Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 2, April 2025, Page. 609-626
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

YOLOv9-Based Object Detection Model For Pig Feces On Pig SKIN: Improving Biosecurity In Automated Cleaning Systems

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Received : Dec 20, 2024; Revised : Jan 21, 2025; Accepted : Jan 23, 2025; Published : Apr 26, 2025

Abstract

This study developed an object detection model using YOLOv9 to identify pig feces on pig skin, addressing challenges in automating pig cleaning systems and reducing the spread of African Swine Fever (ASF). The aim was to enhance biosecurity measures by minimizing human-pig contact through automation. A specialized dataset comprising 5,404 images was collected from Nyoman Farm in Bali, Indonesia, under various lighting and cleanliness conditions. These images were annotated into two classes, namely 'feces' and 'pig,' following strict criteria to ensure clarity and distinction. YOLOv9 was chosen as it is an advanced update of YOLOv8 with enhanced object detection capabilities. The model was iteratively trained and optimized to achieve the best performance. The results achieved a mAP_0.5 of 70.5%, precision of 70.6%, and recall of 72.1%. However, the model faced challenges in distinguishing pig skin patterns from feces and managing false positives caused by similar-looking objects in the barn environment. Despite these challenges, integrating this model into an automated cleaning system can reduce human-pig contact by up to 76%, which is expected to significantly lower the risk of ASF transmission. This study contributes to automated farming technology, demonstrating how well YOLOv9 can detect complex objects in agricultural settings and providing practical solutions to enhance biosecurity in pig farming while improving productivity.

Keywords : *automated cleaning, biosecurity, deep learning, object detection, pig feces detection, YOLOv9*

1. INTRODUCTION

From 2019 to the present, Indonesia's livestock industry has been affected by a mass mortality outbreak among pigs caused by the African Swine Fever (ASF) virus. This outbreak was officially declared through the Minister of Agriculture Decree No. 820/KPTS/PK.320/M/12/2019, which recognized ASF as an epidemic spreading across several provinces in Indonesia [1].

ASF, or African Swine Fever, is a disease affecting omnivorous mammals of the Suidae family and Sus genus, particularly pigs. The domestic pig species (*Sus scrofa domesticus*) has been domesticated by humans for thousands of years [2]. Pigs are highly susceptible to various diseases, especially those caused by viruses like ASF. Hygiene is one of the primary factors influencing the risk of viral infections in pigs [3].

The disease spreads through the mobility of humans and other living beings from infected areas to uninfected areas where contact with pigs occurs. Physical contact between humans and pigs is often

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inevitable, especially during activities such as cleaning livestock waste. This has become a significant factor contributing to the rapid spread of ASF in Indonesia [4].

Although the government has promoted biosecurity measures for livestock, enforcement remains inadequate [3]. Biosecurity involves preventive actions against biological threats to livestock, including maintaining cleanliness, sterilization, and isolating animals [5], [6]. However, traditional farming practices still face challenges in avoiding physical contact between humans and animals, particularly during the cleaning process.

Currently, the cleaning process requires farmers to enter pens and use a hose to spray clean water on the pigs' bodies and legs to remove dirt, a task typically performed in the morning and evening. A potential solution to minimize human-animal contact is the implementation of a livestock cleaning robot capable of detecting dirt on the animals and automatically spraying water on the affected areas. However, the main challenge lies in developing a dirt detection model to replace human eyes in identifying dirt on pigs' skin and determining where to spray water. The ability to detect specific objects can be achieved using machine learning algorithms, known as object detection.

Object detection is a fundamental task in computer vision that involves identifying and localizing specific objects within images or videos. This technology surpasses image classification, which only categorizes objects into predefined classes. Using bounding boxes, object detection provides accurate spatial information about an object's position within an image. Automated object detection allows systems to identify objects without human intervention and has been applied in various fields, such as surveillance, autonomous vehicles, medical imaging, and robotics [7]. In this context, object detection plays a critical role in identifying dirt on pig skin. This approach aims to reduce direct human-animal contact during the pen-cleaning process.

In recent years, various studies have explored object detection models in pig farming using different machine learning methods and algorithms. For example, Artificial Neural Networks (ANNs) have been used for automated learning, which later evolved into Convolutional Neural Networks (CNNs). CNNs are frequently applied for digital image segmentation and analysis [8]. Among CNN-based methods, one of the most resource-efficient algorithms is YOLO, a state-of-the-art object detection technique known for its speed and accuracy in identifying and classifying multiple objects [9], [10], [11].

YOLO (You Only Look Once) is a high-speed object detection algorithm that uses a single convolutional network to classify and localize objects within an image. The algorithm divides the image into grids, identifies each grid section, and predicts bounding boxes using a regression-based approach [12]. The latest version, YOLOv9, was released in February 2024 and introduces innovations such as the Generalized Efficient Layer Aggregation Network (GELAN) and Programmed Gradient Information (PGI). These features improve accuracy and efficiency, making YOLOv9 an outstanding solution for real-time object detection tasks [11].

However, no studies to date have specifically focused on object detection for livestock dirt using YOLO. The latest version of this method, YOLOv9, developed by Ultralytics, introduces groundbreaking techniques such as Programmed Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN). These innovations enhance object detection models' performance [6].

Therefore, this study aims to implement the YOLOv9 method to develop a model for detecting dirt on pig skin. The proposed model is intended for integration into livestock cleaning robots in future research, enabling real-time dirt detection on pigs' skin for more effective and efficient cleaning. The primary challenge in this research is creating a high-quality dataset for training YOLOv9 to achieve optimal outputs. Datasets are critical elements in developing object detection models and are typically designed by collecting data from various sources, including the internet or direct field collection, which is then strictly annotated using cloud-based dataset management tools as input-output pairs to train machine learning models [13], [14], [15].

Most datasets are designed as natural experiments due to the challenges and complexities associated with data imbalance and class overlap [16]. Factors such as fair representation, transparent documentation, and ethical data collection practices play a crucial role in creating effective and inclusive datasets [17]. These are expected to produce favorable evaluation metrics such as mAP, Precision, and Recall, ensuring the model's reliability in real-world scenarios [18], [19], [20].

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

Additionally, data must undergo pre-processing a crucial stage for ensuring data quality and extracting valuable information from datasets [21]. This stage directly affects the efficiency of model training and the predictive ability of machine learning models and involves augmentation, splitting, conversion, and configuration, often carried out using tools like Roboflow [21], [22], [23].

Therefore, this research will focus on creating a high-quality dataset and training an object detection model using YOLOv9.

2. METHOD

In this methodology section, the steps involved in creating a high-quality dataset will be explained, with the goal of developing an optimal model for detecting dirt on pig skin using YOLOv9. The various steps outlined in this section include data collection, annotation, preprocessing, training, validation, and testing. The research workflow will be illustrated in Figure 1.

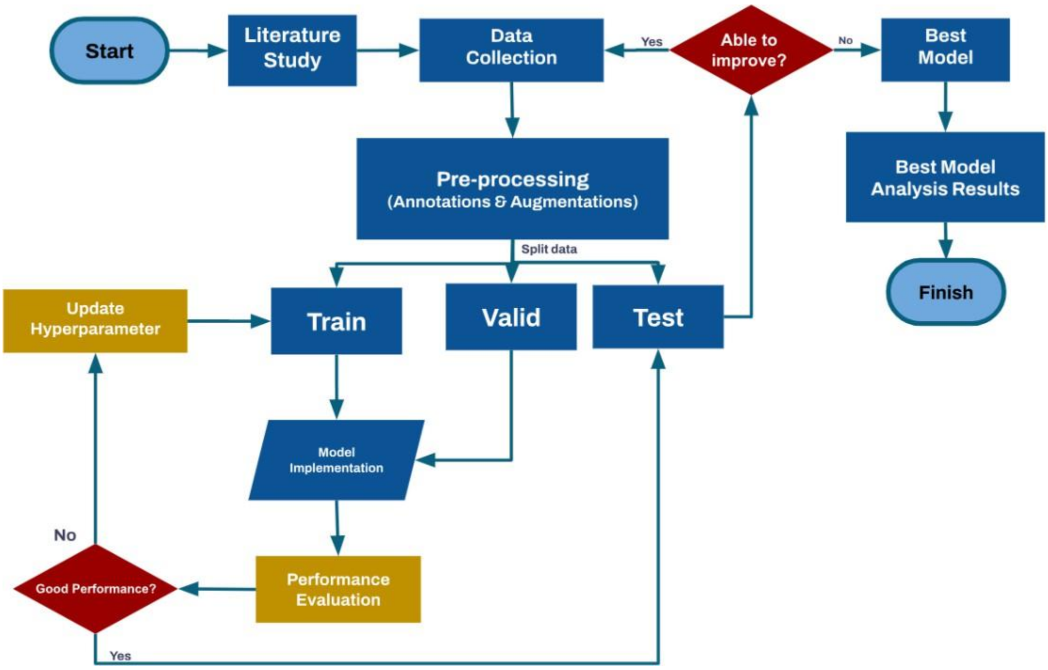

Figure 1. Research Flow

2.1. Data Collection

Data collection aims to provide the materials for creating a dataset, which is a critical element in building an object detection model, particularly with the YOLOv9 architecture. In this study, the dataset was collected using a scraping technique by taking photos of pigs in four colony pens, each containing 2–7 pigs. Data collection was conducted at 7:30 AM and 4:30 PM, under conditions where the pigs had not yet been fed, bathed, or had their pens cleaned. Photos of the pigs were taken individually from a wide-angle perspective using a Canon EOS 650D DSLR camera, positioned at a height of approximately 1.3 meters from the pen. Data collection took place over 92 days across the four different colony pens.

Several challenges arose during this data collection process, such as distinguishing the pigs' patterned skin, which closely resembled feces. This was noted during the annotation stage to ensure that the annotated objects were feces and not skin patterns that looked similar to feces.

As a result of this phase, the number of unique images collected increased with each iteration, starting from 434 unique images and eventually growing to a final total of 5,868 unique images. Examples of the unique images collected are shown in Figure 2.

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
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Figure 2. Examples of unique images collected.

2.2. Pre-processing

Preprocessing is essential for ensuring data quality and extracting useful information from datasets. It directly affects the efficiency of model training and the predictive ability of machine learning models [21], [23]. Proper preprocessing can prevent the loss of predictive information and avoid the introduction of erroneous data. In this stage, the dataset will be processed to adjust it according to the needs of the method used to build the model, which in this case is YOLOv9. In the processing step, use the Roboflow tool to perform the following processes [22].

a. Data Annotation

Data annotation is a process to prepare data for machine learning that requires careful annotation, where raw information is tagged and organized. This critical process helps AI systems understand and learn from the data more effectively. While historically challenging and resource-intensive, new technological developments are making data preparation easier and more streamlined [24]. The data annotation process was performed using a cloud-based workflow management system orchestrating the pipelines of developing AI-enhanced robots, called Roboflow [12]. This striking property makes it especially suitable for developing AI-enhanced in which data play a central role [15]. This annotation process was done manually, one image at a time. Two classes were used for annotation: feces (fecal matter adhering to the pig's skin) and pig (the pig's body).

The bounding boxes for the feces class were applied based on several criteria. The first criterion is that the feces should be clearly visible on the pig's skin, without any ambiguity or the need for zooming in to identify it as fecal matter. The feces should not appear as small dots or stains. The second criterion is that only dark-colored feces that clearly contrast with the pig's skin color are annotated. An example of the images after the annotation process is shown in Figure 3.

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E-ISSN: 2723-3871
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

Figure 3. Examples of annotated data.

The composition comparison between the pig and feces classes in this dataset was performed using an experimental ratio and the class it will overlap. Comparison of the composition of pig classes and feces in this dataset was carried out using experimental ratios and the classes will overlap. Comparison of composition between classes in a dataset is considered experimental primarily due to the challenges and complexities associated with data imbalance and class overlap [16]. Class overlap has an impact on the performance of learning algorithms in the classification of imbalanced data, but this is something that cannot be avoided in the data collection process, this has both good and bad impacts in machine learning [17]. The initial ratio v1 dataset of pig class to feces class is shown in Figure 4. This ratio is influenced by the fact that the number of pigs in one pen ranges from 2 to 7, while the number of visible feces occurrences is usually 2 to 6 times the number of pigs in the image.

COLOR	CLASS NAME	COUNT
	feces	19,231
	pig	10,060

Figure 4. Comparison of the pig class with the feces class in the v1 dataset.

b. Augmentation

In the process of creating a dataset, there is a stage aimed at enhancing the quality and uniqueness of the annotated data, known as the augmentation process. This process aims to create variations in the image data within the dataset to prevent the object detection model from becoming overly rigid in detecting the desired objects due to a lack of diversity in the dataset (overfitting). If this occurs, the model may lose precision. This study employs several augmentation techniques, namely [16]:

a. *Flip: Horizontal*
   This technique is used to introduce variation in the dataset and prevent overfitting.
b. *90° Rotate: Clockwise, Counter-Clockwise, Rotation: Between -15° and +15°*

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The purpose of this technique is to create image variations under the best conditions for objects, enhancing the dataset's diversity. This helps the model adapt to detecting objects in inverted orientations.

c. *Shear: ±10° Horizontal, ±10° Vertical*
This technique generates skewed image variations to increase the diversity of data within the dataset.

d. *Outputs per training example: 3*
This approach aims to capture moments in time and synthetically generate new image variations for the dataset, improving training quality and preventing overfitting.

2.3. Training

At this stage, the pre-processed dataset will be used for training. The dataset split for training is automatically selected by the Roboflow system using a cross-validation method, where the images are sorted, and every image in a position that is a multiple of a certain value (depending on the percentage set for the dataset split) is chosen for the training dataset. In this study, the training dataset accounts for 70% of the total dataset. This 70% is the default format in Roboflow, which can be experimentally increased or decreased to test the training results if the performance is not deemed optimal.

The training process will utilize a cloud-based platform that provides a hosted Jupyter notebook environment. It is designed to facilitate machine learning and data science education and research by offering free access to computational resources such as GPUs and TPUs [25], called Google Colab with GPU infrastructure and hyperparameter settings as shown in Table 1. The training process will produce a model whose results will be validated in the next stage.

Table 1. YOLOv9 Hyperparameters First Iteration Training Step

Parameter	Default Setting	Modified Setting	Notes
Epochs	20	20	Extended to allow for more thorough training.
Input size	640	640	Adjusted for balance between accuracy and speed.
Batch	32	16	Increased to improve training efficiency.
Close mozaic	15	15	The ratio of image to combine in the mosaic
Weight	gelan-c.pt	gelan-c.pt	A file that content the weight setting

2.4. Validation

After the training process is completed, model will be carried out to validation step to obtain the values of mAP (how often the model's predictions are correct), precision (measures how often the model's predictions are correct), and recall (measures what percentage of relevant labels were successfully identified), for the purpose of evaluating the training results to model helps in assessing the robustness and applicability of the model in real-world scenarios [18].

YOLOv9, developed by Ultralytics, uses standard evaluation methods to measure model performance by calculating Precision, Recall, and mean Average Precision (mAP). The following are the formulas used to calculate Precision, Recall, and mAP [19]:

$$\text{Precision}=\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Positives\ (FP)}$$

$$\text{Recall}=\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Negative(FN)}$$

$$\text{AP}=\int_{1}^{0}\text{Precision}(\text{Recall})\ d\text{Recall}$$

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E-ISSN: 2723-3871
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

Precision measures how accurate the model's predictions are by comparing the number of correct predictions (True Positives/TP) against all positive predictions, including incorrect ones (False Positives/FP). On the other hand, Recall calculates the model's sensitivity, which is the percentage of actual objects that were successfully detected (True Positives) compared to the total number of objects, including those missed (False Negatives/FN). To determine the correctness of a prediction, YOLOv9 uses IoU (Intersection over Union), which is the overlap ratio between the predicted bounding box and the ground truth. A prediction is considered correct if the IoU value exceeds a certain threshold (usually 0.5 or 0.5:0.95).

For a more in-depth evaluation, YOLOv9 calculates Average Precision (AP), which is the area under the Precision-Recall curve (PR Curve) for each class. The PR Curve is built by plotting precision against recall at various confidence score levels. YOLOv9 computes mAP by averaging the AP values across all classes in the dataset. Typically, mAP results are reported in two metrics: mAP@0.5, which calculates mAP with an IoU threshold of 0.5, and mAP@0.5:0.95, which is the average mAP over IoU thresholds ranging from 0.5 to 0.95 with a step size of 0.05. This evaluation provides a deep insight into how well the model detects objects overall, including class-wise performance [19].

In this validation phase, the dataset used will account for 20% of the total dataset. The selection of unique images for the validation dataset split is automatically done by Roboflow using cross-validation techniques, just like the training dataset split. If the results are unsatisfactory, the hyperparameters will be updated again with the hope of generating a better model output, aiming to improve the model. The hyperparameters in the validation step are initially set as shown in Table 2.

Table 2. Hyperparameter Validation Step

Parameter	**Default Setting**	**Modified Setting**	**Notes**
Learning rate (IoU) Threshold	0.7	0.7	Adjusted to fine-tune model convergence.
Confidence Threshold	0.001	0.005	Used to filter out predictions that have a low confidence score.
Batch	16	32	Adjusted for balance between accuracy and speed.
Input size	640	640	Increased to improve training efficiency.

2.5. Testing

If the model validation results are satisfactory, the process will proceed to the testing step. In machine learning, the testing step is crucial for evaluating the performance and generalization ability of a trained model. It helps in assessing how well the model can predict outcomes on unseen data, ensuring that it is not just memorizing the training data but can also perform well in real-world scenarios, and also this step is vital for evaluating a model's performance, ensuring its generalization to new data, and detecting potential biases or errors. It plays a critical role in validating the model's effectiveness and is essential for making informed decisions about model deployment and resource allocation [20], [26], [27].

In this testing phase, the testing dataset will be used to evaluate the model, where the model will be presented with images that it has not seen during the training and validation processes. As with the split dataset for training and validation, the testing dataset is also selected using a cross-sampling technique that sets aside 10% of the total dataset. After that, the model will undergo a result analysis phase to determine the final outputs of mAP, precision, and recall. The model will then be assessed using various metrics, including mAP, precision, and recall. For this study, at least two iterations will be performed. In the first iteration, the dataset will be evaluated and used as a reference for potential improvements, such as adding more data or refining annotations and dataset composition, which will serve as the basis for the second training iteration. If the results of the second iteration do not reach

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

100%, additional iterations will be conducted until further improvements become negligible. The following shows the performance results of the YOLOv9 model, which can be seen in Figure 5.

3. RESULT

3.1. Data Collection

The data collection process is carried out iteratively, from the first iteration to the last iteration. Each iteration involves increasing the amount of data in the dataset to ensure the model can be trained more optimally. The results of the data collection process at each iteration are shown in Table 3.

Table 3. Data collection result

Iteration	Dataset Version	Dataset Qty
1	v1	434
2	v2	3.215
3	v3	4.557
4	v4	5.181
5	v5	6.769
6	v6	6.174
7	v7	5.404
8	v8	5.868

In the initial iteration, the amount of data used was still relatively small, which was 434 data in the v1 dataset version. However, as the iteration progressed, the amount of data continued to increase significantly until it reached its peak in the fifth iteration with 6,769 data in the v5 dataset version. After that, there was a slight fluctuation in the amount of data until the last iteration, which was 5,868 data in the v8 dataset version.

The increase in the amount of data in each iteration aims to improve the performance of the YOLOv9 model in detecting objects. This shows that the continuous data collection process is very important in ensuring the accuracy and efficiency of the model.

3.2. Pre-processing

In this study, this process involved annotation and data augmentation. The aim was to ensure that each dataset iteration could include more variations, allowing the model to detect objects more effectively.

Table 4 shows the results of annotation and data augmentation from the first iteration to the final iteration, including the total number of data and the class distribution within the dataset.

Table 4. Data annotation dan augmentation dataset

Iteration	Dataset Version	Augmentations	Dataset Qty	Feces Class	Pig Class
1	v1	Outputs per training example: 3 Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	434	3.278	1.246
2	v2	Outputs per training example: 2 Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	3.215	9.860	6.426
3	v3	Outputs per training example: 3 Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	4.557	14.276	8.898

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P-ISSN: 2723-3863
E-ISSN: 2723-3871
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DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

4	v4	Outputs per training example: 3 Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	5.181	15.541	10.381
5	v5	Outputs per training example: 3 Flip: Horizontal, Vertical 90° Rotate: Clockwise, Counter-Clockwise Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical Blur: Up to 2.5px	6.174	21.897	12.349
6	v6	Outputs per training example: 3 Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	6.174	20.248	12.987
7	v7	Outputs per training example: 3 Flip: Horizontal 90° Rotate: Clockwise, Counter-Clockwise Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	5.404	19.231	10.060
8	v8	Outputs per training example: 5 Flip: Horizontal 90° Rotate: Clockwise, Counter-Clockwise Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical	5.868	19.897	10.476

The increase in data at each iteration was achieved through various augmentation methods, such as rotation, shear, flip, blur, and others. Additionally, the ratio between the "feces" and "pig" classes also shows an increasing trend, with the largest data count recorded in the fifth iteration—21,897 data for the "feces" class and 12,349 data for the "pig" class.

3.3. Training

The iteration history will present the data settings for each iteration and the number of datasets used during training to compare the performance of each hyperparameter setting and dataset quantity. Table 5 which contains the results of all iterations conducted to obtain the model with the best performance.

Table 5. Training result of all dataset iteration with hyperparameter tuning perform

Iteration	Dataset Version	Dataset Qty	The best hyperparameter	Precision	Recall	mAP_0.5
1	v1	434	Epochs= 25, IoU= 0.70, Conf= 0.001, Input size= 640	69.7%	66.9%	63.9%
2	v2	3.215	Epochs= 25, IoU= 0.70, Conf= 0.001, Input size= 640	66.0%	70.4%	69.1%
3	v3	4.557	Epochs= 25, IoU= 0.70, Conf= 0.001, Input size= 640	67.5%	69.9%	69.3%
4	v4	5.181	Epochs= 20, IoU= 0.70, Conf= 0.001, Input size= 640	44.3%	44.2%	43.7%
5	v5	6.769	Epochs= 35, IoU= 0.70, Conf= 0.001, Input size= 640	67.3%	69.8%	68.2%
6	v6	6.174	Epochs= 35, IoU= 0.70, Conf= 0.001, Input size= 640	67.4%	70.5%	69.4%
7	v7	5.404	Epochs= 35, IoU= 0.70, Conf= 0.001, Input size= 640	70.6%	72.1%	70.5%

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8	v8	5.868	Epochs= 35, IoU= 0.70, Conf= 0.001, Input size= 640	70.4%	71.3%	70.4%

At stage the training results will also be evaluated. If the performance is found to be lacking, the hyperparameters will be updated until the training results reach their maximum potential. In the initial iterations, the model's performance was relatively low due to the limited amount of data. However, after updating the dataset with augmentation methods and adjusting the annotations, the values for Recall, Precision, and mAP_0.5 showed improvement. The seventh iteration recorded the highest values, with Recall at 70.6% and Precision at 72.1%, indicating that a dataset with specific augmentations can enhance object detection accuracy.

3.4. Validation

From the iterations that have been carried out, this study produced a matrix as presented in Table 6, and the corresponding dataset updates implemented to address these problems.

Table 6. Result of validation, dataset problem and dataset update for next iteration

Iteration	Dataset version	Recall	Precision	mAP_0.5	Problem/opportunity findings	Dataset update for next iteration
1	v1	69.7%	66.9%	63.9%	The data is still limited.	Adding more unique images to dataset
2	v2	66.0%	70.4%	69.1%	The model detects objects outside the pen as pigs and feces.	Adding unique images and decreasing the hyperparameter confidence for subsequent iterations
3	v3	67.5%	69.9%	69.3%	Precision has decreased, and object loss has increased.	Adding unique images but not annotating the pig class to see how it affects the results.
4	v4	44.3%	44.2%	43.7%	There has been an increase in object loss.	Adding annotations for the pig class
5	v5	67.3%	69.8%	68.2%	The output is lower than the v3 dataset.	Adding annotations for the pig and feces classes to dataset v5 and reselecting the dataset.
6	v6	67.4%	70.5%	69.4%	The analysis output shows a slight improvement.	Selecting images containing pigs with faded feces and dominant fecal stains in the dataset and updating the feces class annotations.
7	v7	70.6%	72.1%	70.5%	The analysis output does not show a significant improvement.	Adding unique images to dataset
8	v8	70.5%	71.3%	70.4%	The analysis output does not show a significant improvement.	-

Table 6 showing dataset v1 yielded satisfactory results, achieving an mAP of 63%, precision of 66.9%, and recall of 69.7% despite having only 434 images. To further improve model performance, the dataset was updated by adding unique images, resulting in dataset v2 which was used for training in the 2nd iteration. The 2nd iteration showed a significant increase in mAP to 69.1%, precision to 70.4%, but recall decreased to 66.0%. This decrease in recall was attributed to overfitting, caused by the limited variation in the training dataset. To address this, data augmentation techniques such as rotation, flipping, zooming, etc., will be applied to the next dataset update. Iteration 3, with various hyperparameter adjustments, showed only a minor improvement of 0.2% in mAP_0.5, indicating underlying issues with the dataset. The dataset was updated again by adding more unique images for the 4th iteration. Iteration 4 results, as shown in Figure 5, indicated an increase in class loss during validation, suggesting annotation errors in the dataset. Specifically, the imbalance between the "pig" and "feces" classes was identified. To address this, the dataset will be updated by adding more images of the "pig" class. Iteration 5 results, as shown in Figure 6, demonstrated a decrease in class loss and an improvement in mAP to 68.2%, precision to 69.8%, and recall to 67.3%. While this is an

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improvement over iteration 4, it is still lower than iteration 3. Therefore, the dataset will be further updated by adding more "pig" class images to balance the classes.

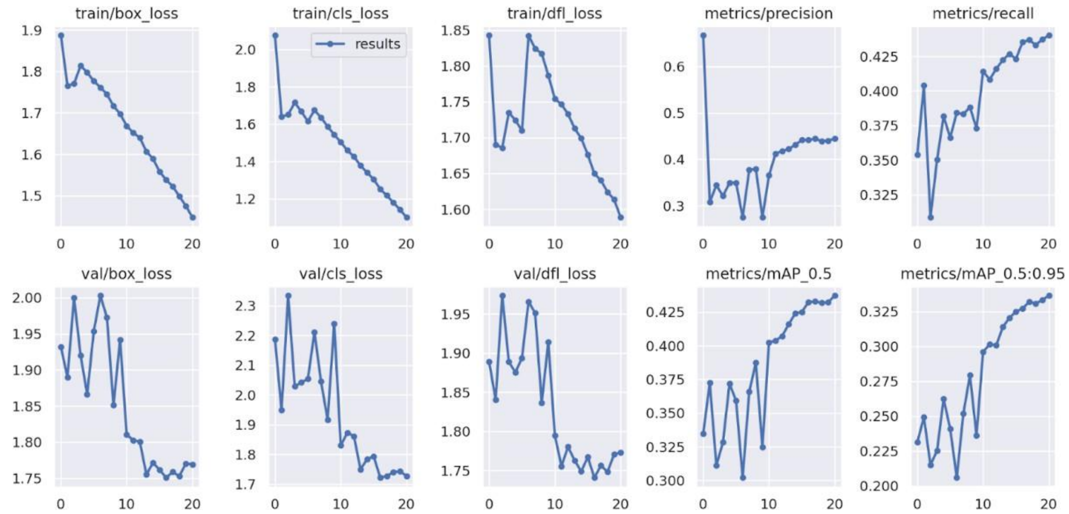

Figure 5. Validation graphs of 4th iteration

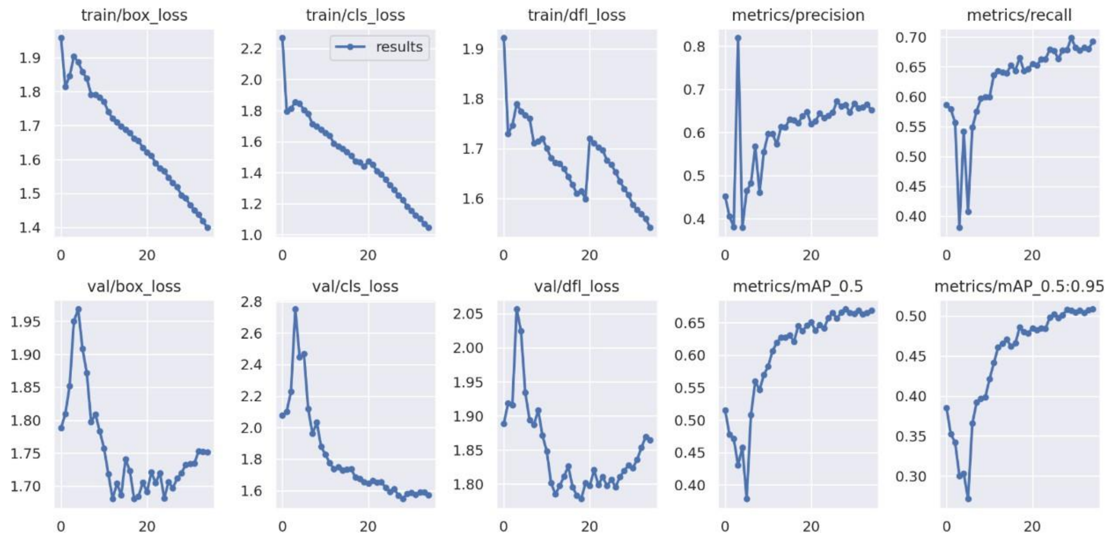

Figure 6. Validation graphs 5th iteration

In the 6th iteration, the training results showed an improvement, although not substantial, with a mAP of 69.4%, Precision of 67.4%, and Recall of 70.5%, which represent increases of 0.1%, 0.7%, and 1.2%, respectively. Therefore, the dataset will be updated again for the 7th iteration. In the following iteration, the output results were also not significant, with a mAP of 70.5%, Precision of 70.6%, and Recall of 72.1%, as shown in Figure 7. To ensure the conclusion of the iterations, this study will proceed with the eighth iteration by updating the dataset once more.

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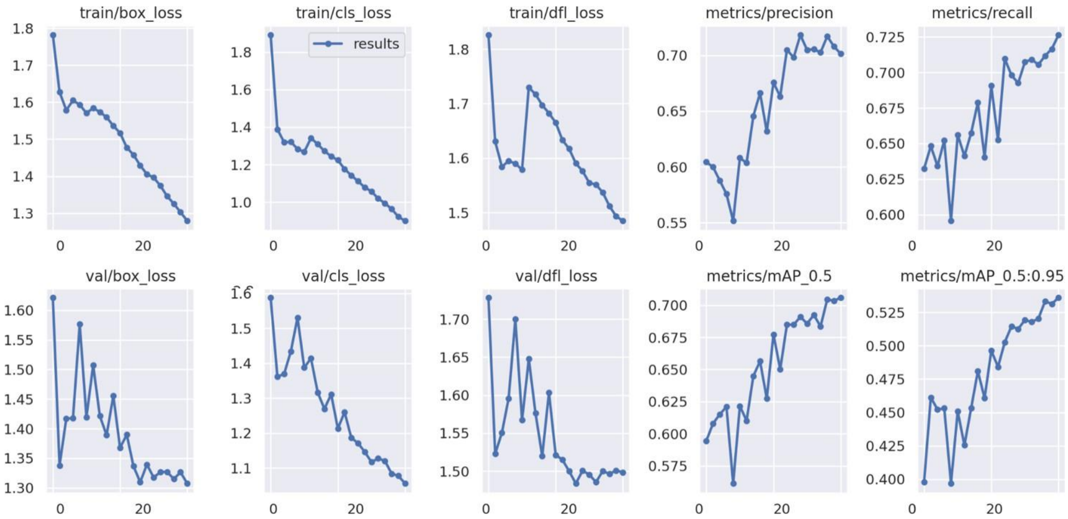

Figure 7. Validation graphs 7th Iteration

In the eighth iteration, although the quantity of the dataset was increased, the output showed a decline. The mAP decreased by 0.1%, from 70.5% to 70.4%. Precision increased by 0.2%, from 70.1% to 70.3%, while recall decreased by 0.1%, from 70.6% to 70.5%.

In addition to these results, the author identified two limitations in this study that indicate areas where the model can still be improved. First, the model is not yet capable of distinguishing between pigskin patterns and feces. Second, several other objects resembling feces around the pen are often incorrectly detected as feces, such as holes in the floor of the pen and openings for waste disposal outside the pen.

3.5. Testing

There a visualization of the testing results of the model formed from the best iteration (7th iteration). It can be seen that the model can detect which is pig and which is feces from the visualization shown in Figure 8.

Figure 8. Example of detection results perform of YOLOv9 model

3.6. Impact prediction

To calculate how big the percentage impact of reducing interaction time between humans and pigs that occurs if this model is applied to automatic cleaners, it is calculated using the following formula:

$$\text{Interactions reduction (\%)} = \frac{\text{number of interactions without automatic cleaning tools} - \text{number of interactions with automatic cleaning tools}}{\text{number of interactions without automatic cleaning tools}} \, x \; 100\%$$

Then the author has designed a scheme for the duration estimation of interaction between humans and pigs in the pig care process as shown in table 7.

Table 7. Estimated data on the number of interactions in 30 days

Interactions	Without tools (minute)	With tools (minute)
Bathing livestock	600	0
Cleaning the cage	600	0
Feeding	300	300
Maintain tools	0	60
Total	**1500**	**360**

From the results of calculations using this formula, the predicted reduction in interaction time between humans and pig in 30 days when the model is applied to an automatic cleaning device is a reduction in interaction time of 76%.

4. DISCUSSIONS

The results of this study demonstrate the feasibility and potential of YOLOv9 for object detection in agriculture, specifically for identifying feces on pig skin. The model's ability to achieve a mAP of 70.5%, precision of 70.6%, and recall of 72.1% in the seventh iteration highlights the reliability of this approach, especially considering the variability in lighting and environmental conditions during data collection, as well as the complex and irregular shape of the feces objects. These results indicate that YOLOv9 can serve as a practical solution for applications requiring real-time object detection in farming environments.

From a technical perspective, the high recall value indicates the model's strength in detecting relevant objects (feces), which is crucial for minimizing human-animal interaction and improving biosecurity measures. However, the relatively lower precision reveals challenges in distinguishing between feces and similar visual patterns on pig skin or other objects in the environment. This limitation reflects the need for further refinement of the dataset or model enhancement to improve detection specificity.

When compared to related studies, this research builds on advancements in object detection models for applications in pig farming. For example, the model for detecting pig faces for health evaluation in the study by Zhe Yin (2024), titled "Lightweight Pig Face Feature Learning Evaluation and Application Based on Attention Mechanism and Two-Stage Transfer Learning," utilized various methods, including EfficientDet, SDD, YOLOv5, YOLOv7-tiny, YOLOv8, and Swin Transformer. The study showed that the YOLO method, particularly YOLOv8, achieved the highest mAP of 97.73%. In contrast, the author’s research applies YOLOv9, the latest improvement over YOLOv8 [10], focusing on detecting feces in the pig pen environment. The feces objects are more complex than pig faces, demonstrating that the YOLO model can consistently be adapted for various detection needs in the livestock sector.

Additionally, the study by Marko Ocepek (2021), titled "DigiPig: First Developments of an Automated Monitoring System for Body, Head, and Tail Detection in Intensive Pig Farming," showed that YOLOv4 achieved a precision of 90% for detecting pig body parts such as the head, body, and

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P-ISSN: 2723-3863
E-ISSN: 2723-3871
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

tail, which is significantly higher than Mask R-CNN, which only reached 77% precision. This study highlights YOLO's superiority in accurately detecting objects in intensive farming environments [28]. In the context of this research, the application of YOLOv9 provides a more advanced approach by incorporating features like GELAN and PGI, contributing to better feature integration and gradient optimization.

The iterative approach to dataset augmentation and model training played a crucial role in achieving these results. Previous research, such as that by Singh and Kaur (2021), highlighted the importance of diverse and high-quality datasets in enhancing model performance [29]. Similarly, this study's findings confirm that gradual improvements in mAP, precision, and recall can be achieved by increasing dataset size and refining annotation quality through several iterations. This approach not only strengthens the model's reliability but also validates the importance of developing adaptive datasets to address specific domain challenges.

The urgency and significance of this research lie in its contribution to the fields of livestock farming, computer science, and informatics. Automating pig feces detection addresses critical challenges in the livestock industry by minimizing human-animal contact and enhancing biosecurity, which is particularly relevant in the context of the African Swine Fever (ASF) outbreak. Beyond agriculture, this research provides insights into YOLOv9's capabilities for broader implementation in domains requiring real-time detection of complex objects in dynamic conditions, such as traffic, healthcare, and industrial robotics.

Future research should explore the integration of more advanced data augmentation techniques, such as Generative Adversarial Networks (GANs), to further enrich the dataset's diversity. Additionally, incorporating domain-specific knowledge—such as modeling particular environmental factors or introducing new classes like mud or feed residues—could improve the model's ability to distinguish feces from similar substances. Techniques such as ensemble modeling or integrating YOLOv9 with complementary algorithms, like transformer-based architectures, could further enhance detection accuracy and robustness.

Despite its limitations, the current model provides a promising foundation for integration into automatic cleaning systems. Such systems could significantly reduce human-pig contact by 76%, decrease disease transmission risks, and improve overall farm management efficiency. By advancing the application of YOLOv9 in agriculture, this research highlights its potential as a transformational tool at the intersection of computer science and agricultural technology.

5. CONCLUSION

Based on the findings of this research, the best-performing model was achieved in the seventh iteration using the v7 dataset, with an mAP of 70.5%, precision of 70.6%, and recall of 72.1%. These results demonstrate the model's effectiveness in detecting pig feces under various conditions and highlight its suitability for implementation in automated cleaning systems.

This research has significant implications for the livestock industry, particularly in advancing automation in pig farming. By addressing the challenge of detecting feces in pig pens, the study contributes to improving farm hygiene and minimizing direct human-animal interaction by up to 76% (from 1,500 minutes/30 days to 360 minutes/30 days), which is crucial for preventing the spread of diseases such as African Swine Fever (ASF), which can be highly dangerous. Furthermore, the automated solution developed from this research can enhance operational efficiency, reduce labor costs, and improve animal welfare, benefiting both small-scale farms and the larger industry.

One of the key elements of this research is the use of appropriate data augmentation techniques. Augmentation proved valuable in the 5th and 6th iterations, where it played a critical role in improving the dataset's diversity, allowing the model to recognize patterns in a wider range of conditions, such as variations in lighting, angles, and background. The different augmentation techniques used in this study had varying impacts on model performance, emphasizing that the correct choice of technique can lead to a more reliable model for detecting pig feces in various real-world situations.

From the perspective of Informatics and Computer Science, this research demonstrates the practical application of YOLOv9 for object detection in challenging real-world environments. The findings highlight the importance of effective augmentation strategies, dataset diversity, and model optimization in achieving reliable performance. This study also offers valuable insights for researchers

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240

working on similar applications in agricultural technology. Additionally, the research underscores the potential for cross-disciplinary collaboration, bridging the gap between artificial intelligence and livestock management to tackle pressing global challenges.

To further improve the model's performance, future research should focus on enhancing dataset diversity, particularly by including images of patterned pig skin and other potential contaminants. Expanding the model's ability to distinguish between feces and other visually similar objects, such as holes in the pen floor or feces sticking to the pen walls, will be crucial. Moreover, exploring alternative architectures, integrating YOLOv9 with other complementary methods, and developing new augmentation techniques could lead to better detection accuracy.

In conclusion, this study successfully demonstrated the potential of YOLOv9 in object detection within pig farming, providing a solid foundation for the development of automated cleaning solutions. The results not only support broader goals of minimizing human-animal contact and improving biosecurity but also pave the way for future innovations in automated farm management systems. Furthermore, the findings are ready to be implemented in robotic cleaning systems for pig pens, aligning with the initial objectives and showcasing the relevance of Informatics in addressing real-world challenges in agriculture.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest among the authors or with the research object discussed in this paper.

ACKNOWLEDGEMENT

The authors would like to express their gratitude to Nyoman Farm, Bali, Indonesia, for granting permission and support during the data collection process. Special thanks are extended to Udayana University for providing the facilities and technical support necessary for this research. The authors also acknowledge the contributions of students from RMIT University who provided additional assistance in annotating the dataset. Appreciation is also given to the Google Colab platform for enabling model training with GPU infrastructure.

The authors are also grateful to all individuals and organizations who provided valuable feedback, suggestions, and support throughout the research process.

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Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 2, April 2025, Page. 609-626
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.2.4240