UNIVERSIDADE FEDERAL DE UBERLÂNDIA
NOME DA UNIDADE ACADÊMICA

MAURYCIO RODRIGUES OVIEDO ESPINOSA

Detecção automática de aves em imagens coletadas com aeronaves remotamente pilotadas parauso em gerenciamento de risco à vida selvagem em aeroportos

MONTE CARMELO
AMINAS GERAIS - BRASIL
2023

MAURYCIO RODRIGUES OVIEDO ESPINOSA

Detecção automática de aves em imagens coletadas com aeronaves remotamente pilotadas parauso em gerenciamento de risco à vida selvagem em aeroportos

Dissertação apresentada ao Programa de Pós-Graduação em Agricultura e Informações Geoespaciais da Universidade Federal de Uberlândia, Campus Monte Carmelo, como parte das exigências para obtenção do título De "Mestre".

Orientador:Prof.Dr. Rodrigo Bezerra de Araújo Gallis

Coorientador:Prof.Dr. Flavio Antonio Coimbra Mendonca

MONTE CARMELO

AMINAS GERAIS - BRASIL

2023

Dados Internacionais de Catalogação na Publicação (CIP)
Sistema de Bibliotecas da UFU, MG, Brasil.

E77d
2023

Espinosa, Maurycio Rodrigues Oviedo, 1997-
Detecção automática de aves em imagens coletadas com aeronaves remotamente pilotadas para uso em gerenciamento de risco à vida selvagem em aeroportos [recurso eletrônico] / Maurycio Rodrigues Oviedo Espinosa. - 2023.

Orientador: Rodrigo Bezerra de Araújo Gallis.
Coorientador: Flavio Antonio Coimbra Mendonça.
Dissertação (Mestrado) - Universidade Federal de Uberlândia, Programa de Pós-graduação em Agricultura e Informações Geoespaciais.
Modo de acesso: Internet.
Disponível em: http://doi.org/10.14393/ufu.di.2024.5025
Inclui bibliografia.
Inclui ilustrações.

1. Agricultura. I. Gallis, Rodrigo Bezerra de Araújo, 1977-, (Orient.). II. Mendonça, Flavio Antonio Coimbra, 1967-, (Coorient.). III. Universidade Federal de Uberlândia. Programa de Pós-graduação em Agricultura e Informações Geoespaciais. IV. Título.

CDU: 631

André Carlos Francisco
Bibliotecário Documentalista - CRB-6/3408

UNIVERSIDADE FEDERAL DE UBERLÂNDIA
Coordenação do Programa de Pós-Graduação em Agricultura e Informações Geoespaciais
Rodovia LMG 746, Km 01, s/nº, Bloco 1AMC, Sala 1A202 , Monte Carmelo-MG, CEP 38.500-000
Telefone: (34) 3810-1033 - ppgaig@iciag.ufu.br

ATA DE DEFESA - PÓS-GRADUAÇÃO

Programa de Pós-Graduação em:	Agricultura e Informações Geoespaciais				
Defesa de:	Dissertação de Mestrado Acadêmico				
Data:	12/12/2023	Hora de início:	21:00	Hora de encerramento:	23:00
Matrícula do Discente:	32122AIG012				
Nome do Discente:	Maurycio Rodrigues Oviedo Espinosa				
Título do Trabalho:	Detecção automática de aves em imagens coletadas com aeronaves remotamente pilotadas para uso em gerenciamento de risco à vida selvagem em aeroportos				
Área de concentração:	Informações geoespaciais e tecnologias aplicadas à produção agrícola				
Linha de pesquisa:	Aplicações e desenvolvimento de métodos em informações geoespaciais				
Projeto de pesquisa de vinculação:	Utilização de imagens multiespectrais na fitotecnia				

Reuniu-se na sala virtual (https://conferenciaweb.rnp.br/webconf/rodrigo-bezerra-de-araujo-gallis) a Banca Examinadora, designada pelo Colegiado do Programa de Pós-graduação em Agricultura e Informações Geoespaciais, assim composta: Dr. Vinicius Francisco Rofatto (UFU), Dr. Flavio Antonio Coimbra Mendonça (Embry-Riddle Aeronautical University – USA, Aeronautical Science Department) e Dr. Rodrigo Bezerra de Aráujo Gallis (UFU) – orientador do candidato. Iniciando os trabalhos o presidente da mesa, Dr. Rodrigo Bezerra de Aráujo Gallis, apresentou a Comissão Examinadora e o candidato, agradeceu a presença do público, e concedeu ao Discente a palavra para a exposição do seu trabalho. A duração da apresentação do Discente e o tempo de arguição e resposta foram conforme as normas do Programa.

A seguir o senhor(a) presidente concedeu a palavra, pela ordem sucessivamente, aos(às) examinadores(as), que passaram a arguir o(a) candidato(a). Ultimada a arguição, que se desenvolveu dentro dos termos regimentais, a Banca, em sessão secreta, atribuiu o resultado final, considerando o(a) candidato(a):

Aprovado.

Esta defesa faz parte dos requisitos necessários à obtenção do título de Mestre.

O competente diploma será expedido após cumprimento dos demais requisitos, conforme as normas do Programa, a legislação pertinente e a regulamentação interna da UFU.

Nada mais havendo a tratar foram encerrados os trabalhos. Foi lavrada a presente ata que após lida e achada conforme foi assinada pela Banca Examinadora.

Documento assinado eletronicamente por **Rodrigo Bezerra de Araujo Gallis**, **Professor(a) do Magistério Superior**, em 18/12/2023, às 16:48, conforme horário oficial de Brasília, com fundamento no art. 6º, § 1º, do Decreto nº 8.539, de 8 de outubro de 2015.

Documento assinado eletronicamente por **Vinicius Francisco Rofatto**, **Professor(a) do Magistério Superior**, em 29/12/2023, às 16:15, conforme horário oficial de Brasília, com fundamento no art. 6º, § 1º, do Decreto nº 8.539, de 8 de outubro de 2015.

Documento assinado eletronicamente por **Flávio Antonio Coimbra Mendonça**, **Usuário Externo**, em 29/01/2024, às 13:26, conforme horário oficial de Brasília, com fundamento no art. 6º, § 1º, do Decreto nº 8.539, de 8 de outubro de 2015.

A autenticidade deste documento pode ser conferida no site https://www.sei.ufu.br/sei/controlador_externo.php?acao=documento_conferir&id_orgao_acesso_externo=0, informando o código verificador **5052003** e o código CRC **D501188A**.

Referência: Processo nº 23117.089033/2023-83 SEI nº 5052003

AGRADECIMENTOS

Começo estes agradecimentos em primeiro lugar a Deus, que todos os dias me da a paz e o discernimento, de poder cumprir todos os desafios que a mim são colocados.

Agradeço a minha família, minha mãe Katia, minha avó Zilma, ao meu irmão Mathews e minha Tia Danda, que não importa o que aconteça sempre estão me apoiando e ao meu lado em minhas decisões, me incentivando em meus estudos e na minha vida.

Agradeços aos meus eternos amigos do peito Rafael e José, que por diversas vezes sempre estiveram do meu lado em todas as minhas escolhas, em momentos bons e ruins.

Aos docentes Rodrigo Bezerra de Araújo Gallise a ao Dr. Flavio Antonio Coimbra Mendonca pela grande contribuição e colaboração para o desenvolvimento do trabalho, que acreditaram em mim e no meu trabalho, e que compriram com maestria o trabalho de orientar um aluno na produção da ciência.

Por fim, agradeço à Universidade Federal de Uberlândia pela estrutura, suporte e ambiente amigável oferecido.

BIOGRAFIA

Maurycio Rodrigues Oviedo Espinosa nasceu no dia 22 de agosto de 1997 em Itaqui, Rio Grande do Sul, Brasil. Engenheiro Cartógrafo e Agrimensor pela Universidade Federal do Pampa - Unipampa (2021). Mestrando no Programa de Pós-Graduação em Agricultura e Informações Geoespaciais - UFU (2021 - 2023), com foco na área de inteligência artificial para a detecção automática de animais em imagens coletadas com aeronaves remotamente pilotad

Sumário

ABSTRACT

Wildlife strikes to civil aircraft frequently occur worldwide and are a major safety problem. In the United States alone, from 1990 to 2019, approximately 209,950 strikes were recorded, causing material damage and loss of life. In this study, we aimed to develop a method for using images acquired by remotely piloted aircraft and a process of automatic detection of patterns in such images to create a robust monitoring system for detecting animals and birds at the Coe Field private airport (8FA4), with a hit rate of 96% or higher for the animals and birds present in images at the time of flight.

Keywords: Automatic detection of animals in images; UAV; wildlife strikes to civil aircraft.

RESUMO

OVIEDO, MAURYCIO RODRIGUES ESPINOSA. Detecção automática de aves em imagens coletadas com aeronaves remotamente pilotadas parauso em gerenciamento de risco à vida selvagem em aeroportos, 28 páginas. Dissertação (Mestrado em Agricultura e Ingormações Geoespaciais) – Universidade Federal de Uberlandia, Campus Monte Carmelo, Minas Gerais, Brasil.

As colisões de animais com aviões são um problema de segurança que ocorre frequentemente em todo o mundo. Nos Estados Unidos da América, entre os anos de 1990 e 2019, ocorreram cerca de 209.950 colisões, causando danos materiais e perdas de vidas. Este projeto busca desenvolver uma metodologia que utilize imagens coletadas por aeronaves pilotadas remotamente e um processo automático de detecção de padrões nas imagens, a fim de criar um sistema de monitoramento robusto, capaz de detectar animais e aves em um aeroporto privado chamado Coe Field (8FA4), com uma taxa de acerto de 96% ou mais dos animais e aves presentes nas imagens no momento do voo.

Palavras-chave: Detecção automatica de animais em imagens; UAV; Colisões de animais selvagens com aviões.

1 INTRODUCTION

Wildlife strikes to civil aircraft are a growing safety and economic concern [1]. Avia-19 tion accidents resulting from these strikes have gained media and public attention, especially after the well-known case of US Airways Flight 1549, which had to make an emergency landing in the Hudson River in 2009. Since then, the risk to wildlife and human life has been widely debated in the media [2]. Therefore, the Federal Aviation Administration (FAA) produced report number 28 entitled Wildlife Strikes to Civil Aircraft in the United States, 1990–2019.

From 1990 to 2019, approximately 720 civil aircraft reported aviation accidents involving birds, including 52 with land mammals, 44 with bats, and 29 with reptiles, totaling 745 wild species. Each species has unique characteristics, body, physical density, behavior, and habitat. Moreover, 90% of these birds that encounter aircraft are protected species under federal law through the Migratory Bird Treaty Act, and the remaining 10% have state or local protection [3].

Wildlife strikes to civil aircraft involving birds or other animals have become an increasing concern for the aviation industry in recent years [4,5]. Aviation accidents on January 15, 2009 and August 15, 2019 highlighted this vulnerability. US Airways Flight 1549 (Airbus 320), with 155 people on board, made an emergency landing on the Hudson River because several Canada geese flew into both engines at 2,900 feet shortly after takeoff from LaGuardia Airport in New York [2,6]. In 2019, Ural Airlines Flight 178, an Airbus 321 with 234 people on board, made an emergency landing in a cornfield approximately three nautical miles from Zhukovsky International Airport in Moscow, Russia, after seagulls flew into both engines of the aircraft [7].

The Federal Aviation Administration (FAA) specifies that the first step in risk maagement is safety hazard identification [8]. As established by the FAA, all airports operating under the Code of Federal Regulations (CFR) Part 139 must conduct a Wildlife Hazard Assessment (WHA) when a wildlife strike occurs at an airport or in the nearby areas, involving wild and domestic animals beyond the control of their owners. A WHA must be conducted by a Qualified Airport Wildlife Biologist (QAWB), who identifies local animals, sometimes rudimentarily, using binoculars or just the naked eye. WHA reporting may take up to a year because data on wildlife species must incorporate daily and seasonal factors [9], making it a laborious task. Therefore, innovative approaches such as machine learning (ML) with Remotely Piloted Aircraft (RPA) and high-resolution satellite (HRS) images, which are also used for other purposes and in other contexts and situations [10,11,12,13,14], are being used to detect these animals.

RPAs have been successfully applied in various fields and activities for data collection and research projects [15,16,17]. As such, RPAs are becoming a commonly used tool for research, commercial, and private purposes. Mlambo et al. [16] indicated that RPAs can be used to inspect hazardous wildlife habitats, such as lagoons and farms, in the areas around airports. In identifying wildlife attractions, RPAs facilitate access to inaccessible areas by land. Moreover, RPAs can be used to monitor wildlife around airports as well as to deter wildlife species from living near airports [18].

RPAs acquire remote sensing images for wildlife risk assessment owing to their versatility, logistical ease, and ability to collect data on demand and at spatial resolutions unobtainable by satellites and piloted aircraft. Additionally, they can fly in congested airspace and at low altitudes where piloted aircraft cannot operate safely. Fixed-wing RPAs provide an opportunity to continuously cover large horizontal and vertical distances at low altitudes with high spatial resolution. [19]. Therefore, RPAs can help bridge this major knowledge gap and help airport operators conduct a WHA.

The inclusion of ML is also essential for WHA reporting. A convolutional neural ne**t** work can extract highly accurate features for classification and prediction [20,21]. AbdElrahman et al. [22] examined the potential of using pattern recognition in images to observe waders on a local scale. They acquired such images in the Everglades Agricultural Area (EAA) and the Goodwin Wildlife Management Area in southern Florida with a small unmanned aerial vehicle (UAV) with digital video cameras. They automatically analyzed UAV images using pattern recognition techniques to identify and count birds. The algorithm developed leveraged the spectral characteristics of the images and matched images of the birds.

Hong et al. [23] developed deep learning-based bird detection models and estimated using aerial photographs acquired by a UAV. They constructed a dataset with aerial photographs of wild birds in various environments, including lakes, beaches, reservoirs, and farms in South Korea, and applied five different deep learning-based object detection methods to analyze UAV aerial photographs. They flagged difficulties in ascertaining whether the objects were birds, concluding that the pixel image size of a bird must be larger to improve detection performance. Further, Dolbeer et al. [3] recommended robust research projects and the use of new technologies and innovative approaches involving current technologies, as well as emphasized the need for public outreach and education as strategies for mitigating the risk of wildlife strikes to civil aircraft**.**

Considering the above discussion, we aimed to alleviate these problems by developing an innovative system for automatically detecting birds in RPA images. The current method used to collect data in airport areas is laborious and often non-standardized, heavily relying on the QAWB's experience. Furthermore, surveys conducted with RPA equipped with cameras produce a large dataset, which requires time and training to identify animals. Therefore, our system may help to streamline WHA reporting**.**

2 MATERIALS AND METHODS

The study area was in Florida, United States of America. We collected data at Coe Field (8FA4) (Figure 1), a private, general aviation airport in Class G airspace, with a runway of 29° 00' 37" N latitude and 81° 07' 56" longitude, covering approximately 90,000 m2.

Figure 1. Location of data collection.

2.2 Data collection

In this study, we collected remote sensing data using a DJI Mavic 2 Enterprise Drone 99 with a forward-looking infrared (FLIR) camera. This drone is versatile, safe, efficient, and suitable for short, detailed missions [24]. It has a battery autonomy of approximately 35 minutes, which can be easily and quickly replaced in the field, improving the data collection process and facilitating access to more closed or constraining locations.

We conducted the flights autonomously and according to flight plans (Figure 2) on different days and times to identify daily, seasonal, and other potential variations that could affect the results, following all protocols [25]. The QAWB helped the field team develop and execute the project. Furthermore, we conducted all flights using DJI Go 4 software, which enables researchers to create flight plans and store telemetry data for each flight. The drone operator monitored the RPA flight through a ground station screen, including the current altitude and speed of the RPA and GPS coordinates. The pilot operated the drone outside the control station while another team member monitored the survey through a TV screen inside the trailer, recording wildlife activity and identifying habitats that could attract species to the area. Another task conducted inside the trailer involved monitoring by aircraft near the location.

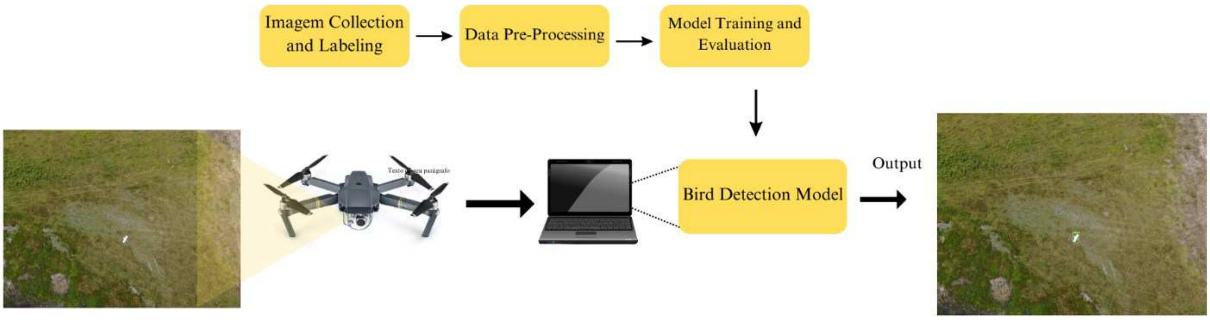

Figure 2. Proposed framework for automatic detection of forest fires by RPA.

Whether grid or manual, flights help the team capture multiple images of the location, providing QAWB with a better view of the wildlife and highlighting potential locations these animals can use. For this purpose, we conducted flights lasting 22 to 28 minutes at an average speed of approximately 20 miles per hour. On-site, researchers identified and recorded other animals not included in the flight plan, cataloging the species, number of animals, and their location.

2.3 You Only Look Once

We designed You Only Look Once (YOLO) for real-time object detection, using convolutional neural networks (CNN) to identify objects within an image. YOLO is a popular because it is a fast and highly accurate tool. With a multi-scale architecture and anchor boxes, YOLO can enhance its detection performance and the adjustment of bounding boxes, thus improving accuracy. In January 2023, Ultralytics [26] updated the latest architecture version, YOLOv8, which uses Feature Pyramid Network (FPN). We assessed model performance using the metrics of Mean Average Precision(mAP), Precision, and Recall.

Mean Average Precision: mAP is the metric used to measure the efficiency of the object detection model and is calculated using the average precision in all classes. The higher the mAP, the higher the precision of the model, given by equation 1.

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \tag{1}$$

Precision and recall: precision measures how positively a classification is made. TP and FP stand for True Positive and False Positive, and the number of correctly detected [27] and undetected birds, respectively, as expressed below. (Equation 2):

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall measures the rate of true positives, indicating the proportion of positive instances that were correctly identified, which can be expressed as follows in Equation 3.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

LeCun et al. [27] showed that various studies used YOLO precisely because it provided high performance and precision and proposed a method for automatic wildlife detection in challenging environments. YOLO architecture has also been applied to develop bird detection models in a wind farm [28] and even using UAVs [29, 30]. However, finding animals on-site is difficult, as is acquiring enough images to train the network. Therefore, we trained with one identification class called the *bird.*

In addition, we used 7784 images from the Open Images Dataset to calibrate the neural network weights. We used 70% of the images for training, 20% for tests, and 10% for validation. We also used transfer learning from YOLOv4 and YOLOv8 starting from the 137th convolution layer of the network (Figure 3). Hence, our models did not learn standard information such as lines, edges, and colors from the start. Lastly, we trained with a dataset for animal identification for 50 epochs.

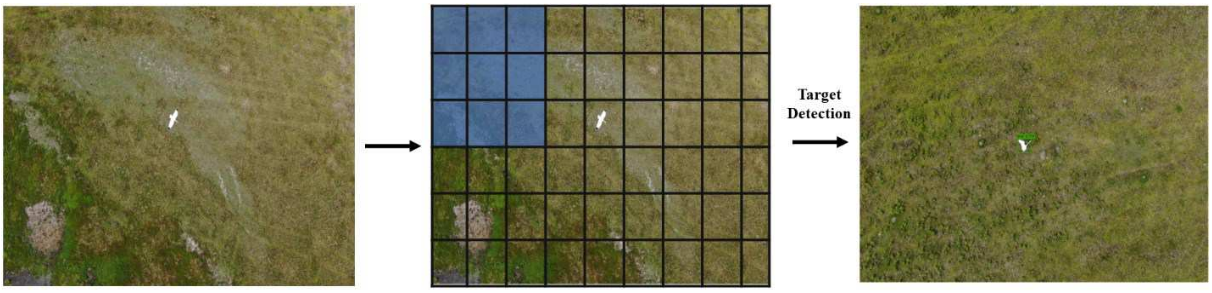

Figure 3. Bird detection model workflow.

2.4 DALL·E images

OpenAI revealed the DALL·E tool in early 2021, and it became popular for its ability to create several new images from simple sentences. In this study, we calculated some images in the DALL·E tool to assess whether birds could be detected in different habitats around airports.

We created 510 bird images in swamps, plantations, and mangroves to evaluate the performance of the bird detection algorithm in these artificially generated environments, and Figure 4 shows some detection results.

Figure 4. Image produced by the DALL-E tool of a bird in a flooded habitat and plantation field.

3 RESULTS

3.2 Test results

In this section, we compare the performance of our YOLOv4 model with the state-of-the-art object detection model, YOLOv8. [26]. Initially, we attempted to implement the more established YOLOv4, but new versions emerged as the architecture continued to evolve. We compared using the established metrics, the same dataset, and training parameters. The results are shown in graphs for each model tested in this study (Figures 5 and 6).

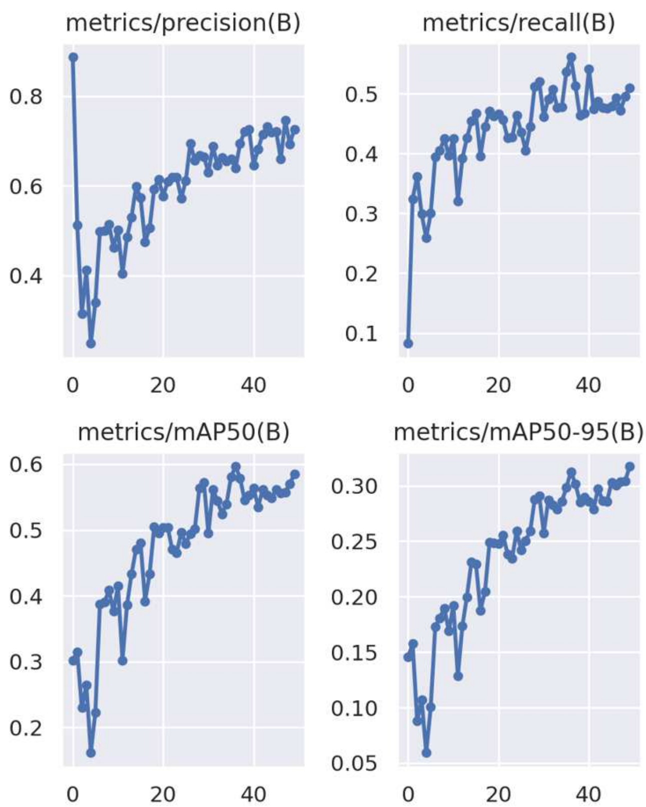

Figure 5. Image with YOLOv4 performance metrics.

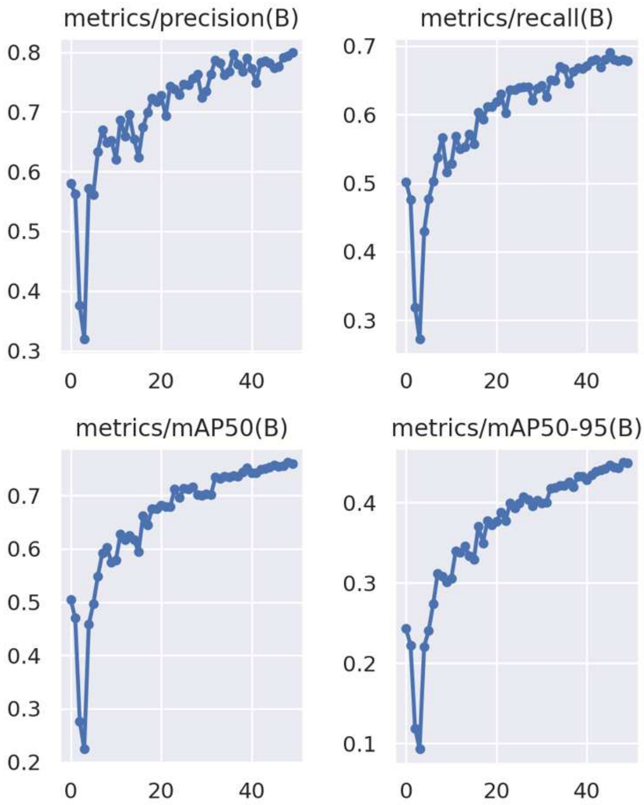

Figure 6. Image with YOLOv8 performance metrics.

The training precision reached 75% in the first model (Figure 4), with 58% recall and 61% mAP. The most recent model, YOLOv8, achieved 81% training precision, with approximately 69% recall and 79% mAP, demonstrating a significant improvement in object detection over the earlier version of the model. In a previous study testing other YOLO versions, such as v2 and v3 [31], Hong achieved mAPs ranging from 58.53 to 54.22%, respectively. These results show that the most recent versions outperformed earlier versions based on these metrics.

3.3 Bird detection and data visualization software

We developed two software programs in Python [32] to process and visualize the dataset even in the field. We chose Python because this high-level, general-purpose programming language provides a wide range of libraries, including PyInstaller, to create a single executable file.

We designed the first software to receive and process data, generating a .txt file with the input data report and a .xlsx file in table format with latitude and longitude coordinates containing the position of each detected animal. The second software served as a data viewer, receiving the data generated by the first software and displaying the image with the detected animal in an interface. Another interface also geolocated the sightings. These two software programs worked together to provide a complete data processing and visualization solution. Python enabled the developers to create efficient and scalable solutions to these problems, making the work easier and more automated. Furthermore, combining a report file with a table file makes it easier for users to gain insights into the data and to perform additional analyses if needed.

We also developed two software programs to allow users to focus on their main tasks without worrying about technical aspects, increasing work efficiency and productivity. Moreover, the automation of processes enabled users to save time and reduce human errors in animal identification, improving the precision of the results.

Ease of use and process automation make using the software in image analysis possible, enabling efficient, accurate, and standardized data collection and analysis of bird identification and distribution. Additionally, the graphical tool provides a clear and intuitive visualization of the collected data and results, facilitating the analysis and interpretation of results and their access. We tested the software using images collected by an RPA flying over the test area and with images artificially generated by the Dall E tool. Table 1 presents data from each collection.

Table 1. Dates of field data collection and the number of images generated by DALL-E.

11/08/2021	05/15/2022	10/21/2022	DALL-E	DALL-E
468	38	100	204	306

The software initially had five files: the first contained configurations of the neural network that identified the birds, while the second was a destination folder where the field-collected data should be placed. The third and fourth were executable files of the tool for data detection and spatial visualization. We created the fifth file as an instruction manual for using the tool. The user does not need to install any files on their computer to run the software, so there are no prerequisite computer skills.

Once the user adds the data collected in the field to the “images” folder and initiates the software's detection process, the first screen shows the images processed by the neural network.

When a bird is detected in the image, a new window displays the image with the detection, offering image manipulation options, such as zooming, editing, and downloading.

Once we processed the images collected in the field, we generated a field report (.txt file) and another report containing the geospatial information of each bird (.xlsx file). The field report contained information on the type of animal found, for example, in which image the animal was found, its geospatial coordinates, and the date and time when this record was made. With the geolocation information resulting from the field data processing, the second software displayed the locations of the sightings for better spatial awareness of where the bird was located and observed, further helping the biologist conducting the research. For visualization, the tool uses Google Marks to identify the object's location and an identification label.

4 DISCUSSION

Wildlife strikes pose a serious and costly challenge to the aviation industry and considerable research efforts worldwide have been made to address this issue. In addition to the material damage caused to aircraft, humans and wildlife are also at risk, exacerbating this problem. Combining drones with artificial intelligence is a new approach to monitoring and identifying wildlife and their habitats in this context. This task relies solely on the on-site biologist's experience and knowledge. This is challenging and tiring because external factors can introduce errors to conclusions. Standardizing this data collection and using a neural network to select and analyze these data can mitigate errors owing to external factors.

The search for standardization in these data or a standardized detection system aims to measure the factors that best interpret reality or deliver the best results for the user in the field. To achieve this goal, we applied some metrics that effectively captured the dataset, such as defining a threshold and data processing time.

The first graphs show the relationship between the threshold and the percentage of positives found in the images, highlighting the percentage of correct detections at each threshold. We calculated the value using the mean of each dataset. The YOLO neural network resizes the images to 448×448, and then a 7×7 convolution is performed on each image. For each detection, we estimated the corresponding precision or the level of correlation between the data and the original image. When identifying an object in an image, an object detection system, such as a computer vision algorithm or a machine learning model, also provides a score associated with that detection. This score indicates how confident the system is because the object is present in that image region. Based on these scores, a confidence limit can be applied to filter the detections. In our study, we called this limit a "threshold." We aimed to identify the best or optimal threshold for the trained dataset.

In both models, the percentage of correct detections ranged from 40 to 70%. At some points, the model can better identify the objects in each dataset. The best threshold for YOLOv4 was T50 (threshold with 50% confidence) (Figure 7). However, this does not necessarily reflect that the model made more correct detections at this threshold than at all others; rather, a higher precision score was achieved because it may contain false positives. In the data analysis, the threshold that best fits the dataset is T70 because it requires greater confidence than the object found in a bird. When comparing them individually, the YOLOv8 model outperformed its v4 model in all thresholds. (Figure 8). The parameters T60 and T70 detected the same number of objects. Hence, 70% confidence should be prioritized to introduce an extra level of certainty when processing a new dataset.

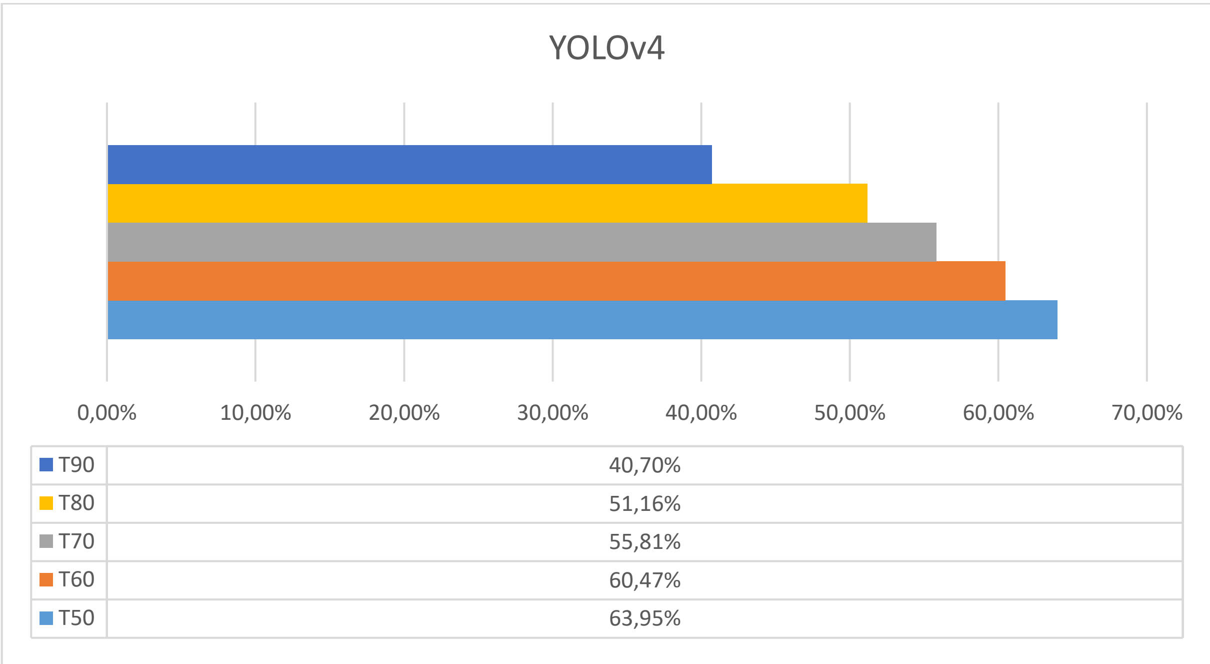

Figure 7. Relationship between the percentage of animals identified in images and the total dataset, where T50 stands for a 50% threshold at each threshold.

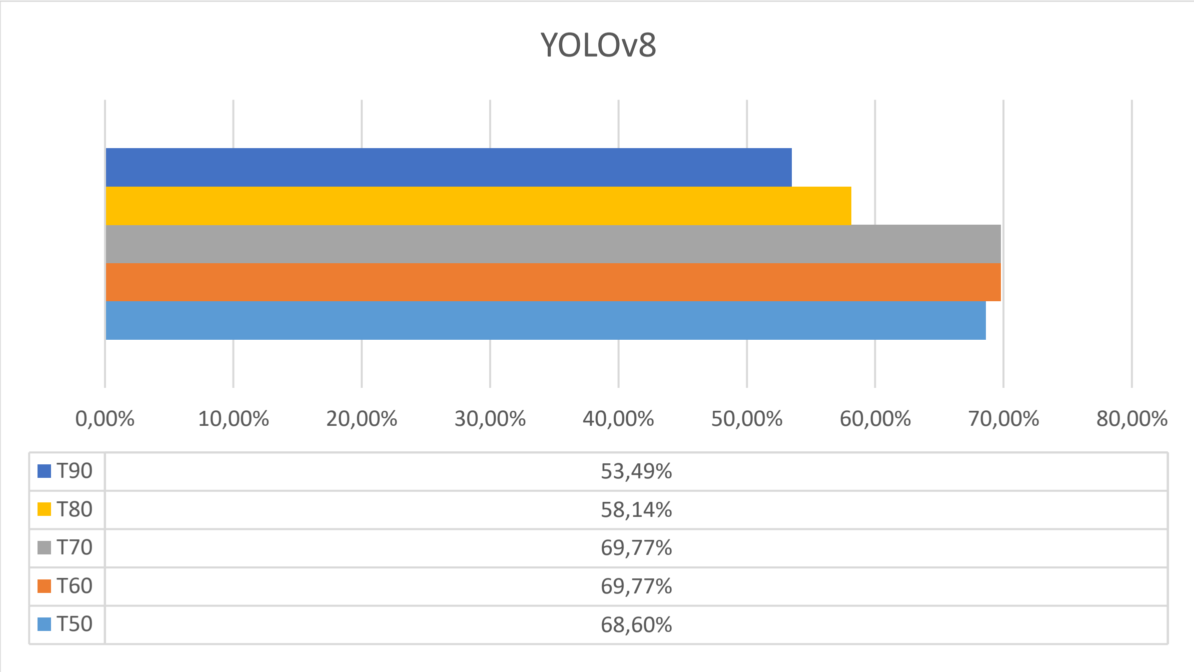

Figure 8. Relationship between the percentage of animals identified in images and the total dataset at each threshold.

We also assessed the processing time for each threshold to identify the fastest processing value of the dataset. We compared the models in Table 2 using each model's average image processing time. The latest model, YOLOv8, is twice as fast as version 4 at some points, with no significant difference when varying the confidence threshold of the model because the change between them is approximately 0.1 s, which can be disregarded. Determining whether the model undergoes significant threshold variations over time would require introducing variations to the datasets.

Table 2. Average image processing times for each model tested at different thresholds

	T50	T60	T70	T80	T90
YOLOv4	1.4228	1.3898	1.4159	1.4349	1.5040
YOLOv8	0.6968	0.6650	0.7874	0.6404	0.6394

Following the same reasoning, we tested the model on various datasets and at different times of the year using artificial image generation models. These evaluations aimed at measuring the model's speed on different datasets and dates to assess its ability to adapt to seasonal variations. Figure 9 shows that no significant changes occurred in response to variations in the dataset, thus demonstrating the model's adaptability to different data sets.

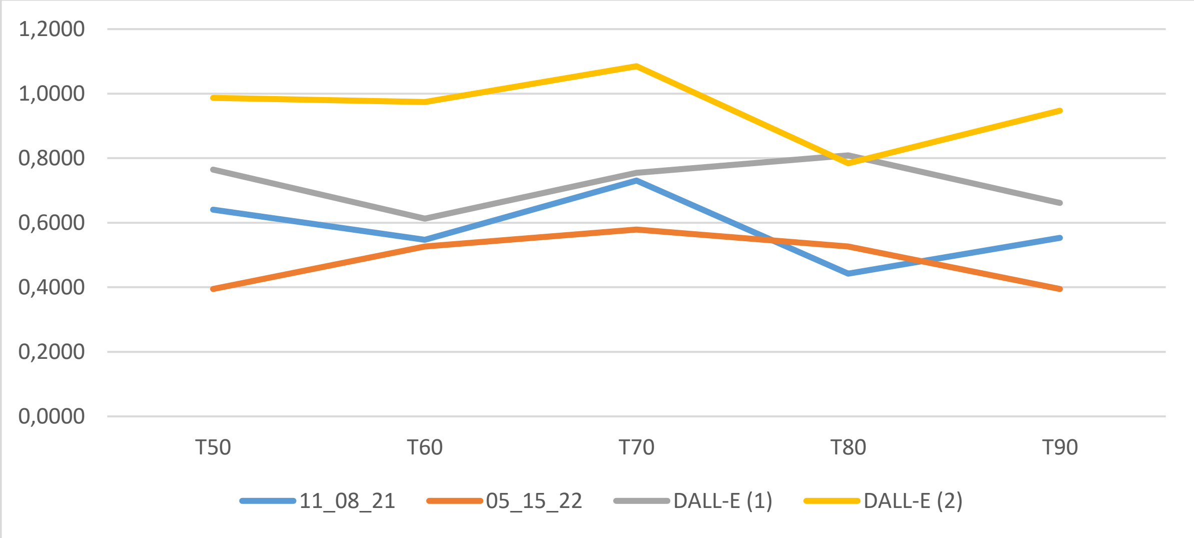

Figure 9. Variation of the model tested at different times and thresholds using YOLOv8.

The current system stands out for its processing speed in analyzing a set of 600 images for bird detection compared to earlier methods used in wildlife risk management research near airports. Previously, the procedure required the user to travel to the location to conduct a WHA. The user then visually analyzed a set of images collected by UAV and annotated the birds captured in the images.

Some identification errors may occur in the dataset because the images produced by a remotely piloted aircraft are nadir photos of the object. Additionally, some errors may be associated with the difficulty in object identification because of bird movement. Other errors may be associated with the difficultly in identification when the animal uses its color as a camouflage to merge with the image background (Figure 10).

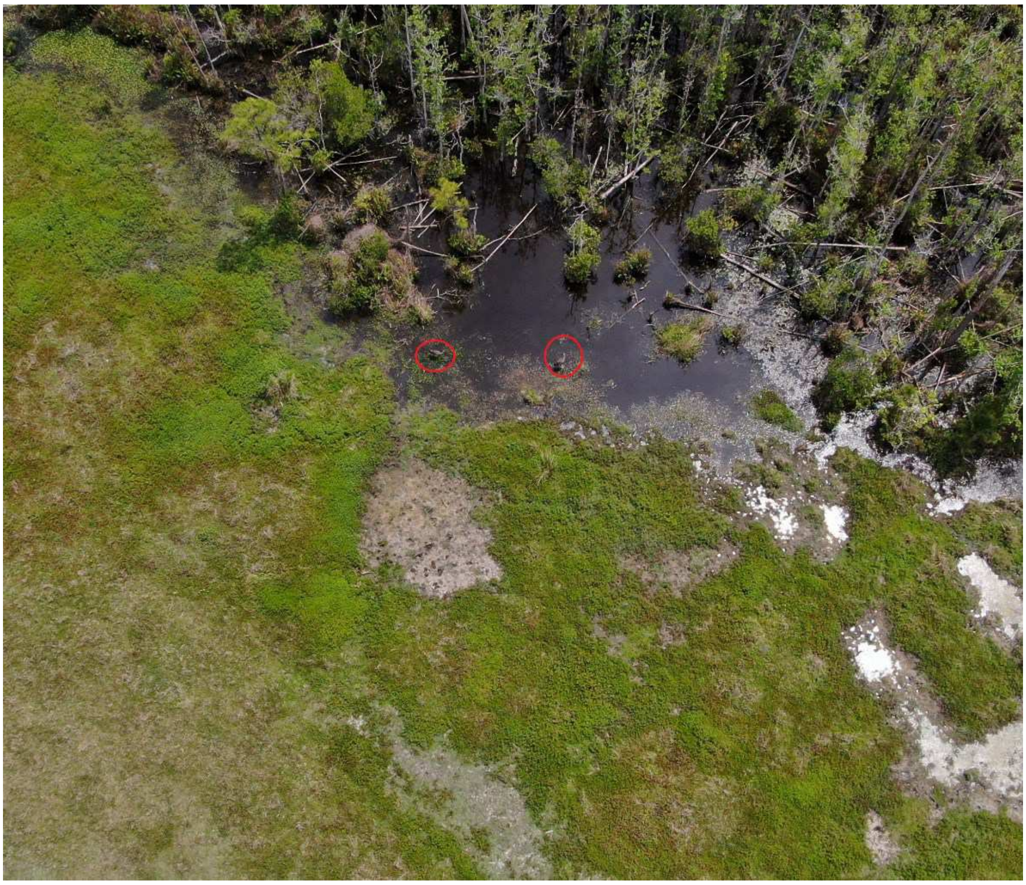

Figure 10. Image of the survey conducted around the Coe Field airport, with birds identified visu-317 ally but not detected by the software, possibly because their color is the same as the background.

5 CONCLUSIONS

The method developed in this study involved the use of images collected by RPAs to monitor and identify wildlife around airports, thus facilitating access to areas inaccessible by land. This method also included a process of automatic detection of patterns in images, yielding a robust monitoring system that helps detect birds in environments near airports. This approach helps decision-makers provide rapid responses to mitigate the risk of aviation accidents caused by wildlife strikes and QAWBs generate WHAs.

Further studies should be conducted in different locations with changing environments and diverse data collection involving various bird species to enhance bird detection and provide more support to field professionals. The use of alternative architectures for this detection type should also be explored.

REFERÊNCIAS BIBLIOGRÁFICAS

1. Martin, J.A.; Belant, J.L.; DeVault, T.L.; Blackwell, B.F.; Berger, L.W.; Riffell, S.K.; and Wang, G. "Wildlife risk to aviation: a multi-scale issue requires a multi-scale solution" (2011). USDA National Wildlife Research Center - Staff Publications. 1311.
2. Marra, P.P.; Dove, C.J.; Dolbeer, R.; Dahlan, N.F.; Heacker, M.; Whatton, J.F.; Diggs, N.E.; France, C.; and Henkes, G.A. Migratory Canada geese cause crash of US Airways Flight 1549. *Frontiers in Ecology and the Environment* **2009**, 7, 297-301. https://doi.org/10.1890/090066.
3. Dolbeer, Richard A.; Begier, Michael J; Miller, Phyllis R.; Weller, John R; Anderson, Amy L. Title: Wildlife Strikes to Civil Aircraft in the United States, 1990–2019 Published Date: 2021-02-01 Report Number: DOT/FAA/TC-21/19 URL: https://rosap.ntl.bts.gov/view/dot/58293.
4. Bogaisky, J. Blood in the sky: 10 years after the miracle on the Hudson, bird strikes remain an unsolved danger for aviation. Forbes Media, 2019.
5. Koerner, B. It's a bird! It's a plane! The midair collisions menacing air travel. Wired, 2020.
6. National Transportation Safety Board. Loss of Thrust in Both Engines After Encountering a Flock of Birds and Subsequent Ditching on the Hudson River US Airways Flight 1549 Airbus A320-214, N106US Weehawken, New Jersey January 15, 2009. 2010.
7. Aviation Safety Network. Airbus 321 accident, Moscow, Russia. 15 August 2019. Flight Safety Foundation. 2021.
8. U. S. Department of Transportation, Federal Aviation Administration, Flight Standards Service. FAA-H-8083-25B.
9. National Academies of Sciences, Engineering, and Medicine. 2010. Guidebook for Addressing Aircraft/Wildlife Hazards at General Aviation Airports. Washington, DC: The National Academies Press. https://doi.org/10.17226/22949.
10. Johannes N.; Deon J. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 2019, pp. 48-55.
11. Duporge, I.; Isupova, O.; Reece, S.; Macdonald, D.W.; Wang T. Using very high-resolution satellite imagery and deep learning to detect and count African elephants in heterogeneous landscapes. bioRxiv 2020.09.09.289231; doi: https://doi.org/10.1101/2020.09.09.289231.
12. Torney, C.J.; Dobson, A.P.; Borner, F.; Lloyd-Jones, D.J.; Moyer, D.; Maliti, H.T., et al. Assessing Rotation-Invariant Feature Classification for Automated Wildebeest Population Counts. *PLoS ONE* **2016**, 11(5): e0156342. https://doi.org/10.1371/journal.pone.0156342.
13. Grenzd¨orffer G. J. UAS-based automatic bird count of a common gull colony. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL1, p. 169–174, August 2013.
14. Seymour, A.; Dale, J.; Hammill, M. et al. Automated detection and enumeration of marine wildlife using unmanned aircraft systems (UAS) and thermal imagery. Sci Rep **2017**, 7, 45127. https://doi.org/10.1038/srep45127.
15. Fraser, B. T., & Congalton, R. G. Issues in unmanned aerial systems (UAS) data collection of complex forest environments. *Remote Sensing* **2018**, *10*(908), 1-21. https://doi.org/10.3390/rs10060908.
16. Mlambo, R., Woodhouse, I. H., Gerard, F., & Anderson, K. Structure from Motion (SfM) photogrammetry with drone data: A low cost method for monitoring greenhouse gas emissions from forests in developing countries. *Forests* **2017**, *8*(3), 1-20. https://doi.org/10.3390/f8030068.
17. Wallace, L., Lucieer, A., Malenovsky, Z., Turner, D., & Vopenka, P. Assessment of forest structure using two UAV techniques: A comparison of airborne laser scanning and structure from motion (SfM) point clouds. *Forests* **2016**, *7*(62), 2-16. https://doi.org/10.3390/f7030062.
18. Prather, C. D. (2019). *Current landscape of unmanned aircraft systems at airports* (ACRP Synthesis 104). Transportation Research Board on the National Academies. http://www.trb.org/Main/Blurbs/180032.aspx.
19. Hamilton, B.A. (2020a). *Airports and unmanned aircraft systems Volume 1: Managing and engaging stakeholders on UAS in the vicinity of airports* (ACRP Research Report No. 212, volume 1). Transportation Research Board on the National Academies. https://www.nap.edu/ catalog/25607/airports-and-unmanned-aircraft-systems-volume-3-potential-use-of-uas-by-airport-operators.
20. DJI (2021). Specs: Mavic 2 enterprise advanced. DJI. https://www.dji.com/mavic-2-enterprise-advanced/specs
21. Shen, W., & Wang, W. "Node Identification in Wireless Network Based on Convolutional Neural Network," 2018 14th International Conference on Computational Intelligence and Security (CIS), Hangzhou, China, 2018, pp. 238-241, doi: 10.1109/CIS2018.2018.00059.
22. Abd-Elrahman, A.; Pearlstine, L.; Percival, F. Development of pattern recognition algorithm for automatic bird detection from unmanned aerial vehicle imagery. Surv. Land Inf. Sci. **2005**, 65, 37. [Google Scholar]
23. Hong, S.-J.; Han, Y.; Kim, S.-Y.; Lee, A.-Y.; Kim, G. Application of Deep-Learning Methods to Bird Detection Using Unmanned Aerial Vehicle Imagery. *Sensors* **2019**, *19*, 1651. https://doi.org/10.3390/s19071651.

24. Adkins, K.; Wambolt, P.; Sescu, A.; Swinford, C.; & Macchiarella, N. D. Observational practices for urban microclimates using meteorologically instrumented unmanned aircraft systems. *Atmosphere* **2020***, 11*(1008), 2-17. https://doi.org/10.3390/atmos11091008.
25. Federal Aviation Administration (FAA). (2018). Protocol for the conduct and review of wildlife hazard site visits, wildlife hazard assessments, and wildlife hazard management plans (AC 150/5200-38).
26. Jocher, G.; Chaurasia, A.; Qiu, J. YOLO by Ultralytics. GitHub. 1 January 2023. Available online: https://github.com/ultralytics/ultralytics (accessed on 13 September 2023).
27. Young, G. O. & Peters, J. (1964). Synthetic structure of industrial plastics (Book style with paper title and editor).
28. LeCun, Y.; Boser, B.; Denker, J.S.; Henderson, D.; Howard, R.E., Hubbard, W.; and Jackel, L.D. “Backpropagation applied to handwritten zip code recognition.” In: Neural computation 1.4, 1989, pp. 541–551 (cit. on pp. 14, 16, 17, 25).
29. Roy, A.M.; Bhaduri, J. Real-time growth stage detection model for high degree of occultation using DenseNet-fused YOLOv4. *Comput. Electron. Agric.* **2022**, *193*, 106694.
30. Alqaysi, H.; Fedorov, I.; Qureshi, FZ; O'Nils, M. A Temporal Boosted YOLO-Based Model for Birds Detection around Wind Farms. J. Imaging 2021, 7, 227. https://doi.org/10.3390/jimaging7110227.
31. Hong S-J, Han Y, Kim S-Y, Lee A-Y, Kim G. Application of Deep-Learning Methods to Bird Detection Using Unmanned Aerial Vehicle Imagery. *Sensors* **2019**, *19*(7), 1651. https://doi.org/10.3390/s19071651
32. Van Rossum, G. & Drake Jr, F. L. (1995). Python reference manual. Centrum voor Wiskunde en Informatica Amsterdam.