Image-based Tail Posture Monitoring of Pigs

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Abstract

Tail biting presents a significant challenge in conventional pig farming, impacting animal welfare and farmers' economic viability. This paper introduces a novel approach for image-based tail posture monitoring, a potential early indicator of tail biting outbreaks. Our two-step tail posture detection approach, consisting of an initial pig detection and a subsequent tail posture detection step, shows significant improvements compared to previous methods. To mitigate ambiguity, our pipeline incorporates an EfficientNetV2 image classification model, filtering out lying pigs in the tail posture monitoring process. When applied to video sequences containing tail biting incidents, our method effectively captures the shift in tail posture from predominantly upright to hanging preceding outbreaks. Our findings offer a promising foundation for an early warning system to aid undocked pig husbandry, improve animal welfare, and provide targeted insights for farmers. The proposed approach demonstrates the potential for real-world applications, fostering proactive interventions to mitigate tail biting.

Keywords: pig, precision livestock farming, tail posture detection, deep learning, computer vision

1. Introduction

Tail biting is one of the biggest problems in conventional pig livestock farming (Schukat & Heise, 2019). It describes an abnormal behavior characterized by manipulating one pig's tail by chewing or biting another pig, which can result in injuries of varying degrees (Schrøder-Petersen & Simonsen, 2001). Not only does this compromise animal welfare, but it also poses substantial economic burdens on farmers. Due to the increased stress levels and occurring injuries, the risk of infection and disease outbreaks is elevated (Larsen et al., 2016), which, in addition to causing economic losses due to reduced daily weight gain of the pigs (Wallgren & Gunnarsson, 2021), can also lead to significant labor and veterinary costs for the farmer (D'Eath et al., 2018).

Tail biting is a multifactorial issue, influenced by both internal factors such as genes, sex, age, weight, health status, and external elements such as housing environment, pen climate, inadequate enrichment material, and high stock density (Schrøder-Petersen & Simonsen, 2001). Given the numerous possible causes and its sporadic occurrence, tail biting is a complex and multidimensional problem that is difficult to detect and is considered to be almost unpredictable (Paoli et al., 2016; Scollo et al., 2016; Valros, 2018).

The most effective preventative measure against tail biting is tail docking (Schukat & Heise, 2019), a surgical procedure involving the removal of a portion of the tail to mitigate the risk of tail biting or related injuries (Valros, 2018). Various studies have shown the effectiveness of this approach (Larsen et al., 2018b; Li et al., 2017); however, this procedure has been criticized because it negatively impacts animal welfare and does not solve the problem but merely suppresses it (Li et al., 2017). According to the EU Directive on the minimum standards for protecting pigs 2008/120EG, tail docking is prohibited and may only be practiced in particular cases (Briyne et al., 2018). Therefore, such practices do not represent a viable long-term option for tail biting prevention.

While tail biting is considered to be unpredictable due to the multitude of possible risk factors and its sporadic appearance, certain studies indicate potential predictors of tail biting, observed consistently before an outbreak. In addition to an increase in general activity inside the pen (Larsen et al., 2016; Statham et al., 2009), studies show that a steady change in tail posture could be observed days before an outbreak, with more pigs having a hanging tail posture and fewer pigs having an upright tail posture (Lahrmann

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et al., 2018; Wallgren et al., 2019; Zonderland et al., 2009). This makes the tail posture a potentially valuable indicator to not only assess the wellbeing of the pigs but also to assess the risk of a potential tail biting outbreak effectively.

Recent advancements in Deep Learning (DL) and Computer Vision (CV) for image analysis present an opportunity to develop systems capable of effectively monitoring these tail biting indicators based on camera data. These systems can enable farmers to comprehensively record these tail-biting indicators, moving away from manual, random sample evaluations that often result in additional labor during day-to-day operations. The availability of these comprehensive records could enhance risk assessment for potential tail biting outbreaks, which would not only help in the husbandry of undocked pigs by potentially mitigating the need for tail docking but also enable prompt, timely and cost-effective early intervention, leading to improved animal welfare and reduced economic burden for farmers.

This paper presents a first step in developing such a system by introducing a novel pipeline for the image-based monitoring of the tail posture indicator based on DL. This work contributes a potentially valuable tool for providing early warnings of tail biting episodes of pigs, enabling proactive interventions that could significantly improve animal welfare and reduce economic losses in pig farming.

2. Related work

Compared to other applications within pig precision livestock farming, research on the image-based tail posture detection of pigs using DL is relatively sparse.

While not directly applying DL methods, D'Eath et al. (2018) used 3D cameras in combination with Linear Mixed Models to detect and measure the tail posture of pigs, resulting in "[…] an accuracy of 73.9% at detecting *low* vs *not low* tails […]". The authors noted that the proposed algorithm performed best when detecting the tucked tail posture.

In a different study, Ocepek et al. (2022) utilized Mask R-CNN for image-based pig, head, and tail detection. The authors curated a dataset of 583 images, utilizing 533 for training and the remaining 50 for evaluation. The dataset consisted of 7,742 individual tail annotations for the classes *tail-curled-good-visibility*, *tail-straight*, and *tail-uncertain*. The trained model achieved a precision of 0.77 and a recall of 0.60 in detecting *straight* vs *curled* tails, indicating that the model has issues detecting all the actual positive samples. The authors also trained a YOLOv4 model based on a dataset of 30 images with an average of six pigs with visual tails, achieving a precision of 90%. However, the authors did not provide additional evaluation metrics, such as the mAP at different Intersection over Union (IoU) thresholds or individual evaluation metrics for both the *straight* and *curled* tail posture class, making further interpretation of the results difficult.

Witte et al. (2022) built on the approach of Ocepek et al. (2022) and trained a YOLOv5 model for *upright* and *hanging* tail posture detection using a dataset consisting of 1000 images with 6391 *upright* and 6412 *hanging* tail annotations. They conducted an evaluation using the YOLOv5 's', 'm', and 'l' models, employing image sizes of 640 × 640 and 1280 × 1280 for each variant. Their findings suggested that larger image sizes for training could enhance detection performance. However, the results are still insufficient, as the top-performing model variant YOLOv5-l using a 1280 image size, only achieved precision, recall, $mAP^{IoU=0.5}$, and $mAP^{IoU=0.5\text{-}0.95}$ values of 0.885, 0.884, 0.879, and 0.511, respectively. Furthermore, the evaluation pointed to limitations of simply using larger model sizes: the performance gain when moving from the 'm' variant to the 'l' was smaller across all measured metrics compared to the leap from 's' to 'm', despite the 'l' variant having over twice the parameter size compared to the 'm' variant. Witte et al. (2022) concluded that performance may not be increased using larger model and image sizes.

Despite these advancements in the field, there are several remaining challenges and limitations, which this study aims to address.

3. Research Contributions

In addition to the insufficient performance of existing approaches for image-based tail posture detection, there is also the prevailing challenge to properly process the tail posture of pigs in a lying position when applying existing approaches. Most prior studies relating to the investigation of the tail posture as an early indicator for tail biting have confined their observations to the tail posture of standing pigs during data collection (Larsen et al., 2018a; Wallgren et al., 2019). This is partly due to the ambiguity associated with the tail posture of lying pigs. because lying pigs often let their tails hang loose, which could lead to misinterpretations when monitoring tail posture as an early indicator for tail-biting However, when conducting tail posture detection directly on the input image, as by Ocepek et al. (2022) and Witte et al. (2022), lying pigs cannot be directly filtered out, as the model is solely trained to predict bounding boxes (BB) for the predefined upright and hanging tail posture classes and cannot make associations between the predicted tail posture and the corresponding pig.

Based on the identified research gaps in the image-based tail posture detection of pigs, our paper introduces several key contributions:

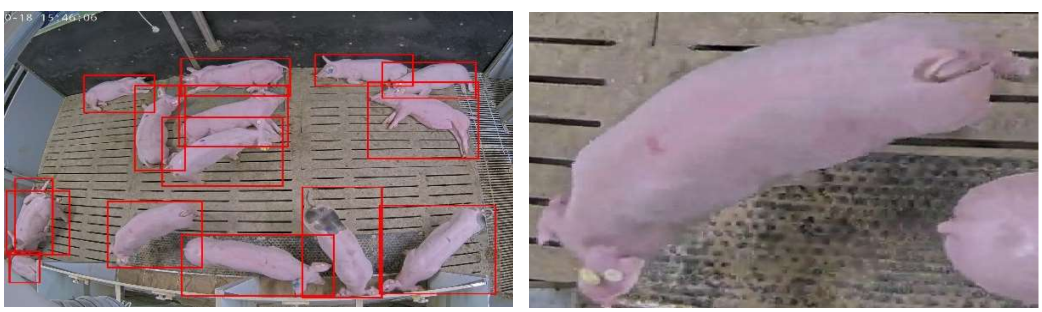
Firstly, to overcome the limitations of previous methods, we introduce a new two-step tail posture classification approach. This method includes an initial pig detection step using a YOLOv8 object detection model, followed by a tail posture detection step conducted on the cropped results from the pig detection phase, also employing a YOLOv8 model. Compared to the previous one-step object detection approaches, where the tail posture is directly predicted on the main input image, this method improved performance significantly, resulting in an approximately 68% increase in mean average precision (mAP) when comparing the evaluation results for both models at the same image size.

Secondly, we address the issue of filtering out lying pigs. Unlike other approaches for pig posture classification like Nasirahmadi et al. (2019) or Luo et al. (2021), we do not detect pig posture directly on the main input image but separate the pig posture classification task into an object detection and an image classification task, as it can increase the accuracy of pig posture classification (Witte & Marx Gómez, 2022). To achieve this, we have integrated an EfficientNetV2 image classification model into the tail posture monitoring pipeline to categorize the results of the pig detection model into *lying* and *not lying* pigs, allowing us to apply the tail posture detection model strictly to pigs with a *not lying* body posture.

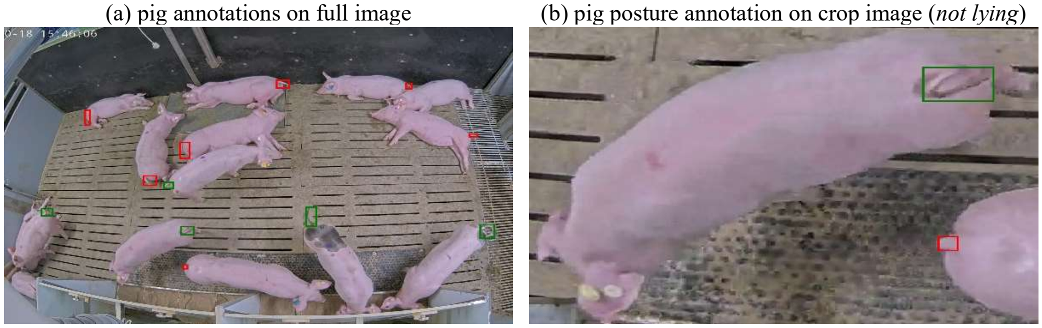
Lastly, we combine the presented models for pig detection, pig posture classification and tail posture detection into a coherent tail posture monitoring pipeline, which we applied to video data spanning up to six days before a recorded tail biting incident. Our method effectively documents the shift in tail posture from predominantly *upright* to increasingly *hanging*, with *hanging* tail postures peaking just prior to an outbreak. The technique proposed in this paper has the potential to provide early warnings and facilitate timely and preventative measures against tail biting, thus enhancing animal welfare and reducing economic losses in pig livestock farming.

4. Materials and methods

The data for this study was gathered as part of the DigiSchwein project, which took place at the Chamber of Agriculture Lower Saxony's pig farming research facility in Wehnen, Germany. The project involved capturing and storing video recordings from piglet rearing and fattening stages for analysis. For piglet-rearing pens housing 24 pigs, we used an AXIS M3206-LVE network camera for video capture. Conversely, an AXIS M3116-LVE network camera was utilized for the fattening pens containing 15 pigs.



(a) pig annotations on full image | (b) pig posture annotation on crop image (*not lying*)



(c) tail posture annotations on full image (left) and crop image (right) with *upright* (green) and *hanging* (red) annotations

Figure 1. Dataset examples.

In both scenarios, cameras were installed beneath the ceiling to ensure a comprehensive top-down view of the entire pen. For the piglet rearing phase, initial recordings were made at 20 frames per second (FPS) with a resolution of 2304 × 1728. However, the FPS was later reduced to 20 to decrease the data volume, and the resolution was adjusted to 1920 × 1080. For the fattening pens, videos were recorded at 30 FPS with a resolution of 2688 × 1512.

4.1 Model selection

Our model selection was based on several key criteria outlined in domain-related research. Norton et al. (2019) emphasized the importance of prediction accuracy, Lee et al. (2019) underscored the need for prediction speed, and Banhazi et al. (2012) pointed out the significance of cost-efficiency in the methods employed. We also considered the prevalence of each method's application in similar research domains, evaluating their empirical validation in prior studies.

We chose the YOLO architecture, specifically its latest version, YOLOv8 (Jocher et al., 2023), for its balanced combination of speed and accuracy. YOLO is able to perform real-time object detection by processing images in a single forward pass, thereby meeting the criteria of prediction speed, accuracy, and efficiency. This architecture has also been extensively applied in related pig precision livestock farming research (Luo et al., 2021; Nasirahmadi et al., 2019; Witte & Marx Gómez, 2022) further validating its suitability for this study.

The EfficientNetV2 model (Tan & Le V, 2021) was selected for its ability to provide high prediction accuracy while maintaining computational efficiency, also aligning with our defined selection criteria.

4.2. Dataset creation

Three distinct datasets were constructed for pig detection, pig posture classification, and tail posture detection tasks. These datasets were created using randomly selected frames from video sequences obtained during data collection from piglet rearing and fattening. Additionally, we incorporated images from publicly accessible datasets and those provided by other projects to enhance our dataset diversity. When curating the dataset, we aimed to represent a wide range of variables, such as diverse backgrounds, camera angles, lens types, and lighting conditions. Additionally, we included images portraying specific challenges relevant to pig livestock farming, like pig pileups, occlusions, and overlapping pigs. The resulting datasets feature a variety of locations, backgrounds, camera angles, fluctuating numbers of pigs per image, and a mix of day and night images. Figure 1 presents an example for each dataset, which will be referenced when describing the respective dataset. Further details are discussed in the subsequent sections.

Pig detection dataset: The training of the pig detection model utilized a dataset comprising 9,218 manually annotated images with a cumulative total of 146,359 bounding box (BB) annotations. The dataset was sourced from various contributors, some of which are publicly accessible, while other external projects supplied others. We included 2,000 images from the dataset shared by Psota et al. (2019), which featured 17 unique backgrounds and locations. Since this dataset only held keypoint annotations, each of the 2,000 images was manually annotated with bounding boxes. Furthermore, 720 images from the KoVeSch (GN 2819109817) project, run by the Chamber of Agriculture Lower Saxony, were included, divided evenly between piglet rearing and pig fattening. An additional contribution came from the InnoPig (GN 2817205413) project, providing 1,268 images for piglet rearing and 418 images for pig fattening, all of which were manually annotated. We also utilized 600 images from the publicly accessible dataset offered by Alameer et al. (2020) and another 305 images from the dataset released by Riekert et al. (2020). The remaining 3,907 images were obtained from video footage recorded as part of the DigiSchwein (GN28DE109B18) project, which covered both piglet rearing and pig fattening. Figure 1 (a) shows an example image for the pig detection dataset.

Pig posture classification dataset: The dataset used for posture classification was derived from the pig detection dataset. Each annotated bounding box within the dataset was cropped from its corresponding image according to the individual annotations provided within the annotation file. In Figure 1 (b), an example of this is shown. These cropped segments were subsequently saved as separate files. The result was an extraction of 146,359 images in total. Of these, 90,048 images were annotated to indicate either *lying* or *not lying* body posture. The annotation process resulted in a dataset comprised of 52,177 images classified under the *lying* category and 37,871 images classified as *not lying*.

Tail posture detection dataset: We created two separate datasets for tail posture detection, as illustrated in Figure 1 (c). For the first dataset, 1,856 images were extracted from the pig detection dataset and subsequently annotated with upright and hanging tail postures. We used the dataset of Witte et al. (2022) consisting of 1,000 images as a baseline and added another 856 new samples. These 1,856 images with upright and hanging tail annotations represent the final dataset for the one-step tail posture detection approach directly on the input image. The tail posture dataset for both the one-step and two-step approach does not contain night images.

To compare the performance of the one-step tail posture detection approach with the two-step tail posture detection approach, the pig annotations of the 1,856 images from the pig detection dataset were cropped and stored as separate files, resulting in 18,289 images. These cropped images were also annotated with upright and hanging tail postures, forming the final dataset for the two-step tail posture detection approach, which will be compared with the one-step approach.

It should be noted that pigs often pile or overlap under commercial conditions. Consequently, a single pig detection crop may contain more than one visible pig. This scenario poses a challenge, as some crops of the pig detection outputs may include more than one visible tail posture, resulting in multiple tail posture annotations for respective crop images. An example of this is illustrated in Figure 1 (c). To ensure accurate results, managing these cases separately during inference is essential, as failing to do so could result in duplicate detections of tail postures. This procedure will be discussed in later sections.

4.3. Training and test environment

The models were trained on a workstation desktop equipped with two Nvidia RTX 3090 graphics cards, each offering 24 GB VRAM. The YOLOv8 implementation from Jocher et al. (2023) was used for the pig detection and tail posture detection models, following the default parameter settings throughout the training phase. Various data augmentation techniques were incorporated, such as image mosaic and mix-up, random image flip, image rotation, image scaling, and HSV-hue and -saturation modifications. The training process was executed over 300 epochs, using a batch size of 128 for 640 × 640 image size and 16 for 1280 × 1280 image size. YOLOv8s, the smallest checkpoint, was chosen for training.

We deployed the official PyTorch version of EfficientNetV2 in the pig posture classification task. As with the YOLOv8 model, the smallest EfficientNetV2 model, B0, was utilized as the base model. Data augmentation included techniques like random horizontal flipping, random auto contrast, random rotation, random color jitter, and random sharpness enhancement. Images were adjusted to a 224 × 224 size while preserving the original aspect ratio by appending black borders to the crop. This

Table 1. Model results.

Pig Detection						
Model	*Image size*	*Class*	*Precision*	*Recall*	*$mAP^{0.5}$*	*$mAP^{0.5\text{-}0.95}$*
YOLOv8s	640 × 640	pig	0.990	0.986	0.994	0.957
Pig Posture Classification						
Model	*Image size*	*Class*	*Precision*	*Recall*	*F1-Score*	
$\text{EfficientNetV2}_{B0}$	224 × 244	lying	0.96	0.99	0.97	
		not lying	0.98	0.96	0.97	
Pig Tail Posture Detection						
Full Image						
Model	*Image size*	*Class*	*Precision*	*Recall*	*$mAP^{0.5}$*	*$mAP^{0.5\text{-}0.95}$*
YOLOv8s	640 × 640	all	0.781	0.687	0.740	0.357
		upright	0.800	0.750	0.802	0.397
		hanging	0.761	0.623	0.679	0.317
	1280 × 1280	all	0.849	0.815	0.845	0.462
		upright	0.881	0.847	0.882	0.503
		hanging	0.816	0.783	0.808	0.422
Crop Image						
Model	*Image size*	*Class*	*Precision*	*Recall*	*$mAP^{0.5}$*	*$mAP^{0.5\text{-}0.95}$*
YOLOv8s	640 ×640	all	0.894	0.884	0.917	0.601
		upright	0.920	0.905	0.948	0.636
		hanging	0.867	0.863	0.887	0.567
	1280 × 1280	all	0.886	0.890	0.917	0.598
		upright	0.913	0.912	0.95	0.631
		hanging	0.858	0.869	0.885	0.565

strategy enhanced performance compared to scenarios where the aspect ratio was not maintained. The training was conducted over ten epochs, with the PyTorch implementation of the cross-entropy loss function being utilized as the loss function and Adam serving as the optimizer.

The datasets were split in an 80/20 proportion for training and testing purposes. Annotations were done using the open-source tool labelme (Wada, 2016).

5. Results

Table 1 outlines the results of different models utilized for pig detection, pig posture classification, and tail posture detection.

The pig detection was conducted utilizing the YOLOv8s model with an image size of 640 × 640 for training. The evaluation on the test set resulted in a precision of 0.990, a recall of 0.986, a $mAP^{IoU=0.5}$ of 0.994 and a $mAP^{IoU=0.5\text{-}0.95}$ of 0.957, showing impressive results for the pig detection task.

For pig posture classification, the EfficientNetV2 B0 model was applied using a 224 × 224 image size, yielding high precision and recall values for both the *lying* (0.96 and 0.99 respectively), and *not lying* (0.98 and 0.96 respectively) classes, with an F1-Score of 0.97 in both cases.

As also shown by Witte et al. (2022), the performance of the YOLOv8s model for the one-step tail posture detection directly on the input image varied with image resolution. For the smaller image size (640), precision, recall, $mAP^{IoU=0.5}$, and $mAP^{IoU=0.5\text{-}0.95}$ values for all classes were 0.781, 0.687, 0.740, and 0.357, respectively. For the larger image size (1280), these values improved to 0.849, 0.815, 0.845, and 0.462, respectively. The results indicate that the larger the image size, the better the model performance for tail posture detection in full images.

The model showed notably superior results when detecting tail posture on cropped images. For the smaller image size (640), the precision, recall, $mAP^{IoU=0.5}$, and $mAP^{IoU=0.5\text{-}0.95}$ values for all classes were 0.894, 0.884, 0.917, and 0.601 respectively, increasing the $mAP^{IoU=0.5\text{-}0.95}$ by approximate 68% comparing to the full image tail posture detection approach. In contrast to the full image tail posture detection, increasing the image size for tail posture detection on crop images results in nearly identical performance with precision, recall, $mAP^{IoU=0.5}$ and $mAP^{IoU=0.5\text{-}0.95}$ values of 0.886, 0.890, 0.917, and 0.598, respectively.

Especially for the 640 × 640 image size, the performance in both the *upright* and *hanging* classes in the cropped images showed a noticeable enhancement in every measured metric compared to the full image scenario. The superior detection performance on cropped images can be attributed to several potential reasons:

Firstly, cropped images focus directly on the area of interest (i.e., the pig tail), thereby reducing the scene's complexity and minimizing extraneous detail that could interfere with the detection task.

Secondly, in the cropped images, the tail constitutes a more significant portion of the image compared to full images. This allows the model to capture more details of the tail, improving its ability to detect the tail posture accurately.

Lastly, the cropped approach may reduce the issues related to object scale invariance, as the tails in cropped images would have less variation in size compared to tails in full images, which could appear larger or smaller depending on the pig's distance from the camera.

In the following, the combination of the presented models into the pipeline for image-based tail posture monitoring will be presented and described in more detail.

5.1. Pipeline

The monitoring process for tail posture encompasses integrating the pig detection model, the pig posture classification model, and the tail posture detection model into a unified pipeline. This process is illustrated in Figure 1.

Initially, a given video sequence is divided into individual frames. Each frame is independently processed, commencing with the pig detection model to identify and localize pigs within the frame. Subsequently, the pig detection model outputs are cropped from the input image and passed to the pig posture classification model for categorizing each

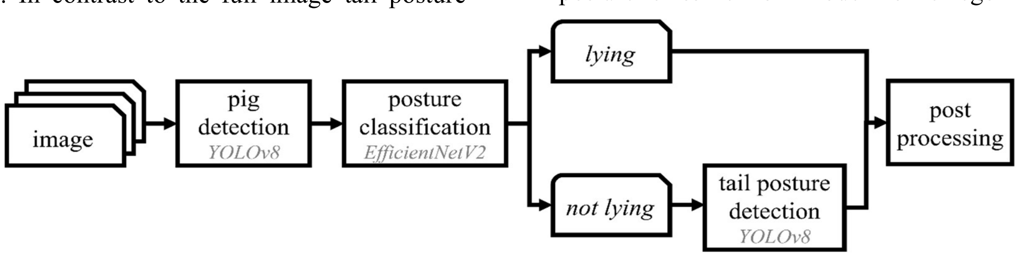


Figure 2. Tail posture monitoring pipeline.

detected pig as lying or not lying. Since the utilized EfficientNetV2 model expects a fixed image size of 224 × 224, the cropped images of the pig detection need to be resized first. During resizing, the aspect ratio of the crop is retained, and the remaining portions of the image are filled with black color. This strategy enhanced the robustness of posture classification during the training and testing stages. The results of the pig posture classification are used to determine which crops are passed to the tail posture detection stage and which are discarded, enabling the exclusive application of tail posture detection to pigs with a *not lying* body posture, thus mitigating potential ambiguity in the tail posture monitoring process.

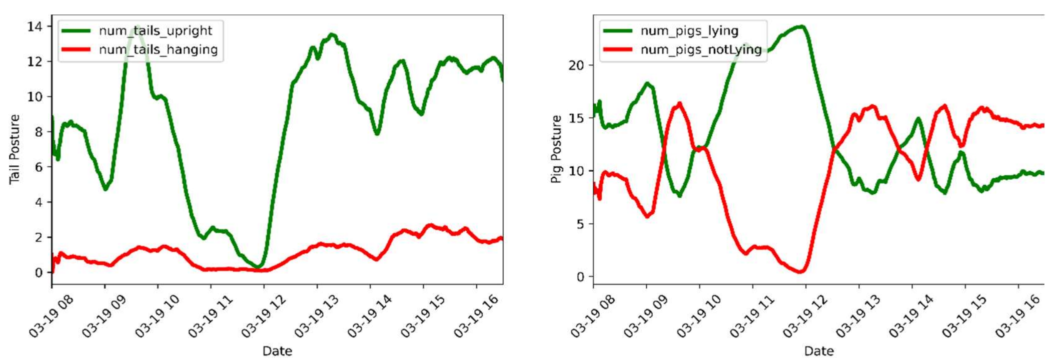
During the post-processing phase, we address the issue of overlapping pigs within individual pig crops, as previously discussed in Figure 1. Overlapping pigs in crops can result in multiple tail posture detections per crop, potentially leading to double counting detected tail postures. To circumvent this, we filter out these duplicate detections by firstly scaling back the bounding box coordinates of the tail posture detections on the cropped image to the original input image size and secondly, eliminating duplicate tail detections based on the Intersection over Union (IoU) of their respective bounding boxes. Upon the final processing of tail posture detections, the numbers of lying and not lying pigs and the counts of upright and hanging tails postures are logged. This process is then repeated for each frame in the sequence.

In the following, we present the monitoring results of the pipeline when applied to different video sequences.

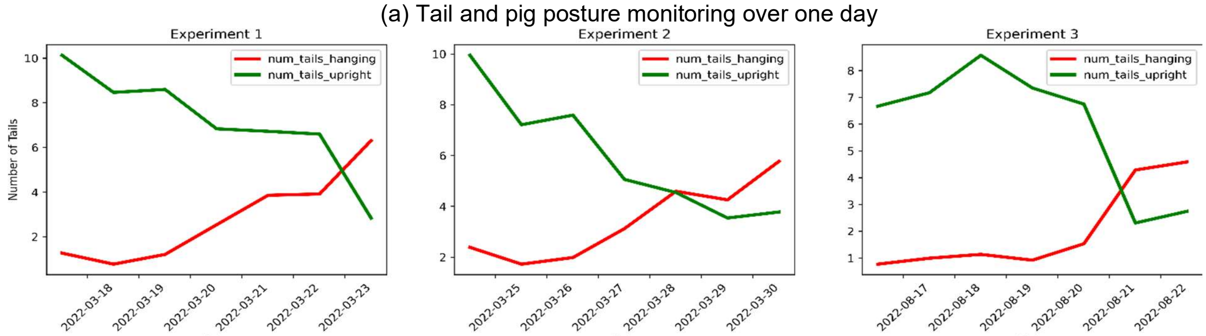
5.2. Tail posture monitoring results

We evaluated the proposed tail posture monitoring pipeline by applying it to three distinct video sequences from different piglet rearing pens where tail-biting incidents had occurred. The selection of time periods to be examined based on the tail posture monitoring pipeline was guided by existing research. Lahrmann et al. (2018) found that a shift in tail posture towards a hanging position could be detected as early as three days before an outbreak. Similarly, Zonderland et al. (2009) observed that piglets with hanging or retracted tail postures were more likely to suffer a tail injury 2-3 days later. Considering these research findings, we decided to analyze video footage up to five days before the tail biting incidents, focusing daily on the periods from 08:00 to 16:30. All video sequences used for analysis originated from the DigiSchwein project and were, in addition to daily in-barn tail posture evaluations, examined by experts for tail-biting incidents. All video sequences were analyzed with one frame per second.

The results can be seen in Figure 3, which is divided into two separate sections: Figure 3(a) displays the results of the tail posture monitoring pipeline for a single day, spanning from 08:00 to



(a) Tail and pig posture monitoring over one day



(b) Tail posture monitoring spanning over six days before a tail biting incident

Figure 3. Results tail posture monitoring.

16:30. The left subplot of (a) illustrates the logged tail postures for the upright and hanging classes. In contrast, the right subplot reveals the counts of lying and not lying pigs. In order to smooth the data, we applied a moving average with a window size of 15 minutes to the recorded results. In this example, the ratio of upright to hanging tails is positive, with a significantly higher number of upright tail postures than hanging tail postures throughout the entire period. The marked decrease in logged tail postures between approximately 11:00 and 12:00 can be attributed to a high proportion of lying pigs during this period, resulting in many pig detections being discarded in the tail posture detection process.

On the other hand, Figure 3(b) displays the pipeline results across several days leading up to the actual tail biting incident for each of the three experiments. We initially took the naïve approach of taking the average of the recorded upright and hanging tail posture counts over the considered timespan. This approach already proved to be sufficient as in each of the three experiments, the results show that the presented pipeline can document the shift in tail posture leading up to the actual tail-biting incident. In all three experiments, it is apparent how the ratio of upright to hanging tail postures decreases steadily, eventually leading to a transition where the hanging class becomes the prevalent tail posture.

Looking into the results in more detail shows that the period in which this transition occurs varies for each video sequence. In experiment 1, the shift in tail postures occurs more gradually, with the upright tail posture slowly decreasing as the hanging tail posture incrementally increases. This transition extends over approximately five days. Conversely, in experiment 3, the transition occurs more abruptly, characterized by a sudden drop in upright tail postures and a more rapid rise in hanging tail postures. Experiment 2, on the other hand, presents a mix of both, with the dominant tail posture transitioning over roughly four days.

Based on the results, the presented pipeline for tail posture monitoring can be used to detect the change in predominant tail postures. In the future, this could open up the possibility of developing camera-based systems in combination with the presented pipeline that would provide warnings to farmers based on defined thresholds if the system detected a gradual or current change in the recorded tail posture. However, the results of this paper present a first proof of concept. To transfer this approach into agricultural practice, many remaining challenges and limitations need to be addressed. These will be discussed in the following section.

6. Discussion and outlook

While this paper's results are promising, several limitations need to be considered when interpreting the results.

Firstly, our pipeline analysis and evaluation were conducted on a limited data set consisting of three video sequences from different pens but the same compartment, spanning five days before a tail-biting outbreak. To make more profound assertions about the effectiveness of the presented tail posture monitoring pipeline, further analysis should be conducted on more video sequences from different pig livestock compartments. This would not only solidify the reliability of the findings but also aid in defining potential thresholds for issuing alerts about alarming changes in tail posture, which is essential when transferring these systems into agricultural practice. Furthermore, a more extended timespan of analysis, e.g., a complete growing phase from rearing to fattening, should be considered to gain a more comprehensive view of tail posture changes over time. In addition, analyzing pens without tail biting incidents would provide valuable reference data for understanding tail posture trends in the absence of tail biting. These reference data could be integrated into the definition of the tail posture monitoring thresholds.

Secondly, the methodology applied in this study involved a relatively straightforward analysis, using only the daily average of upright and hanging tail postures. Future research could benefit from incorporating more sophisticated analysis strategies. For instance, considering only values where the ratio of not lying pigs surpasses a predetermined threshold could provide more nuanced insights. Moreover, it would be worth investigating the optimal period for analysis and what time spans to consider. Adjusting the observation window could allow for quicker alerts when the ratio of tail postures changes. This aspect is of particular interest as it could influence the system's response time and effectiveness in alerting farmers to imminent tail biting incidents, thereby enhancing the overall utility of the proposed methodology in practice.

There is the potential for enhancing the training dataset for tail posture detection. Including more data, specifically video clips featuring high levels of pen activity, could boost the model's performance in terms of precision, recall and mAP, and robustness when handling more complex scenarios.

A current constraint of the pipeline is its ability to analyze tail posture only during daylight hours, given the difficulties in detecting tail posture in low-light conditions. Future research will focus on incorporating night images to evaluate whether tail posture detection is also reliable using night images based on this approach. This would furthermore allow permanent monitoring of the tail posture indicator for tail biting, giving future systems even more profound information to issue potential alerts.

Furthermore, this study narrowly focuses on tail posture as the primary early indicator of tail biting. Existing literature, however, suggests increased activity levels as another valid indicator for tail biting outbreaks. Combining the presented image-based tail posture monitoring pipeline with an image-based method to measure activity insight, the pen could enhance the data basis, on which future early warning systems could issue alerts for the farmer.

To emphasize the transfer of the presented pipeline into agricultural practice, future research should also focus on developing initial prototypes to conduct field tests under real-world conditions. Furthermore, preparations could be made to adapt the pipeline for real-time analysis and automated evaluation. This adaptation would allow for the seamless implementation of the system in practical settings, ensuring immediate assessment and response to changes in tail posture.

7. Conclusion

Tail biting is one of the biggest challenges in conventional pig livestock farming. This paper introduced a novel approach for image-based tail posture monitoring, an important indicator for assessing the risk of a potential tail biting outbreak. We present a new two-step tail posture detection approach, which improved the mAP by approximately 68% compared to previous approaches based on object detection. Additionally, we have addressed the challenge of filtering out lying pigs during tail posture monitoring by including an EfficientNetV2 image classification model in the pipeline, avoiding ambiguous results during tail posture monitoring.

We applied the final pipeline consisting of a pig detection, pig posture classification and tail posture detection model to three different video sequences that contained tail biting incidents. In analyzing the five days leading up to an outbreak from 08:00 to 16:30, the results showed an evident change in recorded tail posture in all three cases. Initially, the tail posture was predominantly upright, but as the tail biting incident approached, the number of hanging tails increased while the number of upright ones decreased.

The findings presented here could serve as the foundation for an image-based early warning system that can be deployed to better capture and assess the risk of a tail biting outbreak. This would not only aid in the husbandry of undocked pigs, thereby improving animal welfare but also support farmers in conducting more targeted sampling within their stock.

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