

Multi-Species Egg Morphometry and Weight Prediction Using Computer Vision

Henna Hamadani

SKUAST Kashmir: Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

Ambreen Hamadani

`escritor005@gmail.com`

SKUAST Kashmir: Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

<https://orcid.org/0000-0002-5455-0468>

Pakcha H Boje

SKUAST Kashmir: Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

Amelia Moyon

SKUAST Kashmir: Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

Maliha Gulzar

SKUAST Kashmir: Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

A A Khan

Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

R Kumar

SKUAST Kashmir: Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir

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Abstract

Egg size and weight are very important for the poultry industry. Automated egg morphometry provides an efficient alternative to manual measurements for poultry breeding, hatchery management, and grading. This study was undertaken to automatically detect and measure eggs using computer vision and predict their weight. We also used species-specific calibration and evaluated weight prediction in chicken and goose eggs. A total of 661 eggs (504 chicken and 157 goose) were photographed using a smartphone together with a calibrated reference object. Computer vision-derived length and width measurements were compared with manual calliper measurements. We used Bland–Altman analysis and species-specific cross-validated linear calibration. Egg weight was predicted using linear, power-law, and Ridge regression models based on morphometric features. The YOLO11x-OBb detector had precision of 99.9%, recall of 100%, and mAP@0.5 of 99.5%. Species-specific calibration substantially improved measurement agreement, reducing chicken length MAE to 0.088 cm and goose length MAE to 0.283 cm. Ridge regression achieved the best weight prediction performance, with out-of-fold R^2 values of 0.962 for chicken eggs. These findings demonstrate that 2D imaging combined with machine learning is practical for non-contact egg morphometry and weight prediction.

Introduction

Egg size and weight are very important for the poultry industry. Egg size and weight are also important indicators of a hen's laying performance, health, and well-being. They are essential determinants for selection and breeding as well. Traditionally, egg size is measured manually or with some mechanical devices (Widiasri et al. 2019). Manual calliper and balance measurements are labour-intensive, slow, and dependent on manual labour.

Artificial intelligence is taking over almost every industry, and computer vision especially is opening up exciting new opportunities in the livestock sector (Hamadani and Ganai 2023). It has been used in animals for classification (Hamadani 2024), sexing (Paneru et al. 2025), breeding value prediction (Hamadani et al. 2022), disease detection (Pranta 2026), performance prediction (Hamadani and Ganai 2023), behavior studies (Lupu et al. 2025), phenotyping (Hamadani et al. 2026a) etc. Computer vision offers alternatives for automatically grading eggs in commercial settings, too using inexpensive cameras. The advent of computer vision technologies in AI provides a non-invasive way to do that. For example, scientists (Yang and others 2017) developed a two-stage model that combines real-time multitasking detection with machine learning (random forest) to predict egg categories and weights. Similarly, Ab Nasir et al. (2018) developed an automated egg grading system.

Liu et al. (2023) used SegFormer image segmentation and single-view metrology to estimate egg length and width from 2D images (Liu and others 2023). They used deep learning with image-based morphometric features for egg defect detection (Luo et al. 2023). Zhu et al. (2024) developed a laser-based three-dimensional imaging system for estimating egg dimensions and weight with good accuracy

(Zhu et al. 2024a). This showed that specialized hardware gave good accuracy but also increased complexity and cost.

Although previous studies have studied computer vision for automated egg grading, there is still a dearth of studies in some areas. An egg has a peculiar shape. It is an asymmetric, three-dimensional ovoid curve (Narushin et al. 2021) and therefore capturing its shape using 2D cameras is a challenge. Relatively few studies have evaluated the accuracy of image-derived morphometric measurements against manual measurements with 2-dimensional imaging. Additionally, the transferability of morphometric models across poultry species remains unexplored to a large extent. Therefore, this study was undertaken to evaluate the accuracy of computer vision-based egg morphometry.

Materials and Methods

Dataset and ethical reuse

A total of 661 eggs were photographed for this study, comprising 504 chicken eggs and 157 goose eggs (Hamadani et al. 2026b). Images were captured using a phone camera. Each egg was placed on a reference object (a notebook with known dimensions). It had a length of 21.1 cm and a width of 16.0 cm for scale calibration. Eggs were photographed with a smartphone camera. Phenotypic records were taken alongside, which consisted of manual length, width, and weight measurements for chicken eggs and for goose eggs. The dataset was randomly split into three subsets, which included the training set (462 eggs, 69.9%), validation set (99 eggs, 15.0%), and test set (100 eggs, 15.1%). Data augmentation techniques were applied, including horizontal flipping, rotation (± 10.0 degrees), translation, and HSV colour space adjustments. For proportional representation, the split was stratified for chicken and goose eggs across all subsets. For model training, each image was manually annotated with oriented bounding boxes (OBB) for two classes: (1) egg and (2) reference object. These annotations were created using specialized annotation tools and verified for accuracy.

Model Architecture: The model was trained on input images of size 416×416 pixels with a batch size of 2. Training was conducted for up to 400 epochs with a learning rate of 0.01, and early stopping was applied with a patience of 50 epochs to prevent overfitting using YOLO11x with Oriented Bounding Boxes (Jocher et al. 2023).

Dimension Calculation: Egg dimensions were calculated from OBB coordinates using a multi-step procedure that converts pixel-based measurements to real-world centimeters. First, the OBB Coordinates were extracted for both the egg and the reference object in each image. From the OBB coordinates, the length and width of each object were calculated in pixel space. For the egg, the longest edge was identified as the length, and the perpendicular edge as the width. Similarly, for reference objects with known dimensions. A scaling factor was computed by comparing the reference object's pixel dimensions to its known physical dimensions. This factor accounted for image resolution and perspective effects. The egg's pixel dimensions were converted to centimeters by multiplying by the

scaling factor derived from the reference object. Correction factors were calculated to minimize systematic errors, which amounted to a length and width correction of -0.058 and - 1.641 cm. These corrections were applied to the converted measurements to improve accuracy.

Species-specific linear calibration

Even after geometric scaling, systematic bias remained. We fitted species- and dimension-specific linear calibrations of the form $\text{manual} = a \cdot \text{cv_raw} + b$ using 5-fold out-of-fold (OOF) predictions so that reported MAE and Pearson r are not inflated by in-sample fit.

Bland–Altman bias, standard deviation and 95% limits of agreement (Giavarina 2015), plus Pearson correlation and MAE were used to compare manual and CV dimensions. The Association between absolute dimension error and OBB rotation angle was checked with Pearson correlation.

Weight prediction models

Weight (g) was modelled from length and width using the following

- ordinary least-squares linear regression on L and W ;
- log-linear power-law form $\log(W) = \log(a) + b \log(L) + c \log(Wd)$;
- Ridge regression (RidgeCV) on an expanded feature set: L , W , $L \cdot W$, L^2 , W^2 , shape index L/W , prolate-ellipsoid volume proxy $(4/3)\pi(L/2)(W/2)^2$, and L^3 .

Features were evaluated on manual dimensions and on Calibrated computer vision dimensions. Performance was reported with Ridge metrics out-of-fold (5-fold).

Results

Detection performance

The YOLO11x-OBB model performed well for the detection on both the validation and test sets, with a precision of 99.93%, recall of 100%, and $\text{mAP}@0.5$ of 99.50%. The $\text{mAP}@0.5:0.95$ values were 99.30% and 98.99% for the validation and test sets, respectively (Table 1, Fig. 1).

Raw morphometric accuracy

Before species-specific calibration, computer vision-derived dimensions were closer to the manual measurements for chicken eggs than for goose eggs. Similar trends were observed in both the validation and test sets, indicating that goose width estimation had more error before calibration. This might be attributed to a smaller dataset for goose than chicken, and smaller datasets tend to amplify variance (Naser 2026). Also, this might be attributable to the lower image resolution and the smaller effective pixel representation of egg width in the available goose images. As a result of this, less actual

information for estimation was available. Now that width contributes to egg volume (Preston 1974) and weight, a higher-resolution camera, closer image acquisition, or multi-view imaging would improve width prediction and subsequently the weight prediction as well (Qiao et al. 2025).

Table 1
OBB detection and overall dimension metrics

Set	Dimension	MAE (cm)	RMSE (cm)	Pearson r	Std error (cm)	MAPE (%)
Validation	Length	0.236	0.357	0.965	0.307	3.16
Validation	Width	0.474	0.674	0.967	0.631	9.42
Test	Length	0.179	0.237	0.982	0.307	3.16
Test	Width	0.452	0.668	0.837	0.631	9.42

3.3 Bland–Altman agreement and calibration

Raw CV length overestimated manual length. This is shown in Table 2 and Fig. 2). Raw width was underestimated for chicken, and the goose dataset had a weak correlation.

Table 2
Bland–Altman statistics for raw computer-vision versus manual dimensions.

Species	Dimension	n	Bias (cm)	SD (cm)	LoA lower	LoA upper	Pearson r	MAE (cm)
Chicken	Length	502	+ 0.691	0.176	0.346	1.035	0.960	0.691
Goose	Length	157	+ 1.558	0.480	0.618	2.498	0.639	1.559

Species-specific OOF linear calibration decreased length bias and also reduced the error. The correlations were unchanged for chicken but were slightly lower for goose. This is due to the fact that calibration corrects bias rather than noise (Gajjar 2017) and is represented in Table 3 and Fig. 3. Width calibration improved chicken MAE but could not do much for goose width correlation, the correlation of which remained low. This limitation also explains the poorer weight prediction obtained from computer vision-derived goose measurements.

Species-specific calibration equations are summarized in Table 3. Calibration reduced systematic bias and improved the consonance between computer vision-derived and manual measurements, particularly for length. These findings demonstrate that a one-time species-specific calibration can substantially improve measurement accuracy when smartphone images are used for egg morphometry. This has also been reported by other authors under different experimental conditions as well (Sun et al. 2012).

Table 3
Length calibration: raw versus species-specific out-of-fold calibrated computer vision.

Species	Method	n	MAE (cm)	Bias (cm)	Pearson r
Chicken	Raw computer vision measurements	502	0.662	+ 0.662	0.960
Chicken	Calibrated (OOF)	502	0.088	≈ 0	0.959
Goose	Raw computer vision measurements	157	1.491	+ 1.487	0.582
Goose	Calibrated (OOF)	157	0.283	≈ 0	0.574

3.4 Weight prediction

Baseline linear L + W models fitted on manual dimensions achieved a high R² in chickens (Table 4; Fig. 4). Power-law models were similar. Chicken linear coefficients obtained were weight $\approx -88.17 + 10.11 \cdot L + 20.30 \cdot W$. For the goose results, additional validation with a larger dataset is required before a prediction equation can be recommended. Expanded Ridge features raised goose out-of-fold R² to 0.816 (MAE 4.52 g), and chicken OOF R² reached 0.962 (MAE 1.41 g). Soltani et al. also predicted egg volume from image-derived major and minor diameters with an R² of 0.99 (Soltani et al. 2015). A weight prediction accuracy of R² of 0.964–0.978 and 0.926 using laser-derived three-dimensional features and a deep learning framework combining egg segmentation and regression, respectively, has also been reported (Zhu et al. 2024b; Jiang et al. 2025). These studies demonstrate comparable predictive performance, but our study used a substantially simpler and lower-cost imaging setup.

Table 4
Weight prediction performance using manual and calibrated computer vision morphometric traits.

Species	Morphometric source	Model	R ²	MAE (g)
Chicken	Manual L/W	Linear	0.959	1.56
Chicken	Manual L/W	Ridge	0.962	1.41
Chicken	Calibrated computer vision	Linear	0.928	2.26
Chicken	Calibrated computer vision	Ridge	0.929	2.21
Goose	Manual L/W	Linear	0.577	7.04
Goose	Manual L/W	Ridge	0.816	4.52
Goose	Calibrated computer vision	Linear	0.455	9.15
Goose	Calibrated computer vision	Ridge	0.436	9.29

Our study shows that with an inexpensive setup, a reference object, OBB detection, species-specific calibration, and morphometric modelling, one can provide an accurate and practical approach for non-contact egg measurement and weight prediction. Handling, despite all advancements, remains a

challenge (Musa and Ameha 2023). This study, therefore, has potential applications in breeding, hatcheries, and egg packing facilities. OBB detection model can be combined with species-specific calibration equations and weight prediction models to accommodate differences in egg morphology.

Conclusions

A smartphone-based OBB detection with species-specific calibration enables accurate, non-contact egg morphometry and weight prediction. Ridge regression provides reliable weight estimates for chicken eggs. This study has applications in automatic grading in the poultry industry.

Declarations

Funding: This research received no external funding.

Competing Interests: The authors declare that they have no competing interests.

Author Contributions: H.H. conceived and designed the study, developed the methodology, performed the software development, data curation, formal analysis, investigation, visualization, and wrote the original draft. A.H.: the methodology, validation, formal analysis, and manuscript review and editing. P.H.B.: data curation and manuscript review and editing. W.A.M.: data curation and manuscript review and editing. M.G.: investigation, data curation, and manuscript review and editing. A.A.K.: methodology and manuscript review and editing. R.K.: manuscript review and editing. All authors read and approved the final manuscript.

Data Availability: The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Approval: This study did not involve live animals, and formal ethical approval was not required.

Consent to Participate: Not applicable.

Consent to Publish: Not applicable.

References

1. Ab Nasir AF, Sabarudin SS, Abdul Majeed APP, Abdul Ghani AS (2018) Automated egg grading system using computer vision: Investigation on weight measure versus shape parameters. IOP Conf Ser: Mater Sci Eng 342:012003. <https://doi.org/10.1088/1757-899X/342/1/012003>
2. Gajjar MJ (2017) Chap. 8 - Sensor calibration and manufacturing. In: Mobile Sensors and Context-Aware Computing. Morgan Kaufmann, pp 213–222
3. Giavarina D (2015) Understanding Bland Altman analysis. Biochem Med (Zagreb) 25:141–151. <https://doi.org/10.11613/BM.2015.015>

4. Hamadani A (2024) Artificial Intelligence on Farms: Sheep Breed Classification Using Computer Vision. *ijapm* 40:260–268. <https://doi.org/10.48165/ijapm.2024.40.4.8>
5. Hamadani A, Ganai NA (2023) Artificial intelligence algorithm comparison and ranking for weight prediction in sheep. *Sci Rep* 13:13242. <https://doi.org/10.1038/s41598-023-40528-4>
6. Hamadani A, Ganai NA, Mudasar S, et al (2022) Comparison of artificial intelligence algorithms and their ranking for the prediction of genetic merit in sheep. *Sci Rep* 12:18726. <https://doi.org/10.1038/s41598-022-23499-w>
7. Hamadani A, Hamadani H, Ali SF, et al (2026a) Integrated Morphometric and Cardiac Phenotyping of Kashmir Sheep Using Digital Auscultation and Machine Learning
8. Hamadani H, Hamadani A, Boje PH, et al (2026b) Automated Egg Grading Through AI and Computer Vision-Driven Morphometric Analysis. In: *Proceedings of the 13th World Congress on Genetics Applied to Livestock Production*. p 23648
9. Jiang Y, Atwa EM, He P, et al (2025) Computer Vision-Based Multi-Feature Extraction and Regression for Precise Egg Weight Measurement in Laying Hen Farms. *Agriculture* 15:2035. <https://doi.org/10.3390/agriculture15192035>
10. Jocher G, Chaurasia A, Qiu J (2023) Ultralytics YOLOv8
11. Liu C, others (2023) Egg Image Segmentation with SegFormer. *Foods* 12:936. <https://doi.org/10.3390/foods12050936>
12. Luo Y, Huang Y, Wang Q, et al (2023) An improved YOLOv5 model: Application to leaky eggs detection. *LWT* 187:115313. <https://doi.org/10.1016/j.lwt.2023.115313>
13. Lupu M, Tăpăloagă D, Mitrănescu E, et al (2025) Aggressive Mating Behavior in Roosters (*Gallus gallus domesticus*): A Narrative Review of Behavioral Patterns. *Life (Basel)* 15:1232. <https://doi.org/10.3390/life15081232>
14. Musa M, Ameha N (2023) Review on Egg Handling and Management of Incubation and Hatchery Environment. *Asian Journal of Biological Sciences* 16:474–484. <https://doi.org/10.3923/ajbs.2023.474.484>
15. Narushin VG, Romanov MN, Griffin DK (2021) Egg and math: introducing a universal formula for egg shape. *Annals of the New York Academy of Sciences* 1505:169–177. <https://doi.org/10.1111/nyas.14680>
16. Naser MZ (2026) A review of machine learning with small and limited data. *Journal of Big Data* 13:18. <https://doi.org/10.1186/s40537-025-01346-9>
17. Paneru B, Bist RB, Yang X, et al (2025) Deep Learning Methods for Automatic Identification of Male and Female Chickens in a Cage-Free Flock. *Animals* 15:1862. <https://doi.org/10.3390/ani15131862>
18. Pranta AM (2026) Machine learning framework for poultry disease detection using vocal pattern analysis. *Smart Agricultural Technology* 13:101816. <https://doi.org/10.1016/j.atech.2026.101816>
19. Preston FW (1974) The Volume of an Egg. *The Auk* 91:132–138. <https://doi.org/10.2307/4084667>

20. Qiao Z, Liu J, Yang F, et al (2025) A cost-effective image-based model without constraint for weight estimation of poultries using deep learning. Smart Agricultural Technology 12:101152.
<https://doi.org/10.1016/j.atech.2025.101152>
21. Soltani M, Omid M, Alimardani R (2015) Egg volume prediction using machine vision technique based on pappus theorem and artificial neural network. J Food Sci Technol 52:3065–3071.
<https://doi.org/10.1007/s13197-014-1350-6>
22. Sun H, Aubrey DP, Teskey RO (2012) A simple calibration improved the accuracy of the thermal dissipation technique for sap flow measurements in juvenile trees of six species. Trees 26:631–640.
<https://doi.org/10.1007/s00468-011-0631-1>
23. Widiastri M, Santoso LP, Siswantoro J (2019) Computer vision system in measurement of the volume and mass of egg using the disc method. IOP Conf Ser: Mater Sci Eng 703:012050.
<https://doi.org/10.1088/1757-899X/703/1/012050>
24. Yang Y, others (2017) Two-Stage Egg Category and Weight Prediction. IEEE Internet of Things Journal 4:1250–1258. <https://doi.org/10.1109/JIOT.2017.2694844>
25. Zhu Y, Song D, Wu X, et al (2024a) FEgg3D: A Non-Contact and Dynamic Measuring Device for Egg Shape Parameters and Weight Based on a Self-Designed Laser Scanner. Agriculture 14:1374.
<https://doi.org/10.3390/agriculture14081374>
26. Zhu Y, Song D, Wu X, et al (2024b) FEgg3D: A Non-Contact and Dynamic Measuring Device for Egg Shape Parameters and Weight Based on a Self-Designed Laser Scanner. Agriculture 14:1374.
<https://doi.org/10.3390/agriculture14081374>

Figures

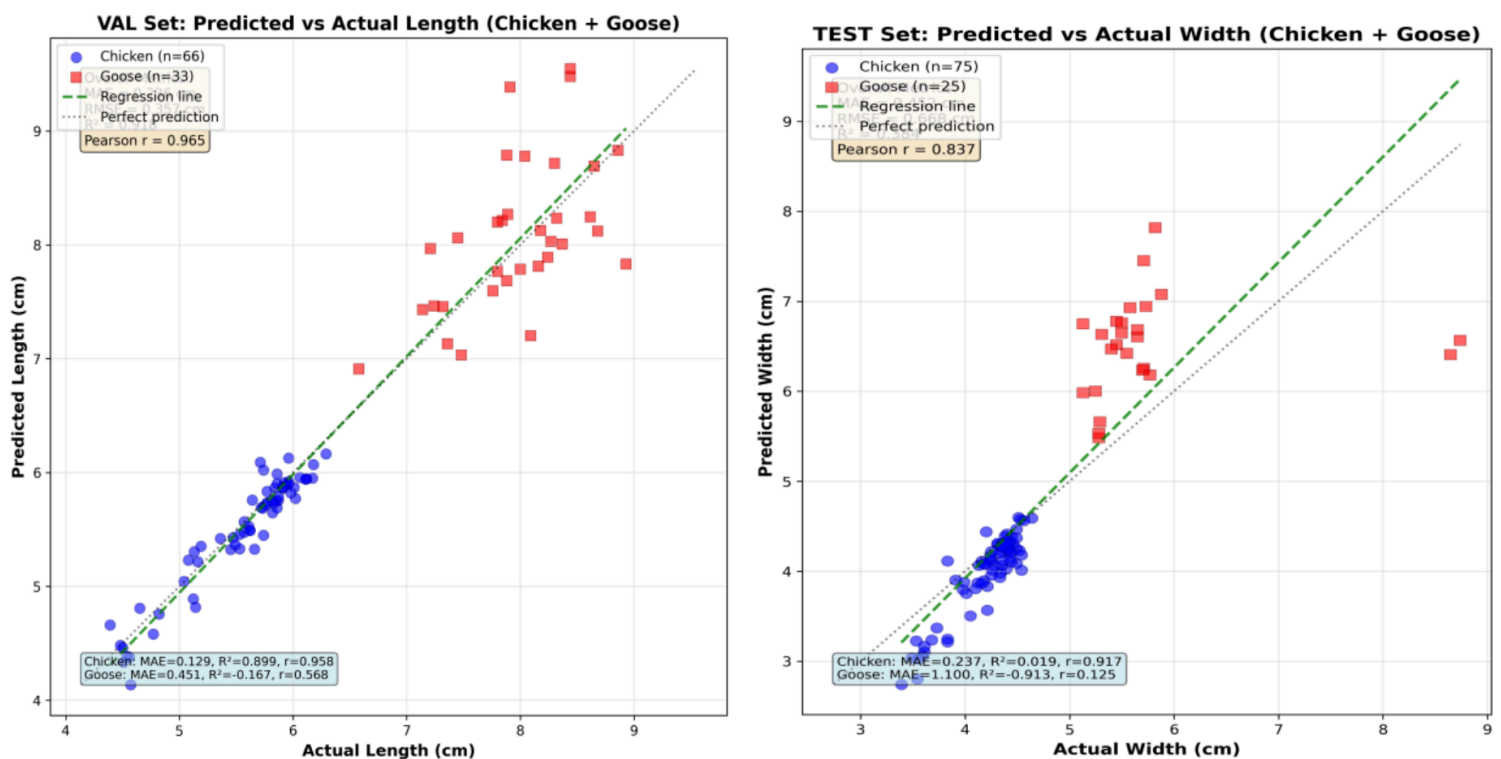


Figure 1

Correlation between the testing and validation datasets

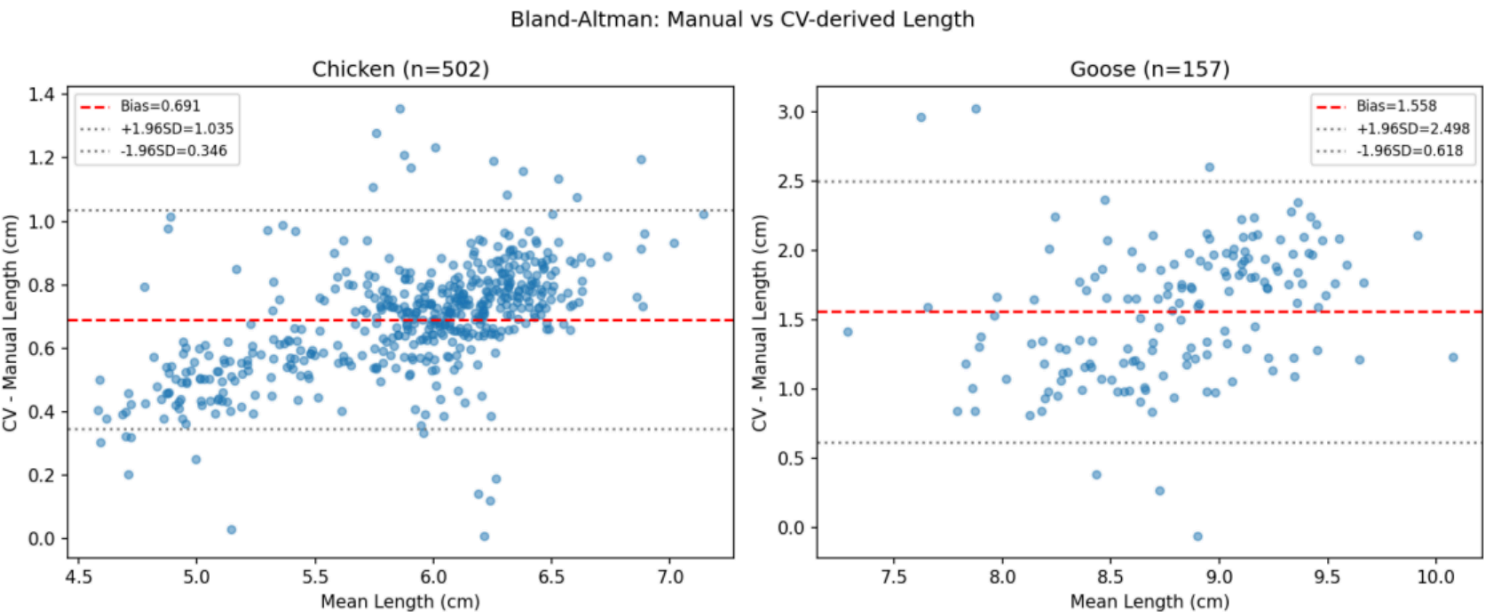


Figure 2

Bland–Altman plots of manual versus raw computer-vision length (cm) for chicken and goose eggs. Solid line: mean bias; dashed lines: 95% limits of agreement.

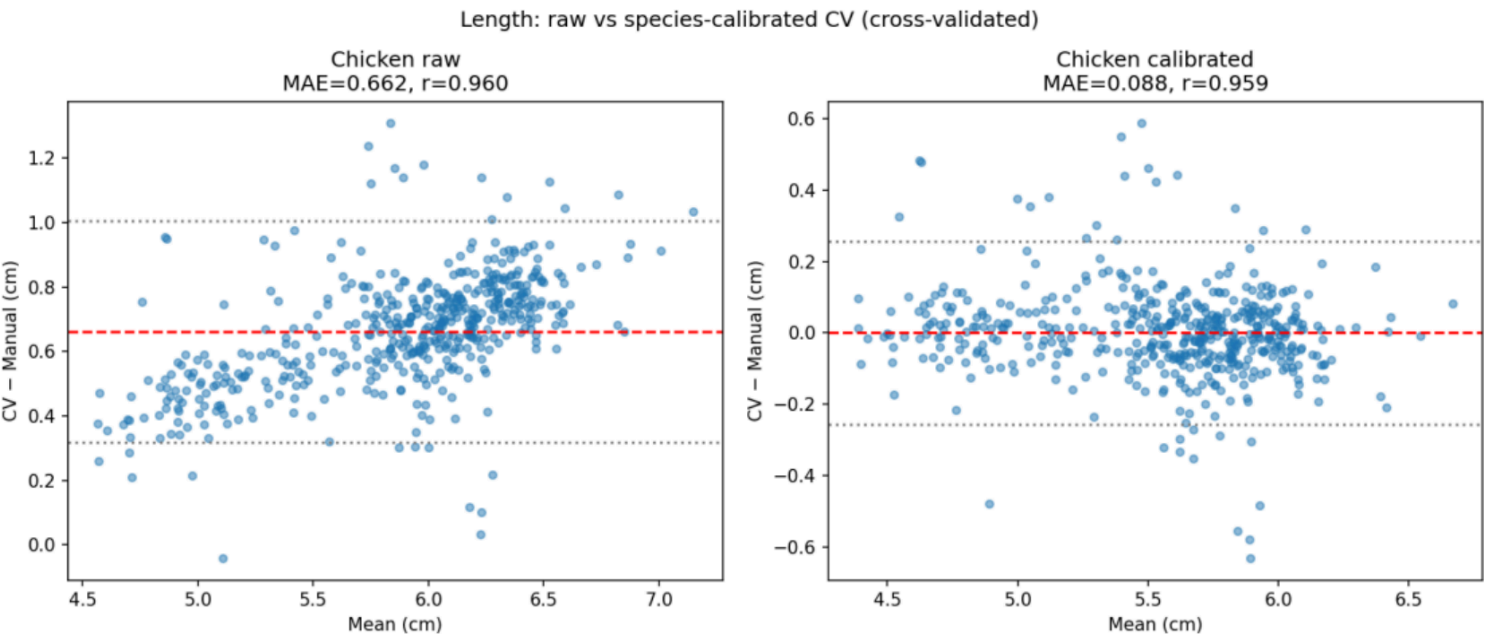


Figure 3

Manual versus computer vision-derived egg length before and after species-specific calibration.

Weight prediction — Chicken (n=502)

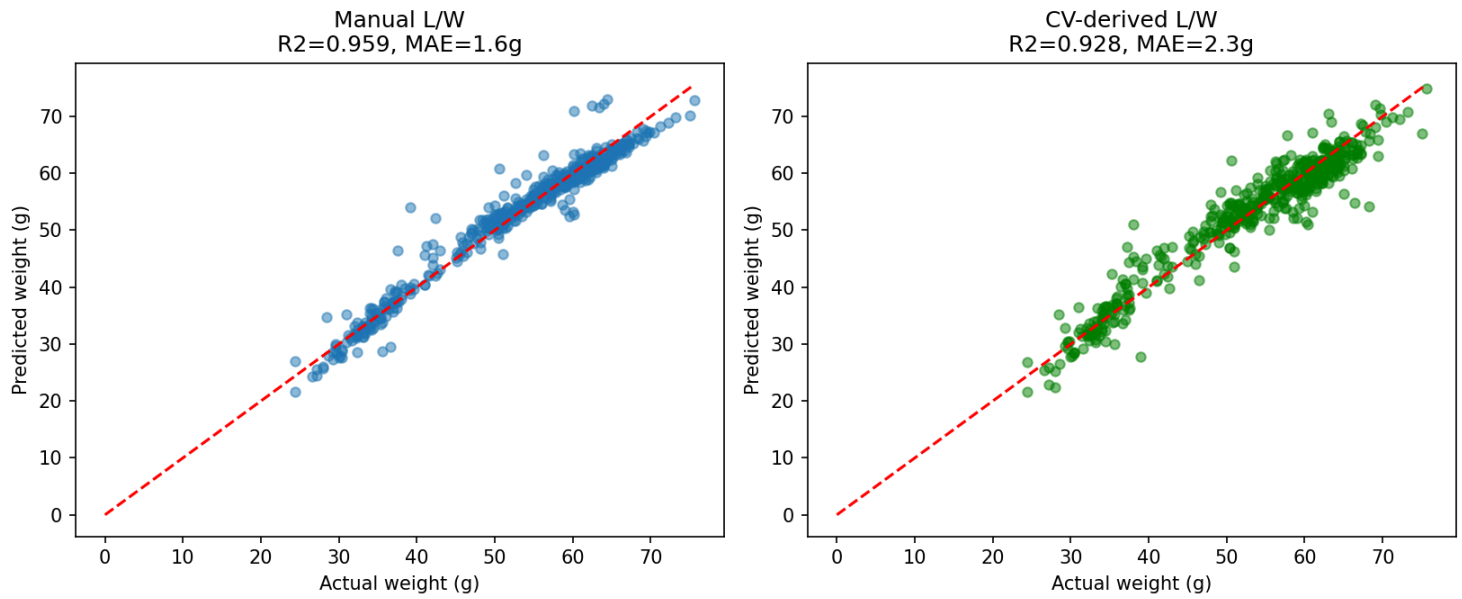


Figure 4

Observed versus predicted chicken egg weight (g) from baseline linear and power-law models using manual length and width