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IncuVision: Android-Based Egg Incubator with Machine Learning Algorithm using OpenCV

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Abstract: The poultry industry is a key part of the Philippines' agricultural sector, with chicken eggs playing a vital role. Traditional methods of assessing egg fertility, such as manual candling, are time-consuming and prone to human error. Despite advancements, local poultry farms still rely on manual methods, lacking automated and real-time monitoring systems, resulting in unreliable evaluations. This study developed IncuVision, an Android-based egg incubator application (app) that uses machine learning and OpenCV to enhance egg monitoring and fertility detection. The app provides real-time data on egg status, monitors embryo development stages, and generates data visualizations. The system was evaluated through feedback from IT faculty, an advisory committee, and egg farmers, focusing on functional suitability, performance efficiency, reliability, and usability. The system achieved a General Weighted Mean (GWM) of 4.30, highlighting its success in delivering an efficient, user-friendly, and reliable tool for egg incubation monitoring. These findings demonstrate the app's potential to modernize hatchery operations through automated monitoring and real-time notifications. This study contributes to SDG 9 (Industry, Innovation and Infrastructure) by introducing intelligent digital solutions that modernize agricultural practices, promote innovative technologies, and strengthen infrastructure in the poultry sector through automation and real-time data systems. The integration of AI and mobile technology can help optimize incubation processes and foster more sustainable and technologically advanced poultry farming practices.

Keywords: egg incubator, machine learning, OpenCV, embryo development, mobile application

INTRODUCTION

Chicken eggs are one of the most important products in the poultry sector and a major contributor to the Philippines' agricultural economy (Fadchar & Dela Cruz, 2020). A critical challenge facing this industry is the early detection of fertility in chicken eggs. Local poultry owners predominantly rely on the traditional candling procedure, which involves examining the egg against a light source to determine its status. While a fertilized egg appears opaque and an infertile one translucent, this manual practice requires significant experience and relies heavily on subjective judgment, making it prone to human error. Consequently, establishing standardized, objective prediction techniques is essential for advancing the poultry industry (Fadchar & Dela Cruz, 2020).

With advancements in technology, the opportunity to modernize and optimize egg incubation processes has emerged. Machine learning algorithms and Computer Vision offer promising solutions to the limitations of traditional methods by providing accurate, objective assessments of egg fertility. The application of imaging technology is becoming increasingly prevalent in industry, improving the identification of fertile eggs and the monitoring of embryo development (Saifullah & Khaliduzzaman, 2022). Furthermore, studies indicate that assessing egg quality traits, such as geometric description and shape index, can significantly improve classification processes through machine learning models (de Oliveira-Boreli et al., 2023).

Several attempts have been made to automate poultry farm monitoring. Saifullah & Drezewski (2022) combined machine learning and image processing for non-destructive fertility detection; however, their technique relied on static image captures rather than real-time video monitoring. Beyond fertility, de Oliveira-Boreli et al. (2023) demonstrated how image analysis can evaluate egg quality traits, while Yang et al. (2023) proved the viability of computer vision-based egg grading in commercial facilities. Similarly, Qi et al. (2020) reviewed non-destructive methods, reinforcing the relevance of spectroscopy and machine vision in poultry science.

Despite the availability of these automated solutions, most existing systems are either cost-prohibitive for small-scale local farmers or lack real-time, intelligent monitoring capabilities accessible via mobile devices. Current literature often focuses on industrial-scale systems or laboratory-based classification, leaving a significant gap in affordable, IoT-driven solutions for micro-enterprises. This study bridges that gap by introducing IncuVision, a novel integration of Android-based mobile computing and OpenCV algorithms. Unlike standard automated incubators, IncuVision democratizes access to advanced fertility detection and real-time environmental monitoring, specifically tailored to the infrastructure limitations and economic needs of local poultry agriculture. This initiative directly supports SDG 9 (Industry, Innovation, and Infrastructure), specifically Target 9.4 (Upgrade infrastructure and retrofit industries) and Target 9.b (Support domestic technology development). By replacing manual, error-prone candling methods with an automated, machine-learning-based system, IncuVision upgrades the technological capability of the local poultry sector. Furthermore, by utilizing cost-effective components like the ESP32-CAM, the system fosters inclusive industrialization, allowing small-scale farmers to adopt resilient agricultural infrastructure that was previously accessible only to large commercial operations.

METHODOLOGY

The development of IncuVision: Android-Based Egg Incubator with Machine Learning Algorithm Using OpenCV, integrated hardware and software to automate egg monitoring and fertility detection. It captures temperature and humidity through sensors and monitors egg status via an ESP32-CAM video feed. Table 1 shows the details of the hardware component used, including the actual budgetary cost. It shows a minimal amount of less than ₱1,000 to complete a single setup.

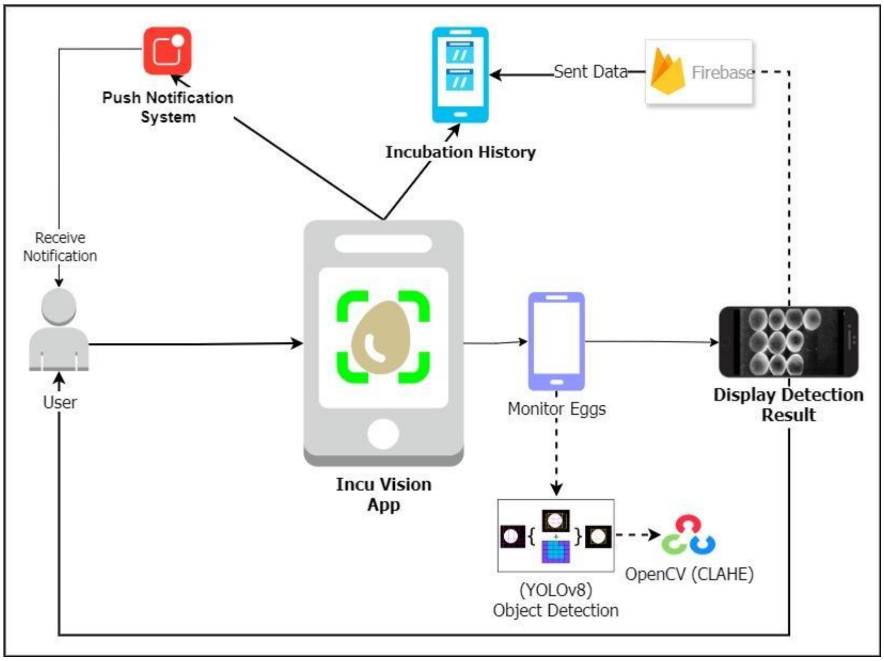

Figure 1. Conceptual framework of the project.

Figure 1 shows the conceptual framework of the study “Android-Based Egg Incubator with Machine Learning Algorithm using OpenCV.” Users monitor eggs through a live video feed from an integrated camera, with OpenCV enhancing video quality using CLAHE. The YOLO algorithm then processes the frames in real time, detecting and classifying eggs by fertility or embryo development stage. Results are displayed in the mobile application with bounding boxes and labels. The system also features real-time alerts for temperature changes, environmental monitoring, and access to incubation history for informed decision-making.

Table 1. Hardware Components, Specifications, and Estimated Unit Costs (PHP) of the IncuVision Prototype

Component	Model / Specification	Function	Cost (PHP)
Camera Module	ESP32-CAM with OV2640 sensor, 2MP resolution (1600×1200 px)	Captures real-time egg images/video inside incubator	349
Temperature Sensor	DHT22, ±0.5°C accuracy	Measures incubator temperature	100
Humidity Sensor	Integrated with DHT22, ±2–5% RH accuracy	Measures incubator humidity	100
Microcontroller	ESP8266 NodeMCU V3	Processes sensor data and streams video feed	106
LED Strip Lights	LED COB Strips	Dimmable color rendering index LED	100

Environmental data is analyzed in real-time to trigger notifications, and video frames are processed using YOLO and OpenCV to classify egg fertility and embryo development. The application displays results, stores historical data. As shown in Figure 2, the level 0 Data Flow Diagram outlines the key components and processes of the project.

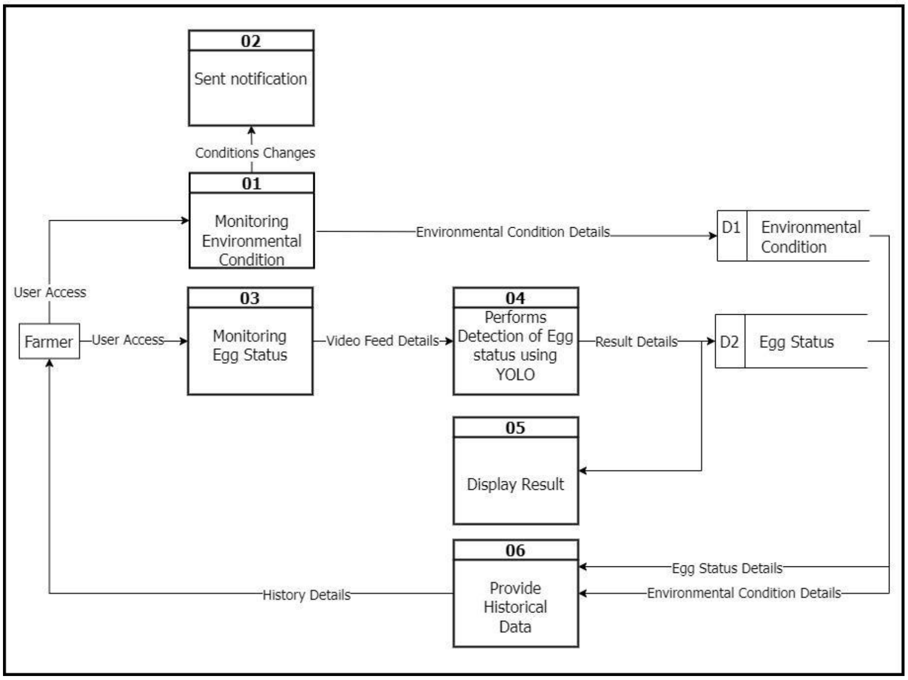

Figure 2. Context-Level (Level 0) Data Flow Diagram of the Project

1.1. Graphical User Interface of the Mobile Application

The Graphical User Interface (GUI) plays a crucial role in the effective implementation of the project by providing a user-friendly, responsive, and accessible design. As shown in Figure 3, the IncuVision app features three main interfaces: (a) the Dashboard for easy navigation to core functions; (b) Monitor Egg for analyzing egg fertility and development using machine learning; and (c) History for tracking and reviewing past data. This intuitive layout ensures a seamless user experience and supports efficient monitoring and decision-making.

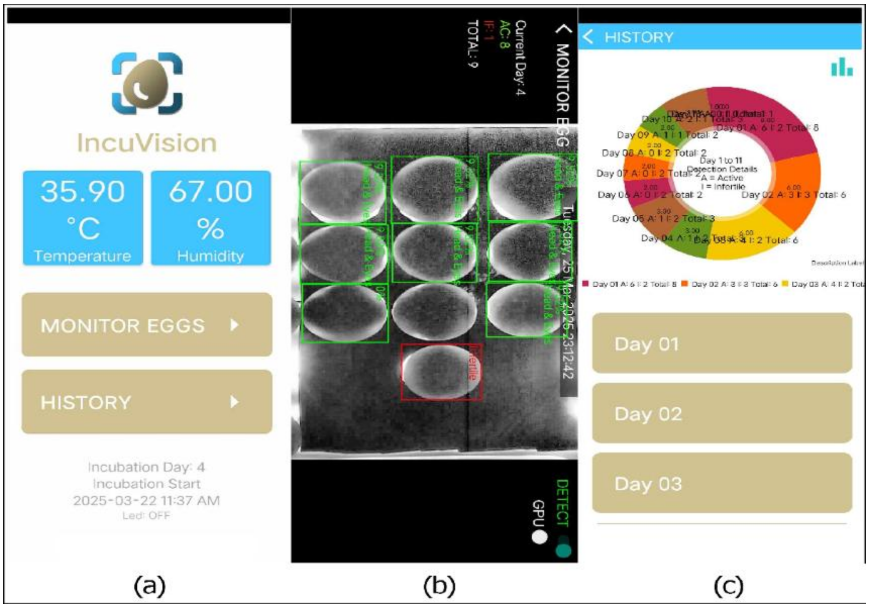

Figure 3. IncuVision Mobile Application Interface showing (a) Main Dashboard, (b) Egg Monitoring Interface, (c) History Interface

1.2. Data Used

The image datasets shown in Table 1 were collected using an ESP32CAM device, which monitored egg development stages daily. The researcher collected 15,000 images, including 11 stages of egg development with 1,000 images each, and an additional 1,000 images representing infertile eggs to ensure comprehensive training of the model.

Table 2. Image Dataset Distribution Across Egg Development Stages for Model Training

Egg Stage Development	Images	Training Data	Test Data	Validation Data
Stage 1	1,000	80%	10%	10%
Stage 2	1,000	80%	10%	10%
Stage 3	1,000	80%	10%	10%
Stage 4	1,000	80%	10%	10%
Stage 5	1,000	80%	10%	10%
Stage 6	1,000	80%	10%	10%
Stage 7	1,000	80%	10%	10%
Stage 8	1,000	80%	10%	10%
Stage 9	1,000	80%	10%	10%
Stage10	1,000	80%	10%	10%
Stage 11	1,000	80%	10%	10%
Infertile Egg	1,000	80%	10%	10%
Total	**15,000**	**80%**	**10%**	**10%**

1.3. Implementation of Egg Development Analysis Using YOLO object detection and OpenCV CLAHE

Low image contrast in incubator videos can slow down the detection of embryos. To address this, the CLAHE (Contrast Limited Adaptive Histogram Equalization) technique is used to boost local contrast, making important features easier for the detection model to see. CLAHE works by adjusting pixel intensity in small areas of the image, helping to highlight subtle details like developing embryos that are often hard to spot. This method has proven effective in enhancing biomedical images. For example, Aziz et al. (2023) used CLAHE to improve the clarity of breast cancer histopathology images, which helped their deep learning model classify cells more accurately. This success supports using CLAHE for egg embryo detection, were faint features and low visibility present real challenges for automation. Figure 4 shows a side-by-side comparison of original and CLAHE-enhanced video frames.

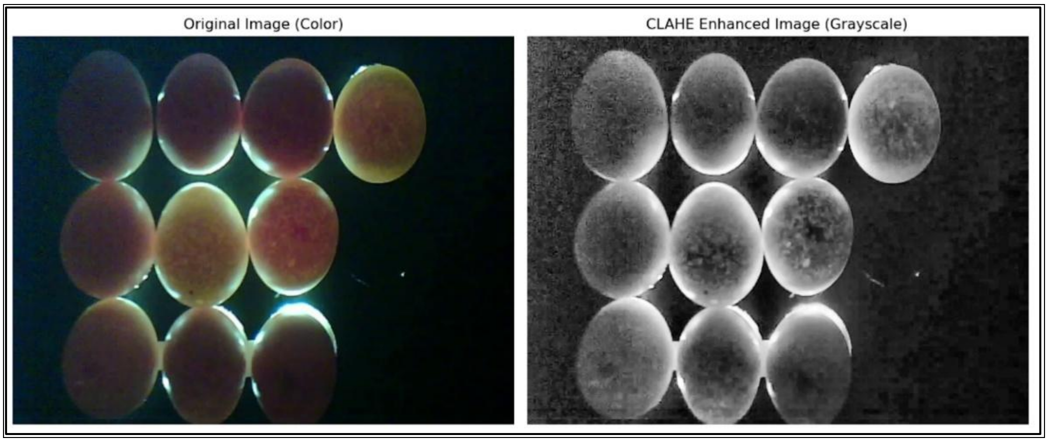

Figure 4. Comparison between original frame vs. CLAHE-enhanced frame

The left side shows the raw frame straight from the video feed, while the right side displays the same frame after applying CLAHE. The enhanced image reveals finer details and clearer edges between objects, which helps the YOLO model detect embryos more accurately.

1.4. Model Training

The model for analyzing embryo development was trained using a dataset of 15,000 images, split into training (80%), testing (10%), and validation (10%) sets. The training process, conducted over 30 epochs with a learning rate of 0.001, demonstrated steady convergence. The loss function combined components for object detection, classification, and localization, which are all crucial for accurately identifying embryos and infertile eggs. These training settings were carefully chosen to strike a balance between computational efficiency and model performance, helping the system perform well for real-time embryo monitoring. As shown in Figure 5, the model's accuracy increased consistently while loss values declined, indicating effective learning of embryonic features without significant overfitting.

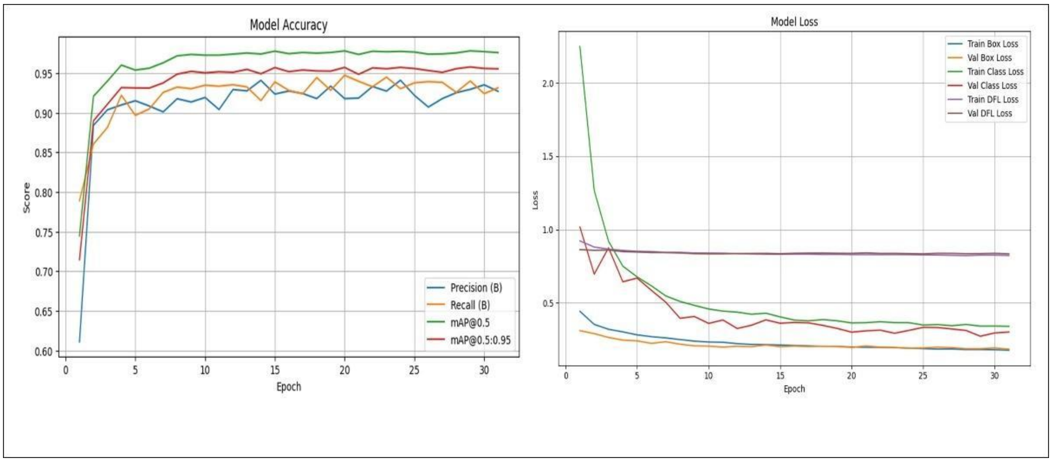

Figure 5. Training Loss and Accuracy Curves Showing YOLO Model Convergence Over 30 Epochs

An in-depth performance evaluation of the YOLO object detection model was carried out using a confusion matrix and F1-score, as illustrated in Figure 6.

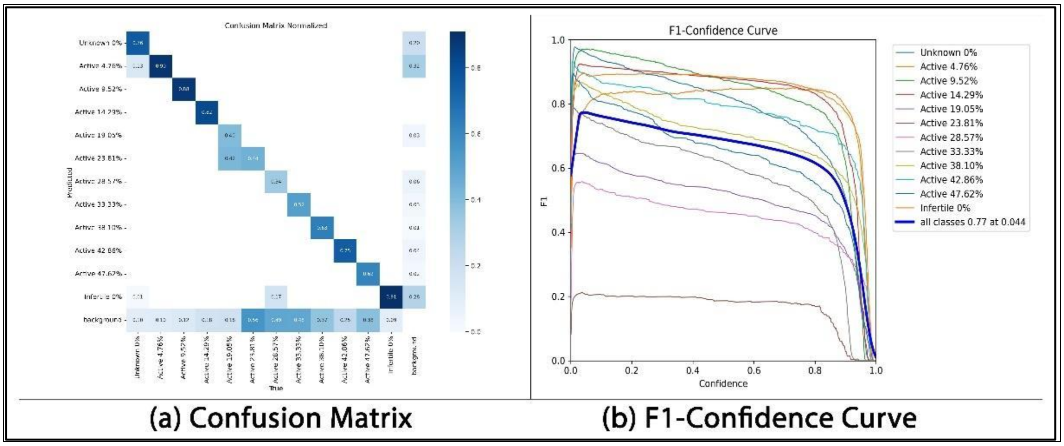

Figure 6. Model performance of YOLO object detection

The confusion matrix (Figure 6a) provides a complete breakdown of classification results, distinguishing correctly and incorrectly identified eggs across various embryonic development stages. It highlights strong classification accuracy in both early stages (Days 2 to 4, 4.76%–14.29%) and late stages (Days 9 to 11, 38.10%–47.62%), with normalized accuracy values ranging from 0.82 to 0.90. In contrast, mid-development stages (Days 5 to 7, 19.05%–28.57%) show higher rates of misclassification due to overlapping visual characteristics among classes. The model demonstrates tough performance in identifying infertile eggs, achieving a 91% classification confidence. However, some confusion remains between embryo classes and the background class, indicating segmentation challenges in cluttered or low-contrast images.

Figure 6b displays the F1-score versus confidence threshold curve. The overall F1-score peaks at 0.77 at a confidence threshold of 0.044, indicating a balanced trade-off between precision and recall. While early and late-stage embryo classifications maintain consistent F1-scores across varying thresholds, mid-stage classifications show more fluctuation, reflecting their increased risk of misclassification. The infertile class sustains high confidence levels but experiences a notable drop in F1-score at higher thresholds. To enhance model accuracy, especially for mid-stage embryos, further improvements can be made through targeted data augmentation, increased representation of underperforming stages in the training set, and fine-tuning of confidence thresholds. These improvements would help make real-time embryo monitoring more accurate and dependable. They align with the key principles behind optimized object detection models like YOLOv4, which focus on using balanced datasets and customized data augmentation to boost accuracy (Bochkovskiy, et al., 2020).

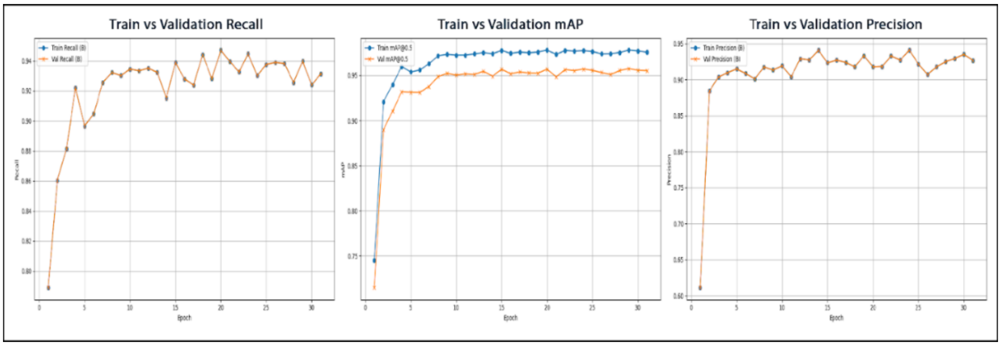

Figure 7. YOLO Model Validation Metrics Showing Recall, Precision, and mAP@0.5 Across Training Epochs

The YOLO algorithm, enhanced with CLAHE preprocessing, achieved robust detection capabilities. Figure 7 highlights the model's validation performance, where recall peaked at 0.945 and mAP@0.5 stabilized at approximately 0.955. These metrics suggest that the system effectively generalizes across different stages of egg development. However, an analysis of the F1-score versus confidence threshold (Figure 6b) reveals a peak F1-score of 0.77 at a confidence threshold of 0.044. While early (Day 1-4) and late-stage (Day 18+) classifications maintained high precision, fluctuations were observed in the mid-stage categories (Gupta et al., 2019).

1.5. Testing and Evaluation

Testing and evaluation are crucial components of the development process, ensuring that the application is functional, reliable, user-friendly, and meets both user and technical requirements. They help in identifying and addressing issues early. Improving overall quality and ensuring that the final product is fit for its intended purposes. Thirteen evaluators including IT faculty, advisory committee members, and egg farmers were purposively selected based on their expertise in software development and poultry incubation. The evaluation included orientation, task-based interactions with the application (e.g., embryo detection, temperature and humidity monitoring, and chart interpretation), and a rating using the ISO 25010 software quality model. Feedback was collected via a 5-point Likert scale, assessing usability, reliability, and feature effectiveness. The responses helped identify areas for improvement in both the mobile application and the ML-based detection system, ensuring that IncuVision aligns with end-user needs and real-world incubation practices. Table 2 shows the distribution of respondents of the study.

RESULTS AND DISCUSSION

1.6. Monitoring Embryo Development Enhanced with CLAHE Technique

The integration of CLAHE (Contrast Limited Adaptive Histogram Equalization) into the embryo monitoring system significantly enhanced the visibility of subtle features in real-time candling footage. This enhancement supports the YOLO object detection model by improving its ability to identify and classify the stages of embryo development, especially in low light and low contrast environment commonly in incubator setup.

As shown in Figure 8, the Egg Monitoring module captures real-time video frames from the ESP32-CAM, enhances them using CLAHE, and applies YOLO-based object detection to classify each egg. Detected eggs are labeled with bounding boxes and categorized as either infertile or at specific stages of embryo development.

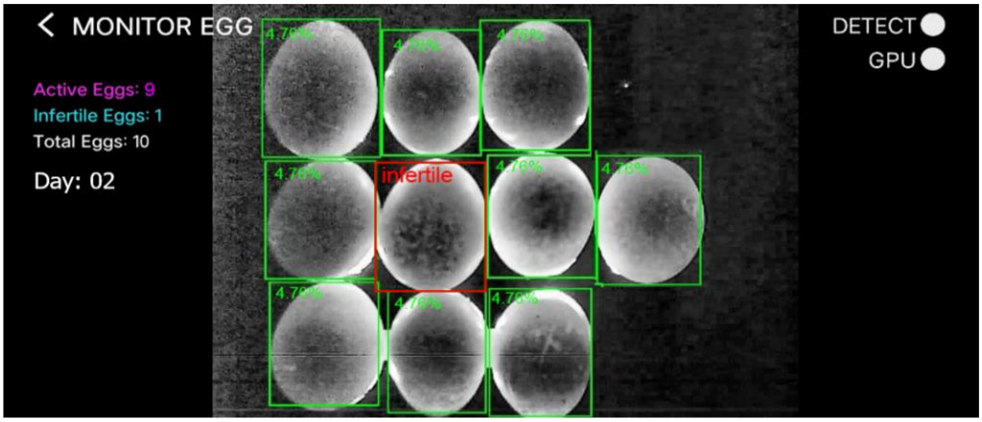

Figure 8. Real-Time CLAHE-Enhanced Egg Monitoring and YOLO-Based Classification Interface in IncuVision

The classification results ranging from heartbeat detection at Day 2 (4.76%) to feather growth and eyelid formation by Day 11 (47.62%) are visually displayed within the mobile application, providing users with clear, real-time insight into each egg's developmental status. From Day 2 to Day 5 (4.76%–19.05%), key early indicators of viability such as the start of heartbeat, formation of the head and limbs, brain development, and early neural organ structures are detected. This stage is critical for confirming embryonic activity and development. As the embryo progresses from Day 6 to Day 8 (23.81%–33.33%), more defined anatomical features such as the beak, egg tooth, eye, and feather tracts begin to appear, marking consistent structural growth and allowing batch-wise comparison of development. In the later stages, from Day 9 to Day 11 (38.10%–47.62%), the system detects advanced features such as the beginning of feather formation, down feather development, beak hardening, and the presence of eyelids over the eyes confirming the embryo's readiness for the final phase before hatching.

1.7. Evaluating the accuracy of YOLO Object Detection in classifying embryo development stages and monitoring egg fertility

The accuracy of YOLO object detection for monitoring embryo development and egg fertility was evaluated by analyzing detection confidence rates from Day 1 to Day 11 of incubation. This evaluation assessed how consistently the model identified embryo stages and fertility over time, revealing strengths in early and late development but challenges with mid-stage embryos due to overlapping features, where yolk sac shadows and overlapping vasculature reduced the model's ability to distinguish between stages. A comparison of embryo development is presented in Figure 9, where it shows the shrinking of yolk from day 2 observation presented in Figure 8. Structural ambiguity in the mid stages highly affects the model performance. Performance metrics such as confusion matrix, F1-score, precision, recall, and mean Average Precision (mAP@0.5) (Figure 5, Figure 6) confirmed high classification accuracy, with mAP reaching 0.955 and F1-score peaking at 0.77, supporting YOLO's suitability for real-time embryo monitoring (Bochkovskiy et al., 2020; Ketkar & Moolayil, 2021; Gupta et al., 2019; Desai et al., 2024).

Biologically, infertile eggs show no development, while fertile eggs progress through well-documented embryonic milestones, including heartbeat and limb formation from Day 2 onwards (Macklin et al., 2019; Vilches-Moure, 2019). The model labels Day 1 eggs as "Unknown" and classifies from Day 2 as "Active" based on visible morphological features aligned with these biological stages.

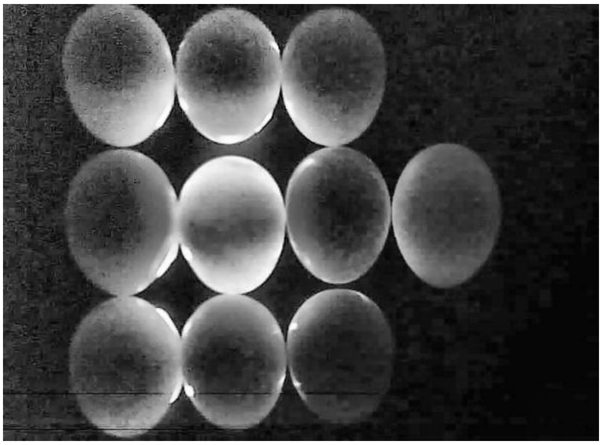

Figure 9. Model Observation in Day where the detected infertile egg shows shrinking of egg yolk

Average confidence rates per day were calculated to evaluate detection reliability, with percentage error indicating deviations from perfect confidence. The study highlights the importance of confidence calibration for enhancing model reliability in precise biological detection tasks (Küppers et al., 2022).

Table 3. YOLO detection confidence rate for embryo development stages from day 1 to day 11.

Day	Class Name	Embryo Development Stage	YOLO Confidence Rate	Percentage Error
1	Unknown 0%	Blastoderm Forms	71.70%	28.30%
2	Active 4.76%	Heartbeat Starts	70.70%	29.30%
3	Active 9.52%	Head & Limbs Form	81.10%	18.90%
4	Active 14.29%	Brain Develops	76.90%	23.10%
5	Active 19.05%	Neural Organs Appear	73.60%	26.40%
6	Active 23.81%	Beak & Egg Tooth Form	79.70%	20.30%
7	Active 28.57%	Eyes & Egg Tooth Develop	74.90%	25.10%
8	Active 33.33%	Feather Tracts & Limb Details	77.50%	22.50%
9	Active 38.10%	Feathers Begin Forming	78.40%	21.60%
10	Active 42.86%	Down Feathers & Beak Hardening	75.60%	24.40%
11	Active 47.62%	Eyelids Cover Eyes & Feathers Grow	72.30%	27.70%

Table 3 shows YOLO's confidence rates for embryo development from Day 1 to Day 11. Early stages (Days 1–2) have moderate confidence (~70%) due to subtle features and eggshell differences between training (pure Rhode Island) and testing (mixed breeds), which reduce visibility (Zhang et al., 2023; Çevik et al., 2022). Confidence improves in mid-stages (Days 3–6), peaking at 81.1% on Day 3, but dips slightly on Days 4–5 due to overlapping features (Lin et al., 2024). Later stages (Days 7–11) stabilize around 74%–78%, with a small drop on Day 11 caused by fine details like feather growth. Percent error ranges from 18% to 29%, lowest during mid-incubation when features are clearer. These results confirm YOLO's effectiveness in embryo and fertility detection but suggest that expanding the training dataset and enhancing imaging could improve early-stage accuracy (Raudonis et al., 2019).

Table 4. Descriptive ratings from respondents in terms of functional suitability

Particulars	Mean	Verbal Interpretation
The IncuVision app accurately produces correct results in analyzing egg status.	3.53	AGREE
The IncuVision app accurately produces correct results in analyzing Embryo development stages.	3.60	AGREE
The IncuVision app features accessible data visualization, making it easy for users to view information on egg status and development efficiently.	4.36	AGREE
The IncuVision app provides a real-time push notification mechanism for temperature and humidity changes in the incubator.	4.42	AGREE
Consolidated Mean	**3.98**	**AGREE**

Table 4 showed feedback from the 13 evaluators consisting of five (5) poultry farmers, five (5) IT experts, and three (3) advisory committee members. The accuracy of the app in analyzing egg status received a mean score of 3.53, and its ability to detect embryo development stages received a mean of 3.60. Both scores were in the "Agree" range (3.51–4.50). This indicated that the features worked well, although some small issues such as occasional inaccuracies were still present. These results suggested that the main features of the app were functional but could be improved, especially in detection precision. In contrast, the data visualization feature received a mean score of 4.36, and the real-time temperature notification received 4.42. These high scores showed that both features were clear, easy to use, and worked effectively in giving important information for incubation monitoring. The General Weighted Mean (GWM) of 3.98 confirmed that the app met most functional requirements and worked as expected in most cases. Based on the Likert scale, this meant that the goals of the system were mostly achieved, although minor improvements could still be made. Overall, the findings highlight IncuVision's achievement in delivering a functional, reliable, and user-centric tool for modernizing egg incubation practices. The application succeeded in automating traditional processes and provided real-time monitoring features that improved decision-making for its users. These results affirm the app's value and relevance in the poultry industry and support its potential for further development particularly in refining detection accuracy to move from “Agree” to “Strongly Agree” in future evaluations.

Table 5 shows the reliability ratings for the IncuVision app, the consolidated reliability score of 4.24 also corresponds to “Agree.” This means respondents found the app dependable under normal use but noted irregular detection inaccuracies, indicating some aspects of reliability could be enhanced.

Table 5. Descriptive ratings from respondents in terms of performance efficiency

Particulars	Mean	Verbal Interpretation
The IncuVision app runs reliably without unexpected shutdowns under typical use conditions.	4.29	AGREE
The IncuVision app provides accurate detection results consistently.	3.73	AGREE
The IncuVision app is available and operational whenever there is an internet connection.	4.62	STRONGLY AGREE
The IncuVision app performs consistently and reliably in delivering data visualization.	4.33	AGREE
Consolidated Mean	**4.24**	**AGREE**

Table 6 shows the usability ratings for the IncuVision app, the usability category received a high consolidated mean of 4.67, falling within the 4.51–5.00 range, which translates to “Strongly Agree.” This signifies that users are convinced that the app's usability objectives—such as interface clarity, ease of navigation, and consistent design were fully met with no significant usability errors.

Table 6. Descriptive ratings from respondents in terms of usability

Particulars	Mean	Verbal Interpretation
The IncuVision app has a clear and easy-to-navigate interface.	4.69	STRONGLY AGREE
The IncuVision app has consistent design and layout.	4.62	STRONGLY AGREE
The IncuVision app is easy to learn and user-friendly.	4.62	STRONGLY AGREE
Consolidated Mean	**4.67**	**STRONGLY AGREE**

Table 7. ISO 25010 Software Quality Evaluation Results of IncuVision Using Mean Scores and Descriptive Ratings

Criteria	**Mean Score**	**Descriptive Equivalent**
Functional Suitability	3.98	AGREE
Performance Efficiency	4.33	AGREE
Reliability	4.24	AGREE
Usability	4.67	STRONGLY AGREE
Overall Average	**4.30**	**AGREE**

To assess real-world applicability, the system was evaluated by thirteen experts, including IT faculty, an advisory committee, and poultry farmers, using the ISO 25010

Software Quality Model. Table 7 summarizes the results, showing an overall General Weighted Mean (GWM) of 4.30, interpreted as "Agree". Among the Software Characteristics, Usability was rated highest, 4.33, indicating the Android interface was intuitive and the data visualizations were easy to interpret. In terms of Performance efficiency, Users found the real-time monitoring responsive, though network stability occasionally affected video feed latency with a score of 4.33. Evaluators rated Reliability with 4.24 which denotes that the system was deemed dependable for daily use, although minor inconsistencies in detection were noted. However, among the four software characteristics, evaluators rated Functional Suitability the lowest with a mean score of 3.98, highlighting that, while functional, this lower score reflects the need for higher precision in the automated candling feature, specifically during the transition phases of embryo growth.

CONCLUSIONS AND RECOMMENDATION

Conclusions of the Project

This study aimed to develop IncuVision, an Android-based egg incubator app that integrates modern technology into poultry egg monitoring. By combining machine learning with OpenCV, the project sought to enhance the accuracy and efficiency of the incubation process. The app was designed to improve fertility detection, monitor embryo development stages, and deliver real-time updates through a user-friendly mobile interface. It used the YOLO object detection algorithm to analyze egg development and applied OpenCV's CLAHE technique to enhance embryo visibility in low-contrast images. In addition, the app featured real-time temperature and humidity monitoring, along with interactive data visualization tools to help users effectively manage hatchery conditions.

Based on the survey results, the system received an overall mean score of 4.30, reflecting generally positive feedback from users. Usability got the highest rating at 4.67, showing strong satisfaction with the app's interface. Performance efficiency (4.33) and reliability (4.24) were also rated well, despite occasional connectivity issues. However, functional suitability received the lowest score at 3.98, indicating areas for improvement—particularly in enhancing the accuracy of embryo monitoring and expanding the app's features to better meet user needs and expectations.

The study concludes that the application effectively modernizes hatchery monitoring by analyzing egg fertility and embryo development using YOLO and CLAHE, with functional ratings of 3.53 and 3.60. It provides reliable real-time alerts (4.42) and clear data visualizations (4.36), supporting efficient management. While effective, improvements are needed for later-stage detection accuracy and external validation.

Despite the successful deployment and high user satisfaction, this study encountered specific technical and methodological limitations that influence the generalization of the findings.

First, the model exhibited higher misclassification rates during mid-stage incubation (specifically Days 5–7 and Days 10–14), when the distinct vascular network begins to blur as the embryo grows into a larger, opaque mass. This lack of high-contrast features makes it difficult for the computer vision algorithm to distinguish between a healthy, growing embryo and a late dead embryo. The frame-by-frame YOLO analysis may struggle in such cases compared to video-based temporal approaches that could detect subtle movement cues.

Second, the use of the ESP32-CAM, while essential for keeping the prototype cost under PHP 1,000, introduced image noise in low-light incubator conditions due to its limited sensor size and dynamic range. This contributed to false negatives in the infertile class when ambient lighting fluctuated, necessitating the use of CLAHE to compensate for contrast limitations.

Third, dataset diversity was limited, as all training images were collected from a single poultry farm using one specific breed. As a result, the model may not generalize to eggs with different shell colors or thicknesses, both of which significantly affect light transmissibility during candling.

Finally, while the YOLO model performed well overall in detecting fertility and embryo development stages, later-stage detection accuracy remains an area for improvement, as reflected in the functional suitability ratings of 3.53 and 3.60, both indicating the need for further refinement.

Recommendations

Based on the findings and limitations of this study, the following recommendations are proposed. Future versions of IncuVision should integrate a wider-view camera to enable simultaneous monitoring of more eggs, particularly in larger hatchery setups. Embryo tracking should be extended to cover Days 12 through 21 to support full-cycle incubation monitoring. The system should also be expanded to support egg detection across multiple species and chicken breeds to improve its generalizability. Offline functionality for accessing historical data and charts should be incorporated to ensure usability in areas with limited or unstable internet connectivity. Furthermore, the detection pipeline should be enhanced by combining manual visual assessments, YOLO-based predictions, and real-time environmental sensor data to improve overall fertility detection accuracy and reliability.

The recommendations aim to improve IncuVision by making it more reliable and versatile for hatchery use. Future updates could include wider or multiple cameras, full stage tracking up to Day 21, support for diverse egg types, offline access, and integration of manual checks with machine learning and sensor data. Enhancing analytics, alerts, and sensor use will further improve monitoring, helping farmers reduce errors, boost efficiency, and increase hatch success.

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CONFLICT OF INTEREST

The authors have no conflicts of interest to disclose.

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