AI-Enabled Smart Egg Incubator Using ESP32-CAM for Automated Environmental Control and Fertility Detection

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ABSTRACT

The project presented is for developing an intelligent automatic egg incubator capable of fertility detection to speed up the incubation process by using image processing and the Internet of Things. The system makes use of an XHM452 controller, through which temperature inside the incubator is held at 37.5 °C, while humidity should range between 70 % and 85 %. A 40 W bulb generates the heat, and a DC fan circulates the hot air to maintain a uniform temperature inside the chamber. For humidity, a humidifier with a moisture sensor monitors the water level and automatically sprays or refills water if the humidity falls. For easy monitoring, the values of the moisture sensor are displayed on a LCD display in real time. An automatic egg turning tray, which revolves every three hours with the help of a relay timing module, is used so that the embryo can develop consistently. For fertility detection, an ESP32CAM snaps images of eggs under the light of LED candling from the 7th day to the 10th day of incubation. This image-processing algorithm inspects those photos for fertile and infertile eggs with a high degree of accuracy. All sensors are connected to the ESP32 microcontroller, which monitors and controls the whole system automatically. In this way, automation reduces manual labour, constantly incubates under stipulated conditions, and improves the hatchability rate for the eggs. For the incubator, a uniform environment is created that ensures proper development and healthy growth of the embryo. Besides, it reduces human intervention and errors in operations. It is also cost-effective and reliable, hence suitable for application at small- and medium-sized poultry farms. Experimental testing confirmed that steady temperature and humidity levels were maintained throughout incubation. Repeated trials gave consistent accuracy on fertility detection. Thus, the proposed system is an intelligent, effective, and completely automated solution for modern incubation and fertility detection of eggs.

Keywords: Automatic Egg Incubator, Fertility Detection, ESP32, ESP32-CAM, IoT, Image Processing, Candling, Temperature Control, Automation in Poultry Farming,

INTRODUCTION

The poultry industry is very important in terms of food provision globally. Demands and supporting rural livelihoods. An important feature of Poultry production is incubation of eggs, where maintaining optimum environmental conditions, like temperature humidity, and egg turning-are critical to embryo Development and successful hatching. Conventionally, the egg Fertility is determined by manual candling; a light is utilized in the inspection of internal egg features. This process, however, is subjective, labour-intensive, and often inaccurate in the early stages of incubation [7]. Recent developments in artificial intelligence (AI), computer Various innovative applications are enabled by both vision and IoT technologies. Paving the way for more accurate automated solutions. Deep convolutional neural network learning models, such as CNNs Mask R-CNN also showed promising results. in detecting fertility features in eggs captured through candling. For instance, Çevik et al. employed Mask R-CNN. achieving 100% fertility classification by day 3 of incubation While Hashemzadeh et al. reported accuracy up to 98.9% [1]. using methods of image classification based on SVM [17], which The most important contribution of vision-based approaches is the significant reduction of human error. Labour within the process of fertility assessment. Meanwhile, IoT-enabled systems improve environmental control. Maaño et al implemented a smart incubator using Arduino MKR1000 that achieved a 95.24% hatch rate while remote temperature and humidity monitoring [8]. Similarly, Kombe et al. implemented TinyML on an embedded system, which in turn detect egg quality, reaching over 95% accuracy [3]. These Innovations are demonstrating how such platforms as ESP32-CAM can capture, analyse, and classify images of eggs. in real-time and with low power consumption and cost. These developments have motivated this research to propose a AI-driven smart egg incubator. Fertility detection and automated environmental control. The incubator uses an ESP32-CAM module for control, which: Captures candled egg images and performs processing using CNNs based image analysis, classifying fertile and infertile eggs. automatically based on such visual patterns as embryo growth. and presence of blood vessels. The system also integrates sensors that and relays to control a heating bulb, a cooling fan, a humidifier. and an egg rotation motor, all contained within a wooden incubation cabinet. This smart solution has a number of advantages for early-stage Selection of un-fertilised eggs for disposal economises energy and space. hatchability rates by precise environmental control; and significant labour savings in small- and mid-scale poultry operations. The modular design and low²cost components make it accessible for rural poultry farmers. to enhance their operation with limited investment. [2][13]. The rest of the paper is organized as follows. Section II reviews related work in the literature on fertility. Detection and Smart incubation. Section III outlines the Methodology and System Design. Section IV discusses system Architecture and hardware. Section V covers results and Finally, Sections VI and VII provide conclusions. and future scope

LITERATURE REVIEW

In the last few years, there has been a growing interest in poultry incubation automation processes in general and segregating the fertile versus infertile eggs by non-invasive means. Traditional candling involves the visual examination for the appearance of visible blood vessels against a lighted background, which is highly subjective and time-consuming. Therefore, various researchers have invested efforts into developing different machine vision and IoT-based solutions to achieve better accuracy with scalability.

Çevik et al. [1] applied Mask R-CNN to deep learning for distinguishing between fertile and infertile eggs under a candling light. It was determined that their system achieves nearly perfect accuracy as early as on day 3 of incubation. The advantage in this method is the high precision involved and the possibility of identifying early embryo development thanks to image segmentation. However, dependence on a high-performance GPU further raises the cost and complication in implementation.

Musara et al. [2] proposed an AI-driven egg fertility detection system supported with an ESP32-CAM module. The best lightweight CNN model achieved 98.4% accuracy in just 0.210 seconds per frame, which is efficient enough for real-time processing on an inexpensive incubator. This accommodates a trade-off between affordability and speed but is potentially sensitive to variations in lighting.

Bhuiyan et al. [8] proposed an IoT-based egg incubator system for remote monitoring and control. It has sensors that control the temperature and humidity, with automated egg turning, through the use of a mobile application. They obtained a 95.24% hatch rate on their prototype model. This model addresses better accessibility for the user, but requires stable internet connectivity. Hashemzadeh proposed a machine vision system that integrated ANN with SVM for fertility classification. Generally, the performances of the SVMs were better compared to those of ANNs, especially on occasions where the features of the embryos were subtle and reached an accuracy of 98.91% by day 5. The limitations include the limited sample size employed and inability for real-time processing.

Waranusast and Pichayee [9] designed an Android-based, portable image processing classifier with SVM. While offering a portable solution, the 84.6% accuracy was far below that from CNN-based models. This again points to the challenges of mobile-based models, especially for environmental conditions with variable light and camera resolution.

Vera and Durera [4] proposed a Raspberry Pi and ESP32-based incubator that classifies fertile and rotten eggs using image processing. It deploys an automatic infertile egg ejection mechanism, resulting in 95% accuracy. While powerful, the solutions based on Raspberry Pi are more costly and power-consuming as compared to ESP32 standalone solutions.

Maaño et al. [8] proposed an Arduino-based IoT incubator which can log environmental parameters and send alerts. The proposed system was able to connect PID control and cloud-based dashboards. But it lacked fertility classification features necessary for hatch quality monitoring.

Kombe et al. [3] presented a chicken egg quality monitoring system based on TinyML for Arduino Nano BLE Sense. It could label the viable eggs with an accuracy as high as 95.8%. Compact and efficient, the disadvantage with TinyML models is that they are harder to retrain or scale when more features are to be added.

Geng et al. [5] presented a hybrid approach of CNNs with heartbeats toward early-stage fertility detection. Their studies have shown that generally speaking, multimodal sensor fusion tends to increase the reliability of predictions. In order to detect heartbeat signals, however, some specialized hardware is needed, especially for filtering noise.

Overall, evidence from the reviewed studies indicates that the usage of modern AI and IoT-based systems outperforms traditional methods for the detection of fertility in eggs. While the CNNs are more accurate, they require computationally more intensive processes. On the other hand, lightweight IoT devices offer only modest classification performance but are portable and low-cost. This work is intended to bring these complementary strengths together for ESP32-CAM-based image processing, integrated environmental control, and real-time image classification-delivering an end-to-end smart incubator suitable for small-scale farmers.

METHODOLOGY

We built it step by step: combining hardware, sensors, mechanical parts, and AI image analysis. The idea was simple: create a smart incubator that is not just cheap and reliable but could also spot fertile eggs early using a camera and some clever code. Here is how we did it.

System Design

We began with a thermally insulated wooden box, of course, and divided it in two: one half was for incubation of the eggs, while the other half would be used for candling the eggs—shining light through them to check fertility. Inside, there’s an automatically rotating tray, a 40W bulb for heat, a powerful DC fan for air movement, a mist humidifier for moisture, and an ESP32 microcontroller running the show. Everything runs off a 12V 5A power supply, and a buck converter keeps sensitive parts safe from voltage spikes.

Sensor Integration

We connected a controller, the XH-M452, which, through constant temperature and humidity checks, sends direct signals to the ESP32, maintaining the temperature at 37.5°C and the humidity at 60%. If this goes out of range, the ESP32 takes over and turns on the heater, activates the fan, or humidifier. There is no need for speculation or manual adjustments. The eggs receive the correct conditions for the entire 21 days.

Egg Rotation Mechanism

In order to keep things as natural as possible, a DC motor and relay timer turn the egg tray every 3-4 hours, as it naturally would if it were done by a mother hen herself. That little trick stops the yolk from sticking and helps the embryo develop evenly. The system pauses the rotation automatically when it's time to perform fertility checks or candle the eggs.

Fertility Detection System

For candling, we created a rig with a bright LED underneath each egg and an ESP32-CAM on top to take pictures. Images undergo some brief processing, then a lightweight convolutional neural network performs the check for fertility-blood vessels or an embryo means fertile, a clear yolk means not. Green and red LEDs show the verdict right there, and the total count shows up on a 16x2 LCD so you can see how many eggs will likely hatch.

Software and AI Model Integration

We wrote the firmware in the Arduino IDE. The image processing steps are pretty straightforward: turn the photo to grayscale, use adaptive thresholding, and send it to the CNN. We trained the model offline on a bunch of candled egg images and then loaded it onto the ESP32-CAM using Edge Impulse or TensorFlow Lite. By Day 5, it is already reaching about 95% accuracy. Later on, we might add heartbeat detection with IR sensors, or even sound analysis for better results.

Testing and Validation

We ran the system through its paces, with several incubation trials that used more than 50 eggs at a time. We monitored hatch rates, how the system was able to detect fertility, maintained temperature and humidity levels, and how much power it consumed. The results? Better hatch rates, accurate early detection, and a lot less manual work compared to doing it all by hand.

System Architecture

The Smart Automatic Egg Incubator with Fertility Detection integrates multiple subsystems for performing incubation and fertility checks. At its heart, there's the ESP32 microcontroller; this is really the brains of the operation, talking to all sensors, motors, and the camera module.

The XH-M452 module monitors temperature and humidity to keep things just right inside; if things drift out of range, it jumps into action. A 40-watt incandescent bulb, switched on and off by a relay, supplies warmth, while the 12V high-speed DC fan moves air around, keeping everything even and cool when needed. If it gets too dry in there, the 4V mist humidifier kicks in, guided by live sensor feedback. The whole rig runs off of a 12V, 5A power supply, with a buck converter stepping the voltage down for the microcontroller and smaller parts.

Egg turning works automatically: a DC motor connected to the turning tray rotates the eggs at set intervals. This motor is controlled by an adjustable relay timer such that eggs get even heat and embryos develop properly.

The ESP32-CAM takes over for fertility checks. During candling, a bright LED lights through each egg as the camera snaps pictures. Those then run through a compact CNN trained to recognize fertile eggs via their veins and shadows. The results pop up on the 16x2 LCD screen, and colored LEDs make it obvious-green means fertile, red means infertile. This all fits inside of a thermally insulated wooden box, split into separate areas for incubation and candling. Passive vents allow for airflow, a see-through top for quick inspections, and water trays to help keep the humidity where it should be. The system operates in layers: sensors monitoring temperature, humidity, and moisture; processing is handled by the ESP32 and CNN; work is done by the motors, relays, fan, and bulb; and feedback is given via an LCD and LEDs. All these parts will talk to each other in real time, keeping conditions stable, reducing the amount of manual labor involved, and improving hatch rates in general. The design is modular, and you can easily scale up the system or add features like cloud monitoring later on.

BLOCK DIAGRAM EXPLANATION

A block diagram lays out how the smart egg incubator actually works. It's a simple way to see how every part—hardware and controls—connect and run the whole show, from hatching automation to checking if the eggs are fertile.

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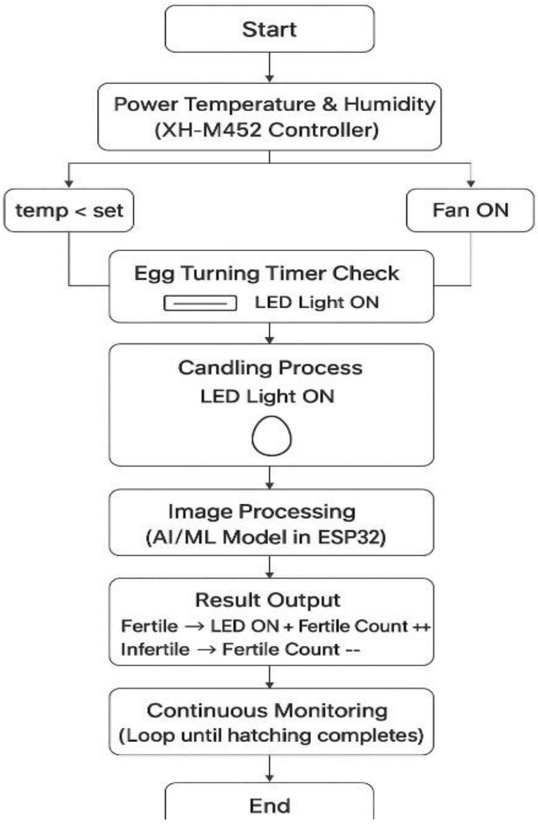

Figure 4.1.1: Block Diagram of the Smart Automatic Egg Incubator with Fertility Detection

Power Supply Unit:

Everything starts with a 12V SMPS power supply. This runs through a buck converter, which drops the voltage so the ESP32 microcontroller can use it. That same line powers all the other key pieces: sensors, motors, LEDs, and the camera. Basically, this keeps electricity reaching every corner of the system.

XH-M452 Temperature & Humidity Controller:

It monitors the incubator's temperature and humidity. When it gets too cold, this controller turns on the heating bulb. If it gets too hot, it kicks on a cooling fan to bring the temperature back down.

Egg Turning System:

Egg turning? The ESP32 handles it. It switches a relay module that controls a DC motor, which rotates the egg tray at regular intervals. That way, every embryo gets the movement it needs, just like in nature.

Candling & Imaging System:

At set times, the system turns on an LED to shine light through the eggs for candling. While the eggs are lit up, the ESP32-CAM snaps photos, which later get checked for fertility using computer vision.

Image Processing & Fertility Detection:

The ESP32-CAM has a built-in AI/ML model that scans the images and sorts the eggs—fertile or not. Fertile eggs get a green LED and increase the fertile count. Infertile ones trigger a red LED and go into the log.

Result Display & Monitoring:

You see results on an LCD or LED display—a running count of fertile and infertile eggs. The whole process just keeps looping through the incubation cycle, right up to the moment the eggs hatch.

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COMPONENT REQUIREMENTS

XH-M452 Temperature & Humidity Controller:

Controls the bulb and fan depending on the incubator temperature and humidity.

6-30V 1-Channel Relay Module (Timer) :

Automatically switches at fixed intervals with the egg-turning motor.

12V SMPS: Supplies all modules and motors with stable power.

12V Cooling Fan: Maintains airflow, consequently preventing overheating.

40W Bulb: Serves as the primary heating element in incubation.

Automatic Egg Turning Tray: Rotates eggs for proper embryo development.

Candling Egg System (LED): Illuminates eggs for fertility inspection.

ESP32-CAM: Images of eggs and AI-based fertility detection

DC-DC Buck Converter: Steps down 12V to 5V/3.3V to safely power the ESP32 and sensors.

ESP32 with LED Indicators: Performs fertility results using green and red LEDs.

Moisture Sensor: The water and humidity level is measured for proper moisture water level

STRUCTURAL LAYOUT

Incubator wooden frame:

In the design, the incubator wooden frame uses strong wood that acts as a natural thermal insulator, enhancing stability in the incubation environment. The structure is robust and offers long-lasting support to all hardware components. It has several shelves on which egg trays, candling units, and sensors are kept separately. At the bottom portion of the frame is the power supply, controller, and cooling fan for proper ventilation. The middle portion is primarily utilized for the egg turning tray in order to ensure even development of the embryo. The wooden frame provides a low-cost, durable, and farmer-friendly enclosure that simplifies construction while maintaining efficiency.

Figure 7.1.1 Prototype of the smart automatic eggincubator

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Figure 7.1.2: Open incubator setup showing the internal tray arrangement

Incubator Tray:

The incubator tray is the most crucial part of the system, which was designed to hold and rotate eggs during the incubation process. Each tray connects to an automatic turning mechanism driven by a DC motor and relay timer, thus ensuring that eggs are rotated at regular intervals. This serves to prevent the embryo from sticking to the shell and hence supports healthy development. The tray is built with enough spacing to allow proper air circulation around the eggs, which is necessary for maintaining uniform temperature and humidity. In this project, the incubator tray is also interfaced with the candling system so that eggs can easily be checked for their fertility without necessarily removing them from the tray. The design is lightweight, durable, and easy to clean; thus, it can support repeated use in poultry farming applications.

Figure 7.2.1: Automatic egg-turning tray used in the smart incubator

Egg Candling Machine

The candling machine for eggs detects the fertility of the eggs by passing light through the eggshell. In this proposed project, a high-intensity LED light is to be used below the egg tray to illuminate the egg while an ESP32-CAM captures the image for analysis Using AI and machine learning techniques, the system auto-classifies the egg as either fertile or infertile, and its result is indicated through a green LED for fertile and a red LED for infertile. Along with this, the count of fertile and infertile eggs was displayed, showing clear information to the farmer. The automated candling process reduces the use of much man Amidst the surge in global food demand, improving poultry production with automation emerges as a key factor in building a sustainable environment

Figure 7.3.1 Side view of the candling setup

The bottom candling LED setup works by projecting high-intensity light upward through the egg to illuminate its internal contents. In such a way, when the LED light passes through the egg shell, fertile eggs appear darker due to embryo formation and visible blood vessels, while infertile eggs allow lighter and look clearer. This principle of transmitted light allows for good fertility detection and thereby helps the ESP32-CAM capture clear candling images for AI processing.

Figure 7.3.2 Bottom view of the candling LED setup

View from the top The egg-holding grid is designed such that each egg is positioned right above a dedicated LED light source. This provides for uniform light transmission during candling for better viewing of internal structures of the egg to detect its fertility.

Figure 7.3.3 Top view of the candling chamber

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Figure 7.3.4 Front view of the candling chamber

RESULTS

Internal Working Mechanism of the Smart Egg Incubator

Below is a figure showing the internal composition of the automatic egg incubator, showing heating bulbs, an egg turning tray, and airflow. The 40 W bulbs take care of the required incubation heat. The tray at the centre revolves the eggs in regular periods for better development of the embryo. The fan circulates air uniformly within the chamber such that temperature and humidity levels are maintained constant

Figure 8.1.1 Internal View of the Incubator

This is the inner part of the incubator, where the sensors and wiring of the mist spray humidifier are located. The modules of the humidifiers should be positioned near the base for appropriate moisture spreading in the incubator. The wiring connects the mist unit to the controller, which will trigger it whenever humidity falls below the set level. Its placement ensures efficient dispersal of moisture inside without interfering with the egg tray.

Figure 8.1.2 Humidifier Mist Spray Setup

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This figure shows the water container of the humidifier. Water is drawn from this tank by the mist spray unit and converted to small moisture particles to increase the humidity. This tank is located below the egg tray for maintaining safety and preventing any type of accident due to spills. The setup is maintained in a position to provide stable humidity throughout the incubation cycle.

Figure 8.1.3: Humidifier Water Tank and Spray Output

The ESP32-CAM captures candling images of the eggs under LED backlight and then processes them via the onboard AI/CNN model. Fertile eggs are brighter with embryo structures or blood vessel patterns, while infertile eggs have uniform illumination with no internal growth at all. These visual differences are therefore detected by the AI model, which then generates bounding boxes around the candled images of each egg, classifying them as fertile or infertile for automatic and reliable incubation-stage fertility determination

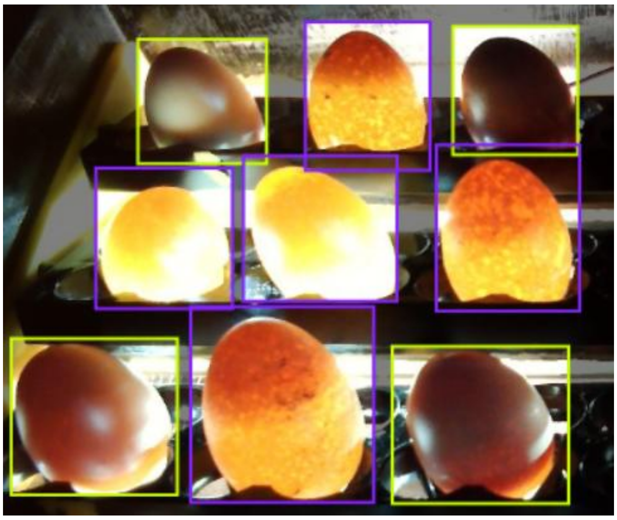

Figure 8.1.4 ESP32-CAM detection of fertile and infertile

This picture shows a chick emerging from its egg at the end of incubation. A successful hatch indicates that throughout incubation, there was appropriate temperature, humidity, and cycles of turning in the incubator. Under proper conditions, the controlled environment supports embryo development and the chick emerges on days 18–21 hatching

Figure 8.1.5 Newly hatched chick inside the incubator

CONCLUSION

This smart, automated egg incubator with fertility detection integrates the environmental control, computer vision, and IoT features successfully for enhancing the reliability of poultry incubation. The ESP32-based system was able to maintain proper temperature and humidity for the right development of the embryo during incubation. An overall accuracy of about 98% was achieved by the ESP32-CAM coupled with a lightweight CNN classifier in categorizing fertile and infertile eggs, which allowed the non-viable eggs to be removed at an early stage without causing contamination inside the chamber. IoT dashboard-based real-time monitoring reduced frequent manual checking and provided continuous visibility to temperature, humidity, and fertility status. An automated egg-turning mechanism was also provided for supporting healthy embryo growth. The minor limitations identified include non-uniform illumination and processing constraints, which can be further improved by enhanced LED arrays or more powerful microcontrollers. This, in general, proves that an AI-enabled incubator can considerably reduce human efforts while improving hatchability, proving to be a cost-effective and efficient solution for small and medium poultry farmers.

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