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Chicken tracking for location mapping of lameness chickens using YOLOv8 and deep learning-based tracking algorithm

Wiwit Agus Triyanto[1,2], Kusworo Adi[3], Jatmiko Endro Suseno[3]
[1]Doctoral Program of Information System, School of Postgraduate Studies, Diponegoro University, Semarang, Indonesia
[2]Department of Information System, Faculty of Engineering, Muria Kudus University, Kudus, Indonesia
[3]Department of Physics, Faculty of Science and Mathematics, Diponegoro University, Semarang, Indonesia

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ABSTRACT

The chicken farming industry is one of the biggest food industries that supports the achievement of food security internationally. Farmers need an independent tool that can monitor the welfare conditions of chickens in cages. Using their tools, farmers can ideally detect the condition of chickens. Lameness chickens, can be known for activity and dredging of their location in the cage. Occlusion, and background in the cage are interesting challenges. By observing behavior, image handling practices can be used to identify tainted chicks and provide an early warning of sickness in chickens. In this study, you only look once, version 8 (YOLOv8) which is a convolutional neural network (CNN) network model was chosen to perform the detection, tracking, and mapping of chicken locations. YOLOv8 was combined with various algorithm optimizers to improve training performance, such as root mean square (RMS) Prop, stochastic gradient descent (SGD), ADAM, and ADAMW. Multi-object tracking algorithms such as BOT-sort and ByteTrack are also used to improve tracking performance. Based on the results, YOLOv8 with combinations of optimizer algorithms ADAMW has the best mAP, support, precision and F1-score values compared to the others, with 0.936, 0.993, 0.990, 0.991. Meanwhile, for multi object tracking, ByteTrack is faster in inference time(s) values compared to the others, with 0.2.

Corresponding Author:

Wiwit Agus Triyanto
Doctoral Program of Information System, School of Postgraduate Studies, Diponegoro University
Semarang, Central Java, Indonesia
Email: at.wiwit@umk.ac.id

1. INTRODUCTION

The chicken farming industry is one of the largest food industries that supports the achievement of food security internationally. The increasing demand for food has made the chicken population increase by 3 times more than the number of humans [1]. The chicken industry has a big role in contributing to the food industry, because chicken farms have a big contribution to the supply of eggs and meat [2], [3]. The demand for chicken is growing rapidly every day. High chicken production can be achieved if environmental factors, breeding processes and chicken farm operations are dynamic. The intelligent process is divided into stages, a few things about nutritional rules, control standards, portions and health [4]. A healthy chicken body, positive activity behavior, and natural activity can indicate that the chicken’s health condition is good [3]. Good chicken welfare based on the criteria of the welfare quality assessment protocol for poultry is the nonappearance of wounds such as lameness, hock burn, and foot pad dermatitis [5]. Therefore, poultry behavior monitoring and fitting administration measures cannot as it were advance chicken development and move forward generation execution, but too ensure chicken wellbeing. In addition, knowing the location of the position of chickens that are in a lameness condition is very important, this is so that chickens that are detected lameness can be handled immediately so as not to spread the disease to other chicken herds in cage.

Researchers have conducted a variety of research projects, some of which include image study using machine learning (ML) calculations might give a degree of creature welfare by measuring consolation practices and undesired practices [6]. In animal husbandry, convolutional neural networks (CNNs), a deep learning technique created especially for object localization and classification, can be utilized to solve problems [7]. By observing behavior, image handling practices can be used to identify tainted chicks and provide an early warning of sickness in chickens [4], [8]. Deep learning approaches [9] have been used to solve problems in chicken coops, estimate the density of swarming chickens using CNN, distinguish debilitated chickens utilizing CNN with ResNet architecture [10], detect chickens, and recognize the wellbeing status of chickens utilizing CNN with single-shot detector (SSD) architecture [8], detect chickens using faster region-based CNN (R-CNN) [11], process of monitoring chicken behavior and welfare [12]–[18], the ordinary show for the location of chicken infections is by visual and sound perceptions made by breeders and veterinarians [19]. Be that as it may, in large-scale generation, this discovery strategy could be a time-consuming, subjective, research facility, and falls flat to supply early discovery [8]. It is possible to determine whether a chicken is healthy by observing its behaviors [20], such as eating, drinking, strolling, and remaining motionless. This allows for early detection of any disease-related symptoms in the chicken [21]. The object detection process based on deep learning has many benefits that can be used for many things, such as traffic light detection using faster-CNN [22], detection of switchgear removal errors using CNN-long short-term memory (LSTM) [23], you only look once, version 5 (YOLOv5) for image and video-based criminal detection [24], you only look once, version 3 (YOLOv3)-based distance detection in public spaces during COVID-19 [25], classifying yoga poses using CNN [26], analyzing human activity using CNN [27], designing a robot design for assisting the elderly using CNN [28], estimating the age of pedestrians using CNN [29], carrying out automatic surveillance at night using CNN [30], identifying human emotions for assistant robots using CNN [31], deep learning can also be used for sound event detection using CNN [32].

A deep learning CNN based technique called you only look once, version 8 (YOLOv8) can maximize object identification speed and accuracy in real time with a variety of complicated background [33]. In improving its performance deep learning has various algorithm optimizers such as stochastic gradient descent (SGD), ADAM, Adagard [34]. Some of these algorithms have limitations, therefore there is a new algorithm, namely the ADAMW optimizer, to overcome the ADAM optimizer problem with overfitting and a sharp decrease in learning rate [35]. Meanwhile, to improve multi-object tracking performance in deep learning, there is the Bot-sort algorithm [36] which is employed to extract movement characteristics from objects, such as displacement, acceleration, and speed; these attributes are then utilized to preserve modifications and ignore failures to identify the desired behavior in the behavior of the chickens [37]. Another object tracking technique, ByteTrack improves its speed on difficult data sets with an easy yet powerful data augmentation method. This shows that ByteTrack performs better than a number of state-of-the-art object tracking algorithms, utilizing fewer parameters and achieving faster inference times. ByteTrack [38]. In this research, a deep learning CNN method based on YOLOv8 is proposed by combining the ADAMW optimization algorithm and the ByteTrack object tracking algorithm to track chicken activity to map the location of lame chickens. Accuracy and efficiency are key in knowing chicken health, this is in line with the process of monitoring chicken behavior and welfare. The process of detecting chickens must be carried out accurately so that it can find out the health condition of chickens. If the detection process does not run well, it will result in incorrect tracking of chickens. Tracking chickens is an important process to determine the behavior and health condition of chickens. The effectiveness of chicken detection aims to track can be used to monitor the movement of chickens in the cage, so that it can find out the position of healthy or sick chickens in which part of the cage. So this research is very important to do, because with knowing the location of sick chickens can help farmers immediately handle to owe the risk of spreading the disease to other chicken herds in the cage.

2. RELATED STUDIES

Several previous research on the detection and tracing of chickens using computer vision technology, but no studies have been published on tracking and mapping the location of lameness chickens with occlusion in cages using YOLOv8. Tracking the activity of lameness chickens or not, obtained by detecting chickens' body posture to create an ID based on the coordinates of the chicken in the image. To better grasp the condition of the hens when raising them in cages, appropriate support and chicken detection are necessary. However, the algorithm's accuracy is frequently impacted by the algorithm ability to recognize hens in the cage. Numerous algorithms utilizing YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x are therefore offered. The findings revealed an increase in chicken detection accuracy of 16.1%, 12.1%, 7.3%, and 5.4% [14]. Body weight and breast muscle weight in broiler chickens influence the risk of leg illness, which has a major negative impact on the chicken's health. Gait scores and x-rays are utilized to immediately identify and assess the health of hens to get around this problem. The detection rate and accuracy of the diagnosis of chicken foot illness may both be improved by combining the gait score and x-ray approaches. When aberrant circumstances are shown by x-rays, scores increase by 70% [13].

In order to boost production and animal welfare, the automatic detection, counting, and monitoring of hens in the chicken coop sector is crucial. Consequently, a YOLOv5-based deep learning model is used to distinguish between chickens from various backgrounds. It is anticipated that YOLOv5, which leverages the multiscale function, would be able to track and count chickens [33]. It is quite difficult to keep an eye on hens in a farm coop all the time. Low-resolution films may be used to detect chickens using YOLOv4 and a modified Kalman filter. This program, which only records grayscale photos, can identify chickens with a high accuracy in low light conditions [39]. Assessing the health and well-being of chickens on the farm involves tracking their movements and categorizing various behaviors, including activity and relaxation. The Bot-sort architecture in YOLOv8 was used for testing to find chicken movements and turned out to be effective in detecting and tracking chickens [37]. A bird's behavior indicates its health and well-being. Birds can show clinical symptoms such as abnormalities. Therefore, for broiler chicken producers, identifying errors at an early stage is very important. The study found lameness in broiler chickens using a pose estimation-based model for the first time. The CNN-LSTM model that was built demonstrates that a pose estimation-based lameness evaluation tool that is both automatic and non-invasive can be utilized to manage poultry farms effectively [40]. It can be difficult to track things in surveillance films at night since the images are typically of low quality, with little contrast and brightness. The task becomes more challenging with little things since they have fewer elements that are visible. This study proposes a CNN algorithm with the ADAM optimizer based on a deep learning technique to take use of its benefits, such as modeling object appearance even at night [34].

Occlusion, and background in the cage are interesting challenges. Occlusion occurs when there is a chicken object covered by other objects, such as a place to eat or other chicken objects. Different camera angles and positions result in different detection views as well, and this can lead to difficulties in identifying chickens. In addition, currently, no research has been conducted on detecting lameness chickens or not, tracking the movement of chickens, and mapping the location of these chickens in the cage. Some previous studies did have high accuracy, but high accuracy is not enough for real-time implementation in cages with the possibility of uncontrolled conditions. In order to ensure that the accuracy of detection can be carried out in real-time to track the movement and map the location of lameness hens in cages, a YOLOv8 based demonstration was constructed in this regard.

3. METHOD

YOLOv8 and DeepSort, two methods for object tracking and detection, are used in this study to employ CNN. CNN networks are a kind of multi-layer neural network made up of neurons with trainable weights and inclinations [41]. YOLO is part of the CNN method that is widely applied to image data. YOLO sees the complete images in the midst of planning and test time so that it certainly encodes important information almost the lesson as well as the appearance of the image. DeepSort is a machine-learning model for tracking and assigning IDs to each object [42].

The proposed model shortens chicken labels according to the given annotations and coordinates that allow tracking the trajectory of chicken objects for mapping the location of chickens in the cage. Figure 1 shows an example image from a video data collection of chickens with different conditions. Figure 1(a) shows an example of an image with bright light occlusion, Figure 1(b) shows an show example of an image with normal lighting, and Figure 1(c) shows an examples of images with different camera angles.

(a) (b) (c)

Figure 1. Sample images from a chicken video dataset; (a) bright light occlusion, (b) normal lighting, and (c) different camera angles

The model used shows the proposed YOLOv8 architecture has steps such as load videos, converting videos to images, labeling, and annotation, dividing images to “train”, “test”, and “Val”, training images and their labels in .xml format, proposing preprocessing (oriented, resize, contrast, grayscale, and tile) and augmentations (flip, rotation, and bounding box brightness) when training. Apart from that, optimization was also carried out using the ADAMW optimizer, evaluation of trained YOLOv8 detection using test data, validation of the trained model with unseen images data, the validation tracking process also uses ByteTrack algorithm to identify each chicken, and the last is show results. The YOLOv8 architecture used in the development of the tracking model for mapping the location of lameness chickens see in Figure 2.

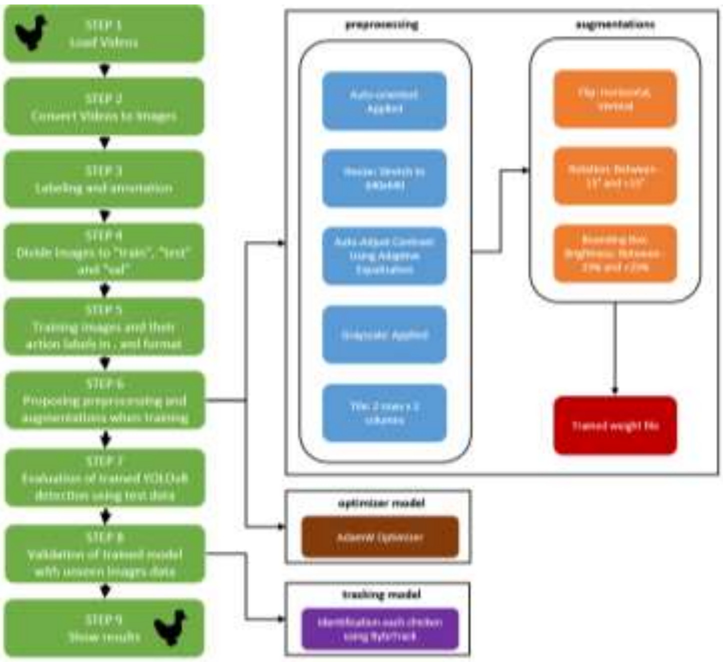

Figure 2. The YOLOv8 architecture was used in the development of tracking models for mapping the location of lameness chickens

Tracking chickens that come from the video, in the process displays the label of chickens that are lameness or not with the coordinated location that is inside the cage. In the proposed model, the detection of chickens in the form of a box frame with labels as well as IDs uses a filter, Kalman. Kalman filter determines the centroid ID on each frame, each detected chicken has an ID one by one, and the ID will follow every movement of the chicken. The ID will sometimes disappear when encountering occlusions such as feed, and will reappear after the occlusion disappears. The movement of the chicken will produce a line trace that can help to map the location at which coordinates the chicken is located. The illustration of the tracking framework and location mapping see in Figure 3.

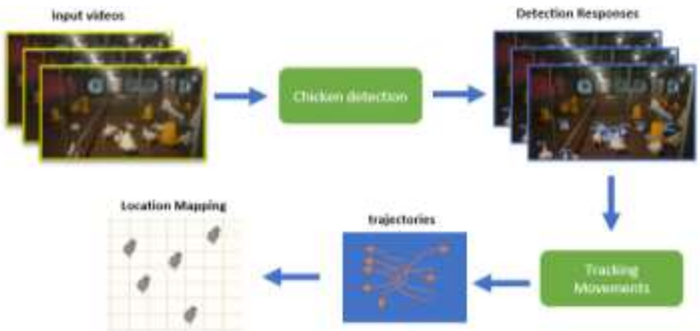

Figure 3. Illustration of location tracking and mapping framework

3.1. Data collection

Dataset used in this consider is video data of broiler chickens taken from a chicken coop for several days with a variety of different lighting conditions, as well as camera positions, angles, and heights for video shooting are varied. The chicken coops are located in two chicken farms located in the Kudus city. The chicken coop is 100 meters long and 30 meters wide, but for data collection the camera is focused on taking video of the insulated coop with a size of 10 square meters.

The camera used is a yi lite action camera with a 150° ultrawide lens capability so that the viewing distance for video data of chickens in the cage obtained will be wider. Video is recorded using a resolution of 1,920×1,080 pixels at 30 fps, with a total of 18,000 frames. For labeling data using labeling, each label is marked with an annotation bounding box.

3.2. Pre-processing of chicken dataset

The chicken dataset automatically changes size, changes orientation, crops and reduces noise from the image data. The Python programming environment was used for the data preprocessing step. In addition, the data was converted to grayscale and contrast-corrected. This is done in order to improve the dataset for analysis purposes and generate a model that performs better. The process carried out at the preprocessing stage is auto-orient with applied value; resize with stretch to 640×640 value; auto-adjust contrast with using adaptive equalization value; grayscale with applied value; tile with 2 rows×2 columns value.

3.3. Augmentations of chicken dataset

Following the previous stage of data preprocessing, the image is flipped, rotated, and its brightness is adjusted to complete the data augmentation stage. By making changes to the current chicken dataset, augmentation is done to expand the amount of data. This data augmentation is done to add more data, which makes the final model more complicated and capable of improving the model's accuracy. The process carried out at the augmentations stage is flip with horizontal and vertical value; rotation with between -15° and +15° value; bounding box with brightness between -25% and +25% value.

3.4. Optimization algorithm for deep learning

An optimizer is an algorithm or technique that changes features of your neural network, such as learning rate and weights, to reduce loss. Optimization algorithms find parameter values, also known as "weights," that reduce errors when connecting inputs to outputs. By minimizing functions, optimizers are used to solve optimization problems [43]. There are various optimizer algorithms that can be used in YOLO such as root mean square (RMS)Pop, SGD, ADAM, and ADAMW.

One of the most well-liked optimizers among deep learning aficionados is RMSProp. This optimizer removes history from the extreme past and optimizes CNN models using the exponential decay average approach. When using RMSProp, different parameters are chosen and the learning rate (LR) is automatically adjusted. LR is divided by the squared gradient's average exponential decay for RMSProp. This optimizer is a highly efficient deep learning method [44]. The algorithm's primary goal is to speed up optimization by reducing the quantity of function evaluations required to get to the local minimum.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{(1-\gamma)g_t^2 + \gamma\, gt + \epsilon}} \cdot g_t \tag{1}$$

In essence, the SGD greatly simplifies gradient descent (GD). Gradient descent is a strategy for minimizing an objective function using the model parameters that involves updating the parameters in the opposite direction of the gradient objective function with respect to the parameters [45]. Unlike the GD, where gradient is estimated precisely for each sample, the SGD estimates gradient based on a single randomly chosen example for each iteration. During SGD, oscillations in either direction of the gradient are used to update the weights. Even so, adding a small amount of the previous version to the current update will speed up the process a little. One thing to remember while using this algorithm is that the learning rate should be lowered by using a high momentum term.

$$\theta_{t+1} = \theta_t - n_t \nabla_{\theta^t}(\theta_t;\, x^{(t)}, y^{(t)} \tag{2}$$

A well-liked deep learning optimization method is the ADAM optimizer, also called the adaptive moment estimation optimizer. It is an extension of the SGD technique and is meant to update the weights of a neural network during training. ADAM lowers the computational cost, uses less memory to implement, and maintains its invariance when the gradients are rescaled diagonally. Large data sets, hyperparameters, noisy data, insufficient gradients, and nonstationary problems requiring minor tweaking are among the challenges this resolves [46]. The creators of the ADAM optimizer used the beneficial features of various optimization methods, such as RMSProp. The ADAM optimizer computes the uncentered variance of the gradients (without subtracting the mean), unlike RMSProp, which also considers the second moment of the gradients.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\left[\frac{\delta L}{\delta wt}\right] v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta \omega_t}\right]^2 \tag{3}$$

ADAMW optimization is a SGD method based on adaptively estimating first- and second-order moments, and it includes a method to decay weights. The ADAMW optimizers were proposed as a solution to the overfitting and steep learning rate drop issues that plagued the ADAM optimizer [35]. By separating the weight decay from the gradient updates, ADAMW, a stochastic optimization technique, addresses the known convergence issues with ADAM by altering the standard implementation of weight decay.

$$\theta_{t+1,i} = \theta_{t,i} - \eta\left(\frac{1}{\sqrt{\hat{v}_{t+\epsilon}}} . \hat{m}_t + w_{t,i}\theta_{t,i}\right), \forall t \tag{4}$$

To put it briefly, optimizer algorithms which alter a neural network's weights and learning rate include RMSProp, SGD, ADAM, and ADAMW. They are used to reduce loss. Consequently, this study broadens the scope of optimizer algorithms in YOLO by employing chicken datasets for analysis.

3.5. Object tracking algorithm

In the field of video analytics, object tracking is an essential function that not only locates and categorizes objects within the frame but also keeps track of each identified object's unique ID during the course of the video. The uses are endless and include everything from real-time sports analytics to security and surveillance. A well-known object tracking program called BotSort tracks items in a video sequence by utilizing deep learning methods. To track things over several frames, it combines appearance matching and object detection. To identify items in each frame, BotSort employs a pre-trained object identification model, like YOLO or faster R-CNN. Subsequently, appearance matching is employed to monitor the identified objects by designating distinct IDs to every object and comparing them according to their visual characteristics. It has been demonstrated that BotSort achieves cutting edge results on multiple object tracking benchmarks [36]. Another object tracking technique, ByteTrack, tracks things in a video sequence by utilizing a thin neural network architecture. Utilizing a Siamese network design, it compares two input frames to determine whether the objects are the same and outputs a similarity score. ByteTrack boosts its speed on difficult datasets with a straightforward yet powerful data augmentation method. It is demonstrated that ByteTrack performs better than a number of cutting-edge object tracking algorithms, utilizing fewer parameters and obtaining quicker inference times [38].

In summary, a key component of computer vision is object tracking, which is the ongoing recognition and observation of objects in a video sequence. It guarantees that, in spite of variations in appearance and circumstances, the course of an object is consistently tracked. For accuracy, a variety of methods are used, such as deep learning techniques and Kalman filters. Well-known item tracking methods include BotSort and Bytetrack.

3.6. Impelentation environment

The environment utilized for YOLO analysis with chicken datasets is implemented using a number of optimizer approaches and multi-object tracking algorithms. The Python programming language was used on the Anaconda platform, utilizing a Jupyter notebook and the sklearn packages [22]. Operating system: Microsoft Windows 10 Pro; Processor: Intel(R) Core(TM) i5-7200U CPU @2.50 GHz (4 CPUs); memory: 12288 MB RAM; Disk: 250 GB SSD; GPU: 2 GB NVIDIA GeForce 940MX; All experiments were conducted using these specifications. In this section, deep learning analysis on the chicken dataset is implemented based on the optimizer algorithm like RMSProp, SGD, ADAM, and ADAMW. Besides that, multi-object tracking algorithm like BotSort and ByteTrack also used to help object tracking analysis.

3.7. Evaluation method

The analysis of the chicken dataset in this chapter is based on four metrics for the optimizer algorithm and two metrics for the multi-object tracking algorithm. The metrics used for YOLO analysis with the algorithm optimizer are mAP, recall, precision, and F1-score. Meanwhile, the metrics used to analyze YOLO with the multi object tracking algorithm are: multi-object tracking accuracy (MOTA) and inference time(s). The analysis in this research is based on experiments, (4) different advanced evaluation metrics have been selected to test the strengths and weaknesses of the YOLO method technique with this optimizer algorithm, as well as (2) evaluation metrics to test the capabilities of the multi-object tracking algorithm. Evaluation metrics in chicken tracking methods for location mapping are presented in this subsection:

$$mAP@_{\alpha} = \frac{1}{n}\sum_{i=1}^{n} AP_i \ for \ n \ classes. \quad (5)$$

$$precision = \frac{TP}{TP+FP} \quad (6)$$

$$recall = \frac{TP}{TP+FN} \quad (7)$$

$$F1 = 2 * \frac{1}{\frac{1}{precison}+\frac{1}{recall}} \quad (8)$$

$$MOTA = 1 - \frac{\sum_t FN_t + FP_t + IDS_t}{\sum_t GT_t} \quad (9)$$

4. RESULTS AND DISCUSSION

After a successful combination of optimizer and object tracking algorithm experimental study of the YOLO model. This section presents the findings and a discussion of the experimental analysis of the chicken dataset used in this investigation. This section presents a detailed analysis of four standard metrics for evaluating chicken datasets, namely; MAp, precision, recall, and F1-score. The method evaluated and discussed is YOLO with a combination of the RMSProp, SGD, ADAM, and ADAMW optimizer algorithms. This section also presents a detailed analysis of the evaluation of the YOLO method with a combination of object tracking algorithms such as BotSort and ByteTrack using the MOTA metric.

4.1. Results

The process of detecting and tracking chickens is a challenging thing to do, by tracking, can produce information about mapping the location of chickens. However, real-time tracking is not something easy, this is because clear video/image data is needed so that it can be verified or detected easily. Unclear video/image data, and many occlusions can cause detection results to be not optimal.

In this study, YOLOv8 with customization was selected to detect, track and map the location of chickens. In the process of detection, chicken objects are labeled into two, namely: healthy chickens and lame chickens. A label maker is a box in which there is a chicken object. The epoch was gradually added to find the best model training results, and at the 100th epoch, the training results were obtained with high accuracy values. The results of chicken detection and tracking samples see in Figure 4.

Figure 4. Chicken detection and tracking sample results

The evaluation results are based on advanced performance metrics in deep learning in general, the metrics are mAP, precision, recall, F1-score [47], all experimental parameters remain the default for the five methods used in combination with the optimizer algorithm and multi object tracking algorithm. As discussed previously in section 3, a comparison of the results of four different optimizer algorithms and two multi object tracking algorithms on the chicken dataset is presented. The values for all other performance metrics range between 0 and 1. The closer the metric value is to 1, the better the method. The results of performance analysis of YOLOv8 methods with optimizer see in Table 1 and the results of performance analysis of YOLOv8 methods with multi object tracking see ini Table 2.

Table 1. performance analysis of YOLOv8 methods with optimizer

Methods	YOLO v8	YOLOv8+ADAMW optimizer	YOLOv8+default optimizer	YOLOv8+ADAM optimizer	YOLOv8+SGD optimizer	YOLOv8+RMSProp optimizer
mAP	0.858	0.936	0.935	0.922	0.905	0.001
Precision	0.986	0.993	0.987	0.989	0.987	0.004
Recall	0.969	0.990	0.928	0.983	0.980	0.127
F1-score	0.977	0.991	0.957	0.986	0.983	0.008

Table 2. Performance analysis of YOLOv8 methods with multi object tracking

Methods	YOLOv8+Bot-sort	YOLOv8+ByteTrack
MOTA	0.893	0.886
Inference time(s)	0.3	0.2

4.2. Discussion
4.2.1. mAP
Figure 5 explains that the mAP of the YOLOv8 methods with optimizer algorithm using the chicken dataset in this research. YOLOv8, YOLOv8+ADAMW optimizer, YOLOv8+default optimizer, YOLOv8+ADAM optimizer, YOLOv8+SGD optimizer, YOLOv8+RMSProp optimizer with 0.858, 0.936, 0.935, 0.922, 0.905, 0.001 respectively. Because the method that has a value closest to 1 is the best method, then YOLOv8+ADAMW is better than the other methods.

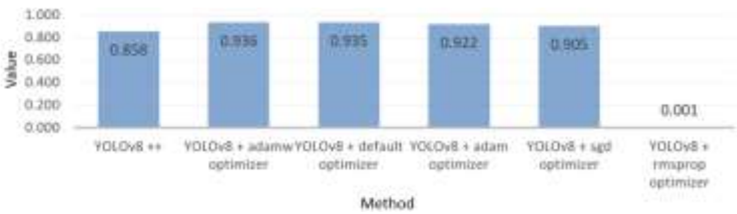

Figure 5. YOLOv8+optimizer for chicken dataset mAP

4.2.2. Precision
Figure 6 explains that the Precision of the YOLOv8 methods with optimizer algorithm using the chicken dataset in this research. YOLOv8, YOLOv8+ADAMW optimizer, YOLOv8+default optimizer, YOLOv8+ADAM optimizer, YOLOv8+SGD optimizer, YOLOv8+RMSProp optimizer with 0.986, 0.993, 0.987, 0.989, 0.987, 0.004 respectively. Because the method that has a value closest to 1 is the best method, then YOLOv8 + ADAMW is better than the other methods.

Figure 6. YOLOv8+optimizer for chicken dataset precision

4.2.3. Recall
Figure 7 explains that the recall of the YOLOv8 methods with optimizer algorithm using the chicken dataset in this research. YOLOv8, YOLOv8+ADAMW optimizer, YOLOv8+default optimizer,

YOLOv8+ADAM optimizer, YOLOv8+SGD optimizer, YOLOv8+RMSProp optimizer with 0.969, 0.990, 0.928, 0.983, 0.980, 0.127 respectively. Because the method that has a value closest to 1 is the best method, then YOLOv8+ADAMW is better than the other methods.

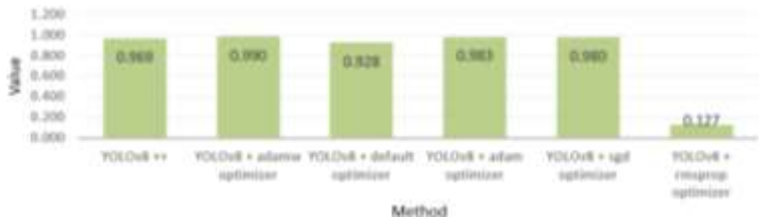

Figure 7. YOLOv8+optimizer for chicken dataset recall

4.2.4. F1-score

Figure 8 explains that the F1-score of the YOLOv8 methods with optimizer algorithm using the chicken dataset in this research. YOLOv8, YOLOv8+ADAMW optimizer, YOLOv8+default optimizer, YOLOv8+ADAM optimizer, YOLOv8+SGD optimizer, YOLOv8+RMSProp optimizer with 0.977, 0.991, 0.957, 0.986, 0.983, 0.008 respectively. Because the method that has a value closest to 1 is the best method, then YOLOv8+ADAMW is better than the other methods.

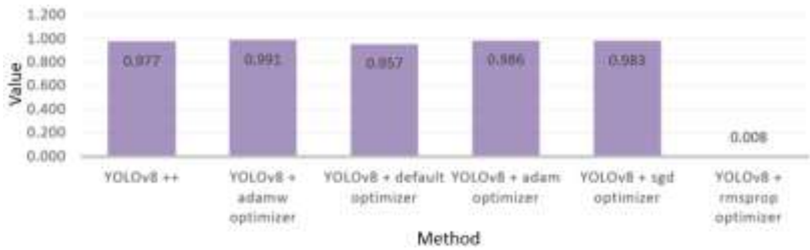

Figure 8. YOLOv+optimizer for chicken dataset F1-score

4.2.5. Multi-object tracking accuracy

Figure 9 explains that the MOTA of the YOLOv8 methods with multi object tracking algorithm using the chicken dataset in this research. YOLOv8+BotSort, YOLOv8+ByteTrack with 0.893, 0.886 respectively. Because the method that has a value closest to 1 is the best method, then YOLOv8+BotSort is better than ByteTrack.

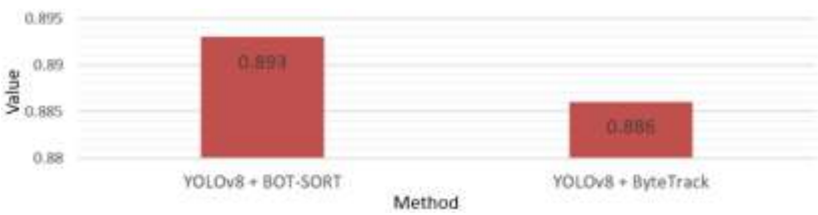

Figure 9. YOLOv8+multi object tracking for chicken dataset MOTA

4.2.6. Inference time(s)

Figure 10 explains that the inference time(s) of the YOLOv8 methods with multi object tracking algorithm using the chicken dataset in this research. YOLOv8+BotSort, YOLOv8+ByteTrack with 0.3, 0.2 respectively. Because the method which takes less time is the best, then YOLOv8+ByteTrack is better than the BotSort.

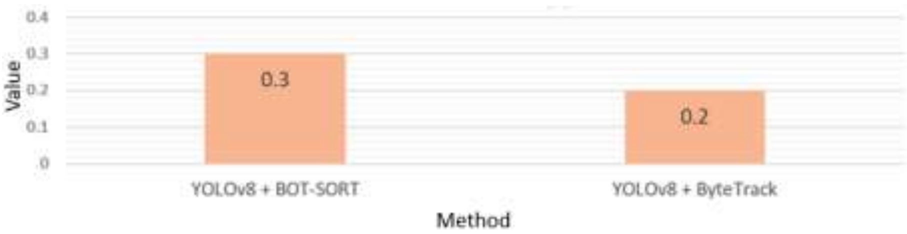

Figure 10. YOLOv8+multi object tracking for chicken dataset inference time(s)

5. CONCLUSION

The following conclusions can be made in light of the research's findings: YOLOv8 with various combinations of optimizer algorithms such as ADAMW, ADAM, and SGD can be used to detect lame chicken objects well, while rmsprop is not able to provide good performance because the training process is completed early because it does not there is an increase in observed epochs. But from the various combinations of optimizer algorithms, ADAMW has the best mAP, support, precision and F1-score values compared to the others. Meanwhile, for multi object tracking, it can be concluded that the BOT-sort algorithm has better accuracy for the chicken tracking process than the ByteTrack algorithm, however ByteTrack is faster in inference time(s) so ByteTrack is more suitable for the real time tracking process. The YOLOv8 custom model also does not limit the possibility of being used in monitoring other livestock, so that the welfare of chickens can be checked in real-time and can avoid crop failure. The color of the background, occlusion, chicken herd, and camera position affect the results in detecting chicken activity. High-accuracy results and a faster detection process, are very suitable for real-time monitoring. The results of this study, lameness chickens or healthy chickens that have been detected will be tracked through movement activities, movement activities produce track tracks that can be used to determine the location of the chicken in the cage.

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BIOGRAPHIES OF AUTHORS

Wiwit Agus Triyanto is a student at Doctoral Program of Information Systems, School of Postgraduate Studies, Diponegoro University, Semarang, Indonesia. Completed the master's education at Dian Nuswantoro University, Semarang, Indonesia and before also completed the bachelor's degree in the information system at Muria Kudus University, Kudus, Indonesia. His work is a lecturer in Department of Information Systems, Faculty of Engineering, Muria Kudus University. His research interest software engineering, data mining and computer vision. He can be contacted at email: at.wiwit@umk.ac.id.

Prof. Dr. Kusworo Adi is Professor at college of Department of Physics, Faculty of Sciences and Mathematics, Diponegoro University, Indonesia. Then the master's education at the Bandung Institute of Technology, Indonesia, majoring in electrical engineering in 2000 to 2002. Doctoral education at the Bandung Institute of Technology, Indonesia, majoring in electrical engineering in 2005 to 2010. Research area in the field of instrumentation and image processing. Several publications received in reputable international journals, especially in the field of instrumentation and image processing. The research being carried out now is about transportation safety by utilizing the development of instrumentation and image processing. He is currently a member of the IEEE. He can be contacted at email: kusworoadi@lecturer.undip.ac.id.

Jatmiko Endro Suseno, S.Si., M.Si., Ph.D., F.Med. is lecturer at College of Department of Physics, Faculty of Sciences and Mathematics, Diponegoro University, Indonesia. Then the bachelor's education at the Diponegoro University, Semarang, Indonesia in 1997. Master's education at the Bandung Institute of Technology, Bandung, Indonesia in 2003. Doctoral education at the University of Technology, Malaysia in 2012. Profession education at the Diponegoro University, Semarang, Indonesia in 2023. Research area in the field of instrumentation and electronics physics. He can be contacted at email: jatmiko@fisika.fsm.undip.ac.id.