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Research article

Counting sheep: human experience vs. Yolo algorithm with drone to determine population

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Abstract

This study assessed the efficiency of traditional human counting methods and the YOLOv7 algorithm in sheep population management at SAIS Pachacutec S.A.C., Peru. Human counters with varying experience levels (M1-M4) and the YOLOv7 algorithm (M5) were evaluated across six sheep flocks of different sizes. Traditional counting involved "linear pair counting" with human assistants, while the YOLOv7 algorithm utilized drone-captured images for automated counting. Using ANOVA and post-hoc tests, data analysis indicated that 24 months of human experience achieved 100% accuracy, highlighting the importance of expertise in accurate population management. The YOLOv7 algorithm achieved 85% accuracy, affected by factors such as the number of training images, hardware limitations, and training parameters. Despite its lower accuracy, YOLOv7 significantly reduced counting time compared to manual methods, making it a viable option for rapid object counting tasks. Further improvements in algorithm training and computational resources could enhance the algorithm's accuracy. These findings suggest that while human expertise remains critical for precise sheep counting, advancements in computer vision algorithms like YOLOv7 offer promising support, particularly for reducing counting time.

Keywords: Computer vision, Counting accuracy, Precision livestock farming, Sheep counting, YOLOv7 algorithm.

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INTRODUCTION

Peru is a megadiverse country with a significant number of sheep in production, with SAIS PACHACUTEC SAC being a representative enterprise for this species (Carhuas et al., 2023). Enumerating livestock is a fundamental practice in managing livestock activities, including dipping, weaning, breeding, lambing, shearing, and particularly for population control (Sarwar et al., 2021; Wu et al., 2022; Carhuas et al., 2024). Accurate livestock accounting is crucial for maintaining precise records of animal populations (Bailey et al., 2021). However, conducting individual sheep counts without technological support presents a considerable challenge for producers, shepherds, and professionals involved in animal production management (Sarwar et al., 2021; Deng et al., 2022). These challenges include time investment and the likelihood of estimation errors, negatively impacting the efficiency and accuracy of the counting process. To address these challenges, research in mathematical models, machine learning, and drone-based algorithms has gained prominence (Sarwar et al., 2018; Lu et al., 2019; Cheng et al., 2021; Deng et al., 2022; Xu et al., 2022). Advanced algorithms such as YOLO (You Only Look Once) facilitate more precise estimates of animal counts. Nonetheless, the application of these technologies is not without obstacles. These limitations include the high cost of equipment, the lack of accessibility for field shepherds, and the ongoing need for research on the accuracy and reliability of these models (Foley et al., 2020).

Previous studies have demonstrated that the accuracy of sheep counting tends to improve as the animal population decreases, yet significant errors persist in larger populations (Fan et al., 2022; Mpouziotas et al., 2023). This issue is particularly relevant for sheep producers, who typically manage flocks ranging from 800 to 1,500 animals (Carhuas et al., 2024). Additionally, ear tagging devices have been used for animal counting but can cause injuries, infections, and shock, not to mention the high cost of the devices (Khan and Basalamah, 2021). Accurate sheep population counts facilitate better record-keeping and animal control and help prevent losses, theft, straying, and deaths (Moharram et al., 2023). Given the current challenges and technological innovations such as the implementation of precision livestock farming, this study aims to evaluate the efficiency of sheep counting between human expertise and the YOLOv7 algorithm. The independent variables considered were M1 (Personnel with no experience), M2 (Six months of experience), M3 (One year of experience), M4 (Two years of experience in sheep counting), and M5 (Counting with the algorithm). The dependent variable was the accuracy and counting time.

MATERIALS AND METHODS

The research ethics with the use of animals was approved by Directorate of Agriculture Junín, with its Agricultural Agency Concepción: with LETTER N° 007-GRJ-DRA-AAC-PERÚ-2023: approves the research “COUNTING SHEEP: HUMAN EXPERIENCE VS. YOLO ALGORITHM WITH DRONE TO DETERMINE POPULATION". The authors followed and complied with ethical principles in the use of animals. In this case, in sheep

Study Area

The study was conducted at the "SAIS Pachacutec S.A.C" enterprise, within the Corpacancha Production Unit (11°21'46'' S; 76°13'11'' W), located in the Marcapomacocha district, Yauli Province, Junín Region, Peru (Figure 1). This enterprise is part of the livestock sector, producing over 60,000 Corriedale sheep, 17,000 alpacas, and 4,000 cattle. Additionally, it produces by-products such as cheese, butter, yogurt, dulce de leche, mortadella, ham, and sausages, which are sold in local and national markets. This geographical area is situated at 4,149 meters above sea level, with dry (May-August) and rainy (September-April) seasons, an average temperature ranging from -0.6°C to 11°C, and an average annual precipitation of 700 mm (Senamhi, 2023).

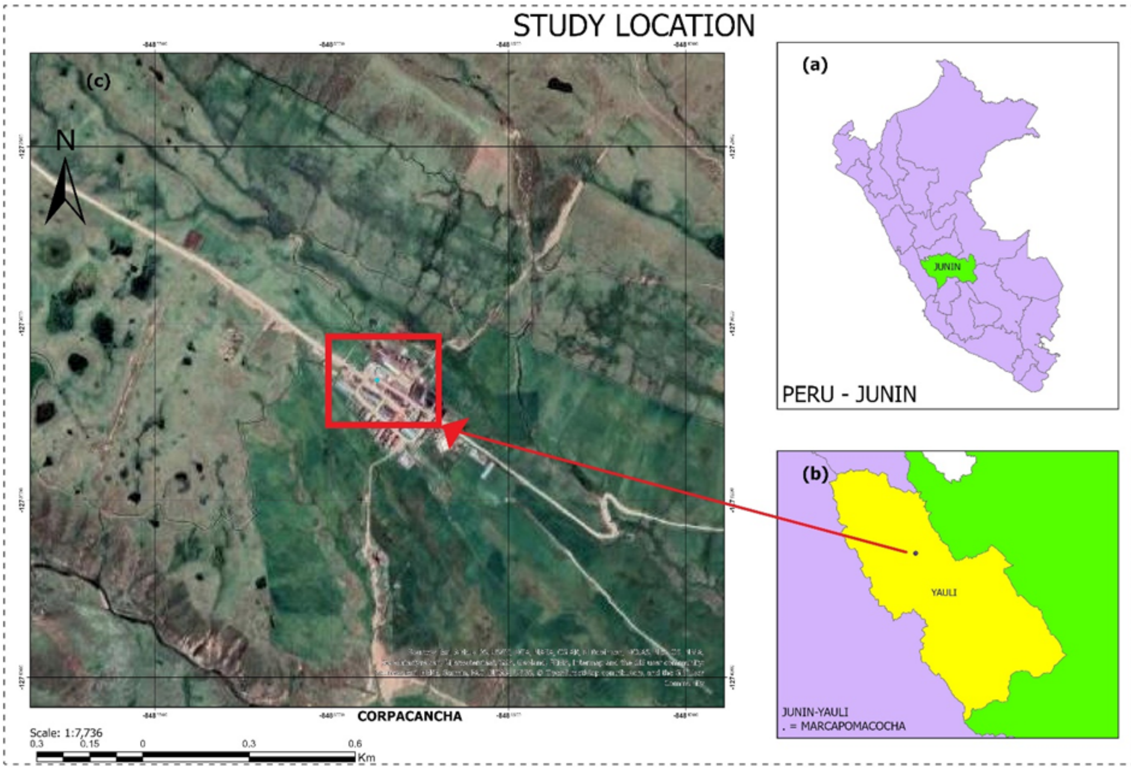

Figure 1 Location of study, (a) map of Peru by regions, green color, shows the Junin region. (b) yellow color, map of the Yauli, (c) map of Corpacancha which belongs to the SAIS PACHACUTEC SAC.

Data collection

Six sheep flocks were visited (n = 26, 50, 105, 324, 600, and 800 animals), all of which were well-controlled and accurately recorded. The study considered human experience (M1, M2, M3, and M4) and image capture for processing with the YOLO algorithm (M5) for sheep counting.

Traditional Counting

The method employed was the "linear pair counting." Two "blockers" (individuals who prevented sheep from crossing sideways) were selected (Figure 2c). Subsequently, one person, referred to as the "pusher" (an individual who used hand movements to direct the sheep linearly), was chosen (Figure 2c). The counter (Figure 2c) was responsible for counting in pairs (every two animals counted as one unit) until all sheep passed the intersection of the counter and pusher. The final count is depicted in Figure 2b. After counting, the number obtained by the counter was compared with the population records maintained by the shepherds. This process was repeated for all the flocks.

Image Capture by Drone

The method was developed using an unmanned aerial vehicle (drone) DJI MINI 3 (Figure 2d) to capture images (3840×2160) of the flocks. These images were taken after each traditional counting and for all the flocks.

Image Processing

A total of 152 images of sheep were captured using the drone for labeling in Roboflow. The YOLOv7 algorithm was utilized on an Intel® Core™ i5-8300H CPU computer, with 8192 MB of RAM and 8039 MB of NVIDIA GeForce GTX 1050. YOLOv7 is renowned for its efficiency and accuracy in computer vision tasks. The torch library was used to handle tensor operations and the training backend. The YOLOv7 model employed consisted of 415 layers, with a total of 37,196,556 parameters and the same number of gradients. The model's processing capacity was 105.1 GFLOPS (Giga Floating Point Operations Per Second). A scaled weight decay of 0.0004921875 was utilized. The optimizer groups were configured with 95 for. bias, 95 for conv.weight, and 98 for other parameters. Automatic anchor analysis resulted in an anchors/target ratio of 3.88 and a Best Possible Recall (BPR) of 0.9996. Training was conducted in batches of 7 over 50 epochs. The accuracy was determined using the following formula:

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

where, TP (True Positive) and FP (False Positive).

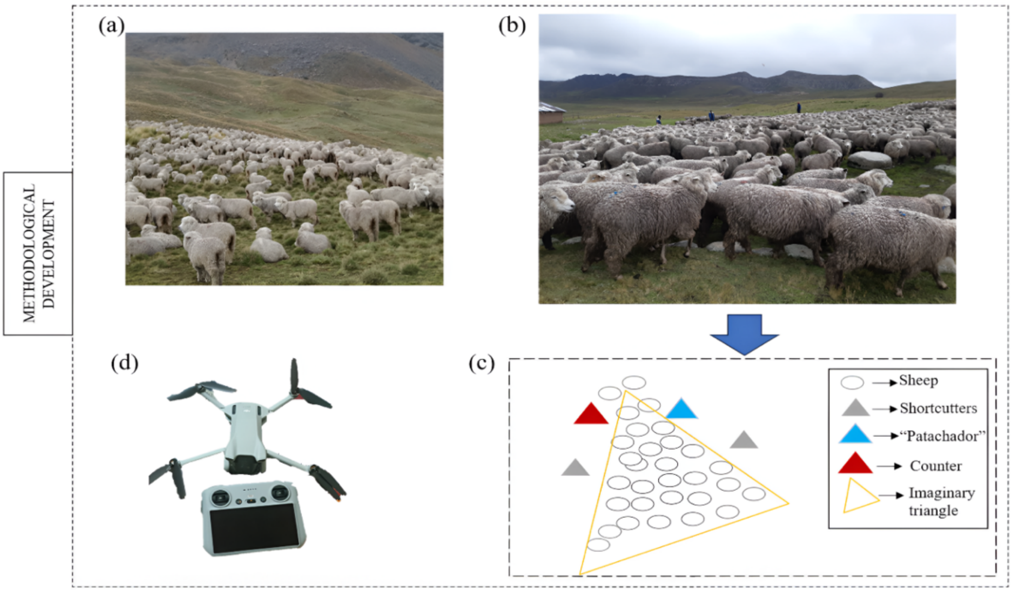

Figure 2 Methodology for data collection. (a) herds of animals; (b) w Traditionally counting; (c) traditional counting method. (d) Drone, which captured images of the sheep herds.

Statistical Analysis

recorded data on counting accuracy and required time were documented in a field book and subsequently entered into Microsoft Excel. Differences between methods (M1, M2, M3, M4, and M5) for the sample groups were analyzed using Analysis of Variance (ANOVA), followed by a post-hoc multiple comparison test. A value of $P<0.05$ was considered statistically significant. All statistical analyses were performed using CRAN R software (R Core Team, 2019).

RESULTS

After training the YOLOv7 model for sheep detection and counting, inferences were made on new images to evaluate its performance. From Figure 3, the model successfully detected and counted 300 sheep. The inference time was 74.8 milliseconds, while the Non-Maximum Suppression (NMS) process took 500.3 milliseconds.

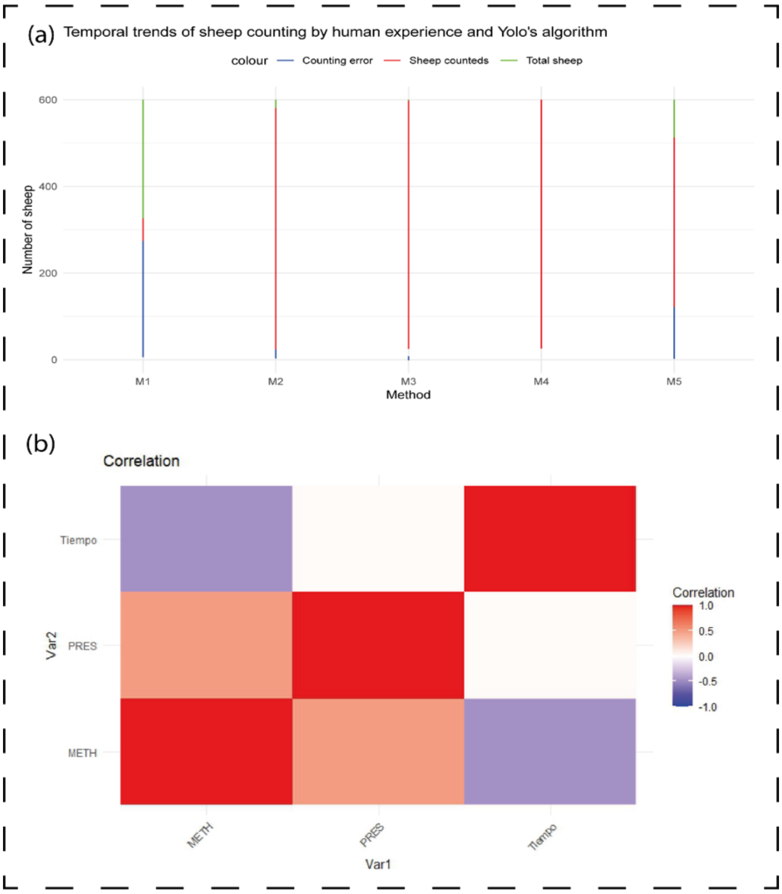

Figure 3 Temporal trends and correlation of the sheep count. Meth = Method, PRES = Accuracy, Tiempo = Time of count.

Recontouring with the Yolov7 algorithm

After training the YOLOv7 model for sheep detection and counting, inferences were made on new images to evaluate its performance. From Figure 4, the model successfully detected and counted 300 sheep. The inference time was 74.8 milliseconds, while the Non-Maximum Suppression (NMS) process took 500.3 milliseconds.

Counting time

From Table 1, significant differences ($P < 0.05$) were observed between the human experience methods and the YOLOv7 algorithm method, with M5 achieving the shortest counting time of 2 minutes, compared to an average of 5.6 minutes for the experience-based methods. No significant differences ($P > 0.05$) were found among the human experience methods. The correlation between the method and time (Figure 3b) showed a negative correlation ($r = -0.46$).

Figure 4 Sheep identified and counted with the Yolov7 algorithm. The green square implies an identification of the sheep.

Counting accuracy

From Figure 5, significant differences ($P < 0.05$) were observed between the methods. M4 achieved the highest accuracy with 100% ± 3.32, followed by M3 with 98.10% ± 3.32, M2 with 91.78% ± 3.32, and the YOLOv7 algorithm (M5) with 85% ± 3.32. M1 had the lowest accuracy, with 60.92% ± 3.32. Regarding the correlation (Figure 3b) between the counting method and accuracy, a positive correlation was found ($r = 0.49$).

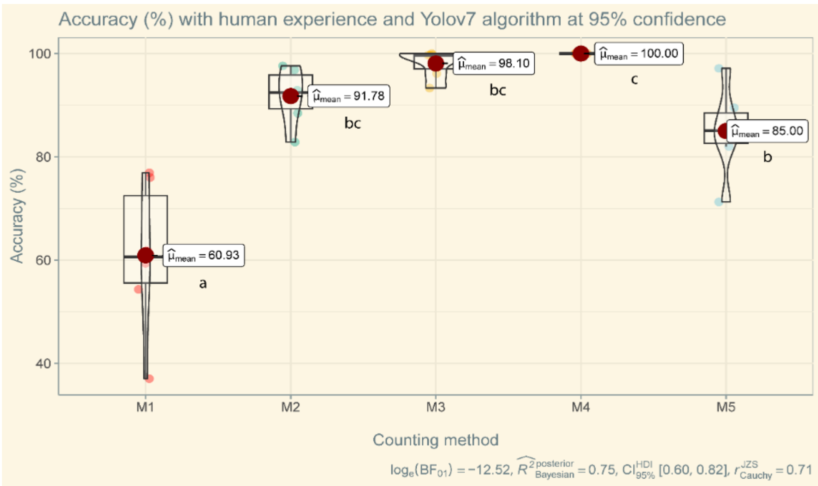

Figure 5 Average accuracy with human experience and Yolov7 algorithm. a,b = equal letters imply statistical similarity P>0.05.

Table 1 Time required for counting with human expertise and computer vision

	Mean	sd	Min	Max
M1	5.6[a]	2.06	3	3
M2	5.6[a]	2.06	3	3
M3	5.6[a]	2.06	3	3
M4	5.6[a]	2.06	3	3
M5	2[b]	0	2	2

[a, b] *different letters imply significant differences by tukey's test (P<0.05)*

DISCUSSION

While human experience proved to be more accurate than the proposed algorithm, with training parameters set to batch = 10 and 100 epochs, there is potential to further develop the algorithm for animal identification and counting.

Counting accuracy and time

The highest accuracy was achieved by individuals with 24 months of experience (100%) in sheep counting, resulting in an exact count of the flock population. Animal counting experience is essential for effective population management. Field personnel typically perform the counting process, but professionals need to master this skill to maintain precise population records. Novices often make numerous counting errors, whereas experienced individuals can achieve nearly perfect counts. The YOLOv7 algorithm, on the other hand, achieved an 85% accuracy rate.

This result is lower than that reported by Moradeyo et al. (2023), who demonstrated up to 95% accuracy using the YOLOv7 algorithm. The disparity is attributable to their use of 1,050 labeled images for training, highlighting that less training data and fewer epochs result in lower object identification accuracy. Conversely, it aligns closely with the findings of Rančić et al. (2023), who reported an 86% accuracy using YOLOv5 for deer counting with 2,340 images for training. However, the counting accuracy of sheep using the YOLOv7 algorithm surpassed that reported by Popek et al. (2023), who found an 83% accuracy, and Takyudin et al. (2023), who observed a 70% accuracy in animal counting.

The superior accuracy in this study compared to others can be attributed to advancements in the YOLO algorithm over time and the number of images used for training, as well as the batch size and epochs employed. Multiple studies have shown that models trained on single-sample datasets collected in the field face significant limitations and experience a notable decline in detection accuracy when applied to other datasets (Cheng et al., 2021; Dandrifosse et al., 2022). The small size of sheep and their quantity in a single image posed challenges for detection models (Song et al., 2022). These structures inevitably involve a greater number of parameters, which impose specific requirements on computer hardware. The computer used in this study had only 8192 MB of RAM and 8039 MB of NVIDIA GeForce GTX 1050, limiting the model's performance due to constraints in batch size and number of epochs. Additionally, the model training process requires a significant time commitment (Deng et al., 2022; Jiang et al., 2022). Therefore, future research should explore the use of computer vision for sheep counting for the first time.

For counting time, the YOLOv7 algorithm outperformed the traditional manual counting method. YOLO's capability to rapidly detect and classify objects in images and videos makes it a popular choice for tasks requiring precise and high-speed object counting (Lu et al., 2019; Wen and Dai, 2021). The traditional method requires support personnel, which adds time, and if counting errors occur, recounting is necessary, averaging 8–10 minutes per count.

CONCLUSIONS

Human experience in sheep counting proved to be unparalleled, achieving 100% accuracy, underscoring the critical importance of experience and expertise in precise sheep population management. Field professionals must master these skills to maintain accurate records, as initial inexperience often results in numerous errors that decrease with increased practice.

The YOLOv7 algorithm, although less accurate than human counting, demonstrated an improvement in counting speed. However, factors such as the number of labeled images for training, hardware capacity, and model parameters influence the algorithm's accuracy. This suggests that more extensive training and better computational resources could enhance its effectiveness in sheep counting.

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CONFLICT OF INTEREST

There is no conflict of interest among the authors regarding the publication of this article.

REFERENCES

Bailey, D.W., Trotter, M.G., Tobin, C., Thomas, M.G., 2021. Opportunities to apply precision livestock management on rangelands. Front. Sustain. Food. Syst. 5, 611915.

Carhuas, J.N., Paco, J.L.C., Martínez, F.G., Gomez, E.A., Camargo, A.C., Aquino, V.S., De La Cruz, A.R.H., 2023. Inclusion of whey in the diet of fattening rams. Rev. Inv. Vet. Perú. 34(6), e25132-e25132.

Carhuas, J.N., Napoleon, M.S., Villar, F.A., Garcia-Olarte, E., Eulogio, C.Q., Mauricio-Ramos, Y., Payano, I.U., 2024. Urachys anomaly in sheep: incidence and considerations presented in neonatal lambs in the Peru. Online J. Anim. Feed Res. 14(3), 211-217.

Cheng, J., Xiong, H., Cao, Z., Lu, H., 2021. Decoupled two-stage crowd counting and beyond. IEEE Trans. Image. Process. 30(1), 2862-2875.

Dandrifosse, S., Ennadifi, E., Carlier, A., Gosselin, B., Dumont, B., Mercatoris, B., 2022. Deep learning for wheat ear segmentation and ear density measurement: from heading to maturity. Comput. Electron. Agric. 199(1), 107161.

Deng, X., Zhang, S., Shao, Y., Yan, X., 2022. A real-time sheep counting detection system based on machine learning. Inmateh – Agric. Eng. 67(2), 85–94.

Fan, Z., Zhang, H., Zhang, Z., Lu, G., Zhang, Y., Wang, Y., 2022. A survey of crowd counting and density estimation based on convolutional neural network. Neurocomputing. 472(1), 224-251.

Foley, C.M., Fagan, W.F., Lynch, H.J., 2020. Correcting for within-season demographic turnover to estimate the island-wide population of King

Penguins (Aptenodytes patagonicus) on South Georgia. Polar. Biol. 43(1), 251-262.

Jiang, P., Ergu, D., Liu, F., Cai, Y., Ma, B., 2022. A review of Yolo algorithm developments. Procedia. Comput. Sci. 199(1), 1066-1073.

Khan, S.D., Basalamah, S., 2021. Sparse to dense scale prediction for crowd couting in high density crowds. Arab. J. Sci. Eng. 46(4), 3051-3065.

Lu, S., Wang, B., Wang, H., Chen, L., Linjian, M., Zhang, X., 2019. A real-time object detection algorithm for video. Comput. Electr. Eng. 77, 398-408.

Moharram, D., Yuan, X., Li, D., 2023. Tree seedlings detection and counting using a deep learning algorithm. Appl. Sci. 13(2), 895.

Moradeyo, O.M., Olaniyan, A.S., Ojoawo, A.O., Olawale, J.A., Bello, R.W., 2023. YOLOv7 applied to livestock image detection and segmentation tasks in cattle grazing behavior, monitor and intrusions. J. Appl. Sci. Environ. Manag. 27(5), 953-958.

Mpouziotas, D., Karvelis, P., Tsoulos, I., Stylios, C., 2023. Automated wildlife bird detection from drone footage using computer vision techniques. Appl. Sci. 13(13), 7787.

Popek, Ł., Perz, R., Galiński, G., Abratański, A., 2023. Optimization of animal detection in thermal images using YOLO architecture. Int. J. Electron. Telecommun. 69(4), 825-831.

R Team Core, 2019. A language and environment for statistical computing. Available online: https://www.R-project.org/ (Accessed on July 10, 2023).

Rančić, K., Blagojević, B., Bezdan, A., Ivošević, B., Tubić, B., Vranešević, M., Marko, O., 2023. Animal detection and counting from UAV images using convolutional neural networks. Drones. 7(3), 179.

Sarwar, F., Griffin, A., Rehman, S.U., Pasang, T., 2021. Detecting sheep in UAV images. Comput. Electron. Agric. 187(1), 106219.

Senamhi, 2023. National Hydrometeorological Data Serv. Nac. Meteorol. e Hidrol. del Perú. Available online: https://www.senamhi.gob.pe/?p=pronostico-meteorologico (Accessed on July 10, 2023).

Song, S., Liu, T., Wang, H., Hasi, B., Yuan, C., Gao, F., Shi, H., 2022. Using pruning-based YOLOv3 deep learning algorithm for accurate detection of sheep face. Animals. 12(11), 1465.

Takyudin, T., Fitri, I., Yuhandri, Y., 2023. Catfish fry detection and counting using YOLO Algorithm. J. Appl. Inf. Comp. 7(2), 192-197.

Wen, H., Dai, F., 2021. A Study of YOLO Algorithm for multi-target detection. J. Advan. Art. Life. Robot. 2(2), 70-73.

Wu, D., Liao, M.W., Zhang, W.T., Wang, X.G., Bai, X., Cheng, W.Q., Liu, W.Y., 2022. Yolop: you only look once for panoptic driving perception. Mach. Int. Res. 19(6), 550-562.

Xu, J., Liu, W., Qin, Y., Xu, G., 2022. Sheep counting method based on multiscale module deep neural network. IEEE. 10(1), 128293-128303.

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