Implementation of a Deep Learning based system for monitoring farrowing in sows

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Gefördert durch

Bundesministerium für Ernährung und Landwirtschaft

aufgrund eines Beschlusses des Deutschen Bundestages

Projektträger

Bundesanstalt für Landwirtschaft und Ernährung

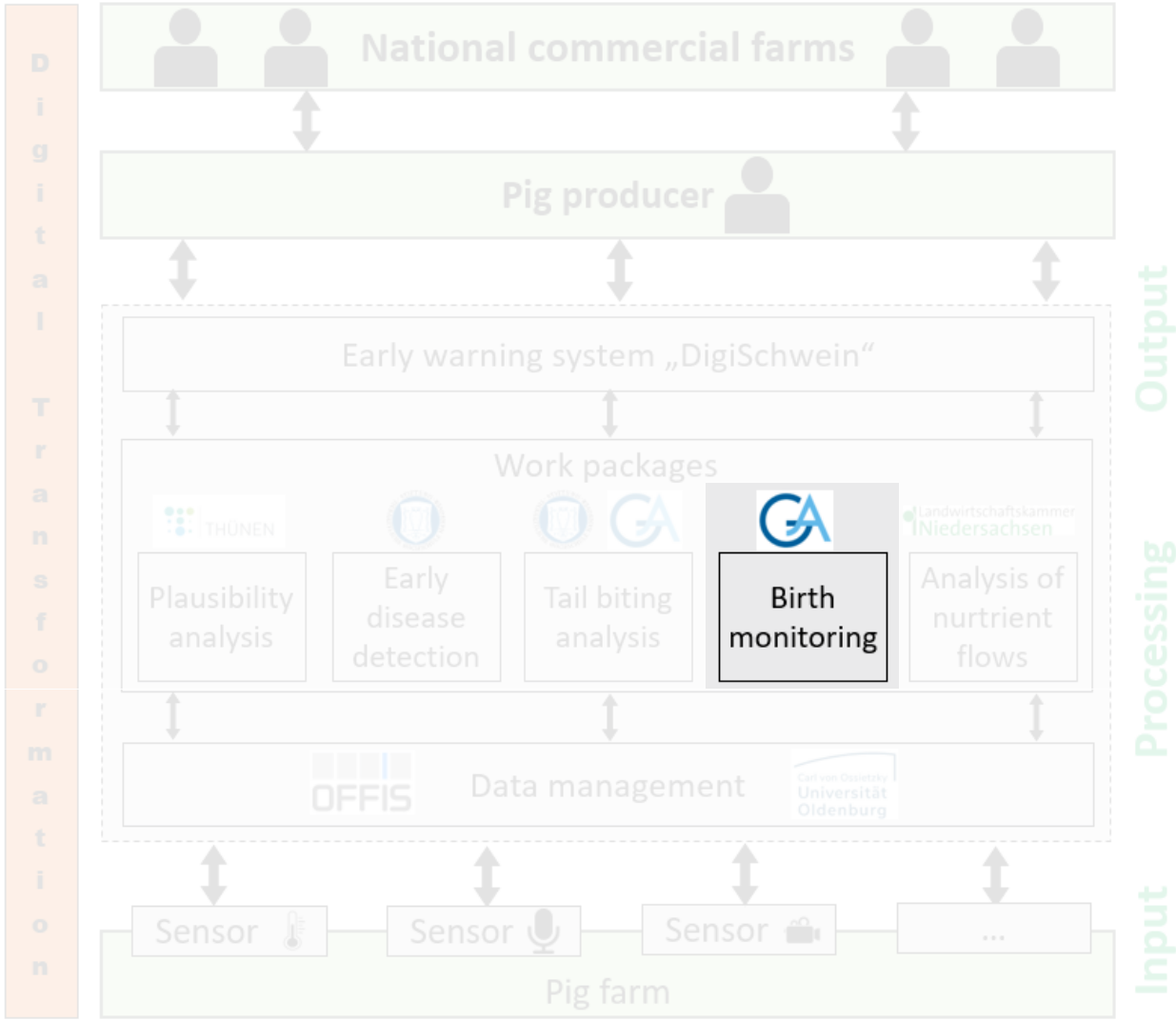
Research project „DigiPig“

Cross innovation and digitalisation in animal-friendly pig farming with consideration of resource protection

Project goals:

- Development of a sensor-based **early warning and decision support system** to support farmers and practicioners with a continuous and goal-oriented sensor data analysis
- Transfer of knowledge („DigiPig– advise, quantify, promote“)
- **Focus of the evaluation**: current and practice-relevant issues in pig farming

Research project „DigiPig“



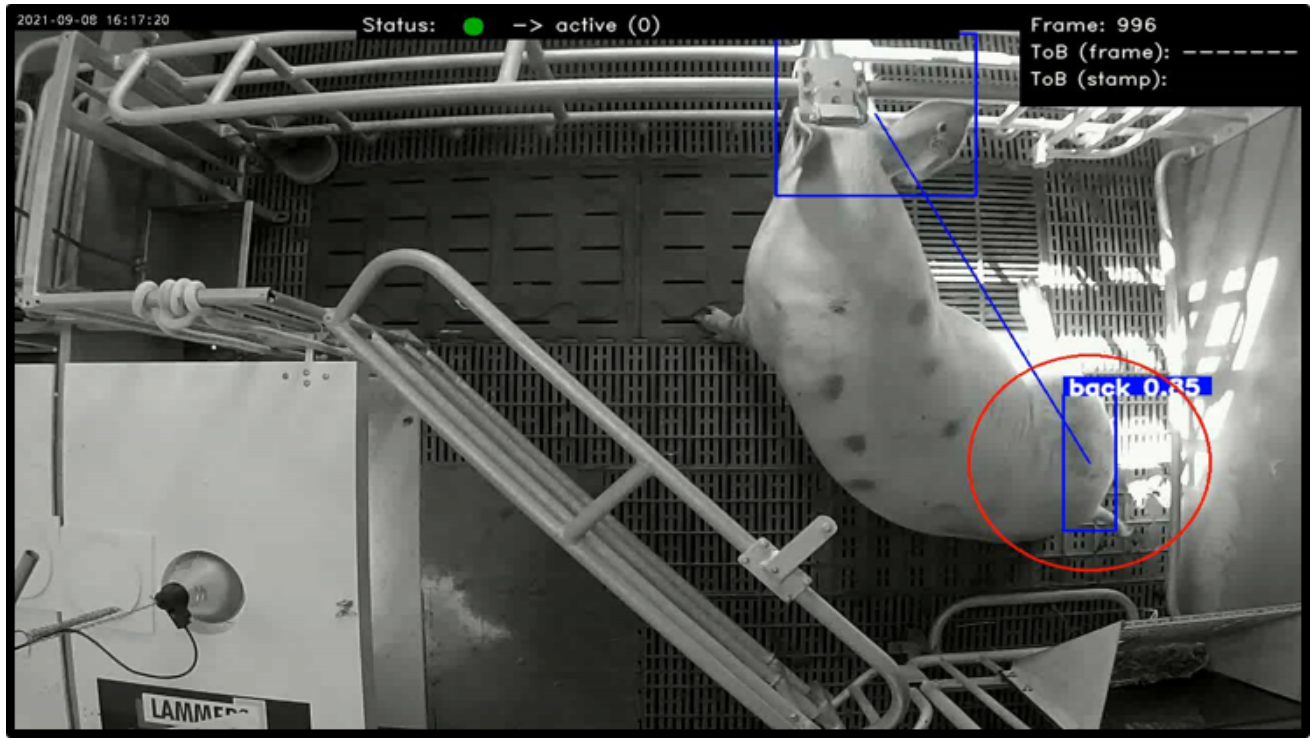
Goals:

- Implementation of a support system for automatic birth monitoring
- Providing critical information of the farrowing process.
- Identify and analyze birth-related events at an early stage

Contributions:

- Address the challenges of birth monitoring
- Reduce piglet mortality & increase animal welfare in the long term

One-stage birth monitoring



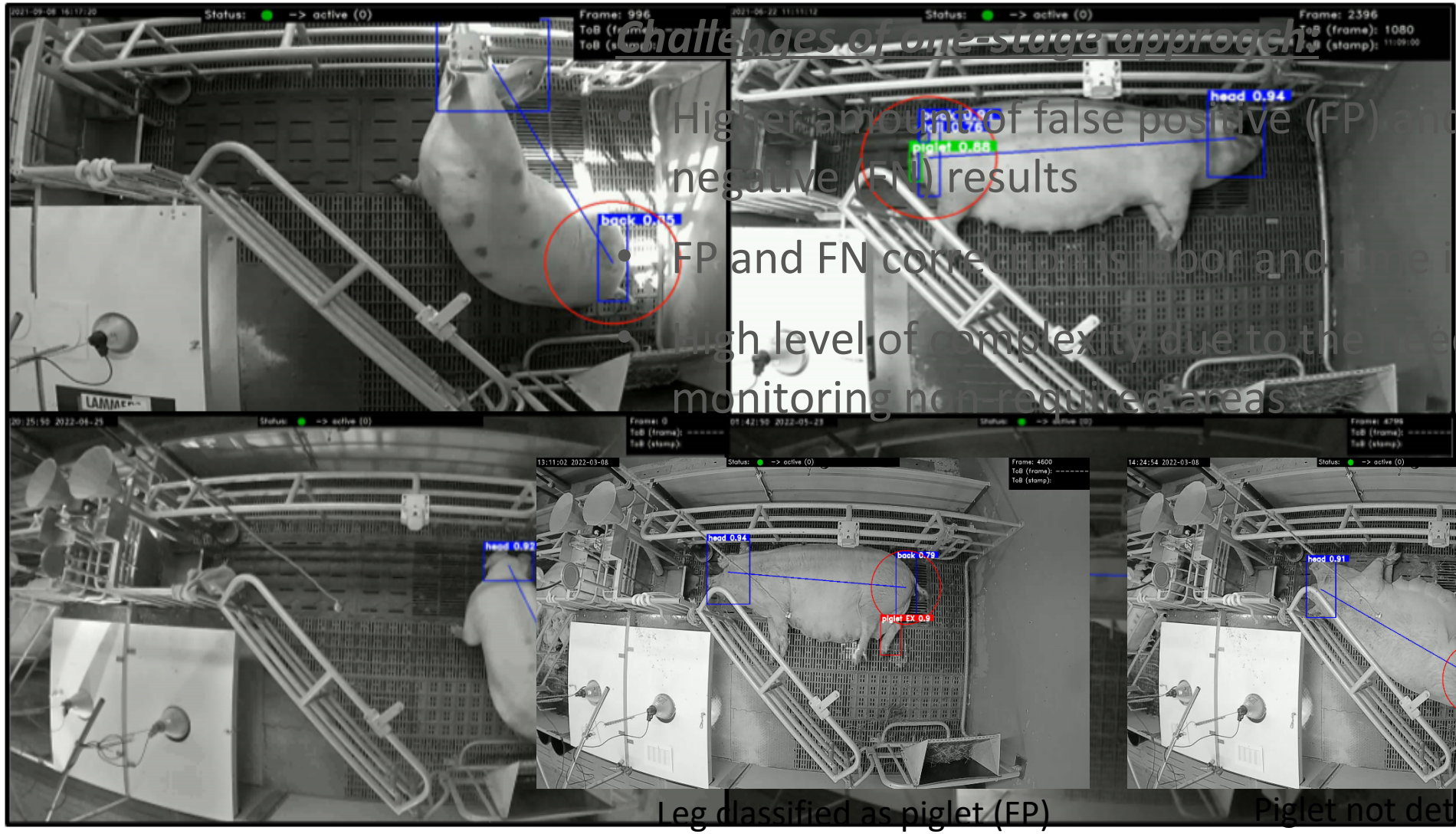
Idea

- Apply object detection for multiple body parts of the sow
- Compute orientation and target area
- Detect piglets within/without target area

Aim

- Determine starting time of farrowing
- Compute individual birth intervals

One-stage birth monitoring



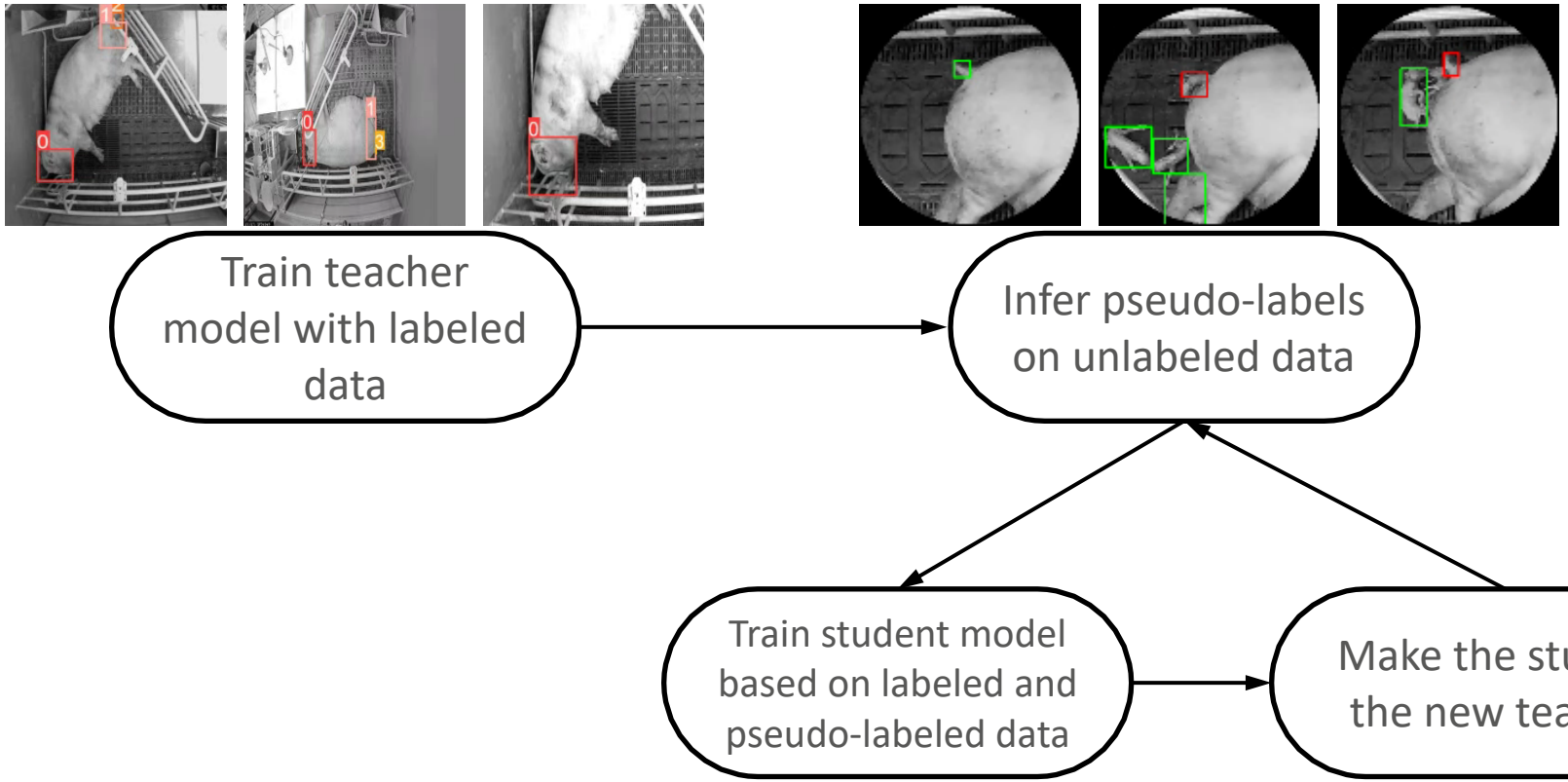
Challenges of one-stage approach:

- Higher amount of false positive (FP) and false negative (FN) results
- FP and FN corrections labor and time intensive
- High level of complexity due to the need of monitoring non-required areas

Leg classified as piglet (FP)

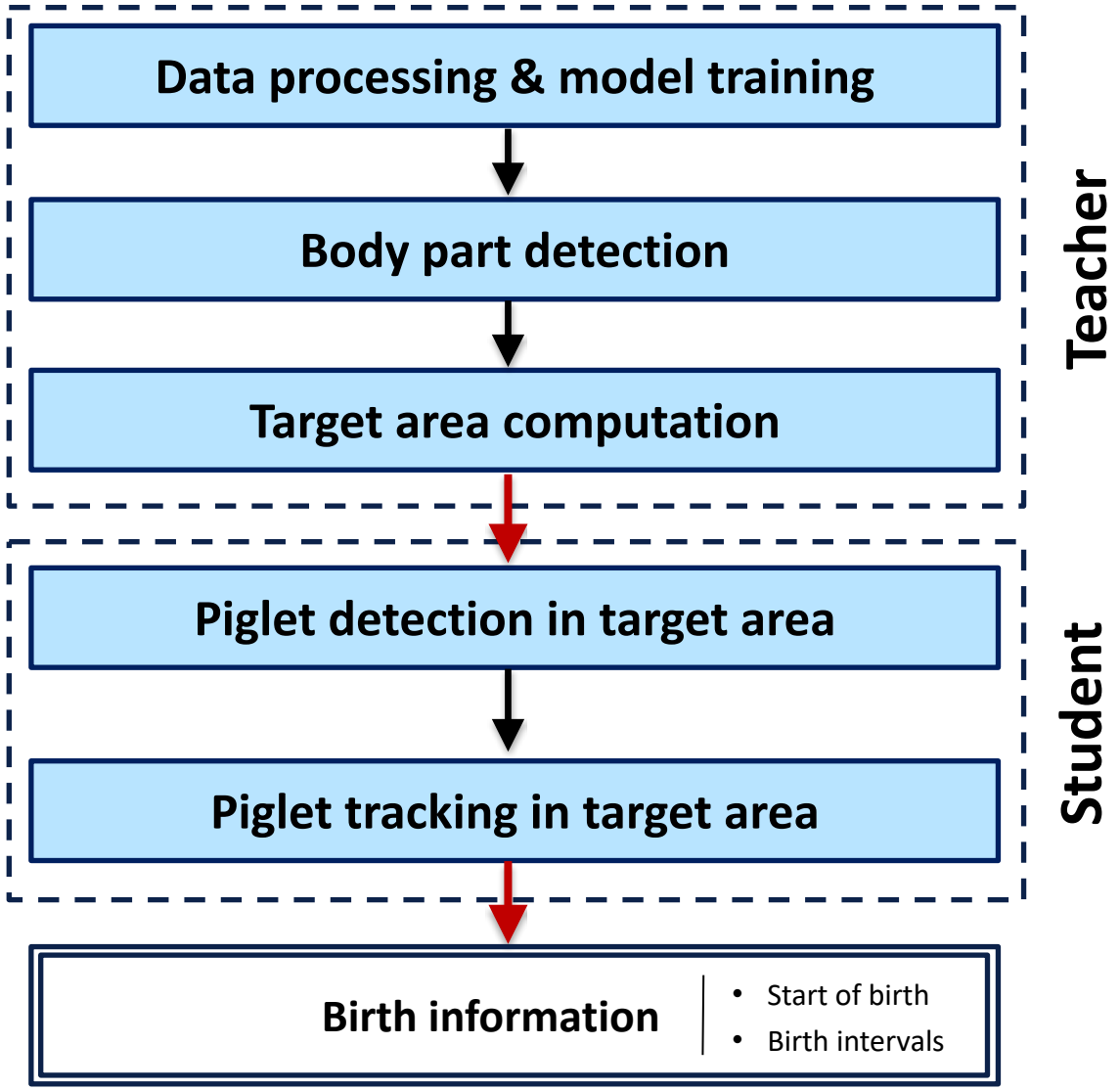
Piglet not detected (FN)

Noisy-student approach



Xie et al. (2020)

Analysis framework



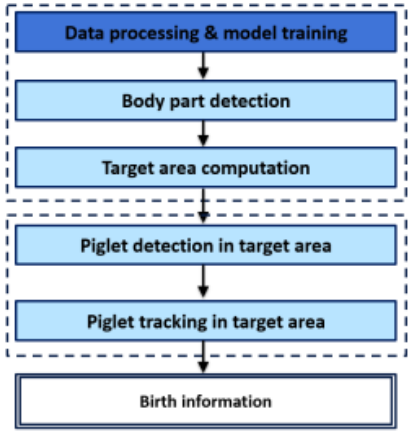
Materials and methods

- Dataset: Birth events of **96 sows** in 12 trials with 8 sows each

  Group structures:

  1. Farrowing: With/ without fixation
  2. Age: Young sows (1.-3. litter) / old sow (at least 4. litter)

Materials and methods



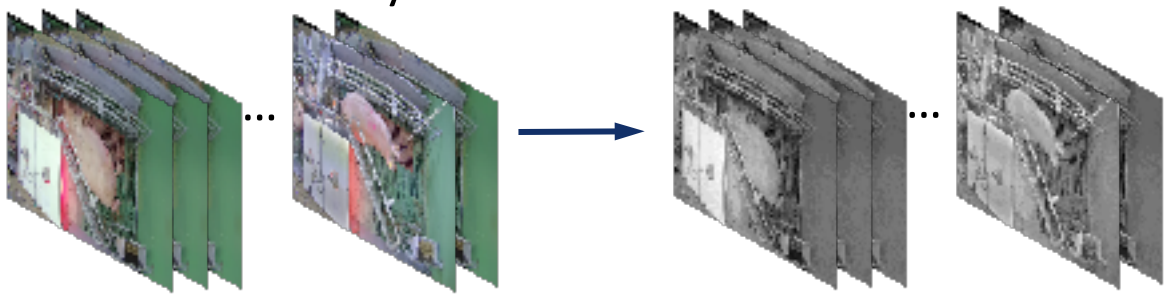
1. Image Annotation

750 images

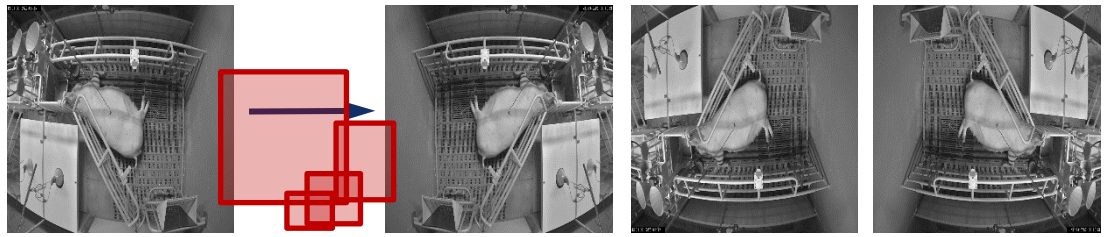
Annotation information

2. Dataset creation

Grayscale transformation



Data augmentation

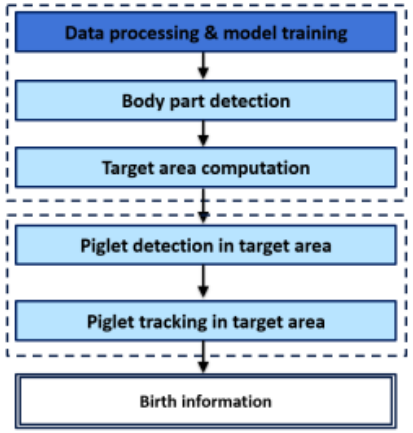


Original | Horizontal flip | Vertical flip | H + V flip

Sample size (training): 2700

Sample size (test): 300

Model training (teacher model)



Training specifications

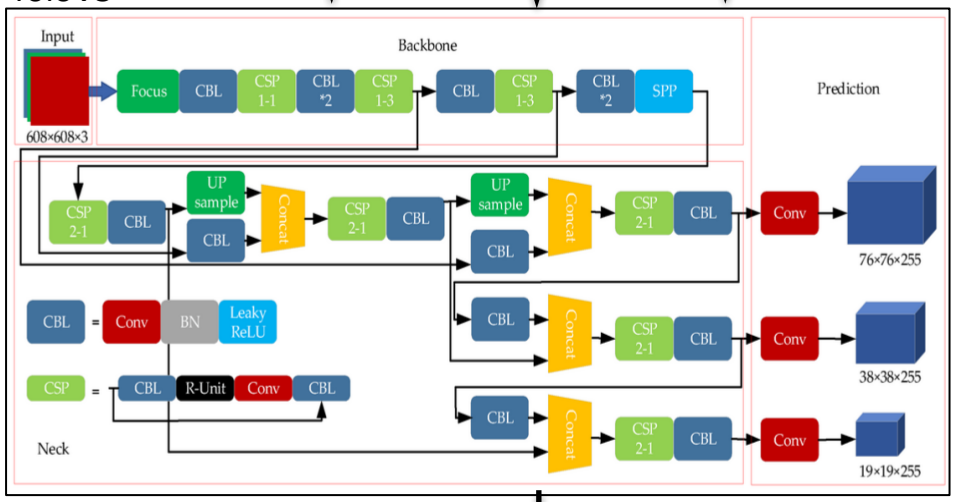
Parameter	Konfiguration
Input Dimension	1 x 640 x 640
Output	BB and class information
Optimizer	SGD
Learning rate	0.001
Loss function	Box loss & CLS loss
Evaluations metrics	Recall / Precision
Activation	Leaky ReLU / Sigmoid
Epochs	50
Training set size	1500
Batch size	50

Modelltraining

Training images

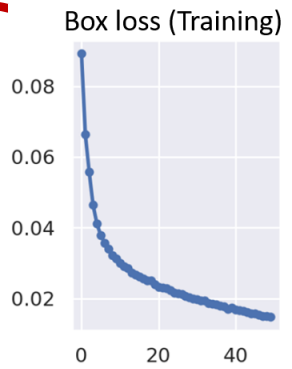
Training annotations

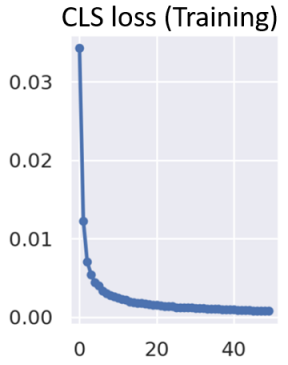
YoloV5

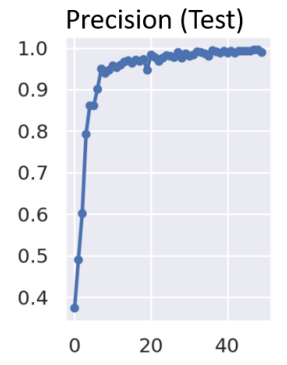


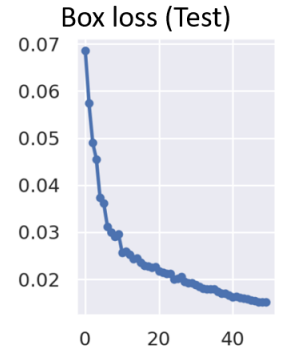
Zhang et al. (2022)

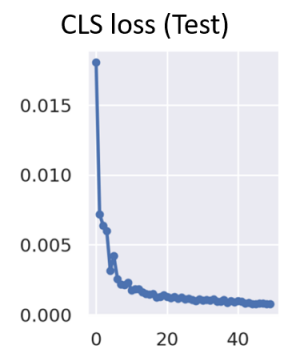
Estimated object positions

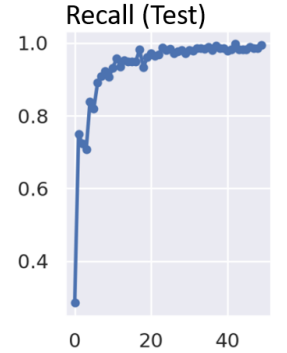




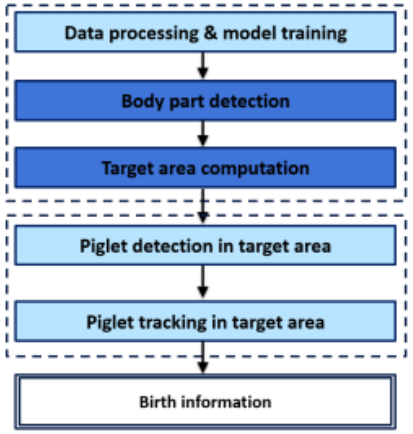








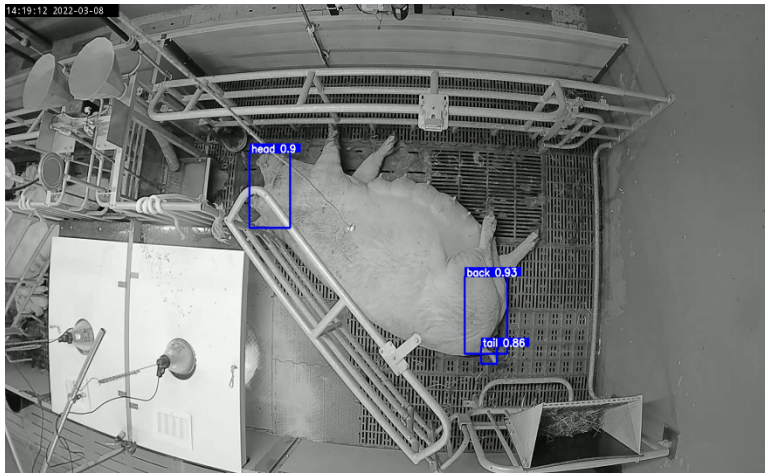
Model application (teacher model)



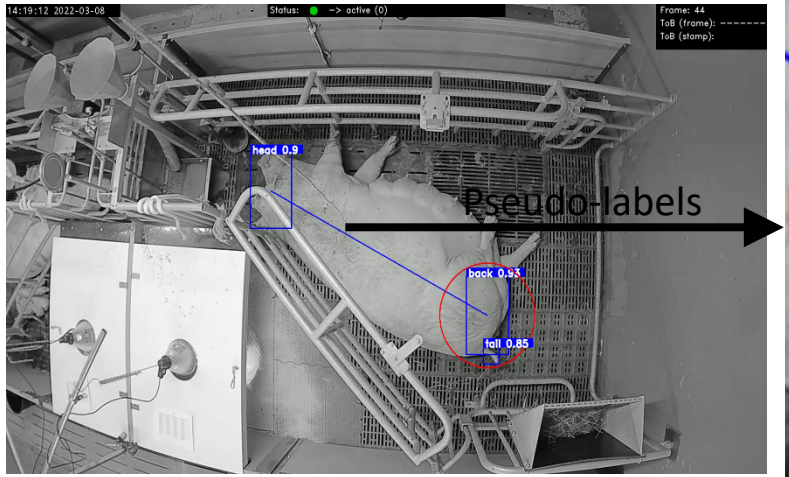
Target area computation

- Body part detection
- Determination of the sows orientation and a delimited birth area

1. Body part detection

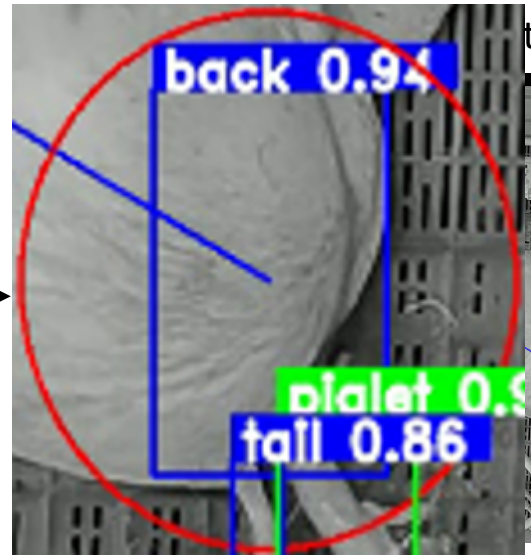


2. Orientation and target area



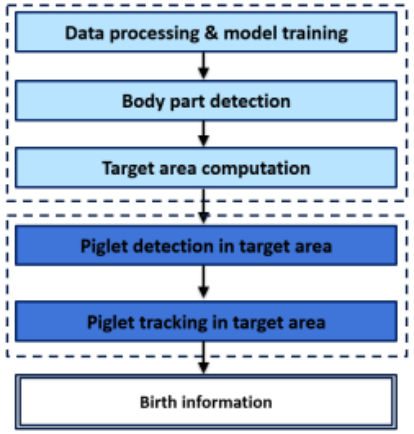
Pseudo-labels

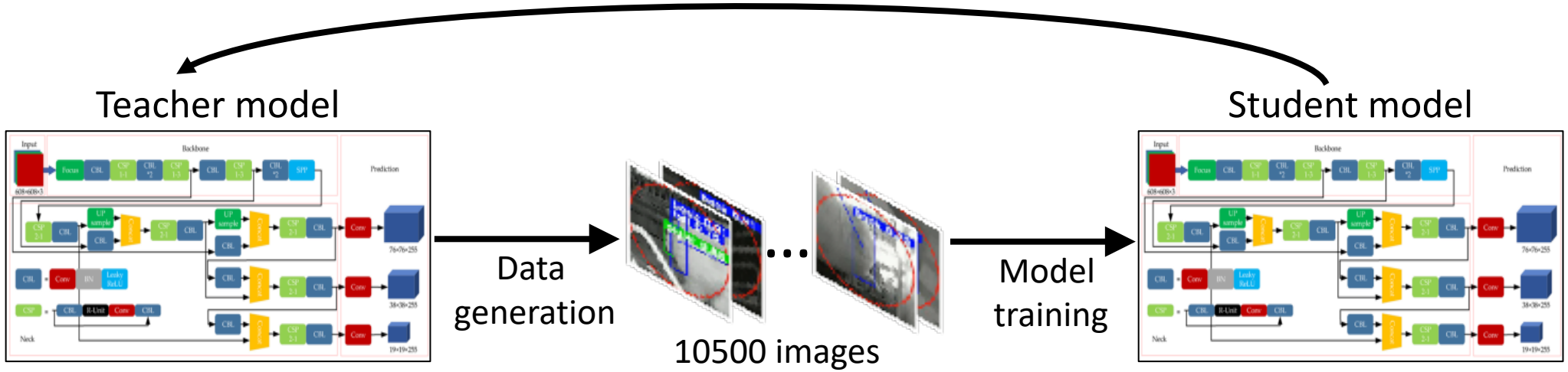
Target region

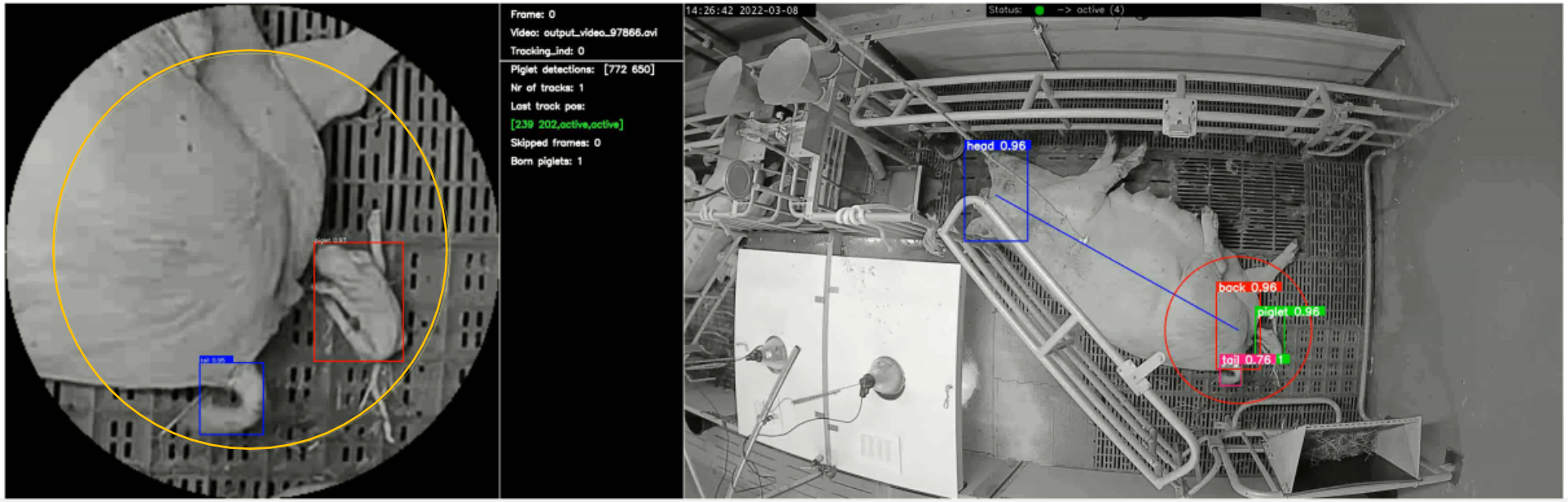


tection

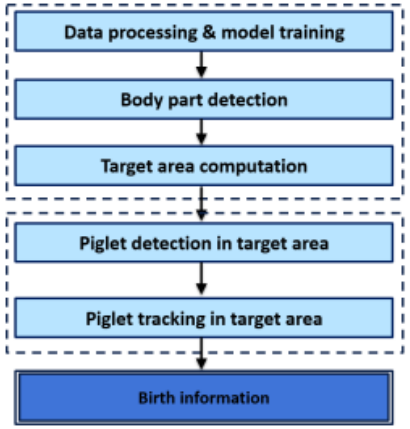
Model training (student)





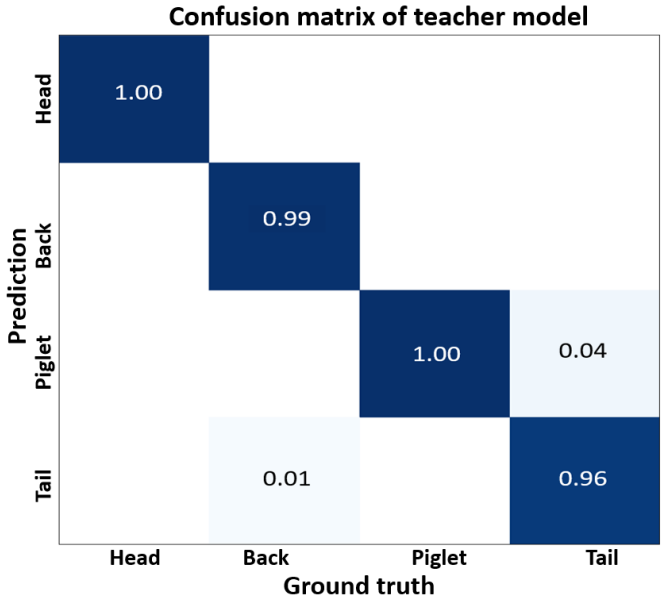


Results



Evaluation (teacher)

- Testdata: 300 images
- Randomly selected
- Manually annotated



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

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

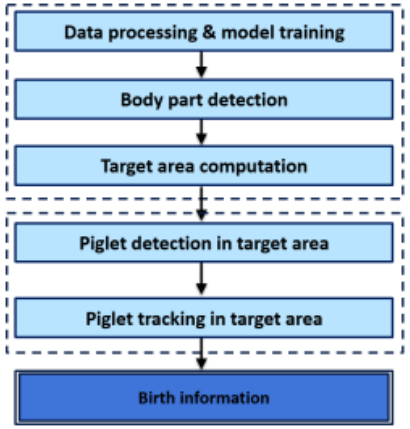
$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$TP = True\ Positive$
$TN = True\ Negative$
$FP = False\ Positive$
$FN = False\ Negative$

- Evaluation on whole video instances

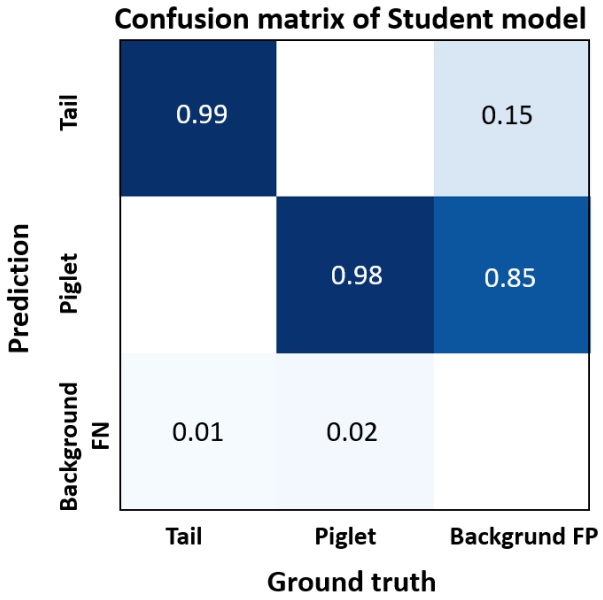
Dataset	# Videos	# Birth detected	Ø Difference (seconds)	Accuracy	Recall	Precision
With birth	10	8	11,5	-	-	-
Without birth	10	0	-	-	-	-
All	20	8	11,5	0,9	0,8	1

Results



Evaluation (student)

- Testdata: 1137 images
- Randomly selected
- Pseudo-labels generated by teacher model



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

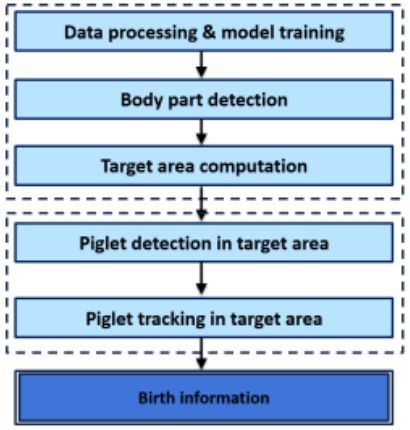
$$Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$TP = True\ Positive$
$TN = True\ Negative$
$FP = False\ Positive$
$FN = False\ Negative$

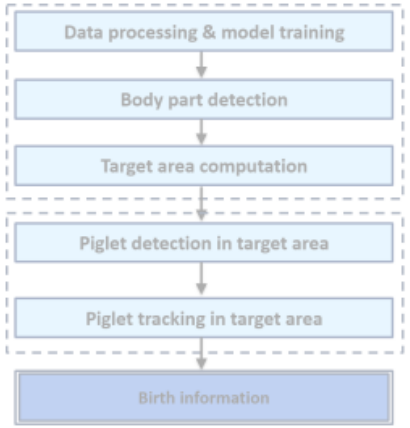
Object class	Frequency	Precision	Recall	MAP
Piglet	744	0.978	0.978	0.991
Tail	827	0.997	0.992	0.995
All	1571	0.988	0.985	0.993

Conclusion and future research



- Increased focus on monitoring target area by using two-stage approach
  - ➢ The degree of complexity can be reduced and piglet tracking can be performed
- Determination of individual birth intervals and identification of problem situations
- Machine learning-based object detection as a basis for further additions (orientation, target areas and tracking).

Conclusion and future research



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Thank you for your attention