

A Feasibility Study on The Use of Artificial Intelligence to Analyze Pig Health in Livestock Farms

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ABSTRACT

Tracking the daily behavior of pigs raised on farms using artificial intelligence technology helps farmers to automatically and quickly assess the health and growth of the pigs. This article presents a feasibility study on using artificial intelligence (AI) to analyze images from CCTV cameras to detect standing, eating, and lying behaviors of pigs in a farm, and to record numerical values of these behaviors over time for health analysis. The study trained the AI with numerous pig images sourced from social media, without using actual farm pig images, and developed a model using YOLO8 tools. The trained model can detect the three behaviors from video clips with approximately 70% accuracy. The analysis shows that this method has high potential for practical application in pig farms, with possible adjustments to the camera setup environment to achieve the best image quality for detection.

Keywords: Artificial Intelligence, Computational Ethology, Pig postures; Animal health and welfare.

1. INTRODUCTION

In an era of rapidly advancing technology, the use of artificial intelligence (AI) to monitor and analyze animal behavior on farms has become an important tool with the potential to transform pig farming management in the future. Tracking the health, growth, and behavior of pigs leads to increased productivity and reduced costs of animal care, as well as helping to reduce greenhouse gas emissions [1], [2]. Additionally, it enables the detection of health issues or abnormal behaviors more quickly,

leading to timely treatment, reduced mortality rates, and minimized resource usage in animal care. lower greenhouse gas emissions and preventing water pollution. In addition, farmers can quickly monitor and address animal health issues, although challenges related to social interactions and individualized nutritional needs remain. The paper highlights the need for real-time monitoring, cost-effective large-scale implementation, and understanding long-term effects on animal health and welfare.

Precision feeding, as explored in [3], involves developing individualized diets for animals based on their specific nutritional requirements. This method utilizes advanced technologies and data analytics to enhance animal nutrition, environmental sustainability, and animal welfare. Sensors and automation are key components, enabling real-time monitoring and data collection, ultimately improving feed efficiency and animal well-being. By reducing feed waste and nutrient excretion, precision feeding contributes to lower greenhouse gas emissions and minimizes water pollution. Furthermore, it allows farmers to rapidly identify and address animal health problems. However, challenges remain, including managing social interactions within animal groups and addressing individual nutritional needs. The paper emphasizes the importance of real-time monitoring, cost-effective large-scale implementation, and further research into the long-term impacts on animal health and welfare.

In the past decade, research has applied various sensors to non-invasively monitor animal behavior. For example, [4] presented a method for detecting posture changes in sows using millimeter-wave radar and deep learning analysis. This method is non-invasive, rapid, and accurate in monitoring sow behavior in pens,

predicting posture changes, and distinguishing dangerous postures that might crush piglets. The study used two radars placed above and on the upper back of each sow to monitor behavior, analyzing the radar data with a convolutional neural network. Five postures were identified, with high sensitivity for standing, lying, nursing, and sitting postures, but low sensitivity for kneeling posture. Additionally, some sows exhibited risky behavior by changing directly from standing to lying without passing through intermediate postures such as sitting or kneeling. This study highlighted the potential of radar in high-level recording of animal activities, which may be used in precision agriculture in the future. A similar study [5] presented a non-invasive millimeter-wave radar system for automatic animal behavior monitoring, applied to sheep farming. This technology allows accurate and rapid tracking and analysis of 2D movements of freely moving animals, without high processing power requirements and independent of light variations, potentially improving animal behavior recording in precision agriculture.

Using AI to analyze images from CCTV cameras installed on pig farms not only helps farmers continuously monitor pigs but also reduces labor and time spent on manual animal checks. This use of AI revolutionizes traditional pig farming management, giving farmers more time for other tasks or improving farm efficiency. For example, research [6] presented image processing and deep learning methods to detect individual pig postures on farms. This research tested methods to detect lying and standing postures of pigs using 2D imaging systems combined with deep learning techniques, using data from various farms for model training and testing. Experimental results showed that the R-FCN ResNet method could detect pig postures with average accuracies of 0.93, 0.95, and 0.92 for standing, side lying, and prone lying postures, respectively. This study illustrated the potential of using 2D imaging systems and deep learning for farm animal posture detection, which could be used for effective health and welfare monitoring. Another study [7] presented a small neural network suitable for resource-limited detection and tracking of individual pig postures 24/7 in crowded pig farms. Testing showed that the proposed model had an average accuracy for detecting various pig postures including standing, prone lying, side lying, sitting, and mounting.

YOLO (You Only Look Once) is a popular and powerful cutting-edge object detection algorithm that excels in speed and accuracy, making it a valuable tool for various real-world applications. In [8] presents YOLO-Behaviour which is a user-friendly framework designed to automate the process of analyzing animal behavior from videos. It addresses the limitations of

manual video analysis, which is time-consuming and prone to inconsistencies. This framework utilizes computer vision techniques to identify and categorize different animal behaviors within video recordings.

Behavior monitoring of pigs is crucial for efficient pig farm management. Key behaviors to monitor include standing, eating, and lying, which provide insights into pig health and needs. Standing reflects activity and readiness to move, eating indicates growth health and quality of food and environment, and lying signifies comfort and stress levels. Close monitoring of these behaviors helps farmers improve pen environments to suit pigs and enhance production efficiency. Additionally, behavior detection aids continuous health monitoring, leading to timely treatment and disease prevention. Thus, technology in pig behavior detection is a significant step towards developing sustainable and efficient pig farming in the future.

This article presents an experiment to create an AI model to predict three pig behaviors—standing, eating, and lying—using image processing, explaining the working methods, benefits, and potential challenges.

2. PROBLEM STATEMENT

This article uses artificial intelligence to analyze three key behaviors: standing, lying down, and eating, from images. A convenient and quick way to train AI for recognition is to use images from social media for training, which provides a larger and more diverse dataset than using images from CCTV cameras installed in a single pen. The Convolutional Neural Networks (CNN) and YOLO8 tools are then used for learning and model creation due to their capability to classify and identify objects accurately. YOLO8 includes several improvements over previous versions, such as increased model accuracy, improved operational speed, and better handling of small objects ([9]). Research from [10] indicates that object detection is nearly perfect even when the model is trained with a small dataset (100 to 350 images). However, the model may not perform well when the same object is in different backgrounds. This research suggests that YOLO8 has high potential for analyzing desired behaviors from videos.

The model is then tested with short video clips, recording behaviors over time with confidence scores, which is crucial for evaluating model performance. The three behaviors are summarized as cumulative numbers over each time period, measured in pig-hours, using the AI model's analysis results to understand overall behavior and effectively analyze animal health.

The scope of the study is summarized as follows:

1. Use artificial intelligence to analyze three key behaviors for future health analysis: standing, lying

down, and eating from images.

2. Use images from social media to train the AI.
3. Use CNNs for learning and model creation with YOLO8 tools.
4. Test the model with short video clips, recording behaviors over time with confidence scores, and summarizing each behavior as cumulative values over time (pig-hours).

3. METHODOLOGY

3.1 DATA PREPARATION

Data preparation for training artificial intelligence is a critical initial process, as high-quality data leads to the creation of highly effective and accurate models. This helps reduce issues of overfitting, where the model fails to detect the desired patterns from data different from the training set, and underfitting, where the model fails to detect the desired patterns due to insufficient learning. The data preparation process includes collecting relevant data, formatting it appropriately, checking and filtering data to minimize errors, and dividing the data into three parts for effective training (training set), validation (validation set), and testing (testing set). The data preparation steps include:

- A. Collecting Pig Images from Social Media Training AI to recognize or create accurate models depends on the quality and quantity of the training data. For diversity and quality images, this article uses pig images from public social media platforms like Pinterest and iStock by Getty, which are available for free to users. A total of 2,642 images will be used.
- B. Determining Boundaries and Separating Pigs in Images from Backgrounds Using Smart Polygon General photographs typically contain pig images along with other backgrounds. Therefore, it is necessary to select only the pig part of the image to be used for AI training. In this step, the Smart

Polygon tool will be used to select the pig boundaries accurately.

- C. Creating Labels Once the pig boundaries are obtained, three types of labels will be created: stand, eat, and sleep for the behaviors of standing, eating, and lying down, respectively. Every image used for AI training will be labeled accordingly.
- D. After preparing the images with labels, the images are divided into three groups: 2,316 images for the training set, 164 images for the validation set, and 162 images for the test set. Additionally, each labeled image is augmented using various image processing techniques, such as rotating the image by ± 90 degrees and ± 15 degrees, scaling the image by 20%, applying blur, and adding noise. This augmentation increases the number and diversity of the training data, enhancing the data quality and variety used for training the model. Examples images used for training are shown in *Fig. 1*.

To reduce the domain gap between high-quality social media images and real CCTV footage, future work will incorporate advanced augmentation techniques such as simulating low-light conditions, adding digital noise, and applying motion blur. These adjustments aim to replicate the visual characteristics of industrial-grade CCTV systems used in pig farms.

3.2 RESULTING MODEL

Training artificial intelligence to create an accurate predictive model with YOLO8 requires multiple training iterations. In each iteration, accuracy is measured against real-world data, determined by the loss index composed of three elements: Box Loss (for predicting the position of the bounding box), Class Loss (for predicting the desired pattern), and Distribution Focal Loss (DFL), which enhances the model's ability to distinguish objects of interest from the background and improves boundary detection efficiency.

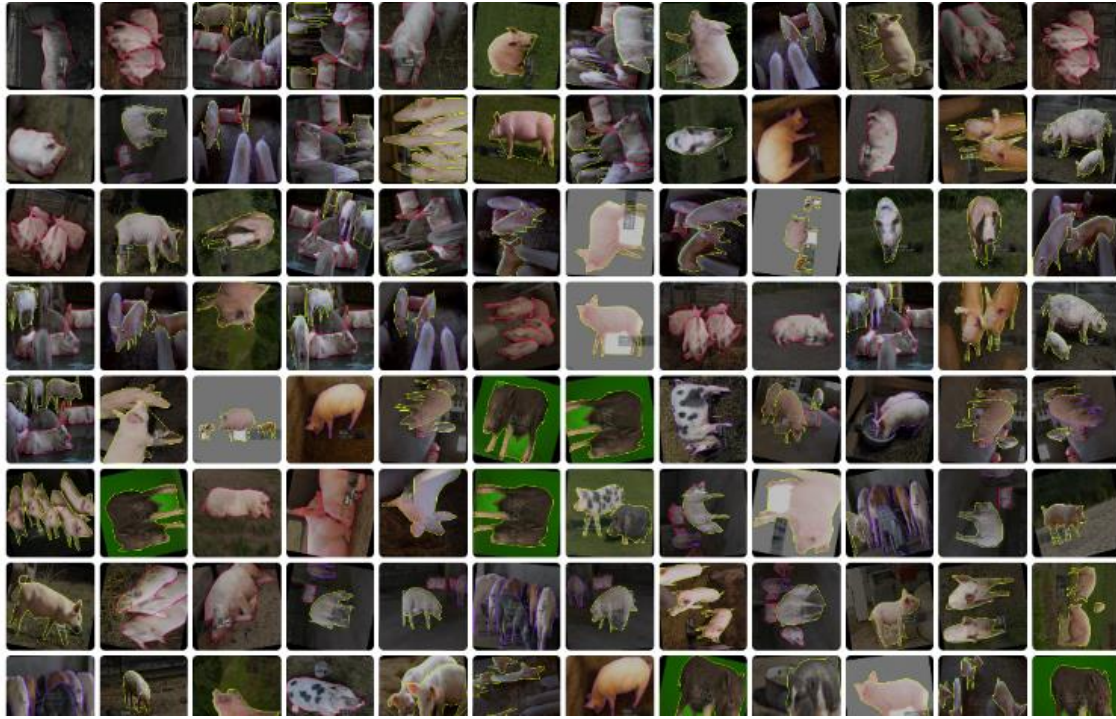


Fig. 1 Example images used for training after boundary selection.



Fig. 2 Loss indexes versus train epoch.

Throughout training, these three loss indexes gradually decrease until they stabilize, indicating that further training would not improve the model. The point at which the three loss indexes plateau is used to decide when to stop training. In this study on pig behavior detection, it was found that approximately 160 training iterations were needed to develop the model as shown in *Fig. 2*.

The results of the model obtained from training, when tested with the testing set, yield precision and recall metrics. Precision is calculated by comparing the number of true positive predictions (where the model's predictions are correct) against all cases that the model predicted as correct, which includes both true positives and false positives. Recall (or sensitivity) is the comparison of true positive predictions to the sum of

true positives and false negatives (cases where the model failed to detect the correct pattern), see e.g., [11].

When these two metrics are compared with confidence levels to determine an optimal confidence threshold for decision-making, the results are as shown in Fig. 3 and Fig. 4.

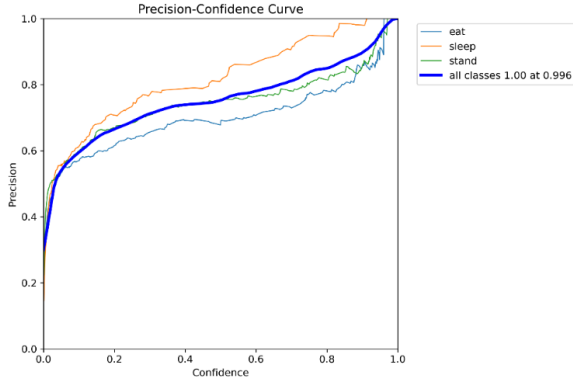


Fig. 3 Precision versus confidence level.

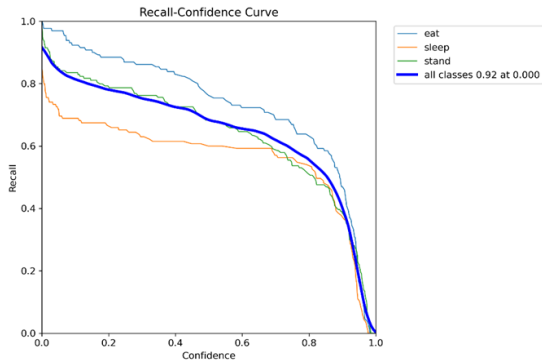


Fig. 4 Recall (sensitivity) versus confidence level

From **Fig. 3**, it is evident that when the confidence level is high, the precision also increases. From **Fig. 4**, however, we can see that when the confidence level is high, the recall decreases. Therefore, when choosing the confidence level for decision-making, both precision and recall must be considered. If the confidence level is set too high, it will result in high precision but low recall, meaning fewer detections. Conversely, if the confidence level is too low to increase recall, the precision will decrease. Comparing the precision and recall in **Fig. 5**, it is observed that the point where both precision and

recall are highest is around 0.7 for both metrics. Additionally, the detection of eating and standing behaviors shows minor differences in precision and recall and trends in the same direction. In contrast, the detection of lying behavior shows significant differences.

To ensure a balanced decision-making level between precision and recall, the harmonic mean of both precision and recall, known as the F1-score, is used for analysis. As shown in **Fig. 6**, the F1-score remains above 0.6 across the confidence range from 0.1 to 0.9. Therefore, an optimal decision-making threshold is approximately 0.5, which provides a balance between precision and recall.

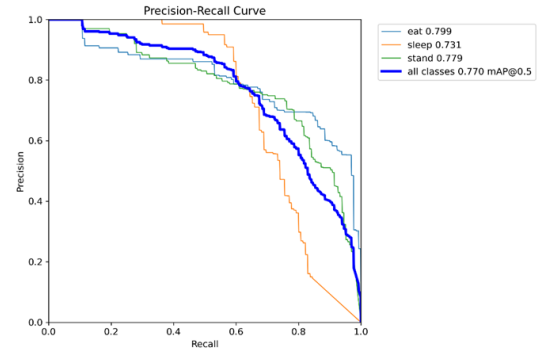


Fig. 5 Precision versus recall.

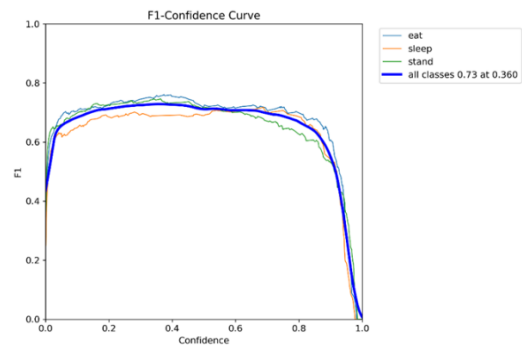


Fig. 6 F1-score versus confidence level.

Using a confidence level of 0.5 to determine the analyzed behavior in the images when tested with the testing set yields the results shown in **Table 1** and illustrated in the confusion matrix in **Fig. 7**.

Table 1 Model testing results.

	TRUE				precision
	eat	sleep	stand	no detection	
total	130	135	164		
Predicted					
eat	101	3	37	36	57%
sleep	2	83	2	32	70%
stand	24	7	115	42	61%
no detection	3	42	10	0	
recall	78%	61%	70%		

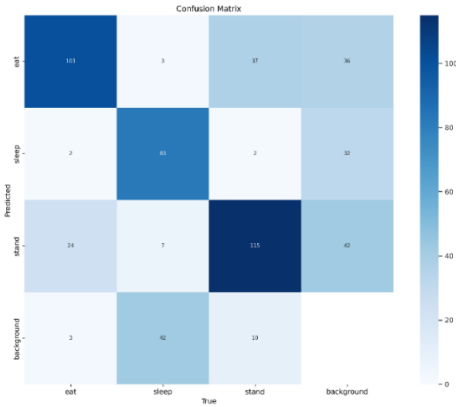


Fig. 7 Confusion matrix

Based on the results shown in **Table 1** and the confusion matrix in **Fig. 7**, the detection of eating and standing behaviors has relatively high recall but lower precision. This might be due to the low confidence threshold used for decision-making. Analyzing the data reveals that the model has significant difficulty distinguishing between eating and standing behaviors. This is understandable, as eating behavior overlaps with standing behavior since pigs need to stand while eating, making it challenging to differentiate between the two, see **Fig. 8** for example. On the other hand, the detection of lying behavior is more accurate but less sensitive. Most detection errors are due to the model's inability to distinguish lying behavior from the background, with minimal confusion with other behaviors. For example, misdetection of lying down as standing is shown in **Fig.**

9.



Fig. 8 Examples of behaviors that are ambiguous between standing and eating.



Fig. 9 Examples of misdetections when lying down is incorrectly identified as standing.

3.3 MODEL TESTING RESULTS WITH VIDEO CLIP IMAGES

Based on the model obtained from training, when tested with consecutive images from various video clips, it was found that the accuracy of behavior detection depends on the camera angle and the density of the pigs. If the density is high and the camera angle is not optimal, it becomes difficult to clearly see all the pigs due to obstruction, which is the main reason for the inability to detect behaviors accurately. For example, in **Fig. 10**, pigs near the camera are clearly visible and easier to detect, whereas pigs that are farther away or obstructed cannot be detected. In **Fig. 11**, despite the high density of pigs, the camera angle allows for almost

complete visibility of all pigs, increasing the chances and accuracy of behavior detection. Also, distinguishing between eating and standing behaviors can be improved with a dedicated feeding area, see **Fig. 12** for example.



Fig. 10 Detection examples from images where high pig density limits camera coverage.

When the model is tested with video frames, it records various behaviors over time. The frequency of operation depends on computer resources and the resolution of the video feed. Testing shows that calculations can be done at frequencies of 1 - 5 Hz. However, high frequencies are not necessary for pig behavior detection; a detection rate of 1 - 2 frames per minute is sufficient to assess overall pig behavior. For each frame, once the model detects different behaviors, it counts the number of pigs displaying each behavior and records it along with the timestamp. This allows for the evaluation of how much time pigs spend on different behaviors each day by calculating the cumulative number of pigs over time, measured in pig-hours. The number of pigs exhibiting each behavior at any given time, as well as the daily cumulative total, can be used to analyze abnormalities in pig behavior within the pen as shown, for example, in **Fig. 13**.

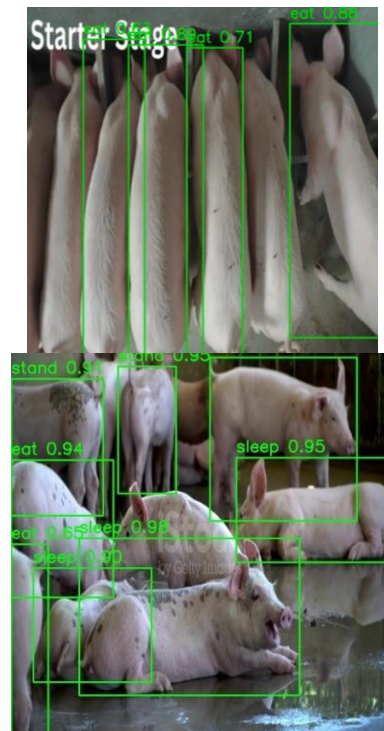


Fig. 11 Examples of detection from images where the pig density is high but the camera angle provides full coverage.



Fig. 12 Clear examples of eating behavior detection.

To improve classification of eating versus standing, two strategies are proposed: (1) defining spatial feeding zones so that pigs detected standing within these areas are more likely classified as eating, and (2) incorporating temporal sequence analysis to capture

continuous head movements characteristic of feeding behavior. These refinements are expected to reduce misclassification and improve precision for the eating class.

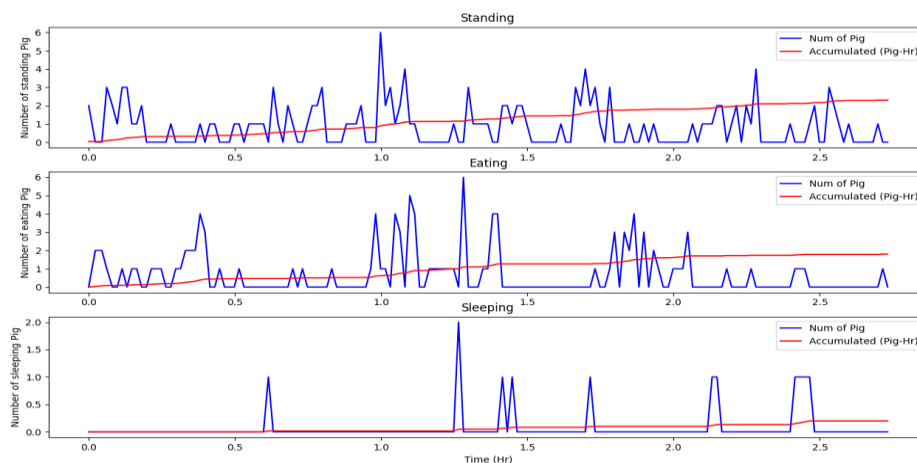


Fig. 13 Examples of recording the three-behavior metrics from multiple consecutive video clips.

4. CONCLUSION

The study applied artificial intelligence to detect pig behaviors in pens by training AI using data from social media, without relying on real data. The results indicate a high potential for AI models to detect pig behaviors and convert them into numerical data for health analysis. Testing with images and video clips from the internet showed about 70% accuracy, with errors often due to camera angle issues and pig density. In practical applications, better camera angles can increase accuracy. While distinguishing between standing and eating behaviors can be challenging, the results show that having a dedicated feeding area makes detecting eating behavior easier and more accurate (as shown in *Fig. 12*). Additionally, training AI with images from actual pens can make the model more accurate for those specific pens, though it might not perform as well in other pens (overfitting).

For practical deployment, camera installation must follow specific guidelines to minimize occlusion. Preliminary recommendations include mounting cameras at heights of 2–3 meters with a 45–60° tilt angle, and using multiple cameras in high-density pens. Dedicated feeding-area cameras can further enhance

detection of eating behavior. The introduction of the Pig-hours metric provides farmers with actionable insights into cumulative daily behaviors, enabling early detection of health anomalies and supporting precision feeding strategies.

The next phase of the study will apply the model to real pig pens and use the recorded behavior data to assess overall pig health, such as size and weight, by comparing it with actual measurements and evaluations by pig farming experts. Another AI model will be developed to analyze these three behaviors metrics for health assessment and monitoring.

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