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Using machine vision to realize semi-automatic sex recognition of chicks

Usando visão computacional para realizar o reconhecimento de sexo semi-automático de pintinhos

Keqiang Li[1]*; Yuqing Wang[2]; Jiannan Yu[3]; Xianglong Li[4]

Highlights

Video-based sex recognition exceeds 90% accuracy with swift inference.
Optimized model cuts parameters by 5%, boosting poultry industry efficiency.
Video methodology enhances reliability, reducing manual workload for scalable sexing.

Abstract

Conventional image-based techniques for discerning the sex of chicks have inherent drawbacks, such as the subjectivity involved in image selection and limited applicability to industrial contexts. In order to tackle these challenges, we employ videos in this study as an alternative to images, and present a more pragmatic approach that is suited to industrial applications. By leveraging an optimized PicoDet model, this methodology identifies telltale reflective attributes within the cloacae region of chicks. This approach also suggests that the sex of the chicks can be determined by calculating the proportion of male chick identifications in the video relative to the total number of images. Experimental findings demonstrate the superior performance of the proposed approach over the YOLO algorithm in terms of both cloacae and chick sex recognition. Optimal recognition efficiency is achieved when the aforementioned proportion falls within the range 60–70%. The accuracy rates for identifying female and male chicks were recorded as 90.34%, 91.33%, and 90.83%, respectively. The scheme developed in this study also achieves a reduction of 5.01% in model parameters, while the running time is shortened to less than 1 s, while maintaining comparable recognition efficiency to that of the PicoDet model. In summary, the method

[1] School of Mathematics and Information Technology, Hebei Normal University of Science and Technology, Qinhuangdao, China. Prof. Dr., Hebei Innovation Center for Smart Perception and Applied Technology of Agricultural Data, Qinhuangdao, China. Prof. Dr., Artificial Neural Network Technology Application and Innovation Team of Hebei Normal University of Science and Technology, Qinhuangdao, China. E-mail: lkq910802@163.com

[2] Hebei Innovation Center for Smart Perception and Applied Technology of Agricultural Data, Qinhuangdao, China. E-mail: 1277579707@qq.com

[3] Artificial neural network technology application and innovation team of Hebei Normal University of Science and Technology, Qinhuangdao, China. E-mail: 18333590625@163.com

[4] Hebei Key Laboratory of Specialty Animal Germplasm Resources Exploration and Innovation, Qinhuangdao, China. E-mail: 15203358192@163.com

* Author for correspondence

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proposed in this paper exhibits enhanced proficiency in regard to recognizing both chick cloacae and their respective sexes. It successfully overcomes the limitations encountered by traditional image-based methodologies, and minimizes model space requirements. Furthermore, by harnessing the power of video, this approach has increased recognition accuracy and operational efficiency, ultimately improving the practicality and dissemination potential of this cutting-edge technology.
Key words: Machine vision. Chick. Sex recognition. Cloaca.

Resumo

As técnicas convencionais baseadas em imagens para determinar o sexo dos pintos apresentam desvantagens inerentes, como a subjetividade envolvida na seleção das imagens e a aplicabilidade limitada em contextos industriais. Para enfrentar esses desafios, neste estudo utilizamos vídeos como alternativa às imagens, apresentando uma abordagem mais pragmática, adaptada a aplicações industriais. Ao utilizar um modelo otimizado do PicoDet, essa metodologia identifica atributos reflexivos característicos na região da cloaca dos pintos. Esta abordagem também sugere que o sexo dos pintos pode ser determinado calculando a proporção de identificações de pintos machos no vídeo em relação ao número total de imagens. Os resultados experimentais demonstram o desempenho superior da abordagem proposta em comparação com o algoritmo YOLO, tanto no reconhecimento da cloaca quanto no reconhecimento do sexo dos pintos. A eficiência ideal de reconhecimento é alcançada quando a proporção mencionada varia entre 60% e 70%. As taxas de precisão para identificar pintos fêmeas e machos foram registradas como 90,34%, 91,33% e 90,83%, respectivamente. O esquema desenvolvido neste estudo também resulta em uma redução de 5,01% nos parâmetros do modelo, enquanto o tempo de execução é reduzido para menos de 1 segundo, mantendo uma eficiência de reconhecimento comparável à do modelo PicoDet. Em resumo, o método proposto neste artigo demonstra uma maior proficiência no reconhecimento tanto da cloaca dos pintos quanto de seus respectivos sexos. Ele supera com sucesso as limitações das metodologias tradicionais baseadas em imagens e minimiza os requisitos de espaço do modelo. Além disso, ao aproveitar o poder dos vídeos, essa abordagem aumentou a precisão do reconhecimento e a eficiência operacional, melhorando, em última instância, a praticidade e o potencial de disseminação dessa tecnologia de ponta.
Palavras-chave: Visão computacional. Pintinho. Reconhecimento de sexo. Cloaca.

Introduction

Determining the gender of chicks is a pivotal task in both traditional and contemporary poultry husbandry. Depending on whether the birds are breeders, broilers, or laying hens, distinct rearing and marketing strategies are employed for each sex. Thus, early knowledge of the chicks' sex and efficient sorting hold the key to optimizing production layout, exploiting the full commercial potential of the operation, and improving industrial efficacy (Rahman et al., 2021; Biederman & Shiffrar, 1987).

At present, the art of chick sexing encompasses two distinct phases: one during egg incubation, and the other post-hatching. Among the post-hatching techniques, the cloacae detection method, feather speed approach, and feather color approach are of paramount significance in determining the chicks' gender. The cloacae detection method, as the most widely used approach, has the virtue of universality, as it transcends the constraints of chick breeds and offers practicality by allowing for sex identification within 5 to 6 h after hatching. Nonetheless, in real-world operations, the accuracy of chick sex identification through cloacae detection remains reliant upon the expertise and experience of the testing personnel. Even skilled technicians can only achieve an accuracy of approximately 95%, which tends to diminish with prolonged identification time (Kaixuan et al., 2022; Escamilla-García et al., 2022).

In recent years, a few scholars have ventured into exploring the use of machine vision technology to determine chick sex. While these efforts have yielded moderate accuracy, they are bound by the cumbersome process of manually screening images, making them unsuitable for the demands of industrial implementation. The feather speed approach and feather color approach rely on the hue of plumage or the growth of wing feathers to differentiate between male and female chicks. However, although this approach seems relatively simple, it necessitates the development of a meticulous genetic characterization system. Constructing such a system through feather speed phenotyping demands a minimum of two or three generations, and given its reliance on advanced breeding techniques, its practicality on a commercial scale is questionable (Robertson et al., 1984; Buitenhuis et al., 2003).

Parallel to these endeavors, numerous scholars have explored the applicability of sex detection methods to hatched eggs, which encompass molecular-based techniques (Harrisson & Vakaet, 1989; Weissmann et al., 2014; Clinton et al., 2001; Weissmann et al., 2013), spectral-based techniques (Rahman et al., 2021; Preusse et al., 2022; Galli et al., 2016; Corion et al., 2022; Göhler et al., 2017; Alin et al., 2019), morphological-based techniques (Zhi et al., 2018; Yilmaz & Dikmen, 2013; 2018; Salgado et al., 2022) and volatile organic compound-based techniques (Webster et al., 2015; Xiang et al., 2021). However, these approaches predominantly target the later stages of incubation, necessitate stringent experimental environments, and entail the use of expensive equipment, which often compromises the integrity of the eggs, thus hindering their broad applicability.

This investigation of the literature illuminates a multifaceted landscape concerning chick sex identification, where the process of determining the chick's sex is intertwined with crucial attributes such as the precision of identification, processing time, cost-effectiveness, and the technology's potential for widespread dissemination. Machine vision, with its vast potential in diverse domains, offers great promise when harnessed for chick sex identification, as this approach is not merely anchored in theoretical underpinnings but can also increase the operational simplicity through a heightened level of semi-automation. Nonetheless, the reliance on image-based approaches for discerning chick gender and the absence of comprehensive cost-effectiveness evaluation diminish the practicality and ubiquity of this cutting-edge technology. To address these gaps, we propose a semi-automatic technique for chick sex identification utilizing the PicoDet framework. A comprehensive evaluation of the model's performance is conducted in terms of model size, number of parameters, execution time, recognition accuracy, and relevant evaluation criteria, thereby representing an in-depth investigation into the feasibility of the method.

Materials and Methods

Ethics statement

This experiment strictly adhered to ethical standards, and no livestock slaughtering activities were involved. All data collection related to livestock was conducted in full compliance with the ethical guidelines set forth by the Animal Ethics Committee of Hebei Normal University of Science and Technology. The experiment received official approval from the committee, confirming that the ethical requirements for conducting the study were met. This approval is documented under certificate number 2024032308.

In order to avoid causing unnecessary pain or stress to the chicks during the anal turning process, the study was performed by professionals with five years of work experience.

To protect data and privacy, data access permissions were strictly limited, and only authorized researchers were allowed to access and process the data, thus ensuring that they were used only for predetermined research or industrial applications. In addition, rigorous privacy and data protection training were provided to all researchers taking part in data processing. The personnel involved needed to understand and follow all data processing policies and procedures to ensure that data processing complied with legal and ethical standards.

Data acquisition

Video data pertaining to the reproductive organs of chicks were acquired through a carefully crafted system comprising an operating table (JIESHIPAI 80cm60cm75cm), a camera device (Apple iPhone 12, HUAWEI nova 10, MI 13), and an illuminating LED desk lamp (MT001CH-11DX). The camera equipment was positioned 40 cm away from the operating table during the video acquisition process.

In order to increase the generalization ability of the model and verify its generality, repeatability and stability, video data on the reproductive organs of 2,000 laying hens of different species were collected in four batches in different production environments between April and August 2023 at Hebei Angel Poultry Breeding Co., Ltd. To adhere as closely as possible to industrial application scenarios, to minimize unnecessary pain and stress to the chicks, and to minimize the impact of prolonged video acquisition time on the birds, the video duration for each chick was set to 2 s. The resolution was 1080×1920 pixels, and the frame rate was 30 frames per second. Professionals were also invited to examine and record the sex of the chicks. In order to avoid the influence of manual discrimination error on the test, multi-strain hybrid chicks were used, as the sex of chicks can be determined according to the color of the feathers, and the accuracy can reach 100%.

Data preprocessing and labeling

Although the video recordings captured the technicians' anal-flip operations, for the purposes of this study, these specific segments were deemed inconsequential and removed, leaving only the images of the complete chick's anus. Artificial identification mainly relies on observing the micro-white globular projection at the junction of the second and third folds on the lower wall of the cloacae, which can be used to judge the sex of chicks based on the refractive effect. When exposed to light, there is a relative relationship between the second and third folds of the lower wall and the white globular projection in male chicks. Specifically, if the second and third folds of the lower wall are bright, the white globular projection will appear dark, and if the second and third folds of the lower wall are dark, the white globular projection will appear bright. It is therefore possible to distinguish the sex of chicks based on these two characteristics of light reflection, and the sex of each chick can be judged according to the degree of light reflection of the two characteristics. Figure 1 shows four images representing different frames of a video of the same chick. The two images in the first row show the reflection characteristics of the male chick's cloaca in the red box, while the two images in the second row do not include the reflex features of the male chick's cloaca.

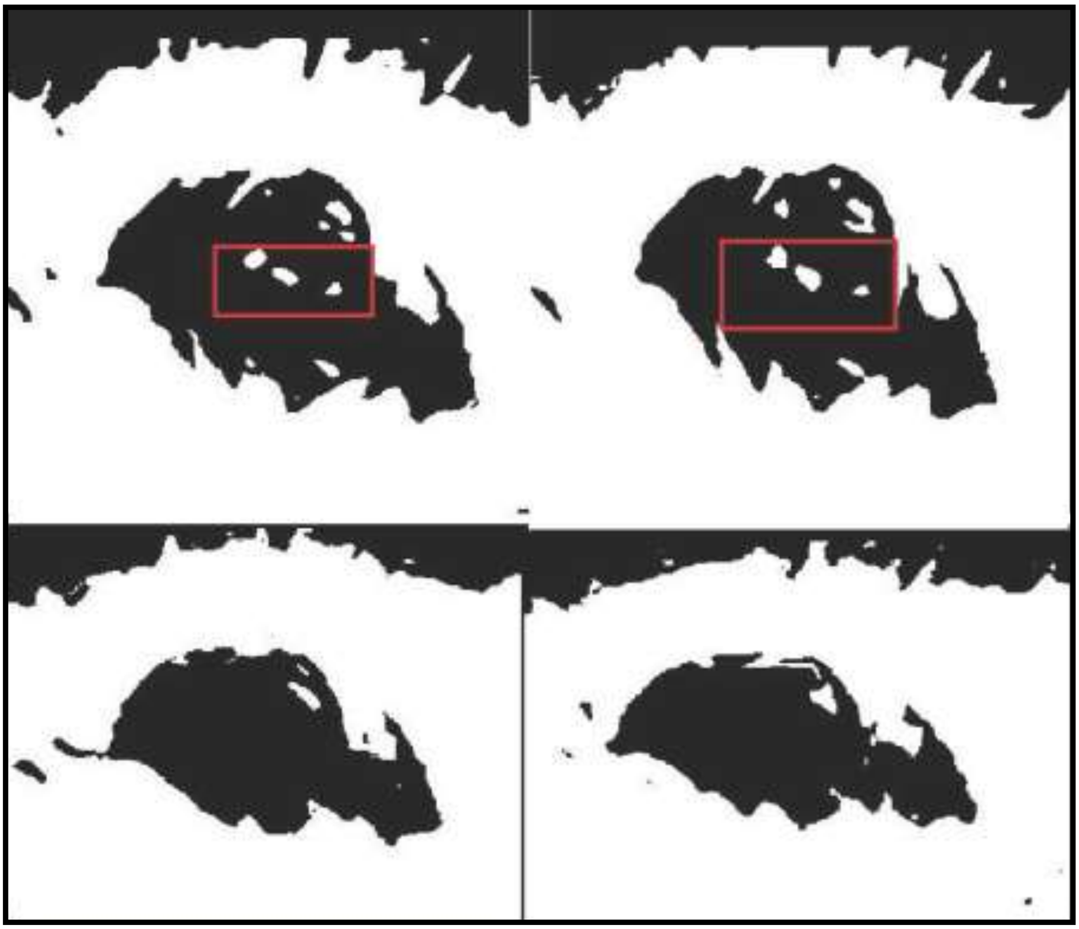

Figure 1. Sex criteria for chicks.

To ensure that the reflective region of each chick's genital organs was appropriately emphasized and to mitigate the impact of noise in the shaded regions on the features, we applied a series of processing steps. Firstly, the genital images of male chicks were subjected to binarization using OpenCV, in order to highlight the reflective region and simplify subsequent feature extraction. Next, the binarized images were converted into 24-bit depth images to facilitate uniformity in the dataset.

To establish ground truth annotations for the genital region and the circular protruding reflections of the genitals in the color images, we sought the expertise of experienced technicians. These technicians manually annotated the relevant regions using the LabelImg annotation tool (version 1.8.6), ensuring accurate and reliable annotations for our dataset. Finally, 25,200 images meeting the criteria were manually screened to form the chick sex identification dataset. The ratio between the samples in the training, validation and test sets was 5:3:2.

Lightweight target detection model

To address the inherent trade-off between detection accuracy and speed in target detection tasks, Yu et al. (2021) introduced the PicoDet model in 2021. By innovatively enhancing the backbone network structure and optimizing the label assignment strategy (LAS) and loss function, PicoDet achieves an impressive balance between detection speed and accuracy. Comparative evaluations against YOLOX-Nano demonstrate its superiority, with an absolute improvement of 4.8% in mean average precision and a remarkable 55% reduction in mobile CPU inference latency.

The PicoDet model adopts a novel backbone, ESNet, based on the lightweight feature extraction network ShufleNetV2. The key innovation lies in the integration of a squeeze-and-excitation (Hu et al., 2018) module within the network blocks, which allows the network channels to be dynamically weighted. This enhancement significantly improves the quality of the features, particularly in the C3–C5 layers, which play a crucial role in generating the ultimate detection outcomes. The feature maps generated by the backbone are efficiently guided through the network neck for further processing.

As depicted in Figure 2, the network architecture of the PicoDet model has an elegant design and seamless integration of its components. The powerful combination of the ESNet backbone, optimized label assignment strategy, and loss function optimization positions PicoDet as an exceptional solution for lightweight target detection. It strikes a harmonious balance between detection precision and inference speed, making it an ideal choice for real-time applications on resource-constrained devices. The empirical results presented in convincingly demonstrate the effectiveness of PicoDet and its potential to advance the field of target detection in agriculture and other related domains.

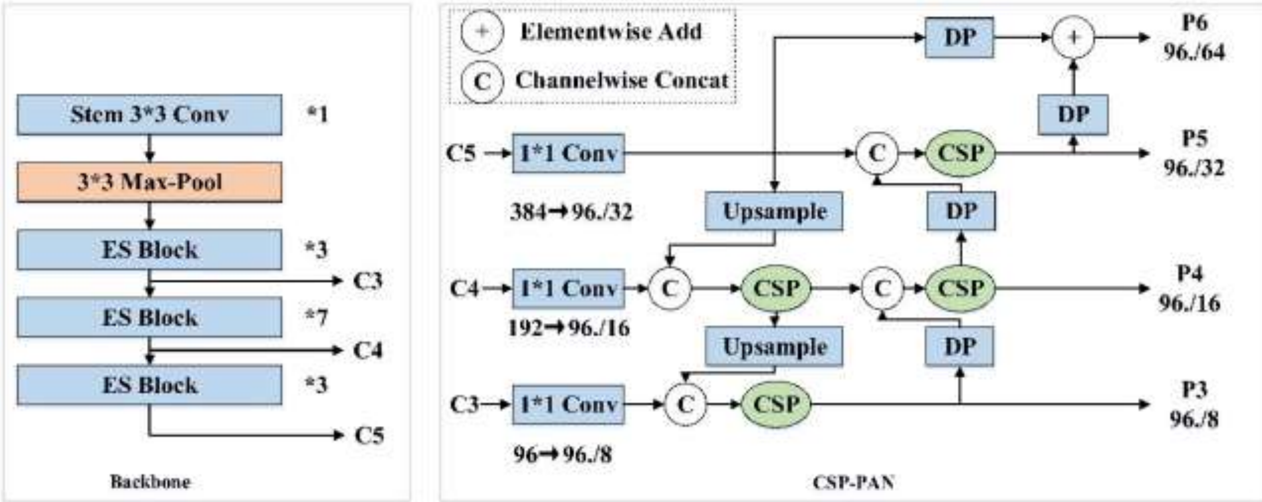

Figure 2. Network architecture of the PicoDet model.

The neck of PicoDet is based on a pyramid attention network (PAN) (Liu et al., 2018) structure, and plays a pivotal role in acquiring multilevel feature maps. The model also uses a cross stage partial (CSP) structure to facilitate seamless feature splicing and fusion between adjacent feature maps.

A crucial consideration in lightweight target detection is the computational cost associated with the number of channels in the network. To mitigate this challenge, PicoDet strategically employs 1×1 convolutions to homogenize the channel numbers of the output feature maps with the minimum channel number originating from the backbone. This approach helps to streamline computations, ensuring a more efficient model.

Furthermore, to enhance feature fusion while simultaneously reducing the computational overhead, PicoDet employs a top-down and bottom-up feature fusion strategy via the CSP structure. This strategy guarantees robust feature fusion capabilities, and allows for effective integration of information across different levels of the network, without incurring a substantial increase in computational burden.

By combining the PAN and CSP structures in the neck, PicoDet achieves a synergistic effect that strikes an optimal balance between detection accuracy and computational efficiency. This is of great importance, particularly in agricultural applications, where real-time, resource-efficient target detection is paramount.

This study focuses on chick cloaca detection and recognition as a binary classification task, meaning that feature extraction is relatively straightforward. Although PicoDet is already a lightweight solution, we go a step further by optimizing the network structure, and particularly the relatively cumbersome neck part of PicoDet. The objective is to obtain a model that is better suited to actual target detection scenarios. The optimized neck stage is illustrated in Figure 3.

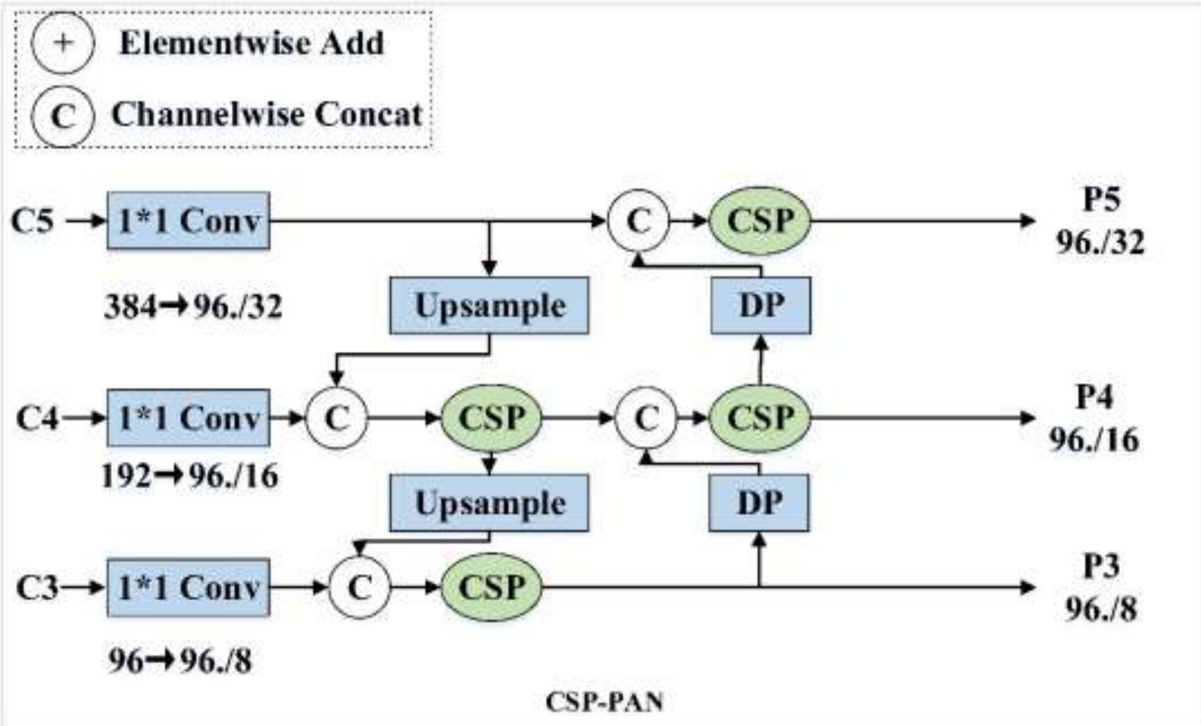

Figure 3. Optimized neck architecture.

The features extracted from the network's feature maps at different depths exhibit distinct tendencies. Specifically, high-level feature maps have a pronounced focus on the overall attributes of objects, such as shapes and edges, while low-level feature maps prioritize the representation of intricate object details, including texture patterns. To enhance the discriminative capabilities of high-level feature maps in regard to detecting large targets with prominent shape features, we employ a bottom-up path aggregation module known as PAN, which facilitates the transmission of information from low-level to high-level feature maps. The spatial concentration of the chick cloaca region within the images enables efficient extraction of the relevant features. As a result, we made the strategic decision to remove the P6 branch from the original structure, which was originally intended for detecting large targets. This optimization contributes to a reduction in parameters and computational operations, thereby enhancing the efficiency of the detection process.

Evaluation criteria

Evaluation criteria for chick cloaca identification

(1) Precision and Recall

Precision and recall are two widely used metrics in various domains, including machine learning, recommender systems, information retrieval, natural language processing, and multimedia vision, among others, to evaluate the quality of results.

Precision represents the percentage of true positives in the recognized images. In this case, it indicates the proportion of true cloacae regions among all recognized chick cloacae. The formula for calculating the precision is as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall represents the proportion of all positive samples in the test set that are correctly identified as positive samples. In this case, it is the ratio between the number of correctly identified cloacae and the total number of true cloacae in the test set under this hypothesis, and is calculated using the following formula:

$$\text{Recall} = \frac{TP}{TP + FN}$$

In this context, TP refers to the number of pixels where positive samples are correctly recognized as positive, signifying the accurate identification of cloacae pixel points. FP represents the number of pixels where negative samples were incorrectly identified as positive, indicating the misclassification of non-cloacae pixel points as cloacae. FN denotes the number of pixels where positive samples were incorrectly recognized as negative, reflecting the erroneous identification of cloacae pixel points as non-cloacae. TN corresponds to the number of pixels where negative samples were correctly identified as negative, representing the accurate recognition of non-cloacae pixel points as non-cloacae.

(2) Number of Parameters

The number of parameters refers to the total count of parameters involved in the model, which directly impacts the disk space required for execution of the model. It is often considered as part of the access volume, which does not directly affect the model's inference performance; however, the number of parameters does influence the memory footprint and program initialization time.

(3) Inference Time

Inference time serves as a crucial reference index for measuring model performance. Due to the asynchronous execution of deep learning inference on GPUs and the specific characteristics of GPU warm-up, conventional methods cannot directly calculate the model inference time. To address this issue, we used a sample program to complete GPU warm-up before the actual measurements were made. The asynchronous mode was also converted to synchronous mode, and timing was halted only after the GPU reasoning of the current round was complete.

Evaluation criteria for chick sex identification

(1) Accuracy Rate

The accuracy rate represents the ratio of samples correctly classified by the classification model (including both positive and negative examples) to the total number of samples. In other words, it is the percentage of correctly recognized videos among all chick videos to the total number of videos. The calculation formula is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP}$$

(2) Female Chick Identification Rate

The female chick identification rate (FCIR) represents the percentage of correctly identified female chick videos out of the total number of female chick videos.

(3) Male Chick Identification Rate

The male chick identification rate (MCIR) denotes the percentage of correctly recognized male chick videos out of the total number of male chick videos.

(4) Running Time

Running time is the duration taken by the program, from the moment the image is input to the output of the chick sex result.

Results and Discussion

Results of chick cloacae identification

Chick cloacae identification is the first step in chick sexing. In this study, we compared the results based on the four metrics of precision, recall, number of parameters, and inference time, using YOLOV3-tiny (Fu et al., 2021), YOLOV4-tiny (Jiang et al., 2020), YOLOV5s (Zhang & Li, 2022), PicoDet, and the method proposed in this study. The results are shown in Table 1.

Table 1
Results of chick cloacae identification

	Precision	Recall	Number of parameters	Inference time
YOLOV3-tiny	0.575	0.710	47.60M	71.42 ms
YOLOV4-tiny	0.723	0.827	32.73M	52.77 ms
YOLOV5-tiny	0.826	0.837	28.81M	38.01 ms
PicoDet	0.992	0.998	11.80M	8.13 ms
Our scheme	0.959	0.923	10.01M	7.81 ms

The precision rates for chick cloaca recognition were evaluated using five algorithms, YOLOV3-tiny, YOLOV4-tiny, YOLOV5-tiny, PicoDet, and the novel algorithm proposed in this study. The precision values obtained for these algorithms were 0.575, 0.723, 0.826, 0.992, and 0.959, respectively, while the recall rates were 0.710, 0.827, 0.837, 0.998, and 0.923, respectively.

Compared to the YOLO algorithms, which achieved precision and recall values of lower than 0.9, the method proposed in this study demonstrated significant improvements in both metrics. Moreover, our novel algorithm significantly reduced the number of parameters, by 78.97%, 69.42%, and 65.26% compared to YOLOV3-tiny, YOLOV4-tiny, and YOLOV5-tiny, respectively. The proposed method had faster inference times, with reductions of 89.06%, 85.20%, and

79.45% compared to the YOLO algorithms, respectively. We can conclude that the proposed method outperformed the YOLO algorithms in all aspects of performance.

Although the proposed method achieved precision and recall values that were reduced by only 3.32% and 7.51%, respectively, compared to PicoDet, it excelled in terms of the two most important performance metrics: the number of parameters and the inference time. The parameter count for the proposed method was 10.01M, significantly lower (by 15.16%) than the 11.80M parameters for PicoDet model. The proposed method also had an inference time of 7.81 ms, 3.93% faster than PicoDet's 8.13 ms. Overall, the proposed method demonstrated superior running speed and execution efficiency compared to all other algorithms considered in this study.

Results of sex identification of chicks

The determination of chick sex relies on identifying chick cloacae reflections, and the frames containing male chick cloacae features in the video represent only a specific percentage of the entire recording. To address this issue, we explored the recognition accuracy of our model with various thresholds, defining a video as containing a male chick when the proportion of frames recognized as a male chick fell within specific threshold ranges.

For the study, 300 videos each of male and female chicks were carefully selected, with each video lasting 2 s. The thresholds were established in intervals of 10% (e.g., 0–10%, 10–20%, and so on, up to 90–100%). Tables 2 to 4 show the results for accuracy, FCIR and MCIR for these different thresholds.

Table 2
Accuracy results for different thresholds

Threshold(%) / Method(%)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
YOLOV5-tiny	0.548	0.555	0.557	0.558	0.612	0.760	0.783	0.773	0.758	0.617
PicoDet	0.603	0.617	0.617	0.642	0.787	0.890	0.922	0.885	0.835	0.660
Our scheme	0.573	0.573	0.573	0.592	0.745	0.857	0.908	0.883	0.830	0.638

Table 3
FCIR results for different thresholds

Threshold(%) / Method(%)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
YOLOV5-tiny	0.950	0.930	0.913	0.900	0.883	0.870	0.863	0.803	0.677	0.297
PicoDet	0.990	0.970	0.953	0.943	0.933	0.930	0.913	0.837	0.727	0.323
Our scheme	0.973	0.943	0.923	0.910	0.900	0.883	0.903	0.827	0.703	0.303

Table 4
MCIR results for different thresholds

Threshold(%) / Method(%)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
YOLOV5-tiny	0.147	0.180	0.200	0.217	0.340	0.650	0.703	0.743	0.840	0.937
PicoDet	0.217	0.263	0.280	0.340	0.640	0.850	0.930	0.933	0.943	0.997
Our scheme	0.173	0.203	0.223	0.273	0.590	0.830	0.913	0.940	0.957	0.973

The performance of YOLOV5-tiny, PicoDet and Our scheme in terms of chick sex recognition was investigated for these varying threshold values. Notably, at threshold values of 0–10%, Our scheme achieved the highest values of MCIR, with results of 95.00%, 99.00%, and 97.33%, respectively, thus indicating the high accuracy of the algorithms in recognizing male chicks. However, corresponding FCIR values at the same threshold were relatively low, at 14.67%, 21.67%, and 17.33%, respectively. This suggests a considerable misidentification rate for female chicks in the recognition process.

The high misidentification rate for female chicks has significant implications for practical applications involving chick sex recognition. As a consequence of the algorithms' misrecognition of female chicks, the overall chick sex recognition accuracy was adversely affected, resulting in values of 55.50%, 61.67%, and 57.33% for the three algorithms, respectively. Such inaccuracies may render the algorithms unsuitable for real-world applications. It is therefore imperative to address this issue and to reduce the misidentification rate of female chicks while simultaneously improving the overall accuracy of chick sex recognition.

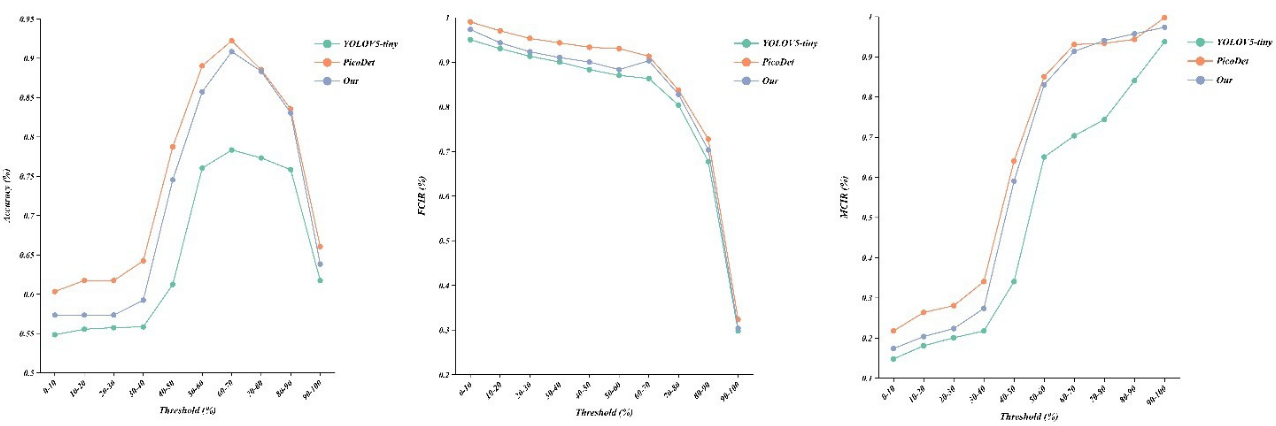

Figure 4. Results from the three evaluation methods for different thresholds.

Figure 4 shows plots of the results from the three evaluation methods under different thresholds. As the threshold values were gradually increased, the MCIR underwent a decline, whereas the FCIR demonstrated a steady increase. At threshold values of between 60% and 70%, the algorithms reached relative optimality, with MCIR values of 86.33%, 91.33%, and 90.34%, and FCIR values of 70.33%, 93.00%, and 91.33%, respectively. The accuracy was also correspondingly high, reaching values of 78.33%, 92.16%, and 90.83% for the three algorithms, respectively. These findings indicate that within this specific threshold range, the algorithms achieved more consistent performance in recognizing the sex of chicks, effectively striking a balance between the recognition of male and female chicks.

However, as the threshold values continued to rise, the FCIR showed continued improvement, while the MCIR and accuracy gradually decreased. At a threshold range of 90–100%, the MCIR values for the three algorithms were 29.67%, 32.33%, and 30.33%, respectively, while the FCIR reached values of 93.66%, 99.56%, and 97.33%, respectively. Similarly, the accuracy values decreased to 61.67%, 66.00%, and 63.83%, respectively. In this case, there was a clear reduction in misidentification of female chicks due to the higher FCIR; however, this improvement came at the expense of lower MCIR and accuracy, indicating a decline in the identification of male chicks.

In this experiment, a thorough comparison of three chick sex recognition models, namely YOLOV5-tiny, PicoDet, and the algorithm proposed in this research, was also conducted based on their final sizes and runtimes. As shown in Table 5, the YOLOV5-tiny model had the highest number of parameters and running time, with values of 57.13 M and 4.22 s, respectively. The PicoDet model had 22.16 M parameters and a runtime of 1.09 s, while the proposed method had a parameter count of 21.05 M and a running time of 0.91 s. These findings indicate that the proposed approach successfully reduced the runtime to less than 1 s, while maintaining equivalent recognition efficiency, specifically when using a 2-s chick video as the study's subject. Furthermore, in comparison to the PicoDet model, the algorithm proposed in this research achieved a 5.01% reduction in the number of parameters.

Table 5
Numbers of parameters and run times for the models

	Number of parameters	Running time
YOLOV5-tiny	57.13M	4.22 s
PicoDet	22.16M	1.09 s
Our scheme	21.05M	0.91 s

These outcomes are of great significance for real-world applications, as more efficient models allow for faster processing of substantial data quantities, thereby enhancing the recognition speed and overall efficiency. The algorithm proposed in this study exhibits superior efficiency and ease of deployment in practical scenarios, rendering it well-suited for application to real-world production environments.

In addition, the use of 2-s chick videos as research objects in this study adds relevance to the practical application of chick gender recognition. Unlike single static images, videos provide a wealth of information, particularly in dynamic environments, leading to more accurate and reliable chick sex identification. Consequently, the selection and utilization of video data in this study enhance its practicality and applicability.

It is essential to highlight that the success of the proposed algorithm in terms of reducing running time and parameters does not involve compromised accuracy. Accuracy remains a critical metric, particularly in chick sex identification applications. As demonstrated by the results, the proposed algorithm effectively shortens the running time and reduces the parameters while maintaining high accuracy levels, which can significantly benefit real-world applications.

Conclusion and Future Work

This study has introduced a novel semi-automated method for chick sex recognition that offers significant advancements over traditional approaches. The proposed innovations address challenges related to workload, efficiency, and applicability, positioning the method as a valuable contribution to the field. The integration of video streams, threshold-based gender recognition, and optimized model features enhances the accuracy and efficiency of chick sex identification, with promise for broader practical applications and widespread adoption in the poultry industry. The method introduces several key innovations, which are outlined as follows:

(1) Adoption of a video stream: Rather than relying solely on images, the proposed method leverages video streams of chick cloacae for sex identification. This approach reduces the manual workload associated with image screening, making the method more suited for industrial-level applicability and facilitating wider promotion and adoption.

(2) Threshold-based gender recognition: We introduce a threshold-based approach for chick sex recognition, which enables evaluation of the model's performance under different threshold values. The evaluation criteria applied here included accuracy, FCIR, MCIR, number of parameters, and operation time, thus ensuring a comprehensive assessment of the model's effectiveness.

(3) Feature extraction and model modification: The proposed method extracts color images of chick cloacae and binary image features, which effectively reflect the reflective properties of chick cloacae. These features serve as input to the model, and maximize the accuracy of chick gender recognition. In addition, the model is modified based on the PicoDet framework by removing the P6 branch from the CSP-PAN structure, resulting in fewer model parameters and faster running times, thereby facilitating ease of deployment.

These innovations contribute to the advancement of chick sex recognition technology, and enhance its efficiency, accuracy, and practicality. The use of video streams enables more streamlined and automated processing, reducing manual efforts and enabling wider-scale implementation in industrial settings. The threshold-based approach provides flexibility in regard to fine-tuning the model's performance, and allows for optimal gender recognition under different conditions. Moreover, the integration of color and binary image features improves the model's discriminative capabilities, and further enhances the accuracy of chick gender identification. The modification to the model based on the PicoDet framework ensures efficient parameter utilization and faster processing times, making it more accessible for real-world deployment.

Future research in this field will focus on two main aspects. Firstly, a concerted effort will be made to enhance the collection and labeling of chick cloacae data. This will involve gathering video data on chick cloacae at various distances to investigate the model's performance in recognizing chick sex at different proximities. This data collection process will provide valuable insights into how the model's effectiveness varies with the distance between the camera and the subject. Secondly, since this study has successfully validated the feasibility of using chick cloacae videos for chick sex recognition, future research will prioritize the development of industrialized software for practical application in relevant scenarios. This will involve refining the algorithms and integrating them into user-friendly software systems for easy implementation and deployment in real-world environments. Furthermore, efforts will be made to accelerate the model's performance through optimization and acceleration techniques, thereby ensuring efficient and rapid processing of large-scale chick cloacae video data.

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