adapted from Tai et. et. al., 2017; Schulter et. et. al., 2015; Kim et. et. al., 2016; Dong et. et. al., 2016)

Data set	PSNR				SSIMs				IFCs			
	SRCNN	RFL	VDSR	DRRN	SRCNN	RFL	VDSR	DRRN	SRCNN	RFL	VDSR	DRRN
Set5	32.75	32.43	33.66	34.03	0.909	0.905	0.921	0.924	4.658	4.926	5.221	5.397
Set14	29.30	29.05	29.77	29.96	0.821	0.816	0.831	0.834	4.338	4.531	4.730	4.878
Urban 100	26.24	25.86	27.14	27.53	0.798	0.790	0.827	0.837	4.584	4.801	5.194	5.456

It can be seen from table 1, that the results obtained with the DRRN method exceed the other methods, for all three data sets but also for the scale factors (PSNR, SSIMs, IFCs), especially for the Urban 100 data set, where DRRN has an improvement margin of 0,38 dB on the scale factor of 3.

Current modern technologies based on machine learning have allowed the collection of acoustic data which must then be processed to extract important information e.g. detection of target species in orchards. Acoustic monitoring must be closely related to efficient automation in order to detect the species of interest.

Next, we will present the results (table 2) obtained after the development and application of a convolutional neural network for the detection of some birds in a forest, by classifying the spectrogram images that resulted from short audio clips (Ruff et. et. al., 2021).

- *Precision* or specificity is calculated as [True Positives]/ [True Positives + False Positives], considering only clips with class score exceeding the detection threshold for each target class. Precision represents the proportion of apparent "hits" that correspond to real instances of the class in question.
- *Recall* or sensitivity is calculated as [True Positives]/[True Positives + False Negatives], considering only clips with class score exceeding the detection threshold for each target class. Recall represents the proportion of real examples present in the dataset that are detected and correctly identified at a given detection threshold.
- *F1 score* is calculated as [2*Precision*Recall]/[Precision + Recall], with both precision and recall calculated at a specific detection threshold. F1 score is intended as a balance of precision and recall and is used to gauge overall model performance (Ruff et. et. al., 2021).

Table 2. Precision, recall and F1 score produced by some birds (adapted from Ruff et. et. al., 2021; Datar et. et. al., 2018; Takeki et. et. al., 2016)

Bird species	Precision				Recall				F1 score				Type detection	References
	Detection Threshold													
	0.25	0.50	0.75	1.00	0.25	0.50	0.75	1.00	0.25	0.50	0.75	1.00		
Band–tailed pigeon	0.68	0.8	0.85	0.90	0.70	0.68	0.58	0.37	0.70	0.72	0.71	0.53	16 sounds	Ruff et. et. al., 2021
Common raven	0.63	0.75	0.85	0.90	0.69	0.66	0.58	0.39	0.59	0.59	0.58	0.58		
Mountain quail	0.37	0.40	0.55	0.75	0.63	0.60	0.52	0.29	0.47	0.51	0.53	0.40		
Pileated woodpecker	0.50	0.65	0.73	0.84	0.85	0.83	0.75	0.50	0.62	0.73	0.75	0.62		
Red–breasted sapsucker	0.32	0.40	0.50	0.68	0.57	0.48	0.37	0.13	0.39	0.42	0.39	0.20		
Steller's jay	0.58	0.75	0.81	0.90	0.56	0.53	0.50	0.37	0.59	0.62	0.62	0.53		
Algoritms type	Precision				Recall				F1 score				325 images	Datar et. et. al., 2018
YOLO–v2	0.9857				0.6933				0.8140					
YOLO–v3	0.8783				0.8660				0.8721					
Mask R–CNN	0.8258				0.9166				0.8688					
Convolutional neural networks(CNNs)	0.598				0.902				0.719					
Fully convolutional networks (FCNs)	0.684				0.519				0.590					
SuperParsing (SP)	1.000				0.366				0.536					

- Precision was relatively low for mountain quail call , and redbreasted sapsucker;
- Recall for birds was less consistent and was highest for pileated woodpecker, moderate for band tailed pigeon and common raven, lower for mountain quail and Steller's jay, and lowest for red–breasted sapsucker; birds showed recall above 50% at thresholds > 0.9.
- F1 scores was the best for pileated woodpecker, common raven, and band–tailed pigeon, depending on threshold.

So, the results showed that the neural network worked well (detected the species of birds present and vocally active), having high precision (over 90%) and high recall (over 50%), at high score thresholds and false positive results recorded they were in small proportion (Ruff at al., 2021).

A study describes an innovative method to reduce poultry–related crop losses in rice cultivation in Nigeria. This method involves integrating UAVs with advanced computer vision models. A YOLOv8 model was trained using complex preprocessing and augmentation techniques using a dataset consisting of 1,113 images of birds captured by ground cameras and UAVs.

The YOLOv8–based system was able to address critical agricultural challenges, acquiring credible detection and deterrence capabilities. Although it works well under standard conditions, the model is less effective in densely populated and occluded areas, indicating that there is room for improvement (Yakubu I et al., 2025).

In another study, a bird rejection system based on MLX90640 infrared sensor was designed and implemented (fig.5).

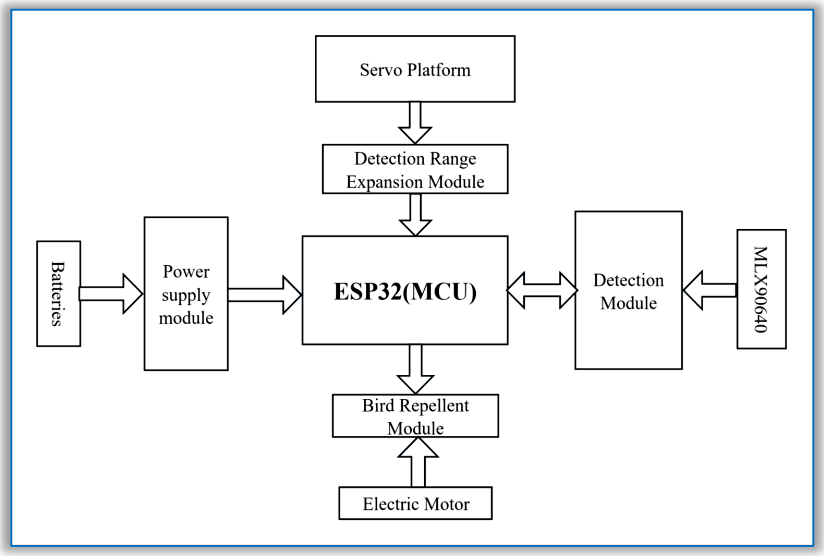


Figure 5. Overall diagram of intelligent bird repellent system

The use of infrared temperature measurement technology is a popular method of detecting birds. However, temperature measurement is influenced by environmental temperatures, distance, and other factors, which can lead to errors in recognition. Thus, to measure temperature, this study uses the MLX90640 non–contact infrared temperature measurement sensor, which has a high measurement accuracy. With its strong anti–interference ability, the sensor detects non–contact, which means it does not harm birds or the environment.

When the infrared sensor MLX90640 detects that the ambient temperature is less than 28 °C, the temperature difference between the ambient temperature and the body temperature of the bird is large, the temperature of one pixel point of the infrared sensor is 2 °C higher than the temperature change of the previous second. It is assumed that there are birds in this range, so the engine begins to reject them. When the temperature changes in a certain part of the pixel, it is considered that the bird has moved away and the motor will no longer work automatically.

When the ambient temperature exceeds 28°C and there are no temperature differences between the bird's body, the temperature near the pixel points of the infrared sensor MLX90640 increase by more than 1°C compared to that in the previous section. This enhances the effect of the repellent. Then it is assumed that a bird has appeared, and the engine begins to reject it. When the ambient temperature returns to its original temperature, the bird is considered driven away and the engine stops working.

This method of indirect detection has been proven to work well in different situations, such as at night or in dense vegetation, where detecting visual birds might be impossible. However, MLX90640 can capture heatmaps without light to detect birds.

4. CONCLUSIONS

In order to have positive results regarding the control and control of harmful birds in agricultural crops, farmers should first develop a well–defined management plan and monitor crops.

Most non–lethal control techniques have short–lived effects, as birds have the ability to learn and get used to threats that are not a negative stimulus. Therefore, in order to achieve success, it is necessary to combine and repeat several techniques.

The review of traditional and more recent pest control methods has shown that integrated pest management strategies are needed for efficiency and environmental sustainability. In the future, automated methods like laser bird scarecrows, UAVs, MLs, and AI could become more common. It turns out that for small and medium–sized farmers, natural predators like hawks, drones with auditory and visual deterrence, and laser bird scarecrow are a great addition. Industrial–scale agricultural companies can conduct research on integrating ML and AI into agricultural practices.

Given that deterrence and control techniques do not yield the same in all areas, more research should be carried out before choosing a method.

Acknowledgement(s): The work has been funded by the Program NUCLEU 2023–2026, PN 23 04 01 06,, Intelligent mixed system for protection of agricultural crops against pests according to the agriculture concept 4.0", Contract no. 9N/01.01.2023.

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ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665