MJI
Media Jurnal Informatika
Vol. 18, No. 1, June 2026
p-issn : 2088-2114, e-issn : 2477-2542

IoT-Based Egg Incubator with MobileNetV2 CNN for Candling Image Classification and Fertility Detection

Irfan Rifqy Widya Syahbani [a,1], Fadila Azahra [a,2], Della Arviyanti [a,3], Christiano Nicoma Boseke [a,4], Ariel Pasha Ramaditya [a,5], Adinda Octhavia Indriyani [a,6], Fathir Gunadireja [a,7], Setya Mega Bagaskara [a,8], Muhammad Nasir [b,9,*], Gema Parasti Mindara [a,10]

[a] Computer Engineering Technology, Vocational College, Institut Pertanian Bogor
[b] Software Engineering Technology, Vocational College, Institut Pertanian Bogor
[1]syahbaniirfan@apps.ipb.ac.id; [2]fadilaaazahra@apps.ipb.ac.id; [3]dellaarviyanti@apps.ipb.ac.id; [4]chrnicoma@apps.ipb.ac.id; [5]arielramaditya@apps.ipb.ac.id; [6]akukeren08adinda@apps.ipb.ac.id; [7]fathirgunadireja@apps.ipb.ac.id; [8]setyamegabagaskara@apps.ipb.ac.id; [9]m_nasir@apps.ipb.ac.id*; [9]gemaparasti@apps.ipb.ac.id
* corresponding author

ARTICLE INFO

Article history
Received 2026-06-05
Revised 2026-06-27
Accepted 2026-06-28

Keywords
Automatic Egg Incubator
Candling
ESP32-CAM
Internet of Things
MobileNetV2

ABSTRACT

Egg incubation and fertility detection are critical processes in poultry production, requiring stable environmental conditions and accurate embryo monitoring. Conventional incubation and candling methods often rely on manual observation, which may reduce efficiency and increase the risk of human error. This study aims to develop an IoT-based automatic egg incubator integrated with a MobileNetV2-based Convolutional Neural Network (CNN) for candling image classification and fertility detection. The proposed system combines an ESP32-based incubation monitoring platform, ESP32-CAM image acquisition module, ESP-NOW wireless communication, and a web-based monitoring interface. Candling images were collected and classified into three categories: live fertile, dead fertile, and infertile eggs. Transfer learning using the MobileNetV2 architecture was employed to train the classification model. The developed CNN model achieved an accuracy of 91.26% on the testing dataset and 82.22% during validation under real-world conditions. Performance evaluation showed precision values up to 0.965, recall values up to 0.967, and F1-scores above 0.89 across the three classes. Furthermore, the integrated system successfully enabled real-time monitoring of incubation conditions, automated image acquisition, and web-based fertility classification. System testing using 45 egg samples demonstrated that the proposed solution could effectively identify embryo development and fertility status. The integration of IoT technology, ESP32-CAM-based candling, and MobileNetV2 CNN provides an effective solution for automated incubation monitoring and egg fertility detection. The developed system improves monitoring efficiency, reduces manual intervention, and supports decision-making during the incubation process.

1. Introduction

The poultry industry plays a crucial role in supporting global food security by providing a sustainable source of animal protein through meat and egg production. One of the most important stages in poultry production is the incubation process, where temperature, humidity, ventilation, and egg turning must be maintained within optimal ranges to ensure successful embryo development and hatchability. In conventional incubation practices, environmental monitoring and fertility assessment are generally performed manually, making the process susceptible to human error and reducing operational efficiency [5], [6], [17], [21], [23].

Recent advancements in Internet of Things (IoT) technology have enabled the development of smart incubation systems capable of real-time monitoring and automated environmental control. Several studies have demonstrated the implementation of IoT-based incubators using microcontrollers, sensors, and wireless communication technologies to monitor temperature and humidity remotely while improving incubation performance [5], [6], [17], [21], [23]. Furthermore, the integration of IoT technologies in livestock and poultry farming has contributed to the emergence of smart poultry management systems that improve productivity, operational efficiency, and decision-making through continuous data acquisition and monitoring [10], [15].

Besides environmental control, fertility detection is another critical aspect of egg incubation. Traditional candling methods require manual observation of embryo development using a light source, making the assessment process highly dependent on operator experience and susceptible to subjective interpretation. To overcome these limitations, various machine vision and image processing techniques have been proposed for automatic fertility detection. Previous studies have shown that image processing-based candling systems can effectively distinguish fertile and infertile eggs while reducing human intervention [3], [4], [8], [20].

The rapid development of artificial intelligence and deep learning has further improved the performance of fertility detection systems. Convolutional Neural Networks (CNNs) have become one of the most widely used deep learning approaches for image classification tasks due to their ability to automatically extract discriminative features from images [2], [11]. Several studies have successfully applied CNN-based methods to egg fertility detection, achieving high classification accuracy using candling images captured during the incubation period [1], [7], [9], [12], [14]. In addition, alternative approaches utilizing support vector machines, transfer learning techniques, hyperspectral imaging, and machine vision systems have also demonstrated promising results for non-destructive fertility assessment [7], [8], [16], [18], [20].

Among various deep learning architectures, MobileNetV2 has gained significant attention because of its lightweight structure and computational efficiency, making it suitable for embedded and edge-computing applications [19]. These characteristics allow MobileNetV2 to be deployed on resource-constrained devices while maintaining competitive classification performance. Such advantages are particularly beneficial for smart agricultural and IoT-based systems that require real-time image analysis with limited hardware resources.

Although numerous studies have investigated IoT-based incubators and automated fertility detection systems independently, the integration of environmental monitoring, wireless communication, image acquisition, and machine learning-based fertility classification into a single platform remains limited. Most existing systems focus either on incubation control or fertility assessment without providing a comprehensive solution that combines both functionalities [3], [5], [6], [14], [21], [24].

Therefore, this study proposes the development of an automatic chicken egg incubator integrated with an IoT-based monitoring platform and machine learning-based candling analysis. The proposed system combines environmental monitoring, automated incubation control, ESP32-based wireless communication, ESP32-CAM image acquisition, and MobileNetV2-based CNN classification to identify egg fertility conditions automatically. The system is expected to improve monitoring efficiency, reduce manual intervention, support decision-making during the incubation process, and provide a practical solution for poultry farming and educational activities in the Technology and Livestock Management (TNK) Study Program.

2. Method

This study was conducted to develop and evaluate an IoT-based automatic egg incubator integrated with a machine learning-based candling classification system. The methodology covers the research approach, object and scope of the system, data collection techniques, tools and materials, research procedures, and data analysis techniques. The proposed system was developed through several stages, including hardware design, IoT monitoring implementation, ESP32-CAM image acquisition, MobileNetV2-based CNN model training, system integration, and performance testing.

2.1 Type and Approach of Research

This study employed a Research and Development (R&D) approach combined with an experimental method to design, implement, and evaluate an automatic chicken egg incubator integrated with Internet of Things (IoT) technology and machine learning-based fertility detection. The R&D approach was selected because the research focuses on developing a functional prototype that combines hardware and software components into a single system. The experimental approach was used to evaluate the performance of the developed prototype in monitoring environmental conditions and classifying egg fertility based on candling images. Similar approaches have been widely adopted in previous studies involving smart incubator systems and intelligent fertility detection technologies [5], [6], [14], [17], [24].

2.2 Object and Scope of Research

The object of this research is an automatic chicken egg incubator equipped with an IoT-based monitoring system and a machine learning-based candling subsystem. The developed system consists of two main sections: the incubation subsystem and the candling subsystem. The incubation subsystem is responsible for monitoring and maintaining environmental conditions such as temperature and humidity, while the candling subsystem captures egg images using an ESP32-CAM module for fertility analysis.

The scope of this study includes the development of an IoT-based monitoring platform, wireless communication between devices, image acquisition using ESP32-CAM, and fertility classification using a MobileNetV2-based Convolutional Neural Network (CNN). The fertility classification process focuses on three categories: live fertile eggs, dead fertile eggs, and infertile eggs [1], [7], [9], [19].

2.3 Data Collection Techniques

Data collection was conducted through several methods. First, a literature study was performed to gather information related to egg incubation systems, IoT monitoring, computer vision, and machine learning-based fertility detection from scientific journals and conference proceedings [1]–[24]. Second, direct observation and discussions were conducted with partners from the Technology and Livestock Management (TNK) Study Program to identify operational requirements and challenges in conventional incubation practices.

For machine learning development, candling images of chicken eggs were collected and categorized according to fertility conditions. The dataset was used for training, validation, and testing of the MobileNetV2 classification model. Additionally, environmental monitoring data such as temperature and humidity were collected during prototype operation to evaluate system performance.

2.4 Tools and Materials Used

The hardware components used in this study include an ESP32 microcontroller, ESP32-CAM module, relay module, LED candling illumination system, temperature and humidity sensors, heating elements, ventilation components, and supporting power supply modules. The ESP32 functions as the primary controller responsible for environmental monitoring and communication between system components, while the ESP32-CAM is used for image acquisition during the candling process [10], [24].

The software tools utilized include Arduino IDE for embedded programming, Visual Studio Code for application development, Python programming language for machine learning implementation, TensorFlow and Keras libraries for CNN model training, and MobileNetV2 as the transfer learning architecture used for image classification [2], [11], [19]. In addition, web-based technologies were employed to develop the monitoring dashboard used for displaying environmental parameters and classification results in real time.

2.5 Research Procedures or Stages

The research was conducted through several stages, including system planning, hardware development, software implementation, machine learning model training, system integration, and performance evaluation. The overall research workflow is illustrated in Figure X.

The first stage involved a literature review and requirement analysis. Relevant studies related to IoT-based incubation systems, computer vision, egg fertility detection, and deep learning techniques were reviewed to identify suitable technologies and research gaps [1], [2], [7], [15].

The second stage focused on hardware and software development. An automatic egg incubator was designed using ESP32 as the main controller and ESP32-CAM as the image acquisition module. Environmental monitoring components such as temperature and humidity sensors were integrated into the incubation chamber. Communication between devices was implemented using the ESP-NOW protocol, enabling wireless transmission of trigger commands for image acquisition.

The third stage involved dataset preparation and image acquisition. Candling images were collected using the ESP32-CAM module under controlled illumination conditions. The collected images were categorized into three classes: live fertile eggs, dead fertile eggs, and infertile eggs. The dataset was then divided into training, validation, and testing subsets.

The fourth stage consisted of machine learning model development. Transfer learning was implemented using the MobileNetV2 architecture to classify candling images according to fertility conditions. The model was trained using the prepared dataset and optimized through multiple training iterations to improve classification performance [7], [9], [19].

The fifth stage involved system integration. The trained MobileNetV2 model was connected to the web-based monitoring platform, allowing image classification results and environmental monitoring data to be displayed simultaneously. The ESP32 controller, ESP32-CAM, monitoring dashboard, and machine learning model were integrated into a unified system.

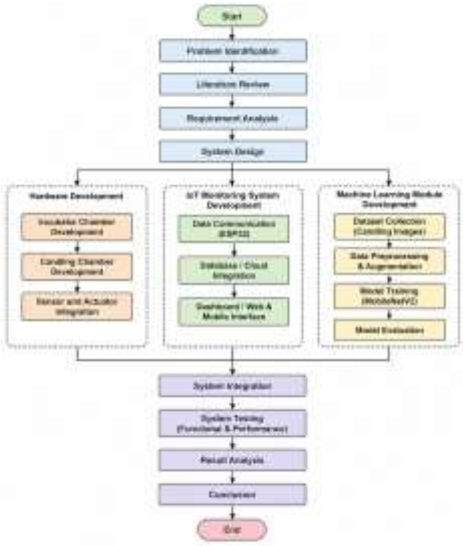

Fig. 1. Research Workflow

The final stage consisted of system testing and evaluation. Performance evaluation was conducted using accuracy, precision, recall, F1-score, and confusion matrix metrics. In addition, functional testing was performed to verify the operation of environmental monitoring, image acquisition, wireless communication, and fertility classification processes under real-world incubation conditions.The research is carried out in several stages involving system design, implementation, and testing. The system consists of two main processes: receiving trigger commands and capturing images using ESP32-CAM, and sending trigger commands from the ESP32 controller.

First, the ESP32-CAM is configured to initialize the camera, SD card, and ESP-NOW communication. A callback function is implemented to receive incoming messages. When the received message matches the predefined command ("Foto"), the system captures an image and stores it in the SD card using an incremental filename. Second, the ESP32 controller is programmed to send trigger commands using ESP-NOW. The system reads input from the serial interface and sends the command to the ESP32-CAM using its MAC address. A callback function is used to monitor the status of data transmission. The system workflow is described in Algorithm 1 and Algorithm 2.

Algorithm 1. Receiving Trigger and Capturing Image using ESP32-CAM

```
Start
Set Photonumber = 0

Function Savephoto:
    Capture Image From Camera
    If Capture Fails Then Display Error
    Save Image To Sd Card With Filename "Foto_[Number].Jpg"
```

```
   Increment Photonumber
End Function

Function Ondatarecv:
   Read Incoming Message
   If Message Equals "Foto" Then Call Savephoto
End Function

Setup:
   Initialize Camera
   Initialize Sd Card
   Enable Wifi In Sta Mode
   Initialize Esp-Now
   Set Ondatarecv As Receive Callback

Loop:
   Wait For Incoming Data
End
```

Algorithm 2. Sending Trigger Command from ESP32 (IoT Controller)

```
Start

Declare Receivermac = Address Of Esp32-Cam
Declare Message

Function Ondatasent:
   If Send Status Is Success Then
      Display "Success"
   Else
      Display "Fail"
End Function

Setup:
   Initialize Serial Communication
   Enable Wifi In Sta Mode
   Initialize Esp-Now
   Register Ondatasent As Send Callback
   Add Receivermac As Peer

Loop:
   Read Input From Serial
   If Input Equals "Foto" Then
      Set Message.Text = "Foto"
      Send Message To Receivermac Via Esp-Now
      Display "Photo Command Sent"
   Endif

End
```

2.6 Data Analysis Techniques

The collected data were analyzed using both machine learning performance evaluation and functional system testing approaches. For the machine learning subsystem, the performance of the MobileNetV2-based Convolutional Neural Network (CNN) model was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics were selected because they provide comprehensive information regarding the model's ability to correctly classify candling images into live fertile, dead fertile, and infertile egg categories [1], [2], [7], [11].

Accuracy was used to measure the overall proportion of correctly classified samples. Precision was employed to evaluate the reliability of positive predictions produced by the model, while recall measured the ability of the model to identify all relevant instances within each class. The F1-score was calculated as the harmonic mean of precision and recall to provide a balanced evaluation metric. Furthermore, confusion matrix analysis was utilized to identify classification errors and examine the performance of each fertility category individually [7], [9], [12].

In addition to machine learning evaluation, functional testing was conducted to verify the performance of the integrated system. The testing process included environmental monitoring functionality, ESP-NOW wireless communication, image acquisition using ESP32-CAM, web-based monitoring, and fertility classification processes. System testing was performed using real egg samples under incubation conditions to evaluate the reliability and effectiveness of the proposed solution.

The classification results obtained from the testing phase were compared with the actual fertility conditions of the eggs to determine the effectiveness of the developed system. The resulting performance metrics were then analyzed and discussed to assess the feasibility of integrating IoT technology and machine learning techniques into an automated egg incubation and fertility detection platform.

3. Results and Discussion

3.1 Hardware Implementation

The hardware implementation of the proposed system focuses on the development of an IoT-based egg incubation and candling platform. The system consists of two main subsystems: the incubation subsystem and the candling subsystem. The incubation subsystem is responsible for monitoring environmental parameters and supporting embryo development, while the candling subsystem performs image acquisition for fertility classification.

The incubation subsystem utilizes an ESP32 microcontroller as the primary controller responsible for collecting sensor data and managing communication between system components. Environmental monitoring is performed using temperature and humidity sensors, allowing incubation conditions to be observed in real time. The use of IoT technology in egg incubators has been reported to improve monitoring efficiency and environmental stability during the incubation process [5], [6], [17], [21], [23].

The candling subsystem employs an ESP32-CAM module integrated with an LED illumination system to capture images of eggs during the incubation period. The ESP32-CAM was selected because it combines wireless communication and image acquisition capabilities within a compact and low-cost platform. Similar image acquisition approaches have been applied in previous automated candling systems for fertility detection and embryo monitoring [3], [4], [24].

Communication between the ESP32 controller and ESP32-CAM is implemented using the ESP-NOW protocol. This communication mechanism enables trigger commands to be transmitted wirelessly, allowing the ESP32-CAM to capture images without requiring additional network infrastructure. Once a trigger command is received, the ESP32-CAM captures an image and stores it on the SD card for subsequent classification. The implementation of wireless image acquisition contributes to the flexibility and scalability of the proposed system

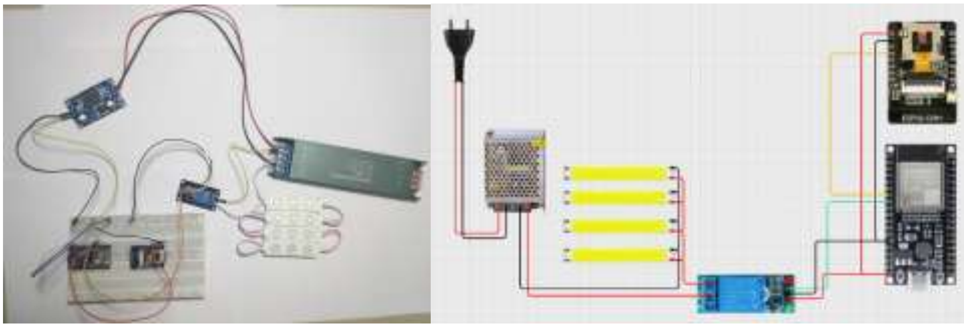

Fig. 2. Hardware Configuration of the Candling Subsystem

Figure 2 illustrates the hardware configuration of the candling subsystem used in this study. The hardware integration successfully enabled image acquisition, wireless communication, and data storage functions required for the fertility classification process.

3.2 System Architecture

The proposed system architecture integrates IoT-based environmental monitoring, wireless communication, image acquisition, and machine learning-based fertility classification into a unified platform. The architecture was designed to support real-time monitoring of incubation conditions while simultaneously providing automated egg fertility analysis.

The incubation subsystem continuously monitors environmental parameters, including temperature and humidity, using sensors connected to the ESP32 controller. The collected data are processed by the microcontroller and transmitted to a web-based monitoring platform, allowing users to observe incubation conditions remotely. The integration of IoT technologies into poultry management systems has been shown to improve operational efficiency and support data-driven decision making in modern farming environments [10], [15], [17], [21].

For fertility analysis, the ESP32 controller communicates with the ESP32-CAM module through the ESP-NOW protocol. When a candling process is initiated, a trigger command is transmitted to the ESP32-CAM, which subsequently captures an image of the egg under controlled illumination conditions. The captured image is then stored and forwarded to the classification subsystem for further analysis [3], [4], [24].

The machine learning subsystem utilizes a Convolutional Neural Network (CNN) based on the MobileNetV2 architecture to classify candling images. MobileNetV2 was selected due to its lightweight architecture and computational efficiency, making it suitable for deployment in embedded and IoT-integrated environments [19]. The classification model categorizes egg images into three classes, namely live fertile eggs, dead fertile eggs, and infertile eggs. Previous studies have demonstrated that CNN-based and transfer learning approaches can provide high classification accuracy for fertility detection tasks [1], [7], [9], [12], [14].

The classification results are subsequently displayed through the web-based monitoring platform, enabling users to evaluate egg fertility conditions without relying solely on manual candling observations. By integrating environmental monitoring, image acquisition, wireless communication, and artificial intelligence into a single framework, the proposed architecture provides a comprehensive solution for smart incubation management and automated fertility assessment.

3.3 CNN-Based Egg Fertility Classification

The MobileNetV2-based Convolutional Neural Network (CNN) model using transfer learning was developed to classify egg fertility into three categories, namely live fertile, dead fertile, and infertile. The model achieved an accuracy of 91.26% on the testing dataset, indicating strong classification performance under controlled conditions. However, a lower accuracy of 82.22% was obtained during validation or real-world testing, indicating performance degradation when handling more diverse and unseen data. This difference is mainly influenced by data distribution variations and visual similarities between classes, particularly between dead fertile and infertile eggs.

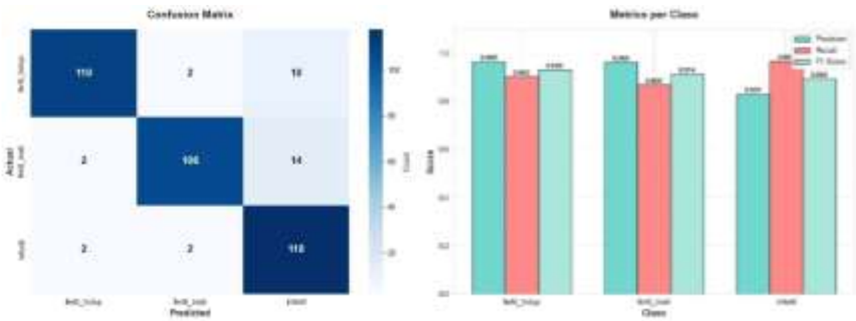

Fig. 3. Model Evaluation Results

As shown in Figure 3, the live fertile class achieved a precision of 0.965, recall of 0.902, and F1-score of 0.932. The dead fertile class obtained a precision of 0.964, recall of 0.869, and F1-score of 0.914. Meanwhile, the infertile class showed the highest recall value of 0.967 with an F1-score of 0.894. The lower recall in the dead fertile class indicates reduced model sensitivity in distinguishing this category, while the high recall in the infertile class demonstrates better detection capability. These variations suggest the influence of feature similarity among classes and potential data imbalance in the dataset.

3.4 Web Application for Egg Candling Classification Using CNN

The trained CNN model was implemented into a web-based system to perform automated candling image classification. The system receives images captured by the ESP32-CAM module and processes them using the trained MobileNetV2 model. The classification results are displayed directly on the user interface in real time, allowing users to monitor egg fertility conditions efficiently.

Fig. 4. Candling Detection Page Interface

The interface displays the captured candling images along with their predicted classes, enabling users to observe embryo development conditions during incubation. This implementation integrates IoT-based image acquisition with deep learning-based classification to support automated egg fertility detection.

3.5 System Performance Testing

System testing was conducted to evaluate the functionality and performance of the developed IoT-based egg incubator system. The testing process included temperature and humidity monitoring, IoT communication performance, and egg candling classification using machine learning. The DHT11 sensor successfully monitored environmental conditions during the incubation process, while the ESP32 module transmitted data to the IoT platform in real-time without significant delay.

The machine learning model was tested using several egg samples categorized as infertile eggs, fertilized live embryos, and fertilized dead embryos. The testing results showed that the system was capable of identifying egg conditions automatically based on candling image characteristics. Most testing data were classified correctly with relatively high confidence values, indicating stable system performance during the testing process.

The implementation of IoT technology and machine learning in the egg incubator system improved monitoring efficiency and reduced manual inspection during incubation. The monitoring system enabled users to observe temperature and humidity conditions remotely through internet-based communication. In addition, the candling image classification system assisted users in detecting embryo development automatically.

Based on the testing results, fertile eggs showed darker embryo regions and visible blood vessel patterns during candling observations. Meanwhile, infertile eggs appeared clearer without embryo development structures. Several prediction errors occurred due to similarities in image characteristics between infertile eggs and dead embryos. However, the overall system demonstrated good performance in supporting automatic incubation monitoring and embryo detection. The system was tested using 45 egg samples consisting of infertile eggs, fertilized live embryos, and fertilized dead embryos.

Table 1. Sample of egg candling classification testing results

No.	Egg Code	Actual Condition	Model Prediction	Confidence	Evaluation Result
1	T1	Infertile	Infertile	96.6%	Correct
2	T2	Infertile	Infertile	80.4%	Correct
3	T3	Infertile	Infertile	73.0%	Correct
4	T4	Infertile	Infertile	70.0%	Correct
5	T5	Infertile	Live Fertile	95.7%	Incorrect
6	T6	Infertile	Infertile	95.8%	Correct
7	T7	Infertile	Infertile	80.2%	Correct
8	T8	Infertile	Infertile	50.2%	Correct
9	T9	Infertile	Infertile	77.9%	Correct
10	T10	Infertile	Dead Fertile	71.6%	Incorrect
11	T11	Infertile	Infertile	84.2%	Correct
12	T12	Infertile	Dead Fertile	89.9%	Incorrect
13	T13	Infertile	Dead Fertile	90.5%	Incorrect
14	T14	Infertile	Infertile	81.0%	Correct
15	T15	Infertile	Dead Fertile	96.2%	Incorrect
16	T1	Dead Fertile	Dead Fertile	90.8%	Correct
17	T2	Dead Fertile	Dead Fertile	85.6%	Correct
18	T3	Dead Fertile	Dead Fertile	98.5%	Correct
19	T4	Dead Fertile	Dead Fertile	57.2%	Correct
20	T5	Dead Fertile	Live Fertile	95.7%	Incorrect
21	T6	Dead Fertile	Dead Fertile	97.5%	Correct
22	T7	Dead Fertile	Live Fertile	56.3%	Incorrect
23	T8	Dead Fertile	Dead Fertile	96.6%	Correct
24	T9	Dead Fertile	Dead Fertile	87.9%	Correct
25	T10	Dead Fertile	Dead Fertile	99.7%	Correct
26	T11	Dead Fertile	Dead Fertile	98.0%	Correct
27	T12	Dead Fertile	Dead Fertile	81.7%	Correct
28	T13	Dead Fertile	Dead Fertile	79.3%	Correct
29	T14	Dead Fertile	Dead Fertile	68.6%	Correct
30	T15	Dead Fertile	Live Fertile	95.6%	Incorrect
31	T1	Live Fertile	Live Fertile	76.8%	Correct
32	T2	Live Fertile	Live Fertile	97.8%	Correct
33	T3	Live Fertile	Live Fertile	95.6%	Correct
34	T4	Live Fertile	Live Fertile	98.5%	Correct
35	T5	Live Fertile	Live Fertile	95.6%	Correct
36	T6	Live Fertile	Live Fertile	97.0%	Correct

No.	Egg Code	Actual Condition	Model Prediction	Confidence	Evaluation Result
37	T7	Live Fertile	Live Fertile	99.3%	Correct
38	T8	Live Fertile	Live Fertile	99.7%	Correct
39	T9	Live Fertile	Live Fertile	99.1%	Correct
40	T10	Live Fertile	Live Fertile	99.9%	Correct
41	T11	Live Fertile	Live Fertile	92.0%	Correct
42	T12	Live Fertile	Live Fertile	99.4%	Correct
43	T13	Live Fertile	Live Fertile	97.3%	Correct
44	T14	Live Fertile	Live Fertile	99.9%	Correct
45	T15	Live Fertile	Live Fertile	99.7%	Correct

The developed machine learning model was tested using 45 egg samples consisting of infertile eggs, fertilized live embryos, and fertilized dead embryos. Table 1 presents several sample testing results generated during the candling classification process.

Fig. 5. Fertile egg detection result during candling process

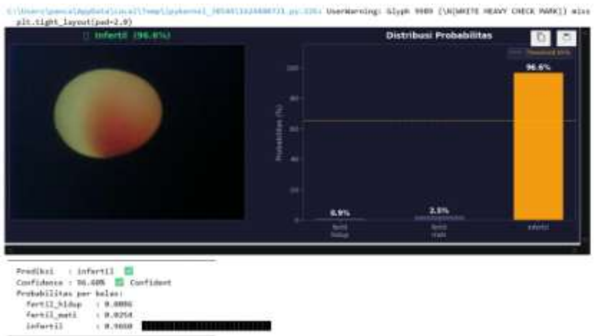

Fig. 6. Fertile egg detection result during candling process

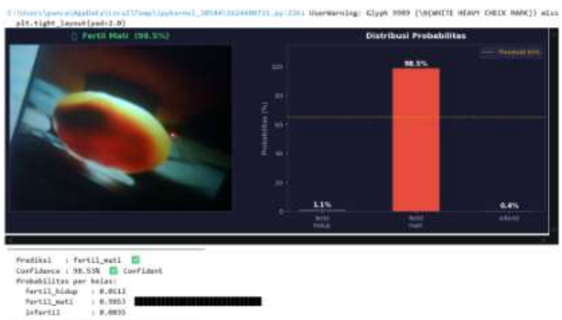

Fig. 7. Fertile Dead detection result during candling process

The candling image classification results demonstrated that fertile eggs were characterized by darker embryo regions and visible blood vessel structures. In contrast, infertile eggs appeared clearer without embryo development patterns. Eggs categorized as fertilized dead embryos showed irregular dark regions and abnormal internal structures during the image analysis process.

Table 2. Performance evaluation results for each egg classification category

Target Class	Total Data	Correct Predictions	Class Accuracy	Average Confidence
Infertil	15	10	66.7%	82.2%
Fertile Dead	15	12	80.0%	85.9%
Fertile Live	15	15	100.0%	96.5%

The developed machine learning model achieved an overall accuracy of 82.22% during testing. The testing results indicate that the developed system was capable of performing automatic egg classification with relatively stable performance and high confidence values.

The accuracy of the developed machine learning model can be calculated using Equation (1).

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100\ \%$$

where:

Accuracy : percentage of system accuracy

Correct : total correctly classified testing data

Total Predictions : total testing samples

Based on the testing results, the developed system correctly classified 37 out of 45 testing samples. Therefore, the accuracy is calculated as follows:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100\ \%$$

$$Accuracy = \frac{37}{45} \times 100\ \%$$

$$Accuracy = 82.22$$

The calculation results indicate that the developed machine learning model achieved an overall accuracy of 82.22% in classifying fertile eggs, infertile eggs, and fertilized dead embryos during the candling process.

4. Conclusion

Based on the results of the research, the IoT-based automatic egg incubator system was successfully designed and implemented to monitor temperature and humidity conditions in real-time. The system is capable of improving the efficiency of the egg incubation process through automatic environmental control and monitoring features. In addition, the integration of image processing and machine learning technology can support the automatic detection of embryo development during the candling process. The developed system provides convenience for users in monitoring the incubation process remotely and reducing the risk of incubation failure. Further research can focus on improving the accuracy of embryo detection, optimizing power consumption, and developing a more stable monitoring system with wider network coverage.

Acknowledgment

The authors would like to express their gratitude to the lecturers, laboratory assistants, and all team members who contributed and supported the completion of this research.

Declarations

Author Contribution. All authors contributed actively to all stages of this research, including system design, hardware and software development, system integration, data collection, system testing, data analysis, and manuscript preparation. All authors have read and approved the final version of the manuscript.

Funding Statement. This research was supported through collaboration with the Computer Engineering Technology Program and the Livestock Technology and Management Program, Vocational College, Institut Pertanian Bogor, which provided implementation support and research requirements.

Conflict of Interest. The authors declare that there is no conflict of interest regarding the publication of this paper.

Additional Information. No additional information is available for this study.

Data and Software Availability Statements

Data supporting the findings of this study, including candling image datasets and system testing results, are available upon reasonable request.

References

[1] K. K. Çevik, H. E. Koçer, and M. Boğa, "Deep learning based egg fertility detection," Veterinary Sciences, vol. 9, no. 10, Art. no. 574, 2022, doi: 10.3390/vetsci9100574.

[2] A. Dhillon and G. K. Verma, "Convolutional neural network: A review of models, methodologies and applications to object detection," Progress in Artificial Intelligence, vol. 9, no. 2, pp. 85–112, 2020, doi: 10.1007/s13748-019-00203-0.

[3] L. K. S. Tolentino, E. J. G. Enrico, R. L. M. Listanco, M. A. M. Ramirez, T. L. U. Renon, and M. R. B. Samson, "Development of fertile egg detection and incubation system using image processing and automatic candling," in Proc. TENCON 2018—2018 IEEE Region 10 Conference, 2018, pp. 701–706, doi: 10.1109/TENCON.2018.8650320.

[4] D. W. Garcia and G. Magwili, "An automated candling system for duck egg fertility detection, sorting, and counting via digital image processing," in Proc. 2021 11th International Workshop on Computer Science and Engineering (WCSE), 2021, pp. 93–100, doi: 10.18178/wcse.2021.06.014.

[5] M. I. S. T. Ariffin, N. I. A. N. Amin, M. A. H. A. Abas, R. L. Jamil, and S. Z. Yusof, "Designing a chicken egg incubator with IoT-based control," Asian Journal of Vocational Education and Humanities, vol. 6, no. 1, pp. 28–33, 2025, doi: 10.53797/ajvah.v6i1.4.2025.

[6] M. C. A. Prabowo, I. Sayekti, S. Astuti, S. T. Nursaputro, and Supriyati, "Development of an IoT-based egg incubator with PID control system and mobile application," International Journal on Informatics Visualization, vol. 8, no. 1, pp. 465–472, 2024.

[7] S. Saifullah, R. Drezewski, A. Yudhana, A. Pranolo, W. Kaswijanti, A. P. Suryotomo, S. A. Putra, A. Khaliduzzaman, A. S. Prabuwono, and N. Japkowicz, "Nondestructive chicken egg fertility detection using CNN-transfer learning algorithms," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, vol. 9, no. 3, pp. 854–871, 2023, doi: 10.26555/jiteki.v9i3.26722.

[8] M. Hashemzadeh and N. Farajzadeh, "A machine vision system for detecting fertile eggs in the incubation industry," International Journal of Computational Intelligence Systems, vol. 9, no. 5, pp. 850–862, 2016.

[9] L. Geng, Y. Hu, Z. Xiao, and J. Xi, "Fertility detection of hatching eggs based on a convolutional neural network," Applied Sciences, vol. 9, no. 7, Art. no. 1408, 2019, doi: 10.3390/app9071408.

[10] B. Praveena, K. Punith, K. Kumar, S. Rabbani, and P. Geetha, "Implementation of smart agriculture using ESP32-based IoT and machine learning for monitoring crop," in Proc. ICTMIM, 2026, pp. 399–

404, doi: 10.1109/ICTMIM68190.2026.11507902.

[11] M. M. Taye, “Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions,” Computation, vol. 11, no. 3, Art. no. 52, 2023, doi: 10.3390/computation11030052.

[12] R. Aisuwarya, R. Ferdian, and S. Wafiq, “Deep learning-based egg fertility classification with Raspberry Pi and color sensor integration,” in Proc. 2025 International Seminar on Intelligent Technology and Its Applications (ISITIA), 2025, pp. 584–589, doi: 10.1109/ISITIA66279.2025.11137566.

[13] J. E. L. Ramos, B. T. Sanchez, J. T. Bojocan, and E. A. Tacda, “Real-time tray-level egg fertility detection on Raspberry Pi using YOLOv5 and custom LED backlighting,” in Proc. 2025 9th International Artificial Intelligence and Data Processing Symposium (IDAP), 2025, pp. 1–7, doi: 10.1109/IDAP68205.2025.11222310.

[14] D. Musara, B. Sarema, D. Mashava, K. Chinguwo, and T. M. Muhla, “Design of an AI-based egg fertility detection system for incubators,” Open Access Research Journal of Science and Technology, vol. 12, no. 1, pp. 1–9, 2024, doi: 10.53022/oarjst.2024.12.1.0109.

[15] J. Astill, R. A. Dara, E. D. G. Fraser, B. Roberts, and S. Sharif, “Smart poultry management: Smart sensors, big data, and the internet of things,” Computers and Electronics in Agriculture, vol. 170, Art. no. 105291, 2020, doi: 10.1016/j.compag.2020.105291.

[16] S. Saifullah and R. Dreżewski, “Non-destructive egg fertility detection in incubation using SVM classifier based on GLCM parameters,” Procedia Computer Science, vol. 207, pp. 3254–3263, 2022, doi: 10.1016/j.procs.2022.09.383.

[17] K. Muttaqin, A. Ihsan, and H. Irawan, “Peningkatan produktivitas ternak ayam melalui teknologi inkubator mesin penetas telur berbasis Internet of Thing,” JMM (Jurnal Masyarakat Mandiri), vol. 6, no. 5, pp. 4395–4408, 2022, doi: 10.31764/jmm.v6i5.10812.

[18] M. W. Ahmed, A. Sprigler, J. L. Emmert, R. N. Dilger, G. Chowdhary, and M. Kamruzzaman, “Non-destructive detection of pre-incubated chicken egg fertility using hyperspectral imaging and machine learning,” Smart Agricultural Technology, vol. 10, Art. no. 100857, 2025, doi: 10.1016/j.atech.2025.100857.

[19] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, “MobileNetV2: Inverted residuals and linear bottlenecks,” in Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 4510–4520.

[20] A. O. Adegbenjo, L. Liu, and M. O. Ngadi, “Non-destructive assessment of chicken egg fertility,” Sensors, vol. 20, no. 19, Art. no. 5546, 2020, doi: 10.3390/s20195546.

[21] S. P. Santosa, J. Jaylana, and N. Naibaho, “Smart egg incubator monitoring system based on IoT and Blynk connectivity,” JTEIN: Jurnal Teknik Elektro Indonesia, vol. 6, no. 2, pp. 172–181, 2025.

[22] M. F. Amrulloh and M. Syarwani, “Sistem monitoring suhu pada kandang ayam menggunakan ESP8266 dan sensor DHT11 berbasis IoT,” Neutral: Journal of Engineering, vol. 1, no. 1, pp. 9–13, 2023.

[23] U. W. Yuda and T. Sutabri, “Pengembangan inkubator telur ayam berbasis IoT dan Arduino dengan metode prototipe sistem kontrol suhu,” Jurnal Sains Student Research, vol. 3, no. 2, pp. 401–409, 2025, doi: 10.61722/jssr.v3i2.4321.

[24] N. M. Nizarudeen, R. Sridhar, J. Abdul Rahman, and A. Sugumar, “AI-enabled smart egg incubator using ESP32-CAM for automated environmental control and fertility detection,” International Journal of Research and Innovation in Applied Science, vol. 10, no. 11, pp. 1510–1521, 2025, doi: 10.51584/IJRIAS.2025.101100138.