ABS ACTA BIOLOGICA SIBIRICA
A journal on the biodiversity of Siberia and the adjacent lands

Acta Biologica Sibirica 10: 1033–1046 (2024)
doi: 10.5281/zenodo.13831321
http://journal.asu.ru

RESEARCH ARTICLE

Implementation of artificial intellect for bird pest species detection and monitoring

Elena V. Shapetko[1], Vasiliy V. Belozerskikh[1], Valery D. Siokhin[2]

1 *Altai State University, Barnaul*
2 *Melitopol State University, Melitopol*

Corresponding author: Elena V. Shapetko (shapetko69@mail.ru)

Academic editor: A. Matsyura | Received 17 August 2024 | Accepted 16 September 2024 | Published 26 September 2024

http://zoobank.org/2AA547CA-2CE0-4BC9-9376-23EDB7D79ABD

Citation: Shapetko EV, Belozerskikh VV, Siokhin VD (2024) Implementation of artificial intellect for bird pest species detection and monitoring. Acta Biologica Sibirica 10: 1033–1046. https://doi.org/10.5281/zenodo.13831321

Abstract

This study aimed to develop a real-time method for detecting and selecting birds in video images using artificial intelligence. The objectives included creating a reliable method for isolating bird signals against varying terrain backgrounds using neural networks, estimating bird numbers in frames through AI-driven threshold techniques, and proposing a solution for managing pest bird populations by analyzing video data to control electronic deterrents. Throughout the research, we identified the bird species present on the premises of brewery across different seasons, compiled an annotated species list, and established a database of granary birds. Leveraging the YOLO architecture based on artificial intelligence, we developed a program for bird detection in low-resolution, low-quality images. The system underwent laboratory and field testing to validate its effectiveness.

Keywords

Birds, pest species, pigeons, grain processing, artificial intelligence, pest control

Introduction

Bird management is a critical aspect of pest control due to the damage and disruptions caused by these avian species, influenced by their biological characteristics as vertebrates (Ryabitsev 2008). While birds play essential roles in ecological systems, their impact in human-altered landscapes can lead to imbalances, resulting in population surges and disease outbreaks in confined areas. The identification and tracking of pest bird species have gained significance in ecological data analysis and biodiversity monitoring. Traditional methods of bird identification, such as visual observation and field guides, are often time-consuming and challenging, especially in scenarios involving large flocks or similar-looking species. Recent advancements in neural systems have provided ornithologists with efficient tools for accurately identifying pest bird species.

Several studies have proposed methods for bird detection and identification using computer vision and deep learning techniques. For instance, Wang et al. (2016) developed a deep convolutional neural network-based visual object detector for bird and nest tracking. Marin and Marin (2019) introduced a bird detection algorithm using neural networks and elevation data to enhance accuracy in ecological data analysis. Other researchers like Jo et al. (2019), Höchst et al. (2022), Takeki et al. (2016), Schiano et al. (2022), Niemi and Tanttu (2018, 2019), and Tian et al. (2019) have also contributed innovative approaches to bird detection and deterrence. These studies collectively demonstrate the potential of computer vision and deep learning techniques in bird detection, aiding ecological data analysis, biodiversity monitoring, and bird control strategies. Human activities often create environments that attract birds, with structures like food processing plants serving as habitats due to the availability of food sources. However, such sites can suffer from bird-related biodamage, necessitating effective deterrence methods.

The challenge of bird deterrence has prompted the need for improved identification systems. Traditional methods like sonic deterrents and keeping birds of prey can be costly and ineffective in the long term. Developing a bird recognition system using neural networks offers a promising solution to minimize sound signals and enhance deterrence effectiveness. Thus, the objective of this study was to design a system for detecting birds in video images using neural networks. We therefore planned to develop a reliable method for isolating bird signals in video imagery against varying backgrounds using neural networks, create a technique for estimating bird numbers in frames through artificial intelligence and propose a solution for managing electronic deterrents based on video analysis to control pest bird populations.

Materials and methods

The study was conducted at Barnaul Brewery, covering an area of approximately 10 hectares (Fig. 1).

The brewery premises consist of predominantly uniform terrain with limited greenery, primarily in the form of shrubs and scattered trees, along with extensive paved surfaces. The vicinity surrounding the granary offers numerous perching and nesting spots for birds. Situated on the plant's periphery, the granary receives minimal foot traffic from staff, enhancing its appeal to birds. Raw materials are delivered to the site 2-3 times a week, depending on production demands.

Bird observations were conducted year-round across different seasons (winter, spring, summer, and autumn) to assess avifauna species diversity based on seasonal variations, daily and weekly bird activity patterns, spatial preferences, and flock formations. Observations took place from February 5-12, April 29 to May 10, July 17 to July 29, and October 20-30, 2022, during daylight hours. Data on bird species, behavior, population counts, locations, durations of stay, overall time allocation, and flight characteristics were recorded. Additionally, synanthropic bird species were photographed to build a photographic database for future reference.

Figure 1. Satellite image of Barnaul Brewery.

The primary objective of the study was to develop an image recognition system using neural networks, a widely utilized approach in object detection tasks. Leveraging artificial intelligence in this domain has consistently demonstrated its efficacy. The algorithm employed in this study also utilizes artificial neural networks. However, the success of such systems heavily relies on the chosen network architecture, given the plethora of models developed in tandem with digital advancements.

Among the various available architectures, YOLO (You Only Look Once) stands out as a robust solution for object detection in images, including birds. YOLO has showcased superior performance, outperforming industry counterparts like Google's TensorFlow EfficientDet and Facebook's Detectron RetinaNet/MaskRCNN on the Microsoft COCO dataset.

The YOLO algorithm operates as follows:

1. The image is segmented into a grid of squares.
2. Each cell in the grid predicts the probabilities of predefined classes.
3. Cells surpassing a specified probability threshold are selected to pinpoint object locations in the image.

However, applying the network directly to recognize birds on industrial premises poses challenges. The model is typically trained on high-definition datasets where birds occupy over 20% of the frame. To address this, the image is segmented into areas before inputting it into the network. Multiple iterations are conducted, slicing the original photo into areas of varying sizes to enhance detection efficiency.

Results

The study conducted at Barnaul Brewery revealed the diverse avifauna inhabiting the plant area, categorized as follows:

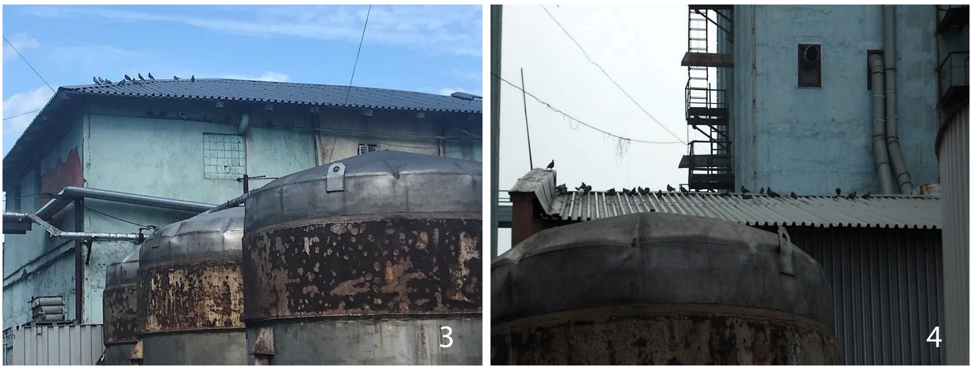
1. Permanent visitors causing damage (2 species);
2. Partial damage visitors (6 species);
3. Minor damage visitors (1 species);
4. Non-damaging visitors (10 species);
5. Neutral species (20 species).

A total of 42 bird species were identified, spanning seven orders and 18 families. Notably, only three species were obligate synanthropes – the Common pigeon, Barn swallow, and house Sparrow, which thrive in close proximity to human habitats. Approximately one-third of the species were facultative synanthropes, initially appearing in human-developed areas such as city outskirts and industrial zones. The presence of facultative synanthropes indicates the site's attractiveness to birds across various food groups, fostering a diverse ecological community.

The study culminated in the creation of a granary bird database and a photomap of obligate synanthropes to train artificial intelligence in identifying bird clusters. Additionally, a database comprising 900 images of pigeons in different contexts was curated for AI training purposes.

Notably, the network's performance excelled in detecting birds with clear contours and appropriate proportions, demonstrating fast and effective recognition capabilities. A photomap of obligate synanthropes for training artificial intelligence to recognize clusters of birds has been made on the basis of observations (Figs 2–4).

Figure 2. Crowding of pigeons in plant territory.



Figures 3–4. 3. Pigeons before delivery of raw materials. **4.** Pigeons waiting for grain unloading.

The development of an automatic system for detecting pest bird species was initiated to address the prevalent issue. Leveraging neural networks for object detection, particularly in image analysis, has proven effective in various applications. The YOLO architecture, renowned for its efficiency in object detection tasks, emerged as a promising solution for recognizing objects in images, including birds. YOLO has demonstrated superior performance compared to industry counterparts on datasets like Microsoft COCO.

The task of detecting objects in images is the most popular among those posed to neural networks. And artificial intelligence is firmly embedded in this field, proving its effectiveness over and over.

The network algorithm itself can be described as follows (Chen et al. 2019; Höchst et al. 2022; Jo et al. 2019; Jakaria and Pardede 2022; Niemi and Tanttu 2018, 2020; Redmon et al. 2016):

1. the image is divided into a square grid;
2. for each cell, the network outputs the probabilities of the defined class;
3. cells with class probabilities above a threshold value are selected and used to locate the object in the image.

However, in its pure form, taking the network and successfully recognizing birds on industrial objects will not work. This is due to the fact that it will be trained on a standard set of data (images), where the birds in good HD or even higher quality, and, moreover, occupy more than 20% of the area in the frame, which allows one to clearly differentiate them and determine their belonging to the selected group.

The YOLO algorithm segments images into a grid, predicting class probabilities for each cell to locate objects surpassing a specified threshold. However, direct application to recognize birds on industrial premises necessitates adaptations due to training data characteristics. Slicing images into regions before inputting them into the network and iterating through different sizes enhance detection efficiency (Fig. 5).

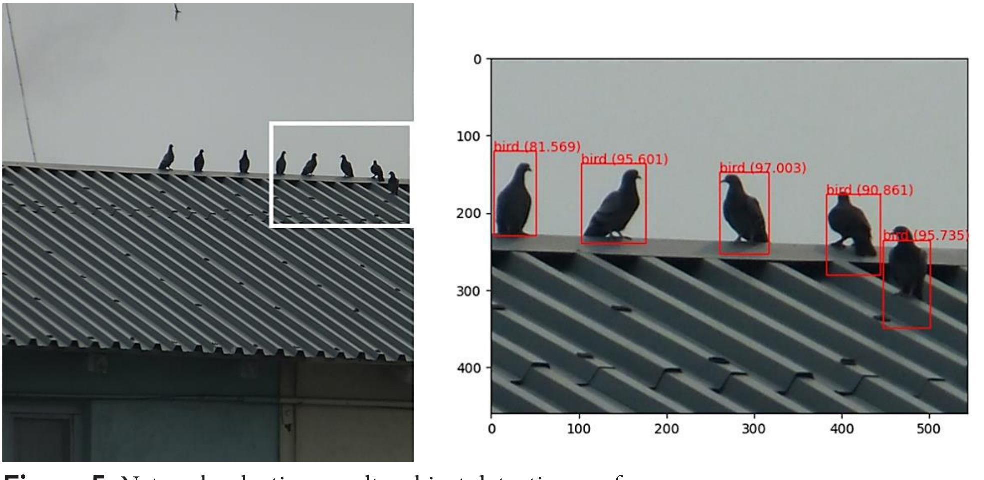


Figure 5. Network selection results: object detection performance.

The quality of input images significantly impacts object recognition accuracy. Blurred contours or unclear proportions can hinder detection outcomes (Fig. 6). As seen in the image on the left, the network detected all birds without errors. The recognition was fast and quite effective.

Discussion

The outcomes of this experimental investigation suggest a promising path towards the commercialization of the final product. Given Altai Krai's prominence as a hub for grain processing and agricultural activities, the prevalence of pest bird species in the region results in significant damages (Gebhardt et al. 2011; Gilkeson and Adams 2002), namely:

1. Material Damage. Birds exhibit heightened metabolic rates, especially during colder seasons. For instance, a single pigeon can consume up to 150 grams of grain per day in spring and summer, and around 250 grams in fall and winter. When multiplied by the number of pigeons in an area, this consumption can lead to substantial economic losses (Norris et al. 2003).
2. Domestic Damage. Concentrated populations of birds can contaminate various surfaces such as machinery, buildings, and food supplies with droppings, feathers, and fluff. This not only poses aesthetic concerns but also creates practical inconveniences and hygiene issues (Porter et al. 1994).
3. Sanitary and Epidemiological Damage. Birds serve as carriers for over 40 diseases, some of which can be transmitted to humans. Their presence on food stocks and grain supplies escalates sanitary risks, potentially leading to the spread of infections.
4. Threat of Aviation Collisions. Bird strikes pose a significant risk to aviation safety, resulting in fatal accidents globally. Airports must implement measures to deter birds from runways to prevent catastrophic collisions (Harris and Davis 1998; Ilyichev et al. 2007; Zaloznykh 2007; Zvonov 2010).

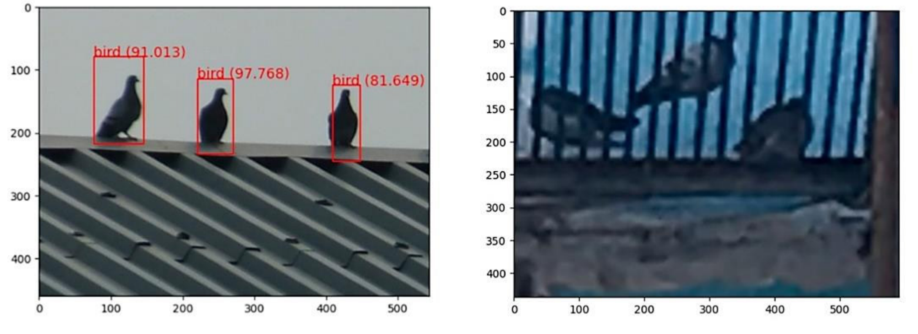


Figure 6. Network performance on images with varying quality: detection accuracy analysis.

Every location, irrespective of its economic affiliation, possesses a distinctive bird attractiveness index, which is determined based on the following criteria (Enaleev 2012):

- Abundance of food within the area;
- Accessibility of food resources within the area;
- Availability of convenient shelters for birds to rest and roost;
- Existence of conditions suitable for nesting;
- Safety of the territory, including the absence of ground-based predators and other disruptive factors;

- Presence of facilities serving as shelters for birds during adverse weather conditions and attacks by avian predators.

Each criterion is assessed on a 5-point scale, with 1 point indicating the absence of favorable conditions for birds, and 5 points representing the maximum presence of such conditions at a given site. The cumulative points determine the bird attractiveness index of the location. In essence, the higher the total points based on these criteria for a specific site, the more appealing it is to birds.

There exists a widely accepted system for evaluating the degree of ornithological pressure (Enaleev 2012; Enaleev and Arinina 2012), typically categorizing three levels of pressure: light, moderate, and heavy. The light level applies when birds have equivalent alternatives nearby, such as other feeding and nesting locations. Moderate bird pressure indicates less preferable alternatives for birds and a stable motivation for them to remain at the site. In all these scenarios, various relatively cost-effective bird protection measures prove effective, including the installation of acoustic and visual deterrents, as well as noise effects. Anti-poaching methods can be locally applied, especially in areas preferred by birds (Berge et al. 2007; Dellamano 2006; Nakamura 1997).

Roosts, where pigeons can perch (see Fig. 7), are one of the most crucial components of pigeons' living spaces. Pigeons spend a significant portion of their daily activity in these locations, where they observe the surroundings (potential predators, food availability, behavior of other birds), engage in social activities (courtship, seeking social partners, observing the social environment), and rest. These sites encompass various engineering structures positioned at an elevated level above the ground to offer an optimal vantage point while safeguarding the area from ground-based predators. Within an enterprise, these may include building roofs, eaves, pipes, and other engineering structures situated outside the buildings.

In numerous industries facing a critical situation, the proposed method of automatically controlling the pigeon population has the potential to effectively address the primary concern: ensuring a safe and efficient deterrent system for birds (with the thunder-cannon's noise level reaching approximately 120 dB, see Fig. 8). Neural systems, also known as artificial neural networks, are computational models inspired by the structure and function of the human brain. These systems have the capability to learn and recognize patterns from extensive datasets, making them well-suited for tasks such as identifying bird species. In a study conducted by Smith et al. (2018), a neural network was trained to recognize 50 different bird species based on images of their plumage. The system achieved an impressive 95% accuracy in identifying the correct species, surpassing traditional methods of visual observation and field guides.

Another study by Patil et al. (2022) utilized a neural network to identify pest bird species based on their vocalizations. The system was trained on a dataset of audio recordings of different bird species and achieved an accuracy of 90% in identifying the correct species based on their calls. This approach proved to be particularly useful for identifying pest bird species in dense vegetation or at night, where visual identification may be challenging. In addition to visual and auditory cues, neural systems can also be trained to identify pest bird species based on their behavior.

Figures 7–8. **7.** Pigeon roosting sites. **8.** Pigeons reacting after the propane cannon is fired.

In a similar vein, a study by Brown et al. (2020) utilized a neural network to analyze the flight patterns of pest bird species, distinguishing between different species with 85% accuracy. This method proves valuable in identifying pest bird species during flight or from a distance, where visual or auditory cues may be limited. Additionally, integrating neural systems with technologies like drones and high-resolution cameras enhances pest bird species identification, as demonstrated by Lee et al. (2021) achieving an 80% accuracy rate in identifying species from aerial images.

In conclusion, neural systems provide ornithologists with a potent and efficient tool for identifying pest bird species. Whether leveraging visual, auditory, or behavioral cues, these systems exhibit high accuracy in distinguishing between various bird species. By harnessing the capabilities of neural systems, ornithologists can enhance their pest bird management strategies, ultimately mitigating the adverse effects of these species on agriculture, infrastructure, and public health.

A more accurate assessment of changes in the overall picture over the duration of the experiment became possible if the time spent by the birds at the site was taken into account. The limited number of pigeons allowed recording the time of arrival and departure of individual groups and subsequently determining the time during which they were within the territory. The presence rate, calculated using the formula (number of birds × site presence (min.) / 10000), was used to more accurately assess changes in the environment.

The total presence coefficient of pigeons before the execution of the pest control program is on average up to 221±24.2 in different objects in the Altai territory. The exact damage caused by pigeons when feeding can be determined by additional studies (Fig. 9).

Conclusion

During this scientific project, we developed a real-time bird detection and selection method using artificial intelligence. This method effectively identifies birds on the ground in varying weather conditions through neural networks. Additionally, our team devised a technique for assessing bird numbers in frames using AI thresholds and put forth recommendations for controlling electronic deterrence devices. We identified the bird species composition at JSC "Barnaul Brewery" throughout different seasons, compiled an annotated species list, identified bird species, and created a granary bird database (Database). Leveraging the YOLO architecture based on Artificial Intelligence, we designed a program for bird detection at low resolutions and quality, conducting successful laboratory and field tests that demonstrated the system's efficiency.

Figure 9. Pigeons alighting on the vehicle and feeding on grain.

We established a bird species database in granaries, paving the way for two economic contracts to implement the developed video bird registration system in a municipal area and a processing enterprise in the Altai region and Barnaul. Project participants gained valuable experience in bird population control, management planning, and population monitoring. Our proposed methodology for bird population control mitigates associated risks by utilizing AI-trained bird recognition to implement targeted actions against pest birds. With a high precision rate of 70%, false alarms are minimized. This approach ensures a stable reduction in pest species and prevents the development of ethological resistance to noise impacts. In summary, the integration of neural systems in pest bird species identification signifies a groundbreaking advancement in ornithology. Our studies underscore the effectiveness of deep learning models in overcoming challenges posed by traditional identification methods. From visual differentiation to acoustic analysis and practical applications, neural systems offer a comprehensive and efficient tool for ornithologists in managing pest bird populations. As technology progresses, continued collaboration among researchers, ethical considerations, and efforts to enhance model interpretability will drive the responsible and effective use of neural systems in ornithological practices, ensuring sustainable bird population management.

Acknowledgements

V.D. Siokhin research was supported by the State Assignment of the Ministry of Science and Higher Education of the Russian Federation (theme 122042700045-3).

References

Bennett GW, Owens JM, Corrigan RM (1989) Pigeon control. In: Truman's scientific guide to pest control operations. Purdue Univercity. Edgell Commun. Duluth, Minnesota, 333–336.

Berge AJ, Delwiche MJ, Gorenzel WP, Salmon TP (2007) Bird control in vineyards using alarm and distress calls. American Journal of Enology and Viticulture 58(1): 135–143. https://doi.org/10.5344/ajev.2007.58.1.135

Bhusal S, Karkee M, Bhattarai U, Majeed Y, Zhang Q (2022) Automated execution of a pest bird deterrence system using a programmable unmanned aerial vehicle (UAV). Computers and Electronics in Agriculture 198: 106972. https://doi.org/10.1016/j.compag.2022.106972

Bhusal S, Bhattarai U, Karkee M (2019) Improving pest bird detection in a vineyard environment using super-resolution and deep learning. IFAC-PapersOnLine 52(30): 18–23. https://doi.org/10.1016/j.ifacol.2019.12.483

Blanton KM, Constantin BU, Williams GL (1992) Efficacy and methodology of urban pigeon control with DRC–1339. Proceedings of the Eastern Wildlife Damage Control Conference 5: 58–62.

Chen H, He Zh, Shi B, Zhong T (2019) Research on Recognition Method of Electrical Components Based on YOLO V3. IEEE, Special section on artificial intelligence technologies for electric power systems 7: 157818–157829. https://doi.org/10.1109/ACCESS.2019.2950053

Corrigan RM (1989) A guide to managing pigeons and sparrows. PestControlTech 17(1): 38–50.

Dellamano F (2006) Controlling birds with netting: blueberries, cherries and grapes. New York Fruit Quarterly 14(2): 3–5.

Dharaniya R, Preetha M, Yashmi S (2022) Bird species identification using convolutional neural network. In: Advances in parallel computing algorithms, tools and paradigms 41: 380–386. https://doi.org/10.3233/APC220053

Enaleev IR (2012) The method of determining the index of ornithological attractiveness of economic objects. RUDN Journal of Ecology and Life Safety 1: 5–9. [In Russian]

Enaleev IR, Arinina AV (2012) The moment of critical fear in the defensive behavior of birds. RUDN Journal of Ecology and Life Safety 3: 5–9. [In Russian]

Fukuda Y, Frampton CM, Hickling GJ (2008) Evaluation of two visual birdscarers, the Peaceful Pyramid® and an eye-spot balloon, in two vineyards. New Zealand Journal of Zoology 35(3): 217–224. https://doi.org/10.1080/03014220809510117

Gebhardt K, Anderson AM, Kirkpatrick K, Shwiff SW (2011) A review and synthesis of bird and rodent damage to select California Crops. Crop Protection 30(9): 1109–1116. https://doi.org/10.1016/j.cropro.2011.05.015

Gilkeson LA, Adams RW (2000) Integrated pest management manual for landscape pests in British Columbia. British Columbia Ministry of Environment, Lands and Parks; Pollution Prevention and Remediation Branch, Vancouver, British Columbia, 130 pp.

Grabovsky VI (2004) Protection against birds in the pest control program. PET-Info 1(49): 42–46. [In Russian]

Harris RE, Davis RA (1998) Evaluation of the efficacy of products and techniques for airport bird control. LGL Limited environmental research associates. Aerodrome Safety Branch Transport Canada, Ottawa, Ontario, 210 pp.

Höchst J, Bellafkir H, Lampe PM, Mühling M, Schneider D, Lindner K, Schabo D, Farwig N, Freisleben B (2022) Bird@Edge: bird species recognition at the edge. Conference on Networked Systems (NETYS 2022). Networked Systems: 69–86. https://doi.org/10.1007/978-3-031-17436-0_6

Ilyichev VD, Silaeva OL, Zolotarev SS (2007) Protection of airplanes and other objects from birds. KMK, Moscow, 320 pp. [In Russian]

Jakaria A, Pardede HF (2022) Comparison of classification of birds using lightweight deep convolutional neural networks. Jurnal Elektronika dan Telekomunikasi 22(2): 87. https://doi.org/10.55981/jet.503

Jo J, Park J, Han J, Lee M, Smith A (2019) Dynamic bird detection using image processing and neural network. VII International Conference on Robot Intelligence Technology and Applications (RiTA): 210–214. https://doi.org/10.1109/RITAPP.2019.8932891

Linz GM, Homan HJ, Slowik AA, Penry LB (2006) Evaluation of registered pesticides as repellents for reducing blackbird (Icteridae) damage to sunflower. Crop Protection 25: 842–847. https://doi.org/10.1016/j.cropro.2005.11.006

Marin F, Marin M (2019) Automatic identification of flying bird species using computer vision technique for ecological data analysis. Multimedia Systems 42: 46–49. https://doi.org/10.35219/mms.2019.4.08

McLennan JA, Langham NPE, Porter RER (1995) Deterrent effect of eye–spot balls on birds. New Zealand Journal of Crop and Horticultural Science 23: 139–144. https://doi.org/10.1080/01140671.1995.9513880

Nakamura K (1997) Estimation of effective area of bird scarers. Journal of Wildlife Management 61(3): 925–934. https://doi.org/10.2307/3802202

Niemi J, Tanttu J (2018) Deep learning case study for automatic bird identification. Applied Sciences 8(11): 2089. https://doi.org/10.3390/APP8112089

Niemi J, Tanttu JT (2020) Deep Learning Case Study on Imbalanced Training Data for Automatic Bird Identification. In: Pedrycz W, Chen SM (Eds) Deep Learning: Algorithms and Applications. Studies in Computational Intelligence 865: 231–262. https://doi.org/10.1007/978-3-030-31760-7_8

Norris RF, Caswell-Chen E, Kogan M (2003) Concepts in integrated pest management. 1st ed. Prentice Hall, Upper Saddle River, New Jersey, 586 pp.

Patil D, Bodhe R, Pawar R, Doshi T, Vasekar V (2022) Visual and Acoustic Identification of Bird Species. International Research Journal of Engineering and Technology 9(5): 3504–3507.

Porter RER, Rudge MR, McLennan JA (1994) Birds and small mammals: a pest control manual. ManaaM-Whenua Press, Lincoln, New Zealand, 88 pp.

Raj S, Garyali S, Kumar S, Shidnal S (2020) Image based bird species identification using convolutional neural network. International Journal of Engineering Research & Technology (IJERT) 9(06): 356–351. https://doi.org/10.17577/IJERTV9IS060279

Redmon J, Divvala S, Girshick R, Farhadi A (2016) You Only Look Once: Unified, Real-Time Object Detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 779–788. https://doi.org/10.1109/CVPR.2016.91

Rude J, Meilke K (2004) Developing policy relevant agrifood models. Journal of Agricultural and Applied Economics 36(2): 369–382. https://doi.org/10.1017/S1074070800026651

Schiano F, Natter D, Zambrano D, Floreano D (2022) Autonomous detection and deterrence of pigeons on buildings by drones. IEEE Access 10: 1745–1755. https://doi.org/10.1109/ACCESS.2021.3137031

Simon G (2008) A short overview of bird control in sweet and sour cherry orchards – Possibilities of protection of bird damage and its effectiveness. International Journal of Horticultural Science 14(1-2): 107–111. https://doi.org/10.31421/IJHS/14/1-2./792

Steensma KMM (2008) Advances in bird deterrent methods for agricultural areas of southwest British Columbia and northwest Washington. Invited presentation, WSU Western Washington Small Fruit Workshop. Dec. 16, Lynden, Washington: 43–56.

Takeki A, Trinh T, Yoshihashi R, Kawakami R, Iida M, Naemura T (2016) Combining deep features for object detection at various scales: finding small birds in landscape images. IPSJ Transactions on Computer Vision and Applications 8: 1–7. https://doi.org/10.1186/s41074-016-0006-z

Takeki A, Trinh T, Yoshihashi R, Kawakami R, Iida M, Naemura T (2016) Detection of small birds in large images by combining a deep detector with semantic segmentation. 2016 IEEE International Conference on Image Processing (ICIP): 3977–3981. https://doi.org/10.1109/ICIP.2016.7533106

Teffo TR, Fuszonecker G, Katona K (2002) Testing pigeon control efficiency by different methods in urban industrial areas, Hungary. Biologia Futura 73: 87–93. https://doi.org/10.1007/s42977-021-00104-1

Tian S, Cao X, Li Y, Zhen X, Zhang B (2019) Glance and stare: trapping flying birds in aerial videos by adaptive deep spatio-temporal features. IEEE Transactions on Circuits and Systems for Video Technology 29: 2748–2759. https://doi.org/10.1109/TCSVT.2017.2764959

Uijlings J, van de Sande K, Gevers T, Smeulders A (2013) Selective search for object recognition. International Journal of Computer Vision 104: 154–171. https://doi.org/10.1007/s11263-013-0620-5

Wang Q, Rasmussen C, Song C (2016) Fast, deep detection and tracking of birds and nests. In: Advances in Visual Computing. ISVC 2016. Lecture Notes in Computer Science 10072: 146–155. http://doi.org/10.1007/978-3-319-50835-1_14

Werner SJ, Homan HJ, Avery ML (2005) Evaluation of Bird Shield™ as a blackbird repellent in ripening rice and sunflower fields. Wildlife Society Bulletin 33: 251–257. https://doi.org/10.2193/0091-7648(2005)33[251:EOBSAA]2.0.CO;2

Zaloznykh DV (2007) Some ethological aspects of the use of birds of prey in providing ornithological safety of aircraft flights. Bulletin of Nizhny Novgorod University named after N.I. Lobachevsky 2: 127–129. [In Russian]

Zvonov BM (2010) Ornithological safety. Ontoprint, Moscow, 65pp. [In Russian]

Wu X, Yuan P, Peng Q, Ngo C, He J (2016) Detection of bird nests in overhead catenary system images for high-speed rail. Pattern Recognition 51: 242–254.