Hamadani, H., Hamadani, A., Boje, P., Moyon, W., Gulzar, M., Khan, A., Kumar, R. (2026) Automated egg grading through AI and computer vision-driven morphometric analysis, *Proceedings 13th World Congress on Genetics Applied to Livestock Production* 23648: https://doi.org/10.31274/wcgalp.23648 ©2026 Hamadani, et al. CC BY-NC-ND

Automated egg grading through AI and computer vision-driven morphometric analysis

H. Hamadani*, A. Hamadani, P.H. Boje, W.A. Moyon, M. Gulzar, A.A. Khan, and R. Kumar

Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, India, Corresponding author: hamadani.hh@gmail.com*

Introduction

The egg size determination is a critical aspect of the poultry industry. That includes hatchery management. The egg size determines the price, packaging, and consumer preference. Egg size is also an important indicator of a hen's laying performance, health, and well-being. It is an essential determinant for selection and breeding as well. Traditionally, egg size is measured manually or with some mechanical devices. This is labour-intensive, error-prone, expensive, and time-consuming. The advent of computer vision technologies within the realm of AI provides a non-invasive way of doing that. For example, scientists (Yang *et al.*, 2017) developed a two-stage model that combines both the detection of real-time multitasking and machine learning algorithms (random forest) to predict egg categories and weights. Similarly, Ab Nasir *et al*. (2018) developed an automated egg grading system. These may not accurately capture the elongated shape of eggs (Mondal, Islam and Yusuf, 2025). However, there is still a dearth of research wherein a single 2D image of an egg is used for the extraction of egg dimensions. This may not fully capture elongated or rotated eggs. This is important for systems where conveyor-based egg transportation is done.

This research aimed to develop efficient automated egg-size estimation methods using advanced computer vision and machine learning techniques. This is an attempt to streamline the grading process and reduce reliance on manual labour. Oriented Bounding Box (OBB) detection is taking over as a superior approach compared to axis-aligned bounding boxes for objects with irregular orientations, such as eggs. This study leverages the YOLO11x-OBB architecture to detect and measure egg dimensions of 2 species (goose and chicken) from 2D images.

Materials & Methods

Data collection and annotation: A total of 661 eggs were photographed for this study, comprising 504 chicken eggs and 157 goose eggs. Images were captured using a phone camera to create a cheaper alternative to more sophisticated systems. 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.

Dataset preparation and splitting: 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.

Dimension calculation: Egg dimensions were calculated from OBB coordinates using a multi-step procedure that converts pixel-based measurements to real-world centimetres. 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' 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 centimetres 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.

Results

The YOLO11x-OBB model demonstrates excellent performance on both validation and test sets. The model showed a recall of 100% on both validation and test sets. In addition, it had a high precision (99.93%) on both sets. mAP@0.5 (IoU threshold 0.5): 99.50% on both validation and test sets indicated good localization accuracy at the standard IoU threshold. The mAP@0.5:0.95 for Validation was 99.30% and 98.99% for the test. Both egg and reference object classes achieved similar high performance, indicating balanced detection across both classes. In the validation set, the model performed best for chicken egg length (MAE = 0.129, r = 0.958), while chicken egg width showed moderate error (MAE = 0.244) and correlation (r = 0.968). Goose egg length had moderate accuracy (MAE = 0.451, r = 0.568), and goose width performed poorly (MAE = 0.934, r = 0.590). The correlations between the predicted and actual values are given in Fig. 1. In the test set, trends were similar: chicken length had MAE = 0.136, r = 0.933; chicken width showed moderate correlation (r = 0.917); goose length was moderate (MAE = 0.309, r = 0.764), and goose width remained poor (MAE = 1.100, r = 0.125). The overall testing and validation results are given in Table 1.

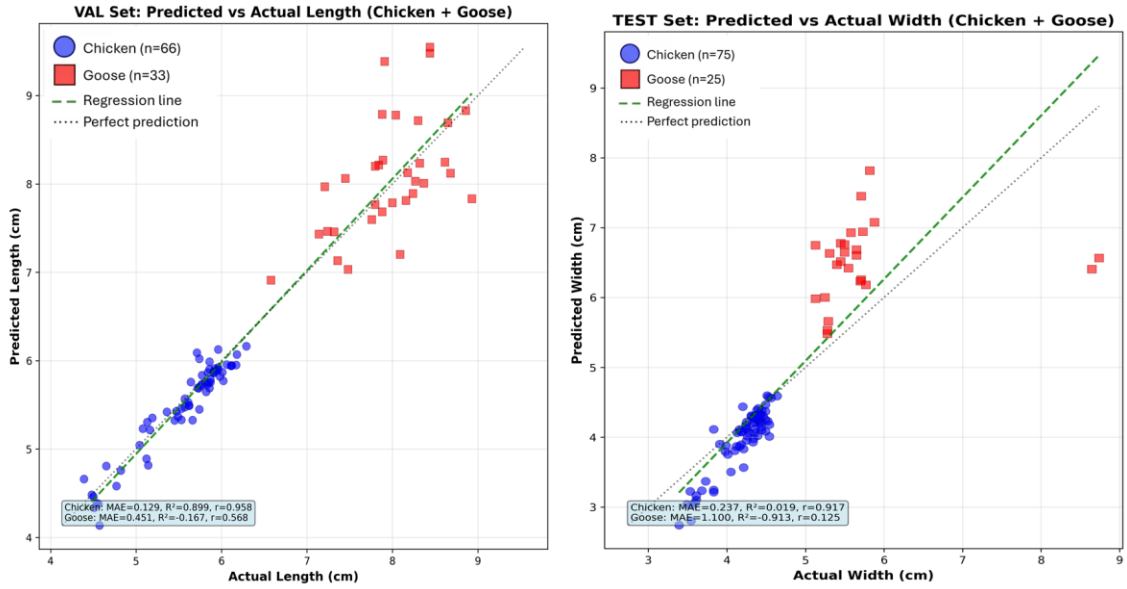

Figure 1. Correlation between the testing and validation datasets

Table 1. Testing and validation results of the overall dataset

Set	Dimension	MAE(cm)	RMSE(cm)	Pearson(r)	StdError(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

MAE: Mean Absolute Error; RMSE: Root Mean Square Error; r: Correlation; MAPE: Mean Absolute Percentage Error

Discussion

The model showed high accuracy in length measurement, which goes on to show that OBB detection for elongated objects like eggs is effective, reliable, and generalizable. The prediction of width was not so accurate, indicating that despite a high correlation (0.922) there errors are higher, and hence the variability of the set might not have been fully captured. The natural variability in egg width and potential perspective distortion effects might also be a reason. Egg orientation variations may also impact width detection accuracy. However, the high correlation may be adequate for practical problems.

These limitations leave a scope for future work. This could explore a bigger goose egg dataset and multi-view imaging. (Yang *et al.*, 2023). The lower correlations for goose eggs, particularly for width measurements, may reflect greater natural variability. Another major factor is the imbalance of data, with the goose images being fewer than the chicken images.

Overall, excellent test set performance showed that the model generalizes well and is not overfitting. This is particularly important for practical deployment, as it indicates the model will perform reliably on new, unseen eggs. Other researchers also worked with YOLO. (Luo *et al.*, 2023) And BiFPN to enhance small object detection accuracy, and a CBAM to improve feature extraction. This has proven to be good for detecting leaky eggs. In comparison to our study, (Ji *et al.*, 2024) suggest that YOLO-TLA demonstrated a 4.6% increase in mAP@0.5 and a 4% increase inmAP@0.5:0.95 over the baseline YOLOv5s model, indicating improved detection capabilities for small objects. Compared to other detection models like Faster R-CNN, Yolo was reported to show superior performance (Jiang *et al.*, 2020). A similar study on hatchery egg classification reported an accuracy of 80.4% using machine learning (Waranusast, Intayod and Makhod, 2016).

This research has applications in breeding, quality control, and marketing. By using only a single camera, the cost of setting up this system is low. However, the spherical nature of eggs introduces slight errors in the testing model since the images are only in 2D. Despite these challenges, studies have demonstrated that models like Segformer achieve a mean intersection over union (IoU) of 96.15% and a mean pixel accuracy of 97.17% for egg image segmentation (Liu *et al.*, 2023). YOLOv11 OBB models, which handle object rotations, also perform well in situations where the orientation of eggs varies. They are superior in performance compared to traditional segmentation. These models can handle complex backgrounds as well (Khanam and Hussain 2024; Li *et al*. 2022). Recent studies prove that convolutional neural networks (CNNs) can improve segmentation accuracy, particularly in complex agricultural imaging tasks (Peng *et al.*, 2024).

Conclusions

This study highlights the significance of AI-driven computer vision techniques to predict egg dimensions from 2D images. By automating the egg grading process in the poultry industry, we can increase efficiency and productivity. Our findings emphasize that machine learning could streamline operations and reduce labor costs.

References

Ab Nasir, A.F. *et al.* (2018) IOP Conference Series: Mater. Sci. Engin. 342:012003. https://doi: 10.1088/1757-899X/342/1/012003

Ji C.-L. *et al.* (2024) J. Real-Time Image Process. 21:141. https://doi: 10.1007/s11554-024-01519-4

Jiang C. *et al.* (2020) Nano Energy 74:104863. https://doi: 10.1016/j.nanoen.2020.104863

Khanam R. and Hussain M. (2024) 'YOLOv11: An Overview of the Key Architectural Enhancements. arXiv. https://doi: 10.48550/arXiv.2410.17725

Li J. *et al.* (2022) International Conference on Machine Learning, Control, and Robotics (MLCR), pp. 91–95. https://doi: 10.1109/MLCR57210.2022.00025

Liu C. *et al.* (2023) Foods, 12:936. https://doi: 10.3390/foods12050936

Luo Y. *et al.* (2023) LWT 187:115313. https://doi: 10.1016/j.lwt.2023.115313

Mondal S.K., Islam M. and Yusuf Md. S. U. (2025) Health. Anal. 8:100432. https://doi: 10.1016/j.health.2025.100432

Peng M. *et al.* (2024) Comp. Electr. Agric. 226:109431. https://doi: 10.1016/j.compag.2024.109431

Waranusast R., Intayod P. and Makhod D. (2016) 2016 Fifth ICT International Student Project Conference (ICT-ISPC). 2016 Fifth ICT International Student Project Conference (ICT-ISPC), Nakhon Pathom, Thailand: IEEE:170–173. https://doi: 10.1109/ICT-ISPC.2016.7519263

Yang X. *et al.* (2023) Animals 13(14). https://doi: 10.3390/ani13142354

Yang Y. *et al.* (2017) IEEE Internet Things J. 4:1250–1258. https://doi: 10.1109/JIOT.2017.2694844