The 11th Asian-Australasian Conference on Precision Agriculture (ACPA 11)
October 14-16, 2025, Chiayi, Taiwan

DUAL-CHANNEL IMAGING AND TWO-STAGE DEEP LEARNING FOR FERTILITY DETECTION OF DUCK EGGS

Chuan-Han Li [1], Chih-Hsiang Cheng [2], Yan-Fu Kuo [1*]

[1] Department of Biomechatronics Engineering, National Taiwan University, Taipei, Taiwan
[2] Eastern Branch, Livestock Research Institute, Ministry of Agriculture, Executive Yuan

* Corresponding Author: ykuo@ntu.edu.tw

Abstract

In Taiwan, the waterfowl industry generates a production value of NT$11.2 billion, of which meat ducks contribute about 80% (≈NT$8.9 billion). As the upstream segment of the duck meat industry, the hatching process of duck eggs plays a critical role in duck production. Fertilized eggs require a clean incubation environment to develop properly. To protect this environment, unfertilized eggs need to be removed at an early stage, which makes fertility detection essential. However, conventional candling inspection is labor-intensive and prone to misjudgment, which may result in economic losses. Recent advances in machine learning, especially convolutional neural networks (CNNs), have significantly improved the accuracy of fertilized egg classification using image features. This project proposes a dual-channel imaging approach. The system uses both visible light and thermal cameras mounted side by side above the egg trays to capture synchronized images. LED lamps beneath each egg simulate manual candling, enabling simultaneous illumination of multiple eggs. Currently, analysis is performed on the visible light images to classify duck eggs as fertilized or unfertilized. A two-stage strategy is adopted: in the first stage, YOLOv8 is used to detect and crop individual eggs from tray images; in the second stage, each crop is classified by a ResNet-18 model. Thermal images have been collected and will be incorporated to enhance classification accuracy and robustness. Experiments based on visible light imaging data demonstrate that the two-stage deep learning pipeline improves early identification of unfertilized eggs and helps reduce contamination risks, achieving a mean average precision (mAP) of 99.9% in detection and over 92% classification accuracy. This two-stage strategy provides a foundation for integrating thermal imaging data to enhance overall system accuracy and robustness in automated hatchery workflows.

Keywords: Duck egg fertility detection, Dual-channel imaging, Two-stage classification

INTRODUCTION

Fertility screening at the upstream hatchery stage reduces contamination risk and stabilizes incubation throughput. Manual candling is labor-intensive and operator-dependent. Image-based deep learning provides repeatable tray-scale inspection from RGB translucency, while thermal sensing contributes complementary temperature cues. Evidence from related domains shows visible–thermal fusion can improve automated recognition, motivating a cautious multimodal extension atop the established RGB baseline.

MATERIALS AND METHODS

In this study, each tray was imaged individually in a dark box with LED backlighting; a top-mounted RGB camera acquired full-tray images (a thermal camera is co-mounted for future fusion). Detection: 26 trays (~165 eggs/tray; 4,290 boxes), split 8:2. Classification: 4,233 crops, split 8:1:1 (fertilized 2,803; unfertilized 1,430). Tray geometry was normalized (perspective), crops resized to 640×640. Stage-1: YOLOv8n, 640×640, 15 epochs, SGD (lr=0.005) with light rotation/flip. Stage-2: ResNet-18, 50 epochs, SGD (lr=0.0005) with cosine annealing, early stopping (patience=8), weighted cross-entropy, similar augmentation. Metrics: mAP@0.5; accuracy and per-class P/R/F1. Thermal frames were co-acquired and will undergo non-uniformity and radiometric normalization, followed by RGB–thermal registration; per-egg thermal crops will be obtained by warping to RGB boxes, and fusion will be evaluated at score-level and with a two-stream classifier under identical splits.

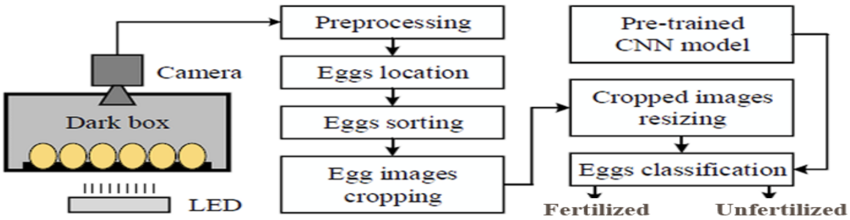

Figure 1. RGB candling rig and two-stage pipeline; thermal stream co-acquired but not analyzed.

RESULTS & DISCUSSION

Across 26 trays (4,290 boxes), the detector achieved mAP@0.5 = 99.9%, supporting reliable tray-level localization and stable per-egg crops for classification. On 4,233 crops (8:1:1), the classifier reached 92% overall accuracy; class-wise, fertilized P/R/F1 = 0.96/0.92/0.94 and unfertilized = 0.86/0.93/0.90, with normalized confusion-matrix diagonals of 0.92 and 0.93, indicating residual errors mainly in borderline early-stage appearances. Operationally, the RGB baseline already enables early removal of unfertilized eggs; remaining risks from illumination/pose shifts and tray variability are mitigated by periodic calibration, exposure control, and targeted augmentation. Because thermal cues complement RGB translucency, once thermal crops are registered to RGB we will evaluate score-level, two-stream, and time-series aggregation across days under identical splits to quantify robustness gains.

CONCLUSIONS

An RGB-based two-stage candling pipeline delivered mAP@0.5 = 99.9% (detection) and 92% accuracy (classification) on 4,233 crops. The same hardware supports a co-mounted thermal stream; we will integrate registered thermal crops and evaluate score-level and two-stream fusion under unchanged splits, with claims limited to verified results. Future work will add time-series RGB–thermal analysis to flag embryonic arrest earlier and cautiously forecast hatchability.