 DOI: 10.3217/978-3-85125-954-4-17

Selection of YOLOX Backbone for Monitoring Sows' Activity in Farrowing Pens with a Possibility of Temporary Crating

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Abstract

Activity monitoring of sows in farrowing pens is an important application of computer vision in Precision Livestock Farming. One example with a benefit for welfare of sows is farrowing prediction in pens with a possibility of temporary crating. In 2 experiments we tested various YOLOX backbones to estimate the generalization ability of the models on seen and unseen farrowing pens and animals. Models performed better on known pens and animals (~0.9 mAP) in comparison to unknown (~0.8 mAP). Results suggest that it is better to include some images of sows in the training set from the environment where the algorithm will be implemented. However, mAP as high as 0.8 suggests that on many farms it might be not necessary to re-train the model. Speed of inference of YOLOX models was ranging from 21 fps (YOLOX-x) to 42 fps (YOLOX-nano) on recorded videos. This should be sufficient to monitor activity level of sows in the farrowing compartment of production unit of VetFarm Medau (20 pens).

1. Introduction

It is common practice in modern intensive pig husbandry to confine sows in farrowing crates including at least a few days before the onset of farrowing. The main reason for this practice is to improve piglet survival rate by protecting newborn piglets from fatal or injurious crushing by the mother sow [1]. However, the confinement of sows in crates has a negative impact on the sows' welfare, such as limited freedom of movement. Farrowing pens with a possibility of temporary crating offer a good compromise between the needs of the farmer, the sow and the piglets [2]. However, due to lack of precision in estimation of expected time of farrowing based on average length of gestation, there is a risk that farmer will keep the sows confined in crates in a period of nest-building, few hours before the start of farrowing, to protect the piglets from crushing.

Automated detection of increase in sow activity with the use of sensor technology makes it possible the prediction of the onset of farrowing [3]. This could be useful in practical conditions to shorten surveillance intervals by farm staff, and the pen with a possibility of temporary crating could be prepared for an optimal farrowing [4].

To detect a sow in a farrowing pen we decided on application of YOLOX from YOLO series of object detection algorithms. YOLOX is a state-of-the-art object detector surpassing YOLOv3, one of the most widely used detectors in industry [5]. We hypothesize that YOLOX will provide an optimal trade-off between the speed and accuracy for real-time applications.

The objective of this study was to select an optimal backbone of YOLOX for real-time measurement of activity of sows, considering generalization ability of the model in unseen farrowing pens and on unseen animals.

2. Methodology

2.1. Animals and housing

Images with sows in farrowing pens were collected at the pig research and teaching farm (VetFarm) of the University of Veterinary Medicine Vienna, Vienna, Austria. Dataset 1 was collected between June 2014 and May 2016, while dataset 2 between December 2021 and July 2022. In total, images of 78 Austrian Large White sows and Landrace × Large White crossbreds sows were recorded. These sows were housed in four types of farrowing pens. Out of 78 sows, 11 were kept in SWAP (Sow Welfare and Piglet Protection) pens (Jyden Bur A/S, Vemb, Denmark), 11 in trapezoid pens (Schauer Agrotronic GmbH, Prambachkirchen, Austria), 11 in wing pens (Stewa Steinhuber GmbH, Sattledt, Austria) and 45 in BeFree pens (Schauer, Prambachkirchen Austria). None of the animals included in the experiment were confined in a farrowing crate from the introduction to the farrowing pen until the end of farrowing.

2.2. Video recording

Behaviour of sows was video recorded from introduction to the farrowing pens until weaning with 2D cameras in order to create a data set that could be annotated. Each pen in dataset 1 (SWAP, trapezoid and wing) was equipped with one IP camera (GVBX 1300-KV, Geovision, Taipei, Taiwan). In dataset 2 each IP camera (GV-BX2700, Geovision) was installed with a view on 2 farrowing pens (BeFree). Additionally, infrared spotlights (IR-LED294S-90, Microlight, Moscow, Russia) were installed in order to allow night recording. The videos were recorded with 1280x720 pixel resolution, in MPEG-4 format, at 30 fps.

2.3. Datasets

Out of 11 232 hours of recorded videos 15 242 images were selected for annotation and training of object detection models. To reduce correlation between sampled images K-means algorithm [6] was applied on recorded videos. For the 1st dataset 14 242 images were selected from videos recorded in SWAP, trapezoid and Wing pens. For the second dataset 1000 images were selected from videos recorded in BeFree pens.

Only one object class, a sow, was annotated on both datasets using CVAT and COCO annotator software packages (Fig. 1).

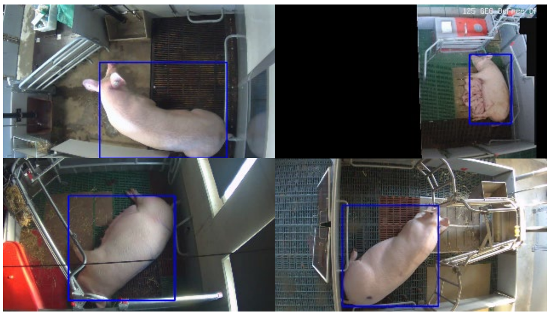

Figure 1. Annotated images with sows: top left – SWAP; top right – BeFree (one of two pens under camera view is masked); bottom left – trapezoid, bottom right – wing.

2.4. Experiments

We designed 2 experiments to test various backbones of YOLOX algorithm (YOLOX-nano, YOLOX-tiny, YOLOX-s, YOLOX-m, YOLOX-l, YOLOX-x) in terms of generalization ability and inference speed. We used MMdetection framework to train, validate and test the models [7]. Training was set to 50 epochs and was done on RTX Titan.

In both experiments out of total 15 242 images, 9969 (65.4%) were selected for the training set, 4273 (28%) for the validation set and 1000 (6.6%) for the test set. In experiment 1 training and validation sets included images from dataset 1, while test set from dataset 2. Thus, in experiment 1 it was possible to test the generalization ability of YOLOX backbones on new unseen farrowing pen (BeFree) and sows. In experiment 2 all 4 pen types and sows were represented in training, validation and test sets.

3. Results

Results of both experiment 1 and 2 revealed, as could be expected, that more complex backbones of YOLOX (YOLOX-m, YOLOX-l, YOLOX-x) had better mAP in both validation sets and test sets (Fig. 2). Higher mAP was achieved for these models after shorter training than for

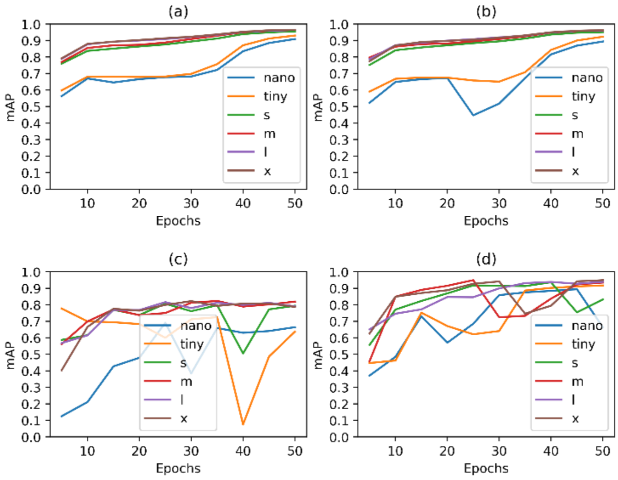

Figure 2. Performance metric mAP on a) validation set – experiment 1; b) validation set - experiment 2; c) test set – experiment 1; d) test set – experiment 2.

simpler models. Performance of models in experiment 1 was generally worse than in experiment 2 in the test set i. e. ~0.8 mAP vs 0.9 mAP for YOLOX-m, YOLOX-l and YOLOX-x. This suggests that for practical implementation of YOLOX for activity monitoring it is better to include some images of sows in the training set from the environment where the algorithm will be implemented. However, mAP as high as 0.8 suggests that on many farms it might be not necessary to re-train the model. Further validation of YOLOX with reference data on activity level of sows is needed to verify it.

Speed of inference of YOLOX models was ranging from 21 fps (YOLOX-x) to 42 fps (YOLOX-nano) on recorded videos. With assumption that 1 fps is sufficient to monitor activity level of sows, even with the most complex YOLOX-x backbone, it would be possible to monitor the whole farrowing production unit at VetFarm Medau with one RTX Titan (20 pens).

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