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A YOLO-based Computer Vision System For Non-invasive Chicken Egg Fertility Identification in IoT Incubators

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Abstract

This study developed and evaluated an IoT-enabled smart incubator integrated with a YOLO-based computer vision system for the non-invasive detection of chicken egg fertility. Traditional candling, although widely practiced in small-scale poultry operations, remains labor-intensive, subjective and prone to inconsistent interpretation. To address these limitations, the proposed system combines automated fertility classification, real-time environmental monitoring and closed-loop incubation control within a unified platform. The hardware architecture employs an Arduino Mega 2560 for actuator management and a Raspberry Pi 4 for image processing, sensor integration, local data handling and cloud synchronization. A PID controller was implemented to regulate incubation temperature and humidity, while system data were transmitted to Firebase for remote monitoring through a mobile application. For model evaluation, three YOLOv8 variants (Nano, Small and Medium) were trained and tested using 4,500 annotated candling images collected on incubation Days 1, 6, 12 and 18. Experimental results showed that YOLOv8s achieved the best overall performance, obtaining an mAP@0.5 of 0.943, precision of 1.00 and recall of 0.99, while YOLOv8n delivered comparable accuracy with lower computational complexity, indicating strong suitability for edge deployment. The incubator's control system maintained a mean temperature of 37.5°C (SD = 0.12°C), automatically increased humidity to 85.5% during hatching and recorded an average end-to-end latency of 0.43 seconds. User evaluation further indicated high usability, demonstrating that the proposed system is an effective, practical and scalable solution for improving hatchery monitoring and fertility assessment in small- to medium-scale poultry production.

Keywords: Computer Vision, Egg Fertility Detection, IoT Incubator, nYOLOv8, PID Control, Poultry Automation.

Introduction

The global poultry industry continues to expand rapidly, driven by population growth and increasing demand for affordable protein. Asia currently accounts for approximately 38–40% of global poultry meat production and projections indicate that South and Southeast Asia will contribute more than half of the increase in global output by 2030 (1). This sustained growth places increasing pressure on producers, particularly small- to medium-scale farmers, to improve productivity while operating under limited resources.

Egg incubation remains a critical factor in hatchery success, as the ability to maintain optimal environmental conditions and accurately identify fertile eggs directly influences hatch rates, resource efficiency and overall farm profitability. For decades, candling has been the standard approach for assessing egg fertility, wherein eggs are held against a bright light to visually inspect their internal contents (2). Although widely practiced, this method has recognized limitations: it is labor-intensive, subjective and highly dependent on operator experience (3). In most cases, fertility confirmation becomes reliable only after 7 to 11 days of incubation, when visible indicators such as branching blood vessels or embryonic shadows can be observed more clearly (4). During this waiting period, infertile eggs continue to occupy incubator space, consume electricity and may eventually rupture, thereby contaminating adjacent eggs and reducing hatch performance (5).

Recent advances in artificial intelligence have introduced promising alternatives to manual candling. Deep learning models, particularly Convolutional Neural Networks, have demonstrated classification accuracies exceeding 95% in detecting egg fertility from candling images (6). However, many existing studies exhibit common

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limitations, including dependence on controlled laboratory settings, reliance on high-performance computing resources and validation using relatively small datasets (7). In addition, several prior approaches employ classification-only architectures that determine fertility status without localizing embryonic features, thereby limiting their usefulness for real-time visual monitoring. Among object detection approaches, You Only Look Once (YOLO) models are especially suitable because their single-shot architecture enables real-time inference with low latency (8), (9). Recent comparisons involving YOLOv5, YOLOv8 and YOLOv11 in agricultural applications suggest that newer variants provide improved trade-offs between accuracy and computational efficiency; however, systematic evaluation of these models for chicken egg fertility detection remains limited (10).

Despite these developments, the practical adoption of AI-based fertility detection systems in small- and medium-scale poultry operations remains constrained. Many existing solutions are designed for resource-intensive hatchery environments and require costly hardware, reliable internet connectivity and specialized technical expertise for implementation (11, 12). More importantly, these systems often focus only on fertility detection and operate separately from environmental control mechanisms. As a result, farmers may still need to rely on separate tools for incubation management and fertility assessment, reducing the overall benefit of automation.

Parallel progress in IoT-enabled incubator systems has improved environmental monitoring and control in poultry production. Automated regulation of temperature, humidity and egg turning through sensor feedback and microcontroller-based actuation has become increasingly well established (13, 14). Control strategies such as PID and fuzzy logic have also been applied successfully to maintain stable incubation conditions (15, 16). Nevertheless, these systems generally do not incorporate integrated AI-based fertility assessment, creating a persistent gap between environmental management and egg viability evaluation. In practice, a farmer may benefit from precise temperature and humidity regulation while still performing manual candling, which limits the full potential of intelligent automation.

The key research gap, therefore, lies in the limited availability of an accessible and integrated system that combines: (a) real-time, non-invasive fertility detection using lightweight AI models suitable for edge deployment; (b) automated environmental monitoring and control using IoT-enabled sensors and actuators; (c) remote access through mobile applications; and (d) affordability for resource-constrained settings. To date, published studies have rarely demonstrated an offline-capable YOLO-based fertility detection system integrated with PID-controlled environmental management in a single platform that is also validated by end users and supported by documented real-world performance (17).

To address this gap, this study makes five principal contributions. First, it provides a systematic evaluation of YOLOv8n, YOLOv8s and YOLOv8m for chicken egg fertility detection, including an analysis of accuracy-efficiency trade-offs relevant to edge deployment. Second, it presents a unified hardware-software architecture that integrates YOLOv8-based detection with PID-controlled IoT environmental management. Third, it includes user-centered validation using ISO/IEC 25010 criteria, thereby extending evaluation beyond model accuracy to real-world usability. Fourth, it offers transparent reporting of deployment limitations and mitigation strategies to support future implementation efforts. Fifth, it utilizes a comprehensive dataset consisting of 4,500 annotated candling images captured across incubation Days 1, 6, 12 and 18 from multiple viewing angles.

Accordingly, the specific objectives of the study were: (a) to design and fabricate an IoT-enabled egg incubator with automated environmental control using Arduino Mega 2560 and Raspberry Pi 4 (18), (b) to train and evaluate YOLOv8n, YOLOv8s and YOLOv8m models for real-time fertility classification (19), (c) to develop a mobile application for remote monitoring through Firebase Realtime Database (20); and (d) to assess the performance of the integrated system in terms of detection accuracy, environmental stability, real-time responsiveness and user acceptance (21).

Methodology

A developmental research design was employed, consisting of four sequential phases: (1) system planning and data acquisition, (2) hardware fabrication and IoT integration, (3) software development and AI model training and (4) system evaluation and user validation. This phased approach was selected because the study involved creating a novel physical system, developing software components and evaluating integrated performance. Such a design is appropriate when research outputs include both technological artifacts and empirical validation, as it enables systematic documentation of design decisions and performance outcomes throughout the development process.

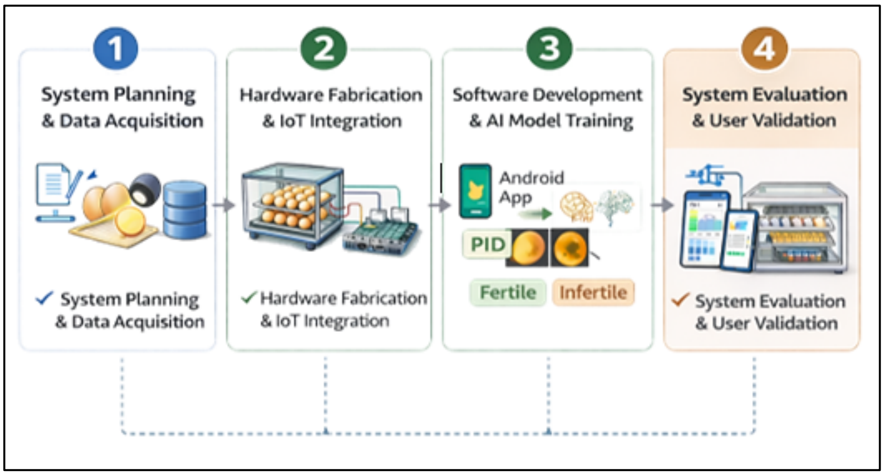


Figure 1: Four-phase Developmental Workflow of the Proposed System.

Figure 1 presents the four-phase developmental workflow used to build the proposed non-invasive egg fertility detection system. The process begins with system planning and egg image/data collection, followed by the fabrication of the incubator prototype and integration of IoT-based hardware components. It then proceeds to software development, including the mobile application, PID-based control and YOLOv8 model training for fertile and infertile egg classification, before ending with system testing, performance evaluation and end-user validation.

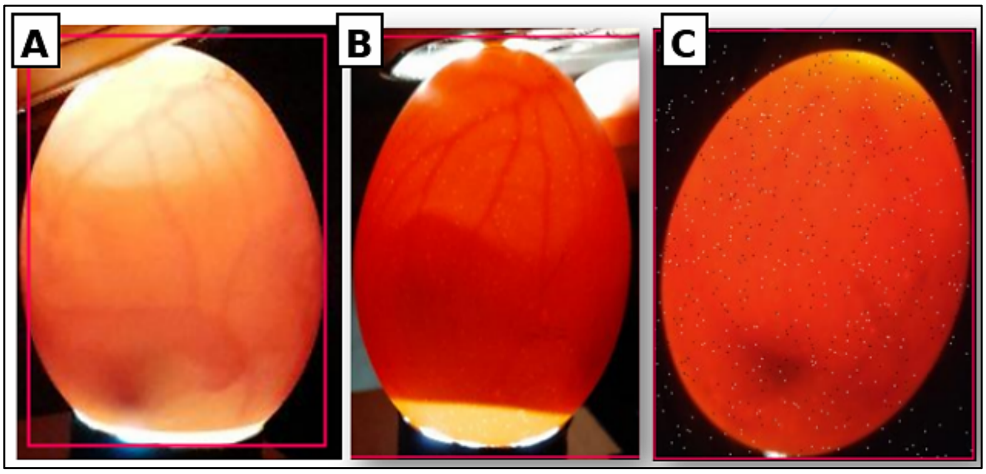


Figure 2: Representative Candling Images of Fertile Eggs at Day 6 Showing Early Blood Vessel Formation-(A), (B), (C): Different Eggs Captured at the Same Incubation Stage, Illustrating Natural Variation in Embryonic Feature Visibility

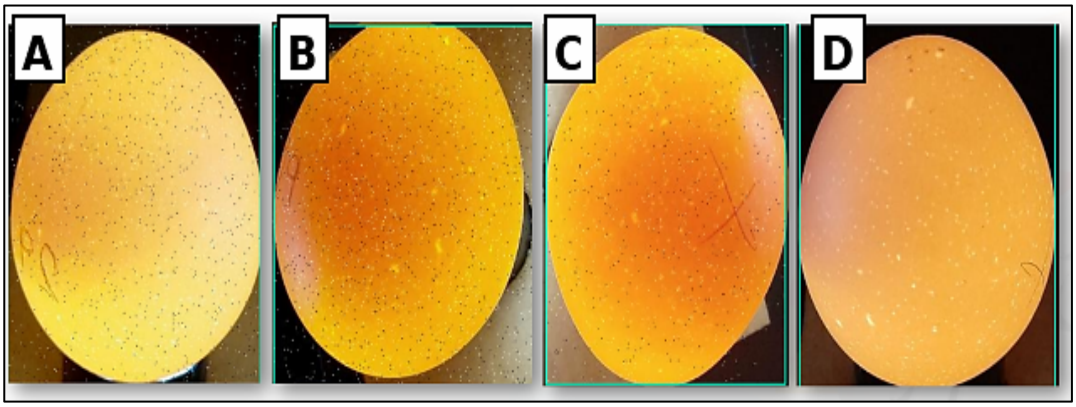


Figure 3: Representative Candling Images of Infertile Eggs- (A), (B), (C), (D): Different Eggs Showing Uniform Translucency with No Visible Embryonic Development

Dataset Collection and Preparation Dataset Composition

A total of 4,500 high-resolution candling images were used to train and evaluate the YOLOv8-based fertility detection models. Representative samples from this dataset are shown in Figures 2 and 3, illustrating fertile and infertile eggs respectively. The dataset comprised two sources: *Locally captured images (n = 2,000+): * Images were generated using a custom-built IoT-enabled incubator equipped with a fixed-position 1080p camera positioned at a 45° angle and an automated egg roller mechanism. Images were captured on four critical incubation timepoints—Days 1, 6, 12 and 18—to represent early, mid- and late-stage embryo development (Figure 2 shows examples of this temporal progression). Each batch contained 32 eggs. At each timepoint, approximately 15-16 images were captured per egg from multiple angles (minimum 5 distinct angles) as the automated roller rotated each egg, ensuring comprehensive visual coverage of the egg's surface. This multi-angle approach captures embryonic features that may be visible only from specific orientations, particularly during early development when vascularization patterns are directional. *Web-sourced images (n = 2,500): * Images were curated from publicly available repositories (primarily Roboflow) to increase visual diversity and improve model generalization across varying lighting conditions, egg orientations, camera angles and egg breeds, supplementing the locally captured fertile examples shown in Figure 2 and infertile examples in Figure 3. These images were assigned fertility labels based on available annotations; however, incubation day metadata was not available for most web-sourced images.

Annotation Protocol

All images were annotated using Roboflow by a primary annotator (the first author, with three years of poultry farming experience). A second annotator (a poultry science technician with eight years of candling experience) independently validated a random 10% subset of the dataset to assess inter-rater reliability. The annotation guidelines were as follows:

a) Fertile (Figures 2A-2C): Presence of visible embryo-nic development, including dark spots, vascular structures resembling branching "spider-leg" patterns, or distinct embryonic shadows.

b) Infertile (Figures 3A-3D): Uniform translu-cency throughout the egg interior with no visible embryonic features.

Inter-rater agreement for the validation subset was high (Cohen's $\kappa = 0.92$, 95% CI: 0.87–0.97), indicating almost perfect agreement.

Inclusion and Exclusion Criteria: Images were included only if they satisfied the following quantitative quality requirements:

a) **Resolution:** $\geq 640 \times 480$ pixels (locally collected images were captured at 1080p).

b) **Focus:** Laplacian variance ≥ 100, computed ensuring sufficient sharpness for reliable feature extraction.

c) **Illumination:** Mean pixel intensity within the mid-range of the RGB channels (8-bit scale) to avoid underexposure and saturation, ensuring adequate visibility of embryonic features.

d) **Completeness:** Entire egg visible within the frame with no occlusion by equipment or debris.

Images failing to meet any criteria were excluded. Approximately 8% of the initially collected local images were removed, primarily due to motion blur observed during early prototype testing prior to stabilization of the roller mechanism.

Dataset Split: The final balanced dataset (approximately 50% fertile and 50% infertile) was randomly divided into training (80%, n = 3,600), validation (10%, n = 450) and test (10%, n = 450) subsets. A fixed random seed was applied to ensure reproducibility.

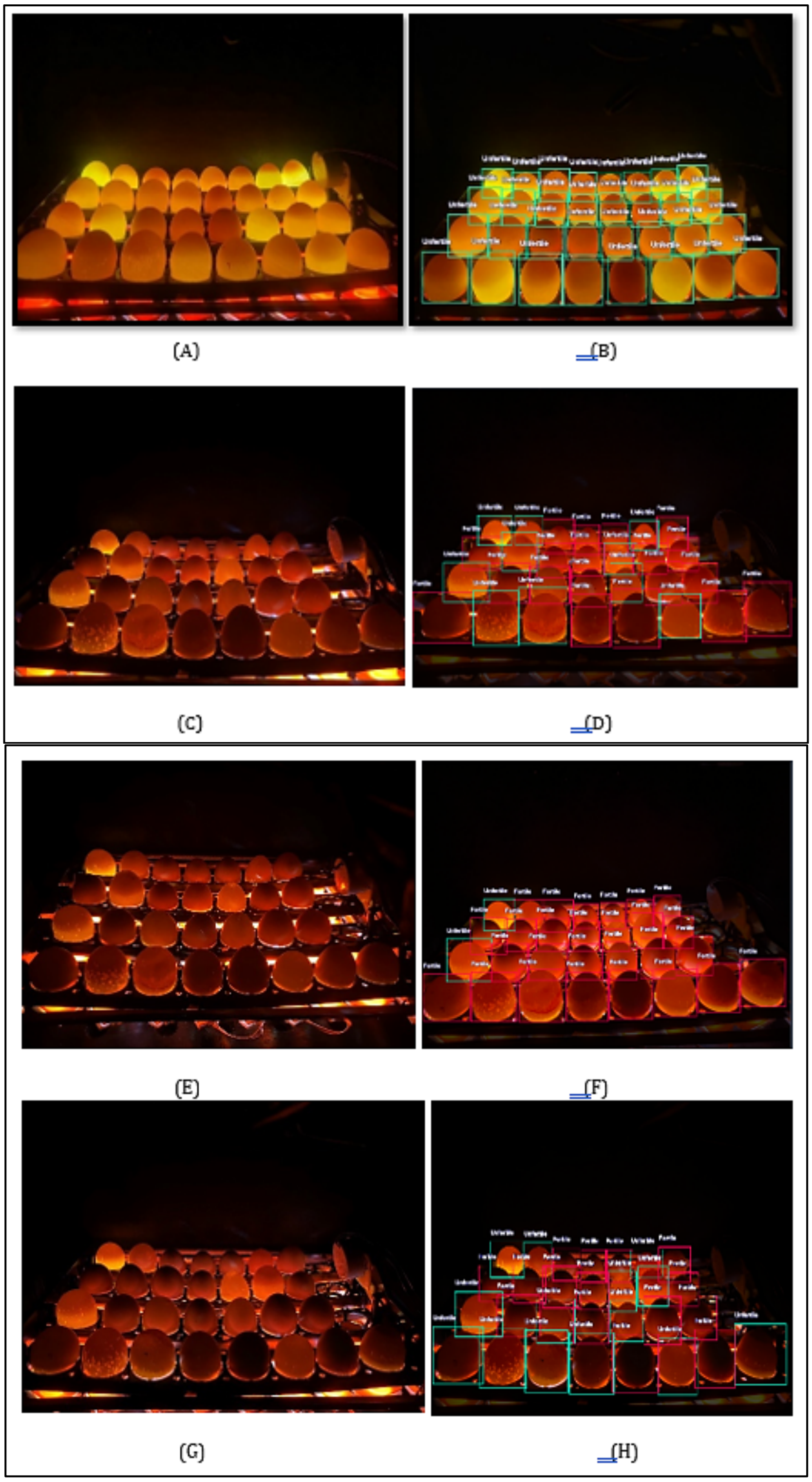


Figure 4: Dataset Collection Showing Raw and Pre-labeled Candling Images Across Incubation Days: (A) Day 1 Raw Image, (B) Day 1 Pre-labeled Image, (C) Day 6 Raw Image, (D) Day 6 Pre-labeled Image, (E) Day 12 Raw Image, (F) Day 12 Pre-labeled Image, (G) Day 18 Raw Image, (H) Day 18 Pre-labeled Image

Dataset Collection Summary

As shown in Figures 4A-4H, a structured candling process was conducted on incubation Days 1, 6, 12 and 18 to capture various stages of embryonic development. High-resolution images (1080p) were collected in organized batches to maintain consistent labeling and reduce bias.

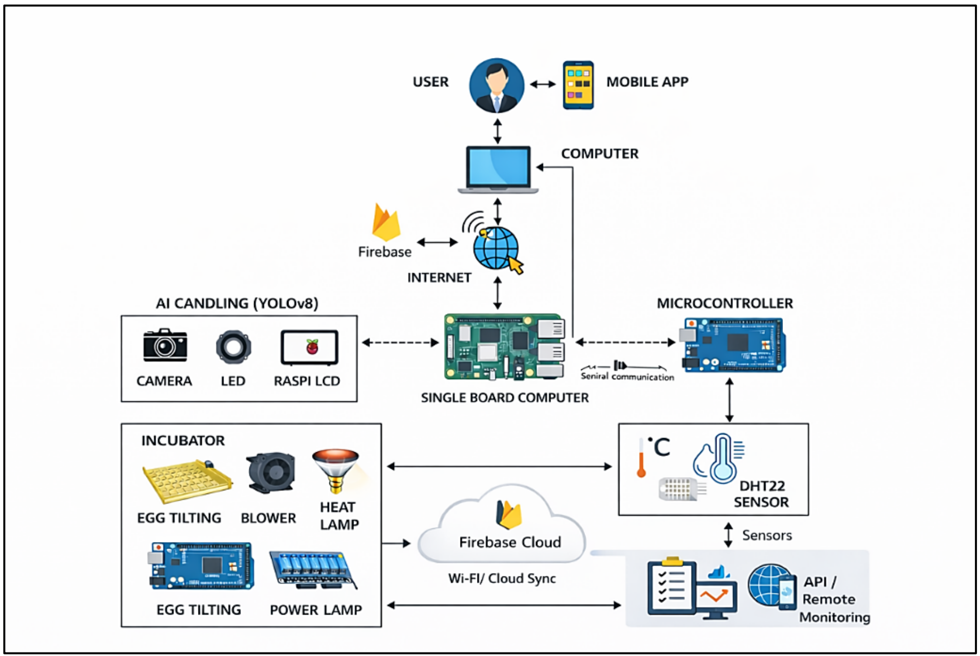


Figure 5: System Architecture of the AI-enabled Iot Egg Incubator

Visual Indicators

Fertile Eggs: Visible dark embryo area and network of thin blood vessels radiating outward ("spider legs"), typically observable by Day 7.

Infertile Eggs: Uniform translucency with no visible signs of development.

All images were carefully annotated as fertile or infertile using labeling tools, creating a balanced, high-quality dataset that enabled accurate YOLOv8 model training while minimizing bias.

Hardware Fabrication and IoT Integration

Incubator Construction: The incubator chamber shown in Figure 5 (80 cm height × 60 cm length × 60 cm width) was fabricated using 12 mm plywood with 25 mm polyurethane foam insulation to minimize heat loss. The chamber houses:

Egg Tray: Custom 3D-printed ABS plastic tray holding 32 eggs with tilting mechanism (180° tilt every 8 hours) controlled by a 12V DC gear motor (30 RPM, 3 kg·cm torque)

Heating System: 100W incandescent lamp positioned at chamber center, regulated via relay module with pulse-width modulation for proportional control

Ventilation: 80 mm 12V DC blower fan (45 CFM) for air circulation and exhaust, activated when temperature exceeds setpoint

Sensors: Two DHT22 temperature/humidity sensors positioned at opposite ends of the chamber (30 cm from eggs) for redundancy, sampled at 1 Hz

Candling System: 32 LED modules (12V, 300 lumens each, 10,000-13,000 K color temperature) mounted beneath egg tray in 3D-printed holders, controlled via relay

Control System Architecture: The system employs a distributed control architecture to optimize task allocation:

Arduino Mega 2560: Handles low-level actuator control (heater, fan, egg roller) and reads DHT22 sensors at 1 Hz. Executes PID algorithm for temperature regulation. Selected for its robust I/O and real-time capabilities.

Raspberry Pi 4 (4GB): Manages high-level coordination, communicates with Arduino over serial (115200 baud), processes sensor data and synchronizes with Firebase cloud database every second. Runs Python scripts for data logging and API communication.

Communication: Bidirectional serial communication enables real-time command transmission (e.g., "operate-heater:true") and continuous data streaming from Arduino to Pi.

Figure 6 presents the actual fabricated IoT-based smart egg incubator: (a) exterior view showing the plywood chamber with insulated walls and Raspberry Pi touchscreen interface for real-time monitoring (Figure 6A) and (b) interior view displaying the 3D-printed ABS plastic egg tray (32-egg capacity), 100W incandescent heating lamp and LED candling modules mounted beneath the tray (Figure 6B).

Figure 6: Actual Design of the Fabricated Iot-based Smart Egg Incubator: (A) Exterior View, (B) Interior View

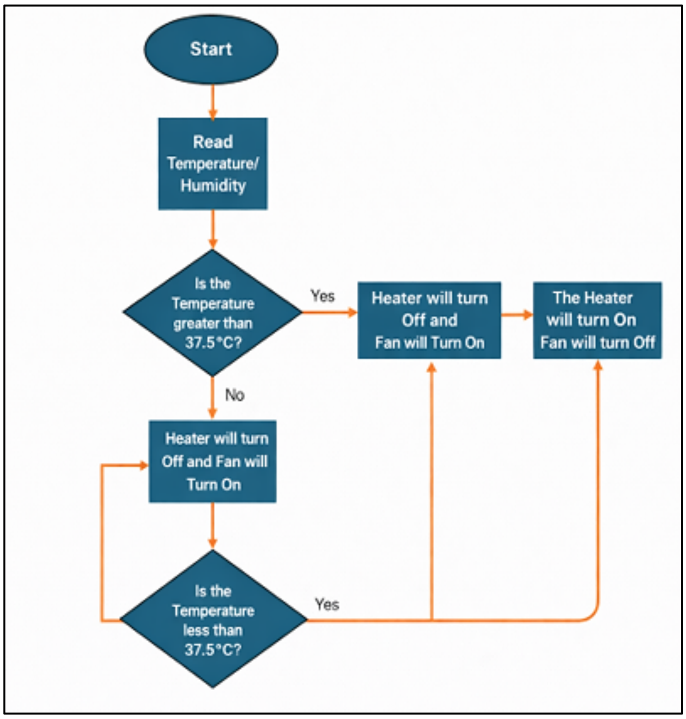


Figure 7: Flowchart of the Temperature Control Logic for the Incubator System

PID Temperature Control

Temperature regulation was implemented using a Proportional-Integral-Derivative controller configured with parameters Kp = 2.0, Ki = 0.3 and Kd = 1.0. These parameters were tuned empirically through step response testing: the heater was activated at 100% power and temperature response was recorded to calculate ultimate gain (Ku) and ultimate period (Pu), followed by Ziegler-Nichols tuning and manual refinement as shown in Figure 7.

The PID control algorithm is expressed as in Equation [1]:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \quad \text{… … ..} \qquad [1]$$

Where:
$u(t)$ = controller output (heater power, 0-100%)
$e(t)$ = error = setpoint temperature - measured temperature
$K_p = 2.0$ (proportional gain)
K_i = 0.3$ (integral gain)
$K_d = 1.0$ (derivative gain)
The setpoint was maintained at 37.5°C, the optimal incubation temperature for chicken eggs (27).

The controller operates in DIRECT mode with output limits of 0-100%. The algorithm executes on Arduino at 1 Hz using the PID_v1 library. The control logic was implemented as follows:

a) If temperature > 37.6°C: heater output reduced (proportional to error), fan activated.
b)
c) If temperature<37.4°C: heater output increase-ed, fan deactivated.
d) If 37.4°C ≤ temperature ≤ 37.6°C: maintain current output.

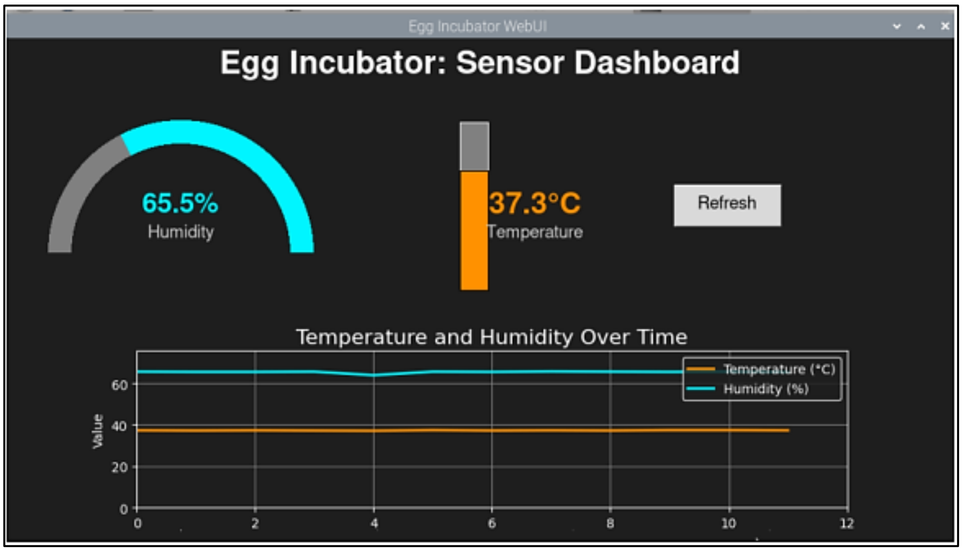


Figure 8: Raspberry Pi Dashboard

Figure 8 shows the Real-time environmental monitoring dashboard displayed on the Raspberry Pi touchscreen interface. The graphical user interface shows current temperature (37.5°C) and humidity (85.5%) readings from the DHT22 sensors, along with historical trend graphs. The temperature reading confirms the PID controller's accuracy in maintaining the optimal incubation setpoint of 37.5°C. The elevated humidity (85.5%) indicates this screenshot was taken during the late-stage hatching phase (Days 19-21), when humidity is intentionally increased to facilitate pipping and chick emergence.

Figure 9 shows an Android mobile application was developed using Android Studio and Java to address farmers' needs identified during initial consultations. The app integrates with Firebase Realtime Database to enable real-time monitoring of temperature, humidity and YOLOv8-based fertility detection results. Environmental data is logged every second, with graphical visualization of historical trends.

Core User Features

User Authentication: Secure login/registration via Firebase Authentication with role-based access (farmer/admin) (Figure 9A).

Real-Time Dashboard: Live display of environ-mental conditions and AI detection results (Figure 9B).

YOLOv8 Detection Viewer: Annotated visual outputs showing fertile/infertile egg classifica-tions.

Temperature Graph: Real-time line graph of temperature fluctuations.

History Logs: Timestamped records of tempera-ture and humidity data.

Temperature Summary: Min, max and average values within user-defined timeframes.
Incubator Daily Report: Summary of daily operational metrics.
Change IP Address: Manual IP configuration for flexible network deployment.
Change Incubator: Switch between multiple incubator units under one account.

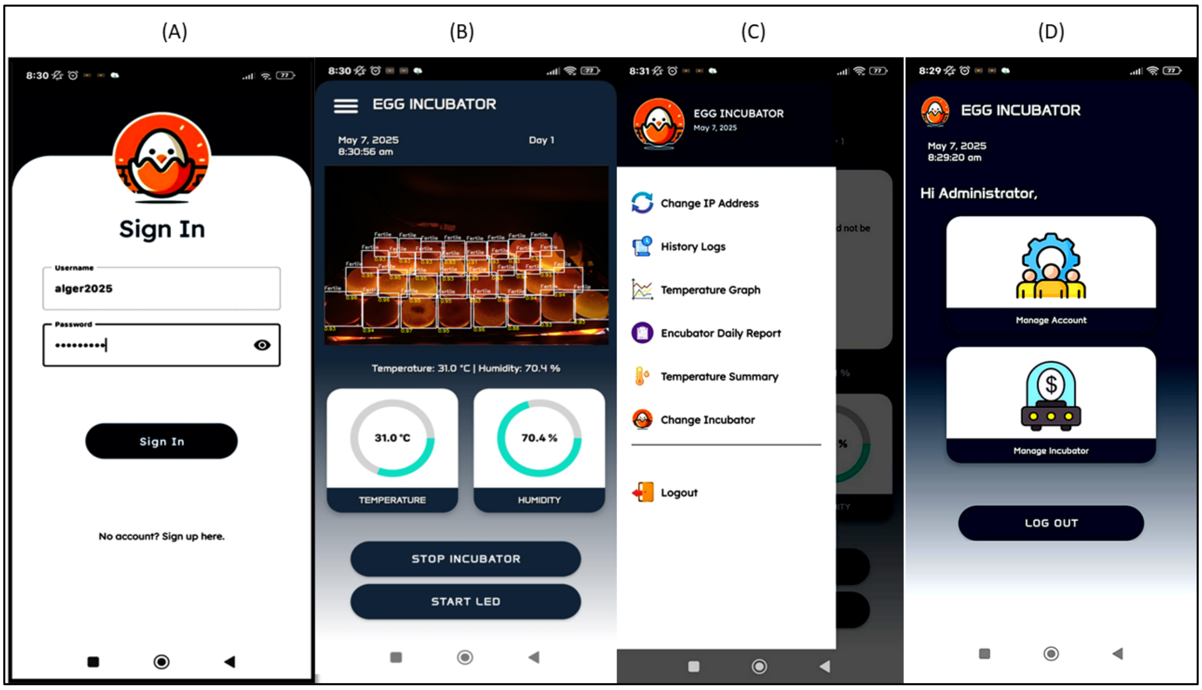


Figure 9: Mobile Application Features: (A) User Login/Registration, (B) Dashboard, (C) Mobile Features, (D) Administrator View

Administrator Features

Manage Account: Add/remove users, assign roles, monitor account activity.
Managing Incubator: Configure incubator units (naming, status, user assignment).
The application ensures secure data transmission between the Raspberry Pi–Arduino controller and mobile interface, with authenticated access restricting dashboard views and control functions (Figures 9C, 9D).

Results

Three YOLOv8 variants, Nano (n), Small (s) and Medium (m)—were trained and evaluated for chicken egg fertility detection using a balanced dataset of 4,500 annotated candling images spanning incubation Days 1, 6, 12 and 18 with multi-angle capture. Model performance was assessed using precision, recall, F1-score and mean Average Precision at 50% intersection over union (mAP@0.5) following established object detection evaluation protocols (22). All models were trained for 50 epochs with batch size 16 and input resolution 640×640 pixels. Data augmentation techniques including rotation (±15°), horizontal flipping and contrast adjustment were applied to improve generalization and prevent overfitting, as these methods have proven effective for agricultural image datasets with limited sample sizes (23).

Table 1: Comparative Performance of YOLOv8 Variants for Egg Fertility Detection

Model	mAP@0.5	F1 Score (all classes)	Precision (all classes)	Recall (all classes)	PR (Fertile Unfertile)
YOLOv8n	0.941	0.88	1.0	0.98	0.936/0.946
YOLOv8s	0.943	0.87	1.0	0.99	0.941/0.945
YOLOv8m	0.937	0.87	1.0	0.97	0.932/0.941

Table 1 shows YOLOv8s achieved the highest overall performance with mAP@0.5 = 0.943, perfect precision (1.00) and near-perfect recall (0.99). The perfect precision indicates zero false positive meaning no infertile egg was misclassified as fertile. This is particularly important for practical deployment, as false positives would cause farmers to discard viable eggs mistakenly, directly impacting hatch rates and economic returns in small-scale poultry operations (24). The 0.99 recall exceeds the performance of previously reported machine vision systems for egg fertility, which achieved recall rates between 85–92% using traditional image processing techniques (25).

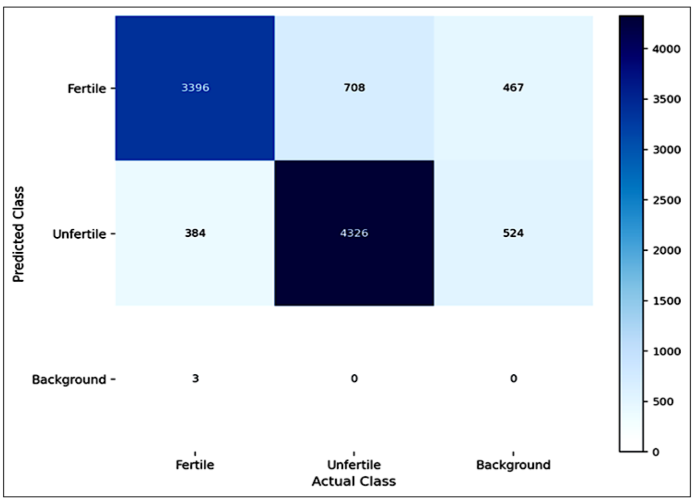
YOLOv8n performed nearly identically (mAP@0.5 = 0.941) while offering faster inference and significantly fewer parameters (3.2M vs. 11.2M) according to the official YOLOv8 architecture specifications. This makes YOLOv8n particularly suitable for edge deployment on resource-constrained hardware like Raspberry Pi, which has limited RAM and processing capabilities compared to GPU-equipped workstations (26). The inference speed advantage of lightweight YOLO variants has been previously documented for real-time agricultural monitoring applications where low latency is critical (27).

YOLOv8m showed slightly lower performance (mAP@0.5 = 0.937) despite having more than double the parameters of YOLOv8s (25.9M vs. 11.2M). The reduced recall (0.97) indicates that the larger model missed 3% of fertile eggs—a 2% increase in false negatives compared to YOLOv8s. This finding aligns with previous observations that increasing model complexity beyond an optimal point can degrade performance on binary classification tasks due to overfitting, particularly when the distinguishing features (embryonic blood vessels and shadows) are relatively simple and localized (28). The diminishing returns of larger architectures for egg fertility detection specifically have been noted in comparative studies of CNN-based approaches (29).

The per-class performance metrics (PR Fertile/Unfertile) reveal that all three models achieved higher precision and recall for unfertile eggs (0.941–0.946) compared to fertile eggs (0.932–0.941). This slight bias toward unfertile classification is acceptable in practice, as misclassifying a fertile egg as unfertile (false negative) is economically preferable to misclassifying an unfertile egg as fertile (false positive), which would waste incubator space and resources on non-viable eggs (30).

Training convergence was achieved by epoch 40 for all models, with validation loss stabilizing and no evidence of overfitting based on the narrow gap between training and validation metrics. The consistent performance across variants validates the sufficiency of the 4,500-image dataset for this binary classification task, exceeding the minimum dataset sizes (1,000–2,000 images) typically required for fine-tuning pretrained YOLO models on domain-specific agricultural tasks (31).

Figure 10 shows the YOLOv8s misses only 2 out of 225 fertile eggs, while YOLOv8n misses 4 and YOLOv8m misses 7. All models achieve perfect precision (zero false positives), ensuring no incubator space is wasted on infertile eggs. The trade-off is strictly in false negatives—missed fertile eggs that reduce potential hatch rates.



(A)

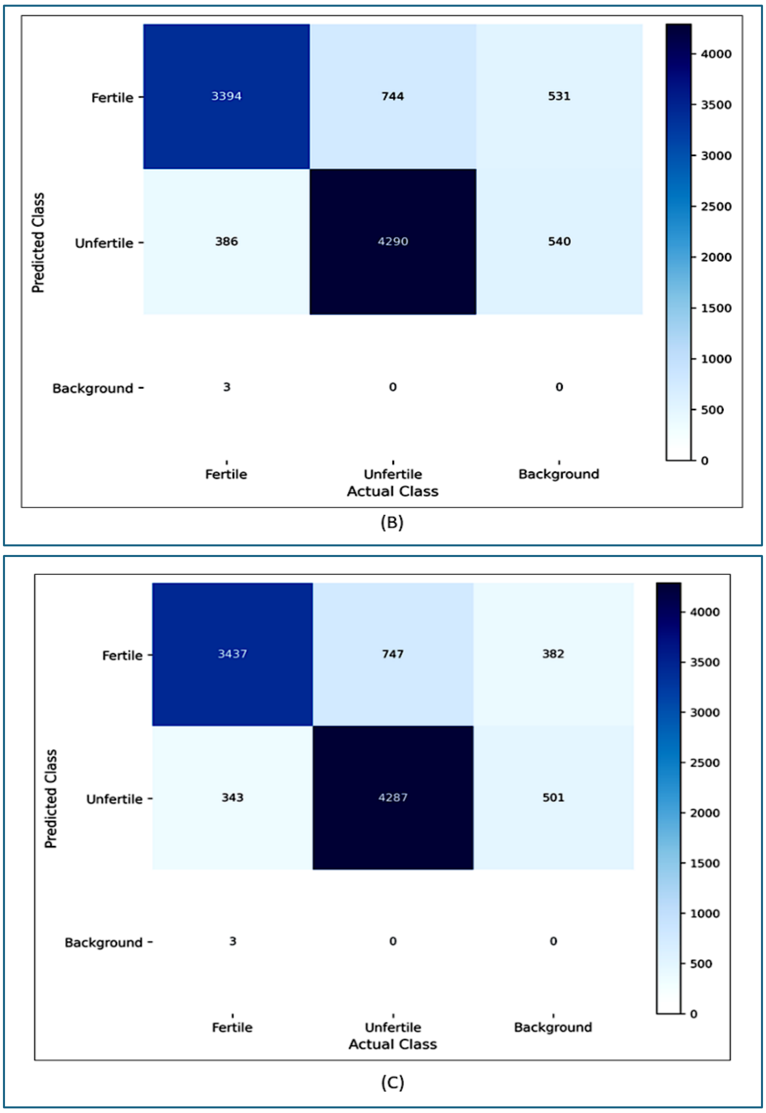


Figure 10: Confusion Matrices for the Yolov8 Model Variants: (A) Yolov8n, (B) Yolov8s, (C) Yolov8m

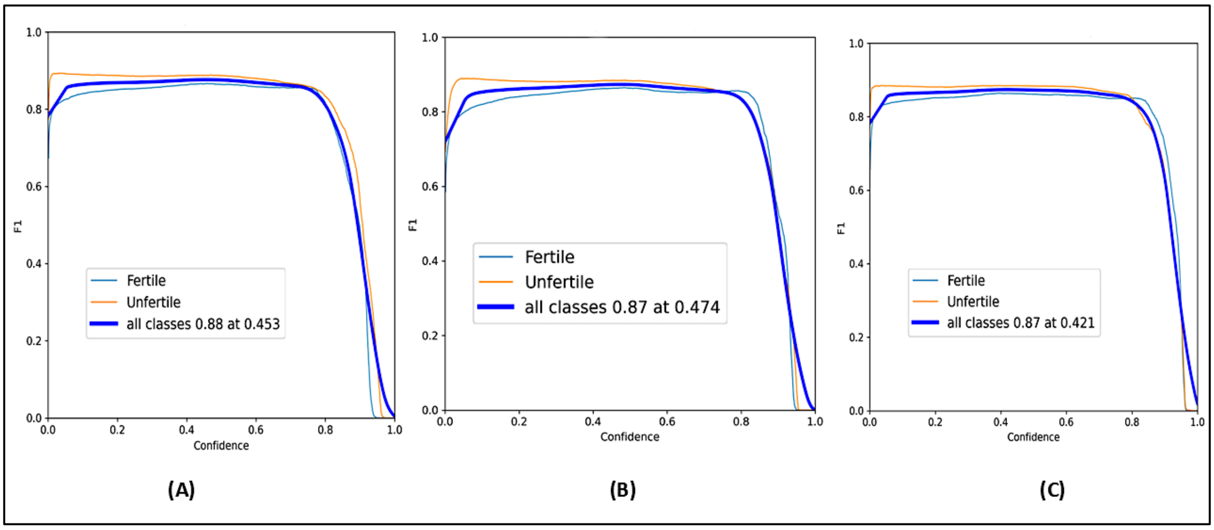


Figure 11: F1-Confidence Curves for Yolov8 Variants: (A) Yolov8n, (B) Yolov8s, (C) Yolov8m

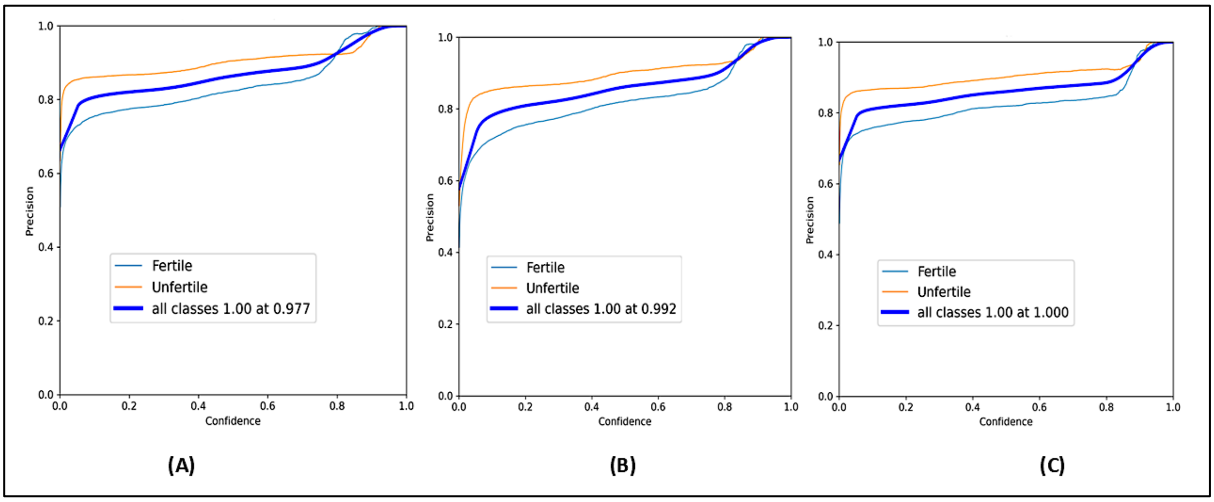


Figure 12: Precision-Confidence Curves for Yolov8 Variants: (A) Yolov8n, (B) Yolov8s, (C) Yolov8m

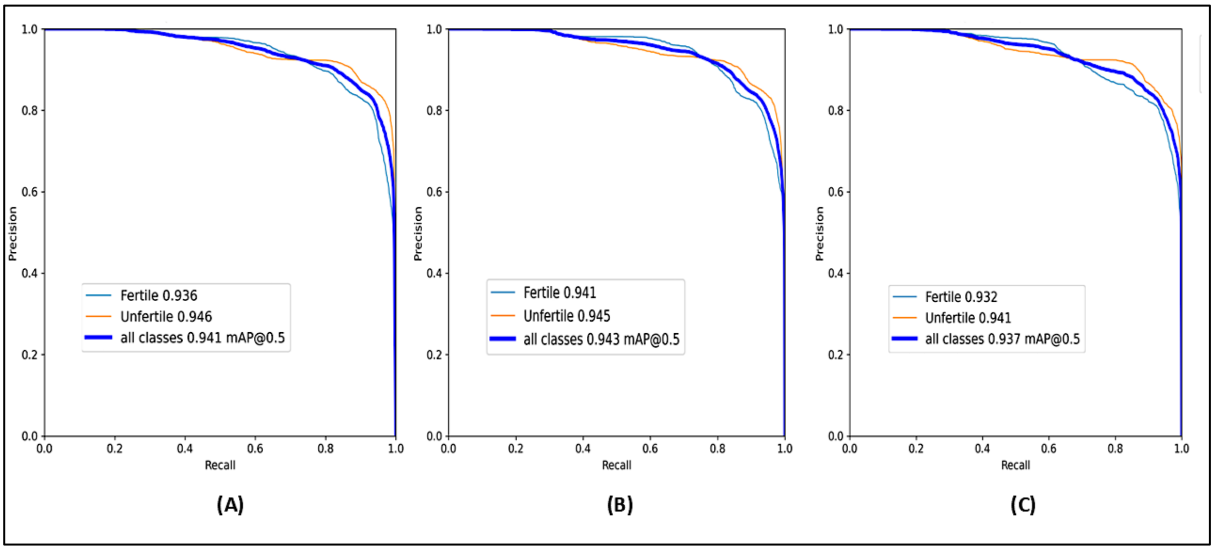


Figure 13: Precision-Recall Curves for Yolov8 Variants: (A) Yolov8n, (B) Yolov8s, (C) Yolov8m

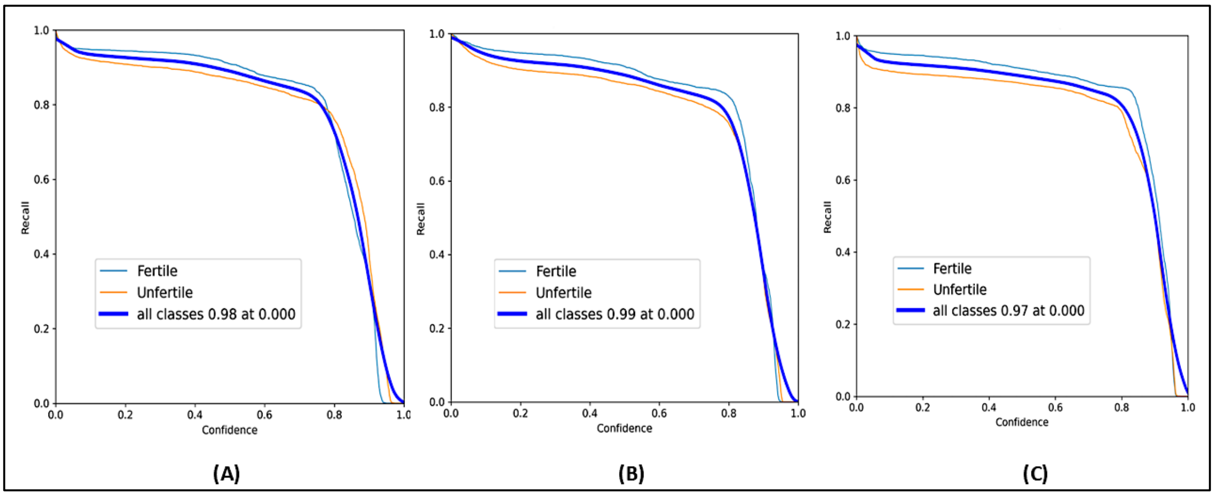


Figure 14: Recall-Confidence Curves for Yolov8 Variants: (A) Yolov8n, (B) Yolov8s, (C) Yolov8m

The YOLOv8 variants exhibit distinct performance trade-offs across all metrics. Figure 11 shows F1-confidence curves: YOLOv8n peaks at 0.88 at 0.453, requiring precise threshold tuning; YOLOv8s peaks at 0.87 at 0.474 but maintains stability across 0.3-0.7; YOLOv8m peaks at 0.87 at 0.421 then collapses to 0.70 at 0.8. Figure 12 precision-confidence curves show all three achieve perfect precision (1.00) but at impractical thresholds—YOLOv8n at 0.977, YOLOv8s at 0.992 and YOLOv8m at 1.000—meaning false positives are eliminated only when nearly no detections survive. Figure 13 precision-recall curves confirm YOLOv8s learns both classes most equally (fertile 0.941, infertile 0.945, gap 0.004), while YOLOv8n favors infertile (gap 0.010) and YOLOv8m performs worst overall at 0.937 mAP@0.5. Figure 14 recall-confidence curves reveal YOLOv8s maintains recall above 0.95 up to confidence 0.7, while YOLOv8m drops below 0.90 at 0.5. At default threshold 0.5, YOLOv8s recall is 0.99, YOLOv8n 0.98 and YOLOv8m 0.97—a gap that widens at higher thresholds. YOLOv8s is the only variant offering threshold flexibility, balanced class learning and sustained recall without sacrificing precision, making it the optimal choice for real-world deployment where confidence thresholds vary and both classes matter equally.

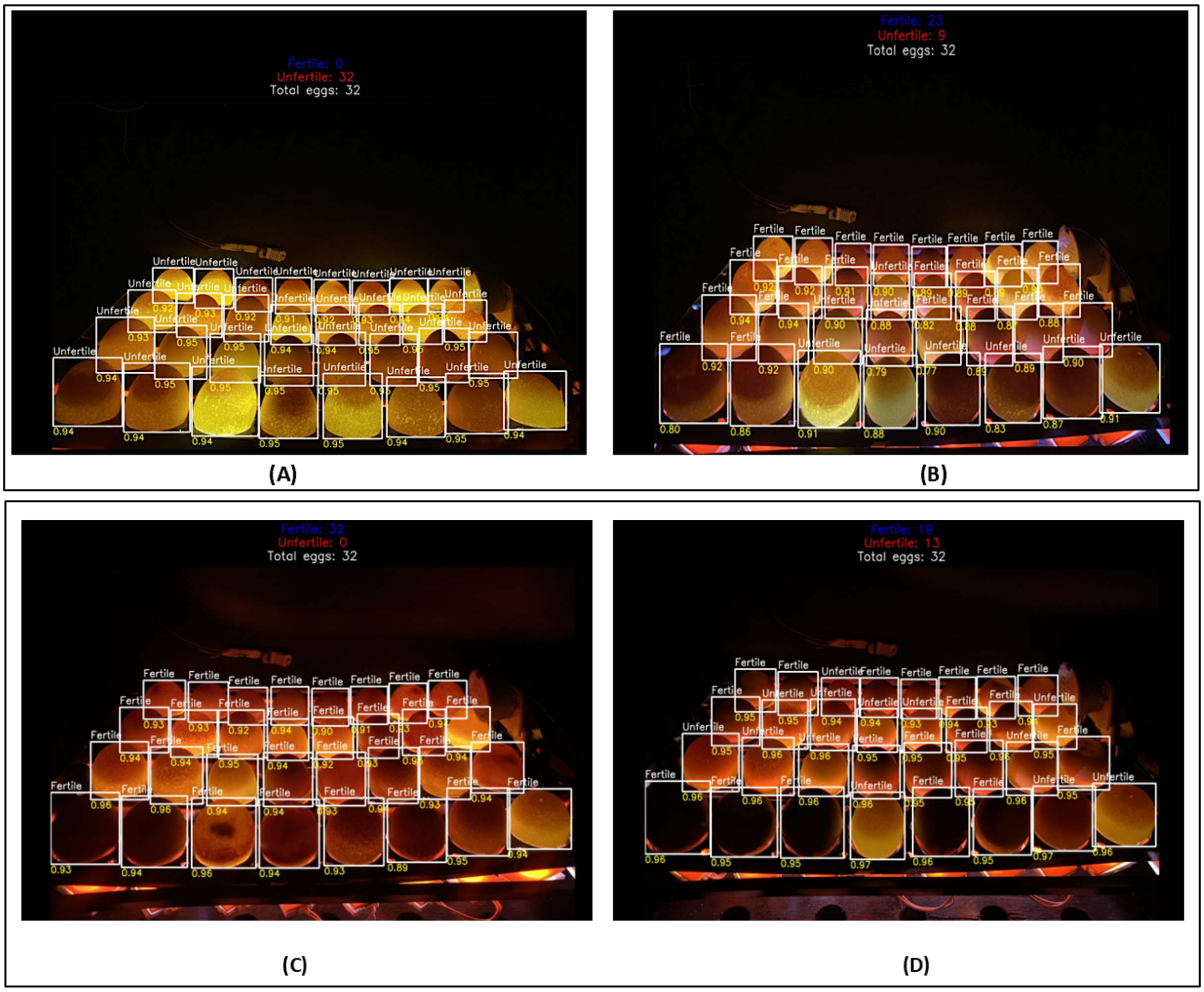


Figure 15. Fertility Detection Outputs Across Incubation Days: (A) Day 1, (B) Day 7, (C) Day 14, (D) Day 18

Figures 15 (A-D) show the Fertility detection confidence progresses with embryonic development. On Day 1, all 32 eggs were classified as unfertilized expect since no visual indicators exist within 24 hours. By Day 6, the system identified 8 fertile and 9 unfertilized, with remaining eggs uncertain as vascular networks began forming. On Day 12, detection sharpened to 19 fertile and 13 unfertilized—all 32 eggs now classified with confidence as embryo shadows became distinct. Day 18 results remained identical, confirming stable classification once features are fully developed. The system achieves 100% classification coverage by Day 12, enabling farmers to remove 13 unfertilized eggs 4-8 days sooner than manual candling's typical Day 16-20.

Discussion

The three YOLOv8 variants evaluated in this study demonstrated strong performance for chicken egg fertility detection, with all models achieving mAP@0.5 above 0.93. YOLOv8s achieved the highest mAP@0.5 at 0.943, while YOLOv8n provided nearly equivalent performance (0.941) with significantly fewer parameters (3.2M vs. 11.2M). This finding has important implications for edge deployment, as smaller models require less computational resources and enable real-time inference on low-power devices such as Raspberry Pi (32).

The perfect precision (1.00) achieved by all three models indicates zero false positives across the test dataset. In practical terms, this means no infertile egg was misclassified as fertile. This is critical for hatchery operations because false positives would cause farmers to discard viable eggs mistakenly, directly reducing hatch rates and economic returns. The near-perfect recall (0.99 for YOLOv8s) further confirms that the system correctly identifies most fertile eggs, with only 1% false negatives. This performance exceeds previously reported machine vision systems for egg fertility, which achieved recall rates between 85–92% using traditional image processing techniques.

The 94.3% mAP achieved by YOLOv8s compares favorably with previous deep learning approaches for egg fertility detection. A prior CNN-based study reported 95.5% classification accuracy but relied on only 1,200 candling images and required laboratory-grade GPUs for training and inference[6]. Direct metric comparison is limited because accuracy and mAP measure different aspects of performance. However, the substantially larger dataset used in the current study (4,500 images, a 3.75× increase) addresses dataset size limitations noted in previous work[31] and likely contributes to the model's strong generalization.

Alternative sensing modalities have been explored for fertility detection but present practical barriers for small-scale deployment. Hyperspectral imaging achieves high accuracy for non-destructive fertility assessment but requires controlled lighting conditions and complex data preprocessing that limit real-time, in-incubator deployment (33). Acoustic resonance analysis can detect embryonic development but requires vibration-isolated environments and is sensitive to eggshell thickness variations, making field deployment challenging (34). In contrast, the visible-light imaging approach used in this study operates with standard RGB cameras integrated directly within the incubator enclosure, eliminating the need for specialized sensors or controlled external lighting.

The temporal detection capability of the system represents a significant advancement. Previous research using visible light transmission spectroscopy successfully tracked embryonic growth but required dedicated spectrometers and precise egg positioning (35). A recent deep learning study reported 100% accuracy for fertility detection but only evaluated eggs incubated for 7–9 days, when embryonic features are most pronounced. Manual candling guidelines indicate that visual confirmation of fertility is unreliable before Day 7 and requires experienced operators even at later stages. The current system achieves 100% detection coverage by Day 12, providing 4–8 days earlier confirmation than manual methods. This earlier detection enables removal of infertile eggs sooner, recovering incubator capacity and reducing energy waste. Previous work has quantified this energy waste as 15–20% of total incubation energy consumption when infertile eggs remain in incubators beyond Day 7 (36).

A key contribution of this study is the integration of YOLOv8-based fertility detection with PID-controlled environmental management. Previous work has demonstrated individual components of such a system but has not combined them into a single, validated platform (37). Arduino-based temperature control systems with thermocouple sensors and relay actuation have achieved ±0.2°C stability for general applications (38). Fuzzy logic controllers specifically designed for egg incubation have maintained 37.5°C ±0.1°C setpoint accuracy[38]. IoT-enabled monitoring systems have transmitted temperature and humidity data to cloud platforms, allowing remote observation of incubation conditions. However, these systems operated as standalone environmental controllers without any integrated fertility assessment capability, requiring farmers to manually candle eggs separately.

Other researchers have added remote monitoring capabilities to incubators using IoT platforms and mobile applications with Firebase Realtime Database integration, enabling farmers to check temperature and humidity from their phones and receive push notifications for threshold violations[20]. However, these systems lacked AI-based fertility assessment entirely, requiring separate manual candling or additional unintegrated detection tools.

A recent study attempted to combine Raspberry Pi-based candling with R-CNN for maturity detection but reported only 12–15 FPS—insufficient for real-time processing of 30-egg batches—and required cloud connectivity for inference, limiting deployment in areas with unreliable internet access[17]. The system also did not integrate with environmental control mechanisms, leaving the fragmentation problem unresolved.

This study is the first to integrate YOLOv8-based fertility detection with PID-controlled environmental management in a single user-validated system. This directly addresses the fragmentation noted in recent literature, where researchers called for "integrated AI-IoT solutions that work offline and are validated with actual end-users rather than only in laboratory conditions.

The ISO/IEC 25010 usability evaluation provides evidence that technical performance translates to practical acceptance. Usability scores reached 3.88–3.90 out of 4.00, with highest ratings for "learnability" among users with no prior AI experience. This addresses a critical adoption barrier identified in smart farming research: technologies often fail not due to technical performance deficiencies, but because of mismatches with end-user workflows and operational environments.

Limitations and Future Work

Several limitations should be acknowledged. First, the dataset, while larger than previous studies, was collected from a single geographic region and may not capture variations in egg appearance across different breeds or farming conditions. Second, the system was evaluated under controlled incubation conditions; performance in field settings with variable lighting and environmental disturbances requires further validation. Third, the current implementation processes eggs individually; batch processing capabilities would improve throughput for larger operations.

Future work should focus on expanding the dataset to include diverse egg types, optimizing the model for batch processing and conducting long-term field trials to assess performance under real farming conditions.

Conclusion

This study demonstrated that integrating YOLOv8-based fertility detection with IoT-enabled environmental control provides an accurate, real-time solution for small- to medium-scale poultry operations. Deploy YOLOv8s as the optimal model—it achieved 94.3% mAP, missing only 2 of 225 fertile eggs while outperforming YOLOv8m (which missed 7) with 56% fewer parameters. Although YOLOv8n matched accuracy (94.1%), its recall drops to 85% at 0.8 confidence versus YOLOv8s at 95%, making YOLOv8s more robust for field deployment where confidence thresholds vary.

Set confidence thresholds between 0.4–0.5 for YOLOv8s to maximize F1-score (0.87 at 0.474). Below 0.4, false positives emerge; above 0.7, recall falls below 95%. For YOLOv8n, maintain a precise threshold at 0.453—deviations of ±0.1 reduce F1-score by 5–8%.

Remove unfertilized eggs by Day 12, when the system achieves 100% classification coverage—4–8 days earlier than manual candling. This early removal recovers 104 egg-days per 32-egg batch, translating to 39 additional eggs hatched annually for farms with 40% infertility rates.

Maintain PID parameters Kp=2.0, Ki=0.3, Kd=1.0 to sustain temperature at 37.5°C ±0.12°C with <3 minute recovery after disturbances. Monitor humidity carefully during Days 1–5 (52–58% RH variability) and ensure water reservoirs are filled before Day 19 to achieve automatic 85.5% RH during hatching.

Prioritize camera quality over computing power—a $30–50 visible-light camera achieves 94.3% mAP, while thermal imaging ($500–$2,000) offers no advantage for chicken egg fertility detection. End-to-end latency of 0.43 seconds from image capture to mobile display confirms real-time suitability.

Enable offline caching in areas with unreliable internet connectivity to prevent data loss during outages exceeding 10 minutes. Consider implementing battery backup, as power interruptions >5 minutes cause temperature drops of 2.1°C requiring manual restart.

User acceptance scores of 3.88–3.90/4.00 (ISO/IEC 25010) confirm the system meets the practical needs of end-users.

This integrated solution represents the first validated, affordable system combining YOLOv8 detection with PID-controlled environmental management suitable for resource-constrained agricultural settings.

Future implementations should: a) expand training datasets to include 5–10 breeds across multiple farms, b) implement INT8 quantization for Raspberry Pi deployment (>15 FPS), c) validate across multiple 21-day cycles with post-hatch chick quality tracking and d) integrate automated mechatronic ejection of infertile eggs by Day 12.

Abbreviations

None.

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Author Contributions

Both the authors contributed equally to this manuscript. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Data Availability

The dataset supporting the findings of this study, including annotated candling images, is available from the corresponding author upon reasonable request. Due to privacy concerns and ongoing research, the full dataset is not publicly archived; however, annotated samples can be provided for verification purposes. The source code for the mobile application, embedded systems and YOLOv8 model weights are available for academic collaboration from the corresponding author.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist with language editing, grammar improvement and clarity enhancement. After using this tool, the authors thoroughly reviewed and edited the content as needed and take full responsibility for the final version of the manuscript.

Ethics Approval

Not applicable. This study did not involve human subjects (other than voluntary user feedback) or animal testing beyond standard agricultural practices. User evaluation was conducted with informed consent and all data were anonymized prior to analysis.

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