USING MACHINE LEARNING TECHNIQUES IN THE VISUAL DETECTION OF STARLINGS IN VINEYARDS

Josef Novotný

Master Programme (2), FEEC BUT

E-mail: xnovot0v@vutbr.cz

Petr Marcoň

E-mail: marcon@feec.vutbr.cz

Abstract: This paper deals with the visual detection of starlings. The aim is to design an early warning detection system that protects crops from flocks of starlings. This system uses computer vision and machine learning algorithms. In the first phase, the activity in the vineyard was collected. Further, the neural network model using a cloud-based AutoML platform was trained and evaluated. The final classifier distinguishes objects into several categories. These categories include individual birds, flocks, and various unintended objects such as flies and bees. Overall, the flock detection algorithm achieved 89 % accuracy and 94 % recall.

Keywords: Starling detection, Flock detection, Computer vision, Machine Learning

1 INTRODUCTION

Vineyards belong to the main area endangered by voracious swarms of starlings. They present the most significant threat of every winemaker or fruit grower. Starlings refer to one of the most invasive species. They leave behind grape crop damaged, which reflects economic losses for winemakers. The use of various scaring systems can prevent the consequences of starling invasion. However, the vast majority of bird deterrent devices do not consider the presence of starlings. It significantly reduces the efficiency of such scaring devices. This paper aims to design a detection algorithm based on computer vision methods to supplement the scaring techniques. According to the current state of the art [1], several studies proposed bird detection based on neural networks (R-CNN, R-FCN, YOLO). The other authors [2] focus on designing a system based on the use of Gaussian and Gabor filters and HOG in combination with convolutional neural networks. This paper proposes to verify another method, namely a neural network architecture search (NAS) using the cloud-based tool Google AutoML to detect individual birds and starling flocks.

2 DATA COLLECTION

First, the activity on the vineyard was collected using a camera and microcomputer Nvidia Jetson Nano by employing an algorithm based on the differential method supplemented by filtering the background image, as shown in fig. 1. This method works as a motion detector with background subtraction. It eliminates the erroneous detection caused by the motion of vine leaves and surroundings.

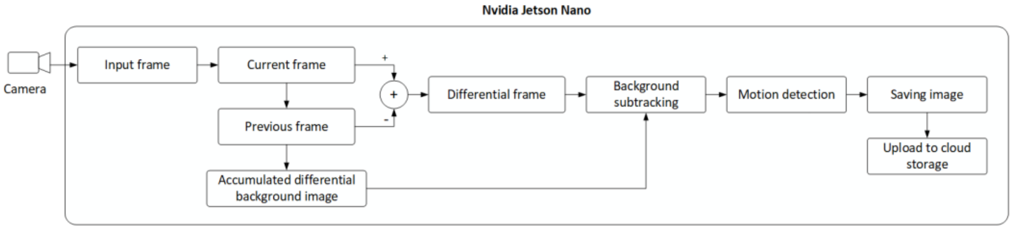

Figure 1: Flow chart of the motion detector for data collection.

3 SET OF COLLECTED IMAGES

The collected images were further divided into three main categories: bugs, birds, and bird flocks. The dataset also includes a helicopter captured entirely randomly. Due to different visual characteristics, birds and bugs were divided further into subcategories, as shown in fig. 2. The set of images contains 993 images, which were annotated for the purpose of supervised machine learning. The annotation of objects was conducted by marking areas of their occurrence with the classification name, detailed described in the tab. 1.

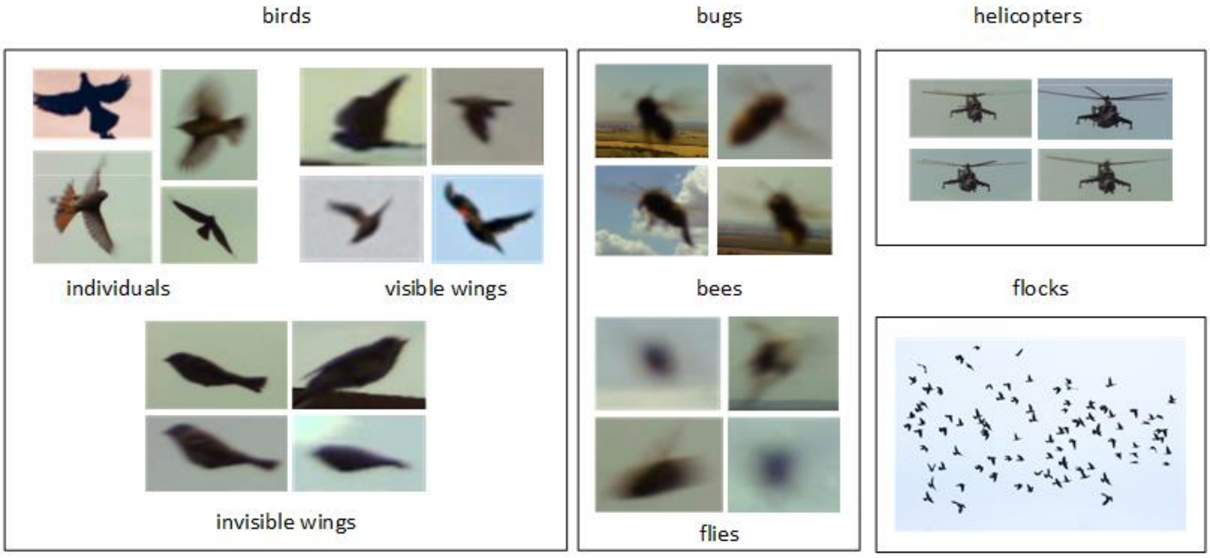

Figure 2: Categorizing the collected images.

The data collected did not contain enough relevant images of bird flocks, so they were supplemented from open datasets. Most of the images contained more objects, so the total number of objects exceeds the number of images collected. The images were divided according to the ratio 8: 1: 1 into a training, validation, and test set within machine learning.

Category		Training set	Validation set	Test set
Bugs	flies	442	41	43
	bees	36	7	4
Birds	individuals	2308	445	228
	visible wings	55	6	6
	invisible wings	160	5	3
Flocks		59	9	6
Helicopters		11	2	4

Table 1: Overview of categories within the training, validation and testing set.

4 MACHINE LEARNING ALGORITHM

The application of cloud-based Google AutoML Vision provided a tool for training a machine learning model. This approach presents Neural Architecture Search (NAS), which searches for an optimal neural architecture to a given problem using a recurrent neural network, as shown in fig. 3. The algorithm designs a basic set of hyperparameters, the number of layers and nodes of the convolutional neural networks. In subsequent iterations, the feedback specifies the individual parameters. This process is performed until the algorithm gradually finds the most optimal neural architecture for a particular dataset. Then, the resulting model is selected from a set of convolutional neural networks based on the optimal properties such as sufficient accuracy and recall of detection. [3] [4]

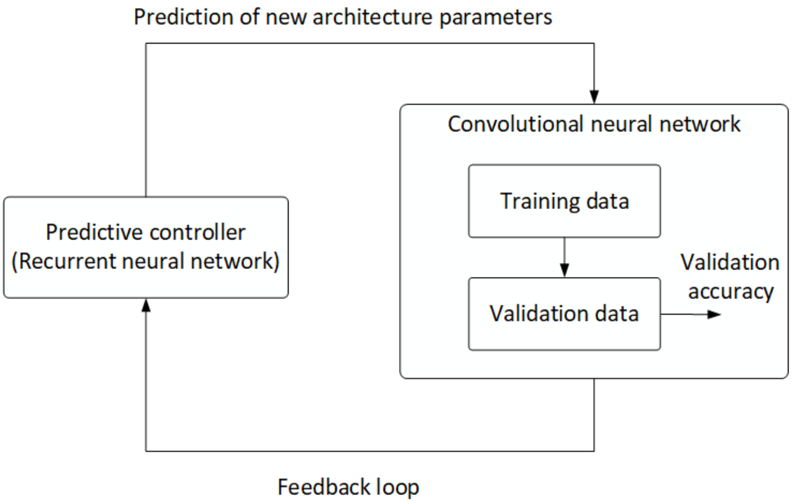

Figure 3: Block scheme of the neural architecture search algorithm Google AutoML. [4]

5 CLASSIFIER RESULTS

The classification model was deployed to the Tensorflow Lite framework for further implementation and evaluation. For evaluation purposes, a separate dataset was used. The classifier result is based on a comparison of classified and annotated ground truth. Objects in images are marked as true-positive if the detected area with the annotated overlap by at least 50 %. The results of the classifier are further presented in tab. 2.

	Birds	Bugs	Flocks
Precision	75.6 %	98.0 %	88.9 %
Recall	76.0 %	67.6 %	94.1 %
F1 score	75.8 %	80.0 %	91.4 %

Table 2: Precision, recall and F1 score of the classifier from image test set.

Precision represents the proportion of true-positive detections from the whole set of detected objects. In the case of birds, it is 75.6 %, which is the lowest value of accuracy from the set of all objects. It was mainly due to the occurrence of a larger number of false-positive images caused by a variability of the object size. For bugs, the accuracy reaches 98 %. The bugs were well recognizable since they occurred mainly close to the camera. The flocks have an accuracy of 88.9 %. Bird flocks were generally defined as a grouping of five or more birds. Another parameter was the recall of birds and bugs, which shows 76 %, resp. 67.9 %. It was caused by a low capture of relatively small and indistinct objects at greater distances. The sensitivity of the bird flock detection reaches 94.1 %, which is due to the relatively well-defined structure of the flock object, as shown in fig. 4. The F1 score evaluates the harmonic average of accuracy and recall. Bird flocks show 91.4 %.

From the results, it can be concluded that the biggest obstacle to the correct classification is too small size of the objects given by the distance from the camera. Conversely, large groups of birds can be detected with a high success rate, presented by accuracy and recall.

Figure 4: Examples of detected objects and corresponding confidence score.

6 CONCLUSION

The aim of this paper was to secure visual detection of starling flocks. First, a data collection of activity in the vineyard was performed using differential motion detection algorithms. However, this method was found unsuitable for detecting starling flocks due to a large amount of erroneous detection caused mainly by flying insect. The collected data were further used as a training set for the purpose of a supervised machine learning algorithm, which presents a cloud-based tool Google AutoML Vision. This method searches optimal neural network architecture and tunes the hyperparameters automatically. In the next step, the classifier was exported to the Tensorflow Lite framework. Subsequently, the results were evaluated on a separate test set of images. The accuracy of detection of bird flocks reaches 88.9 %, with a recall of 94.1 %. The biggest obstacle for the classification algorithm was mainly the distance of detected objects. However, it has been confirmed that the detection method is sufficiently effective and can be used as part of starling scaring device systems.

ACKNOWLEDGMENT

The completion of this paper was made possible by the grant: TJ04000441, Starling scaring system based on a passive optical locator, financially supported by TA ČR.

REFERENCES

[1] 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, doi:10.3390/s19071651.

[2] Ghosh, S.K.; Islam, Md.R. *Bird Species Detection and Classification Based on HOG Feature Using Convolutional Neural Network. In Proceedings of the Recent Trends in Image Processing and Pattern Recognition*; Santosh, K.C., Hegadi, R.S., Eds.; Springer: Singapore, 2019; pp. 363–373.

[3] Zoph, Barret; Le, Quoc V.: *Neural Architecture Search with Reinforcement Learning*, 2016.

[4] *Cloud AutoML Documentation* [online]. Available at: https://cloud.google.com/automl/docs