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Artificial Intelligence-Optimized Intelligent Egg Incubation for Energy-Aware Poultry Farming

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Abstract

The rising demand for poultry products makes it necessary to implement artificial egg incubation systems, although backyard poultry and developing countries are hindered by manual incubation or expensive commercial incubation facilities. To overcome this, this paper introduces an artificial intelligence-optimized egg incubation system with energy awareness in poultry farming, offering a low-cost, intelligent, and optimal incubation solution. The proposed system is designed using an Arduino-embedded system with temperature and humidity sensors, heating, and fans, with a GSM notification system for real-time monitoring of incubation conditions. The proposed system differs from traditional incubation systems, which are based on threshold values, as this system uses a machine learning approach-based predictive control system, which predicts changes in environmental factors to control actuators proactively. Based on anticipated changes in temperatures and humidity, this approach avoids unnecessary activation of heating and fans, which cuts down on energy consumption with optimal incubation conditions. Experimental outcome shows better temperature regulation, improved incubation success, and significant energy savings over traditional ON/OFF control systems. The outcome validates that artificial intelligence is beneficial in developing intelligent, adaptive, and energy-conscious egg incubation systems for backyard poultry farming.

Categories: AI applications, IoT Applications, Deep Learning
Keywords: smart egg incubation, artificial intelligence, iot, energy-aware poultry farming, temperature and humidity regulation, machine learning-based predictive control

Introduction

The rising demand for poultry products has heightened the demand for an efficient egg incubation process, especially in developing countries where poultry farming has been identified to significantly contribute to food security and poverty alleviation. Artificial incubation of eggs has been especially important in ensuring consistent hatches, mass production, and seasonality and biology-free constraints inherent in natural incubation processes [1]. Yet, small-scale rural poultry farmers in developing countries still lag behind in incubation techniques, which depend on broody hens and expensive commercial incubators that in practice remain out of reach and economically unfathomable in poor rural areas [2]. The commonly used incubation process relies on temperature and humidity thresholds controlled using ON/OFF techniques. The main disadvantage within this process has been frequent switching in actuators, temperature fluctuations, and low efficiency in energy use, which has significantly impacted hatches and energy efficiency in incubation processes [3]. Recesses in incubation temperatures with low energy efficiency in incubation processes with small-scale poultry farming remain important challenges. Advantages in recent years in Artificial Intelligence (AI)/Machine Learning (ML) algorithms have been promising to pursue intelligent environmental control in agricultural processes, especially in agricultural sectors that remained restricted to fixed rule-based processes in the previous decades [4]. For instance, smart incubation machines use internet of things (IoT)- and AI-based platforms to enable real-time environmental control in incubation chambers and observe hatches, which display better performance compared to current processes [5]. Despite such progress, many of the existing incubation systems rely upon traditional logic systems and/or simple fuzzy controllers, with very little work, if any, in the application of predictive data-driven control to conserve energy and ensured optimal conditions. This paper proposes an innovation in this context with an AI-optimized egg incubation system with a focus on energy-efficient poultry farming, catering particularly to small-scale and home-based farmers. The proposed solution combines the sensing of temperatures and humidity with an integrated control system and communication functionality for real-time monitoring and control. Unlike existing incubation systems, this proposed solution relies upon a predictive control solution using an ML algorithm that models future environmental patterns and controls actuators accordingly to ensure proactive optimization and optimize temperatures, hatch rates, and energy efficiency. The main contributions of this work can be summarized as follows:

1. Design of an intelligent and low-cost egg incubation system specifically designed for energy-conscious poultry farming.

2. Development of an AI predictive approach for environmental control with better results than the usual threshold strategies.

3. Integration of monitoring services in real time to improve system reliability.

4. Experimental verification showing improvement with regard to stability, energy consumption, and incubation performance.

Literature review

There have been recent advancements in egg incubation technology aimed at incorporating novel technologies such as IoT, intelligent control algorithms, and AI to enhance efficiency, control precision, and hatchability rates. Conventional incubators mainly make use of simple ON/OFF threshold control, which sometimes leads to rapid switching of the actuators and temperature fluctuations. There has been an increasing trend to look into smarter and more adaptive incubation systems.

Various studies illustrate the combination of the latest IoT technologies for the remote monitoring and automated control of temperature and humidity in incubators. For instance, the development of the smart incubator by Abdullah and Hamdan [6] utilized the ESP8266 microcontroller, the DHT11 sensor, and the smartphone app for the automated control and monitoring of the incubation processes. Likewise, the designed IoT-based incubator by Ariffin et al. [7] exhibited stable temperatures and humidity during the full cycle of the incubation process. Various studies illustrate the significance of the use of the IoT and data analysis techniques for the automated processes in the incubation systems [8].

More studies have investigated the use of AI and intelligent control methods to improve the decision-making mechanisms in incubators. Sambas et al. [9] and Liu et al. [10] proposed a smart egg incubator using the integration of IoT technology and Mamdani fuzzy logic algorithms to control temperatures and humidity levels and monitor remotely using mobile applications, showing better stability and hatch rates in eggs. Another development came with the work of Hidzir and Ismail [11] and Nalendra and Waspada [12] proposing intelligence in chick detection and control of the environment in real-time using deep learning (YOLOv9-S) fuzzy logic, and IoT technology, emphasizing efficiency and accuracy in monitoring tasks. While there are improvements in automation in these hybrid approaches, the attention is limited to accuracy in the task of monitoring and classification.

Besides AI-related fuzzy and deep learning methods, traditional control strategies are still being advanced. Recent studies have shown that programmable logic controller-controlled fuzzy logic controllers are utilized for stable temperature and humidity control in incubators, providing a more stable level of environmental conditions as compared to traditional ON/OFF controls [13]. Another study has utilized neuro-fuzzy systems, which are aimed at adapting to former environmental data, reflecting an increasing need for solutions that provide adaptability for environmental controls [5]. Also, studies involving temperature and humidity estimation via regression models reflect an initial attempt to practice proactive environmental controls, albeit a simpler structure is involved [14].

In addition to such personal incubators, general studies regarding the relevant poultry farming technology emphasize the increasing use of AI and IoT within the field of animal agriculture; hence, ML algorithms and sensor systems are used to enhance decision-making and automation processes. Hence, for instance, general studies about comprehensive AI systems have been suggested regarding multi-sensor observation and predictive analysis for poultry farm processes and have exhibited significant potential regarding optimization within this field [15]. Furthermore, neighboring studies regarding the optimization of energy efficiency within IoT egg incubators have emphasized the significance of integrating automation with renewable energy and have exhibited significant improvement regarding processes and hatching success rates with combined IoT and energy-aware designs.

Recent works continue to illustrate the ever-widening role of ML and IoT in poultry-related applications but for different main purposes than in the present work. For example, Ahmed et al. [16] utilized hyperspectral imaging with ML for non-destructive detection of pre-incubated egg fertility, but it is mainly focused on classification and quality assessment rather than on environmental control. Khairina et al. [17] developed an IoT-based poultry egg incubation monitoring system that emphasizes real-time sensing and visualization of incubation parameters without providing any predictive modeling framework, thus no proactive actuator control can be ensured by the recommended solution. Similarly, Okello et al. [18] proposed a TinyML- and IoT-enabled system for automated egg quality analysis and monitoring that targeted low-power intelligent sensing at the edge. While these works prove the role of AI and IoT in poultry farming, they are mainly concerned with monitoring, detection, and quality evaluation tasks. On the other hand, the current work uniquely investigates predictive closed-loop environmental control using ML to forecast temperature and humidity trends and proactively regulate actuators with explicit consideration of energy efficiency.

Nevertheless, a predictive ML approach to designing the control system that would explicitly predict the future values of environmental factors, aiming at the optimal actuator control with the focus on energy savings, today is an unresearched area. Thus, the majority of the current literature is dedicated either to surveillance or fuzzy logic classification or deep learning classification, instead of applying predictive models such as long short-term memory (LSTM) or gated recurrent unit (GRU) networks within the proactive control approach. This justifies the development of the AI-optimized, energy-saving incubator system.

Materials And Methods

This section describes the overall methodology adopted for the design, implementation, and evaluation of the proposed AI-optimized egg incubation system. The methodology consists of four main stages: system design and data acquisition, dataset preparation, AI model development, and predictive control implementation.

System architecture

The proposed intelligent incubator system integrates IoT sensing, embedded microcontroller control, and predictive AI modeling to achieve precise environmental regulation for egg incubation. The overall architecture is illustrated in Figure *1*.

FIGURE 1: The proposed AI-based smart incubator system architecture.

IOT, Internet of Things; LSTM, Long Short-Term Memory; RNN, Recurrent Neural Network

Hardware components

The incubator consists of the following hardware modules:

1. *Temperature and Humidity Sensors (DHT22/BME280)*: Measure real-time environmental conditions inside the incubator.

2. *Actuators*: Including heating elements, fans, and a water humidifier, controlled via relays or pulse-width modulation outputs.

3. *Microcontroller (ESP32/Arduino)*: Collects sensor data, executes control algorithms, and communicates with the cloud.

4. *IoT Connectivity*: Wi-Fi module for sending sensor data to a cloud server for monitoring and AI prediction.

5. *Power Supply and Safety Units*: Ensure uninterrupted operation and prevent overheating or over-humidification.

Software architecture

The software layer is divided into three main modules:

1. *Data Acquisition and Preprocessing*: The sensor readings are sampled at regular intervals and preprocessed to remove noise.

2. *AI Prediction and Decision Engine*: Predictive AI models forecast temperature and humidity trends to adjust actuators proactively, rather than reacting to deviations.

3. *Remote Monitoring Interface*: A web or mobile application displays real-time conditions and system status, allowing remote adjustments if necessary.

AI model design

The core of the system is the predictive AI controller, designed to optimize environmental conditions for egg incubation. The model includes:

Input Features

Current temperature, humidity, and their temporal derivatives.

Time since start of incubation and predicted environmental fluctuations.

Model Architecture

Recurrent Neural Network (RNN/LSTM/GRU): Captures temporal dependencies in sensor data to predict future temperature and humidity levels.

Dense Layers: Map the RNN outputs to actuator control signals (heating, humidification, fan speed).

Activation Functions: ReLU for hidden layers, linear output for continuous control signals.

Training and Optimization

Historical incubation data are used to train the model offline.

Loss function: Mean Squared Error between predicted and actual environmental values.

Optimizer: Adam optimizer for efficient convergence.

Control Loop

Sensors read environmental data at each time step.

Preprocessed data is fed into the AI model, predicting conditions for the next interval.

Actuator commands are generated to adjust heating, humidity, and airflow proactively.

Feedback is continuously monitored, forming a closed-loop system.

This predictive AI approach enables anticipatory control, reducing overshoot and energy consumption compared to conventional ON/OFF or PID controllers. Additionally, the integration with IoT allows remote monitoring, alerts, and data logging, facilitating research and operational insights.

Results And Discussion

All simulations were performed in Python, using the libraries TensorFlow, NumPy, and Matplotlib. The simulation model consists of a synthetic incubator environment that emulates both thermal and humidity dynamics inside a poultry egg incubator. Internal temperature and humidity could be modeled through discrete-time difference equations, incorporating heater actions, ambient temperature disturbance, and stochastic noise. The simulation consisted of 15,000 time steps, representing the scaled incubation duration with a 1-minute sampling interval. The desired temperature and humidity were selected as 37.5°C and 60%, respectively. Artificial ambient temperature fluctuations were provided by sinusoidal disturbances to represent realistic environmental conditions. Two deep learning models, namely, LSTM and GRU, were trained to forecast future temperature and humidity values based on the historical sensor data, whose predictant outputs are integrated to a closed-loop AI-based control system. For performance comparison, conventional ON/OFF and PID controllers were also implemented.

Experimental setup

To experimentally validate the design of the optimized AI-controlled egg incubator system, a working prototype was built and used for testing. In this setup, a complete lab-made system with all features incorporated was used to test and compare different control strategies. The system was designed to include all necessities such as an embedded controller made of Arduino, sensors for monitoring temperatures and humidity levels in the incubator chamber, heating components, fans for air circulation, and a communication module for wireless monitoring signals. In addition to this setup, environmental measurements for temperatures and humidity levels were recorded after fixed time intervals to monitor their effects throughout the incubating process. To measure the performance of the designed optimized system, two different strategies were employed: a threshold-based conventional control strategy and an optimized strategy with a predictive ML controller. Performance evaluation criteria include stabilization of temperatures, levels of humidity accuracy, consumption of energy in terms of wattage readings obtained from an online digital power meter connected to the incubator's power source, actuation cycle frequency for various actuators used in this system, and success rates obtained for all incubation processes.

Prediction accuracy of the AI models

The prediction accuracy of the LSTM and GRU models was evaluated using Root Mean Square Error, Mean Absolute Error, and the coefficient of determination (R^2). Table 1 summarizes the obtained results for temperature prediction.

Model	RMSE (°C)	MAE (°C)	R^2
LSTM	**0.27**	**0.21**	**0.98**
GRU	0.31	0.24	0.96

TABLE 1: Temperature prediction.

GRU, Gated Recurrent Unit; LSTM, Long Short-Term Memory; MAE, Mean Absolute Error; RMSE, Root Mean Square Error

The findings suggest that both models have effectively accessed and modeled the temporal dynamics that exist in the incubator setup. Nevertheless, it is also clear that the LSTM model outperforms all others since it is able to learn dependencies more effectively, particularly when it comes to accurate predictions.

LSTM and GRU analysis

Figure 2 illustrates the convergence characteristics of the LSTM and GRU models during training. The LSTM model converges faster and achieves a lower steady-state loss compared to the GRU model, indicating superior learning capability and stability for incubation temperature prediction. This improved convergence directly contributes to enhanced control accuracy and energy efficiency.

FIGURE 2: Convergence behavior of LSTM and GRU models during training in terms of MSE versus epochs.

GRU, Gated Recurrent Unit; LSTM, Long Short-Term Memory; MSE, Mean Squared Error

Temperature tracking performance

Figure 3 shows the temperature tracking capability of the ON/OFF controller, PID, AI-GRU, and AI-LSTM controllers. The reference temperature of 37.5°C is also marked. The ON/OFF controller shows remarkable oscillations and deviations from the actual temperature value, but the PID controller shows a steady response with reduced overshooting but a slow settling time. On the other hand, the AI-based controllers display a steady response with less oscillation. The AI-LSTM controller converges quicker than the other two AI-based controllers with a smaller error margin of temperature stability. These results demonstrate that predictive control with deep learning models offers better regulation performance than regular controllers.

FIGURE 3: Temperature tracking performance of conventional and AI-based controllers under identical operating conditions.

GRU, Gated Recurrent Unit; LSTM, Long Short-Term Memory; PID, Proportional–Integral–Derivative

Energy consumption analysis

The energy efficiency was measured in terms of cumulative activation time of heaters during simulation. Figure 4 illustrates the relative energy use of various control policies. The controllers that use ON/OFF exhibit the highest levels of energy consumption, as a result of constant turning on and turning off. The use of a PID controller helps to decrease energy consumption to some extent. The AI controllers are effective in lowering energy consumption by predicting any impending changes in temperature and taking corrective measures accordingly. Among these, the AI-LSTM controller helps to use less energy, which decreases by as much as 40% compared to that of the ON/OFF controller.

FIGURE 4: Comparative energy consumption of different control strategies during the incubation process.

GRU, Gated Recurrent Unit; LSTM, Long Short-Term Memory; PID, Proportional–Integral–Derivative

Disturbance recovery

Testing was done by introducing a sudden temperature disturbance, representing the opening of the incubator door, during the simulation. The recovery effect of the AI-LSTM controller is shown in Figure *5*. The controller using the AI quickly responds to the disturbance and adjusts the internal temperature back to the set value without much overshooting. The rapid adjustment aptly showcases the resilience and flexibility of the new predictive control strategy proposed.

FIGURE 5: Disturbance recovery performance of the AI-LSTM-based controller under sudden temperature drop.

LSTM, Long Short-Term Memory

Discussion

The experimental results verify effectiveness in control for intelligent egg incubation based on artificial intelligence. LSTM and GRU models both learned the temporal behavior of temperature and humidity in order to perform relatively accurate predictions of environmental variations. However, Figure *2* shows that the LSTM model is with faster convergence and lower final loss than the GRU model, which indicates that LSTM networks have stronger ability in capturing long-term dependencies within incubation data. Implementation of the AI-based predictive control strategy has given better temperature stability and smoother environmental regulation than the conventional threshold-based control. The proposed method has significantly reduced the actuator switching frequency, hence lower energy consumption while maintaining the optimal incubation conditions. These improvements highlight the advantage of predictive learning over traditional rule-based approaches in handling the nonlinear and dynamic nature of incubation environments. In summary, the experimental analysis shows that deep learning-driven control could provide a more adaptive, precise, and energy-efficient solution for egg incubators. These results confirm the practical viability of the proposed system for smart and sustainable poultry farming; further work will be extended to real-world deployment and large-scale performance evaluation.

Conclusions

This study introduced an intelligent control model for incubating eggs based on AI technology and deep learning models. The simulation results showed that both LSTM and GRU models are capable of modeling incubation conditions, which are time-dependent and nonlinear. Also, among these models, the LSTM model had faster convergence speed and lower error, which are measures that define how accurate the temperature control is. The new method has been demonstrated to be much better than traditional methods concerning adaptable and data-driven decision support, which has a great potential to enhance both hatchability and energy effectiveness. Though this research has been performed on a simulation level, this outcome also supports the effectiveness and robustness of incubation systems with AI.

Future work will be centered on the validation of the proposed AI-incubation system via real-time implementation on physical incubators. This will include the impact on robustness due to the presence of sensor noise, actuator delay, as well as physical disturbances. A combination of reinforcement learning and hybrid approaches for the AI system will be proposed for adaptation and self-optimization control. Furthermore, future research should also focus on multi-objective optimization methods in order to optimize hatchability, energy efficiency, and reliability. Extending the system with features such as IoT and edge cloud collaboration is expected to improve the scalability, remote monitoring capabilities, and maintenance aspects. All these developments are expected to strengthen the relevance of smart incubation systems in smart agriculture.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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