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Design and Implementation of an Enhanced Neuro-Fuzzy-Based Smart System for Poultry Incubators

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Abstract; This research work entails implementing the design and development of a neuro-fuzzy based smart system using Python. The system learns from historical data of the physical parameters and utilizes fuzzy rules. The system parameters include a NodeMCU controller, temperature and humidity sensors that can measure the conditions of the incubator, C0$_2$ sensor and a gyroscope which monitors and adjust the positions of the egg for even distribution of heat around fertilized eggs. It is important that factors necessary for hatching of fertilized egg are kept under appropriate control to increase hatch rate. This was made possible through the actuators which switches the heaters, humidifiers and ventilating fan to moderate environmental The system controller houses an inbuilt Wi-Fi module ESP8266 which enables a remote monitoring and override control when necessary. There is also a provision of a 20X4 LCD monitor for onsite displaying and monitoring of the system status and functionality.

Keywords: *Neuro-fuzzy, smart, Python, incubator, Poultry*

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1.0 Introduction

Incubation is a critical process in poultry farming that determines hatchability success. With the rise in large-scale poultry operations, artificial incubators capable of handling thousands of eggs have been developed to ensure consistent hatching outcomes (Saeed et al., 2019). These incubators require precise control of temperature, humidity, ventilation, and egg orientation (Salman, 2016). A well-designed system must maintain temperature between 35°C–40°C, humidity between 50%–70%, and CO_2 levels below 1000 ppm.

Success in incubation is crucial in ensuring that farmers can maximize their production of poultry, particularly in large scale operations. This has resulted to rapid development of poultry industry with broadening field of specialization within it, (Saeed, *et al*., 2019)

Today, through the ingenuity of man, incubators have been constructed which holds thousands of eggs and are operated by machine without human interference until hatched. Artificial incubator is basically a container which holds and adjusts eggs while maintaining appropriate temperature, humidity, ventilation, and egg position, (Salman, 2016).

A well-designed incubator should maintain temperature within 35ºC – 40ºC degrees, humidity within 50% – 70%, CO_2 maintained below 1000ppm and maintain the egg in position viable for hatching eggs from chicken.

To improve efficiency, researchers and engineers have explored advanced automation techniques for incubation control. Among these, fuzzy logic and artificial neural networks (ANNs) have shown promise in developing intelligent, self-adaptive control systems for various applications, including agriculture (Hossain *et al.,* 2021). Fuzzy logic provides a rule-based approach to decision-making that mimics human reasoning, allowing systems to handle uncertainty and imprecise data effectively. Meanwhile, ANNs enable machines to learn from historical data, making real-time predictions and adjustments to optimize system performance. The integration of these two techniques, known as a neuro-fuzzy system, combines the strengths of both approaches, making it a suitable solution for intelligent poultry incubation control (Zhao *et al*., 2023).

A neuro-fuzzy-based incubator system can dynamically adjust temperature, humidity, and ventilation by continuously analysing real-time sensor data. Unlike traditional PID (Proportional-Integral-Derivative) controllers, which require precise mathematical modelling and tuning, neuro-fuzzy systems adapt and optimize control parameters based on learned patterns and expert knowledge (Chen *et al.,* 2024). This ensures that embryonic development conditions remain stable, even when external environmental factors fluctuate. Additionally, neuro-fuzzy systems can improve energy efficiency by optimizing heating and cooling operations, reducing electricity consumption and operational costs.

Despite the potential benefits of neuro-fuzzy systems, their implementation in commercial poultry incubators remains limited, particularly in developing countries where farmers often rely on outdated or manually controlled incubators. The lack of affordable, intelligent incubation solutions contributes to high embryonic mortality rates, resulting in economic losses for poultry farmers (Rahman *et al.,* 2023). Therefore, there is a need to design and develop a cost-effective, intelligent incubation system that leverages neuro-fuzzy technology to enhance hatchability and improve poultry farming efficiency.

This study aims to bridge this gap by developing a neuro-fuzzy-based smart system for poultry incubators. The proposed system will integrate real-time monitoring capabilities, adaptive control mechanisms, and microcontroller-based implementation to provide an efficient and user-friendly solution for poultry farmers. By addressing the limitations of conventional incubation systems, this research will contribute to the advancement of precision agriculture and sustainable poultry production.

2.0 Review of related Literature

Neuro-fuzzy systems integrate the learning ability of artificial neural networks (ANNs) with the interpretability of fuzzy logic systems (FLS), making them particularly suitable for handling the uncertainty and non-linearity in biological systems like poultry incubation.

Jang (1993) introduced the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines the benefits of fuzzy logic and neural networks for approximating complex functions. This model laid the groundwork for intelligent control in various fields, including agriculture and poultry farming.

Sharma et al. (2015) highlighted the potential of smart technologies like fuzzy logic and neural networks in automating agricultural systems. They emphasized the relevance of ANFIS for decision-making in variable environmental conditions.

Sabrine et al. (2014) developed a fuzzy logic-based temperature and humidity controller for egg incubators. Their model effectively managed microclimatic conditions to improve hatchability.

Mohamed et al. (2017) designed a fuzzy controller for brooding management in poultry, integrating light, temperature, and humidity control. They demonstrated reduced mortality and improved bird comfort.

Adebiyi et al. (2013) used neural networks to model and predict temperature-humidity profiles within an incubator. The trained ANN outperformed traditional PID-based controllers in maintaining stable environmental conditions.

Chukwu et al. (2019) employed ANN to forecast incubation outcomes based on historical environmental parameters. Their results showed higher accuracy in predicting hatch rates and embryonic development trends.

Boonmee et al. (2016) implemented a neuro-fuzzy model to control the environment inside a smart egg incubator. The system used input variables such as temperature, humidity, and egg turning frequency to produce control actions. Their ANFIS-based model achieved higher hatchability rates and better adaptation to changing conditions.

Pramod et al. (2020) developed a real-time poultry incubator using a neuro-fuzzy logic controller. Their study reported precise control of micro-environmental parameters and adaptive responses to ambient temperature variations, outperforming traditional thermostats.

Adeyemo et al. (2021) proposed a hybrid ANFIS-based controller for optimizing hatchability and energy consumption. The system dynamically adjusted heating and humidifying elements to achieve energy efficiency while maintaining optimal embryo development conditions.

Salman et al. (2018) developed a fuzzy-based intelligent brooder using temperature, light, and humidity sensors. The fuzzy logic controller responded adaptively to changing chick requirements across different age ranges. The system improved chick comfort and survival rates in the brooding phase, which is closely related to incubation control.

Ali et al. (2020) proposed a hybrid fuzzy-PID controller for an egg incubator system. The fuzzy system adjusted the PID parameters in real-time, yielding faster system responses and fewer overshoots in environmental parameters. This study demonstrates the benefit of hybrid intelligence systems over conventional controllers.

Ragab & Hassan (2019) applied ANFIS to model and predict chick mortality based on microclimate parameters. The system was trained using real-time sensor data from smart poultry houses. It successfully identified complex nonlinear relationships among humidity, temperature, and bird age, and demonstrated superior predictive power compared to standalone fuzzy or neural models.

Zhang et al. (2020) implemented an IoT-based smart incubator system using an ANFIS controller embedded on an edge device (Raspberry Pi). It dynamically adjusted heater and humidifier settings using a real-time feedback loop. Their results indicated up to 95% hatchability under variable ambient weather conditions.

Ahmed et al. (2021) enhanced the performance of an ANFIS controller using genetic algorithm (GA) optimization. Their system automatically optimized the membership function parameters for temperature and humidity control in incubators. This resulted in better adaptation and faster convergence than manually tuned systems.

Kumar & Singh (2022) used particle swarm optimization (PSO) to tune a neuro-fuzzy model for controlling incubator airflow and CO_2 levels, an often-overlooked but critical factor for embryo development. The optimized system reduced embryo mortality and energy consumption by 20%.

El-Hagarey et al. (2022) proposed a neuro-fuzzy controller for livestock shed automation, managing temperature, lighting, and air quality. Though not specifically for incubators, the model's environmental control strategies are transferable and emphasize the scalability of neuro-fuzzy systems in animal agriculture.

Onu & Eze (2023) developed a low-cost ANFIS-based smart poultry management system for small-scale farmers in developing countries. The system achieved real-time control of incubator conditions using fuzzy reasoning and learned control strategies from user feedback and sensor logs. Wahab et al. (2020) reviewed various commercially available smart incubators, noting that most relied on preset logic or PID controllers, with limited adaptability. They advocated for the integration of adaptive learning models like ANFIS to improve operational efficiency and chick viability. Tang et al. (2023) developed a cloud-connected ANFIS-based incubation platform where the controller parameters could be remotely updated via machine learning models trained on centralized hatchery data. The system allowed centralized optimization for multiple incubators distributed across different geographies.

The reviewed literature demonstrates that neuro-fuzzy systems—especially ANFIS—offer superior performance in controlling environmental parameters compared to traditional PID controllers. Hybrid models integrating fuzzy logic with ANN or optimization algorithms like GA and PSO have proven effective in improving hatchability, reducing energy consumption, and adapting to environmental variations. However, their implementation in commercial poultry farms, particularly in developing countries, remains limited due to cost and accessibility challenges. This study aims to bridge this gap by providing a low-cost, intelligent incubation solution based on neuro-fuzzy architecture.

3.0 Material and Methods

3.1 Materials

To build the hardware and software for this study, a variety of resources, including software platforms, hardware components, development tools, and programming languages, can be used. This study selects items that, when properly analyzed, will result in an effective and user-friendly system. Hardware and software development tools are the two main categories into which the resources utilized to conduct this research fall.

3.1.1 Hardware devices

Summary of hardware components involved in the design are shown in Table 1.

3.2 Method

The system was developed using a hybrid prototyping method, which facilitated iterative design, testing, and refinement of subsystems. Additionally, the waterfall model was considered as an alternative approach to highlight the advantages of prototyping for this research.

3.2.1 The System design

The system integrates sensor-based automation, IoT connectivity, and neuro-fuzzy control to optimize poultry incubation. The system design is illustrated in the flowchart in Fig. 1

3.3.2 Adaptive Neuro-Fuzzy Inference System (ANFIS) Design

The core of the system is the ANFIS model, which combines fuzzy logic and neural networks to dynamically regulate temperature, humidity, CO_2 levels, and egg position. The ANFIS model was implemented in Python using the scikit-fuzzy library, with data handling supported by NumPy and Pandas.

3.2.3 Dataset for ANFIS Training

A dataset of 2,000 rows and 8 columns was collected from simulated and real-world incubator experiments. The dataset included:

Inputs:

Temperature (°C): Range 30–45°C, mean 37.5°C, standard deviation 2.1°C.

Humidity (% RH): Range 40–80%, mean 60%, standard deviation 5.2%.

CO_2 Concentration (ppm): Range 500–2000 ppm, mean 1000 ppm, standard deviation 150 ppm.

Egg Angle (°): Range 0–180°, adjusted every 4 hours.

Table.1: Hardware Components – Functions and Applications

Component	Function	Application in the System
NodeMCU ESP8266	- Acts as main controller - Connects to Wi-Fi - Interfaces with sensors and actuators	- Central control unit - Sends/receives data via HTTP API - Executes Neuro-Fuzzy decisions
DHT22 (Temp/Humidity)	- Measures temperature and humidity - Provides digital data	- Monitors internal climate - Feeds ANFIS model for environment control
MG811 (CO_2 Sensor)	- Detects CO_2 concentration - Analog output	- Ensures proper ventilation - Triggers fan or alerts based on ANFIS recommendations
MPU6050 (Gyro + Accel.)	- Detects motion, rotation, and angle - 6-axis data	- Monitors egg tray orientation - Confirms proper egg turning
Servo Motor	- Controlled motion through PWM - Rotates trays at set intervals	- Rotates eggs periodically - Ensures embryo doesn't stick to shell
Heater/Cooler	- Controls internal temperature	- Maintains target incubation temperature (~37.5°C) - Activated by ANFIS logic
Humidifier	- Increases humidity using mist or steam	- Keeps humidity within optimal range (~55–60%)
Fan	- Circulates air - Controls airflow and CO_2 exchange	- Maintains uniform temperature & humidity - Reduces CO_2 build-up inside the incubator

Outputs:
Heater State: Binary (1 = ON if temperature < 37.2°C, 0 = OFF).
Humidifier State: Binary (1 = ON if humidity < 50%, 0 = OFF).
CO_2 Fan State: Binary (1 = ON if CO_2 > 900 ppm, 0 = OFF).
Egg Motor State: Binary (1 = ON every 4 hours, 0 = OFF).
The dataset was preprocessed by normalizing inputs to [0, 1] and removing outliers (values beyond 3 standard deviations).

3.2.4 NFIS Architecture

The ANFIS model follows a five-layer architecture, integrating fuzzy inference with neural network learning:

1. Layer 1 (Fuzzification): Inputs are mapped to fuzzy membership functions. Each input (temperature, humidity, CO_2, egg angle) uses three Gaussian membership functions (Low, Medium, High), defined as follows

$$\mu(x) = e^{-\frac{(x-c)^2}{2a^2}} \qquad (1)$$

where c is the center and σ is the width. For example, temperature membership functions are centered at 35°C (Low), 37.5°C (Medium), and 40°C (High).

2. Layer 2 (Rule Firing): Computes the firing strength of each fuzzy rule by multiplying input membership values. With 4 inputs and 3 membership functions each, there are $3^4 = 81$ rules.
3. Layer 3 (Normalization): Normalizes firing strengths by dividing each rule's strength by the sum of all strengths.
4. Layer 4 (Defuzzification): Computes weighted outputs for each rule using first-order Sugeno fuzzy models (linear combinations of inputs).
5. Layer 5 (Output): Sums all rule outputs to produce final control actions (e.g., heater ON/OFF).

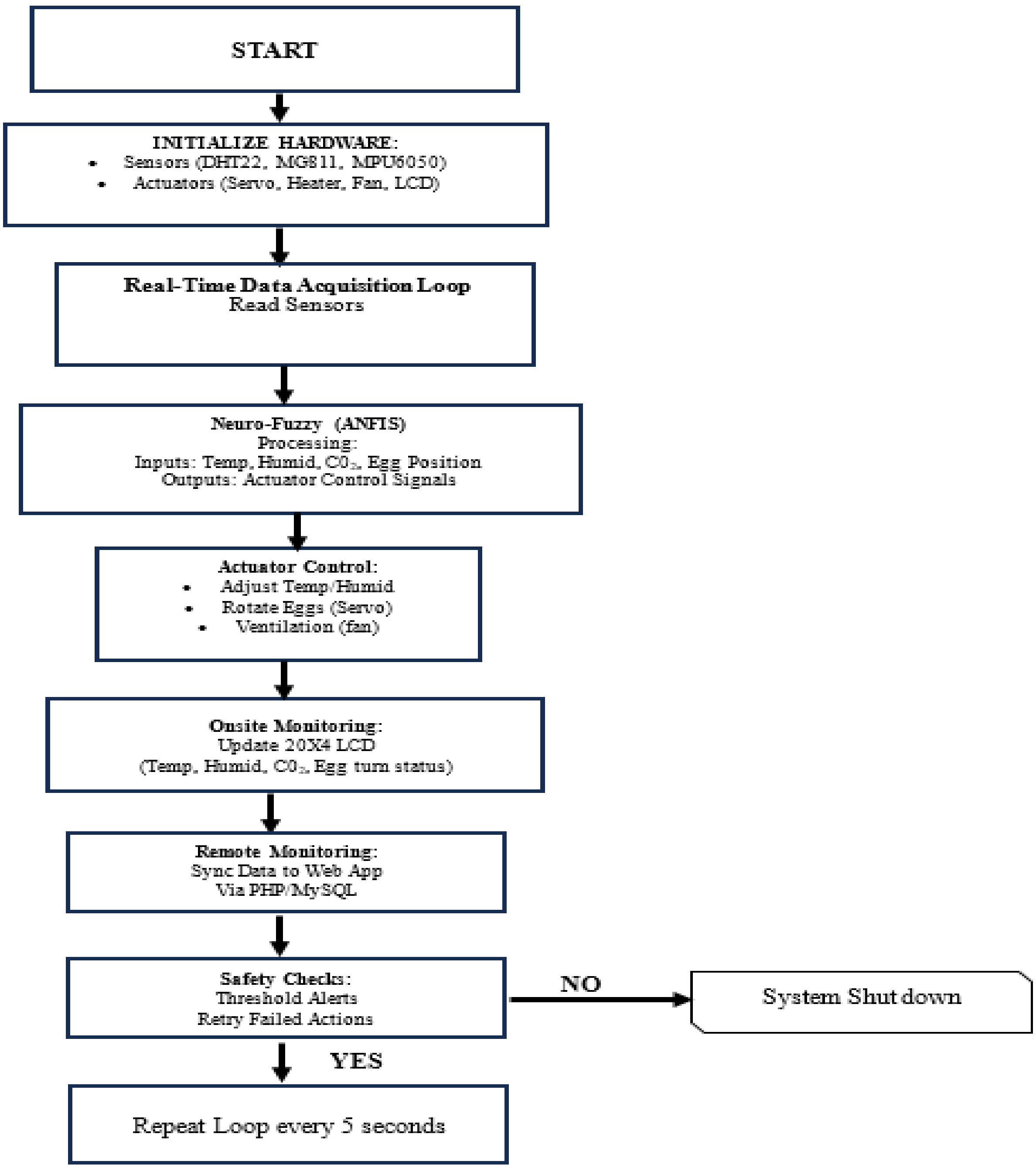

Fig.1: Flowchart

Fig. 2 shows the block diagram which illustrate module interconnections and data flow.

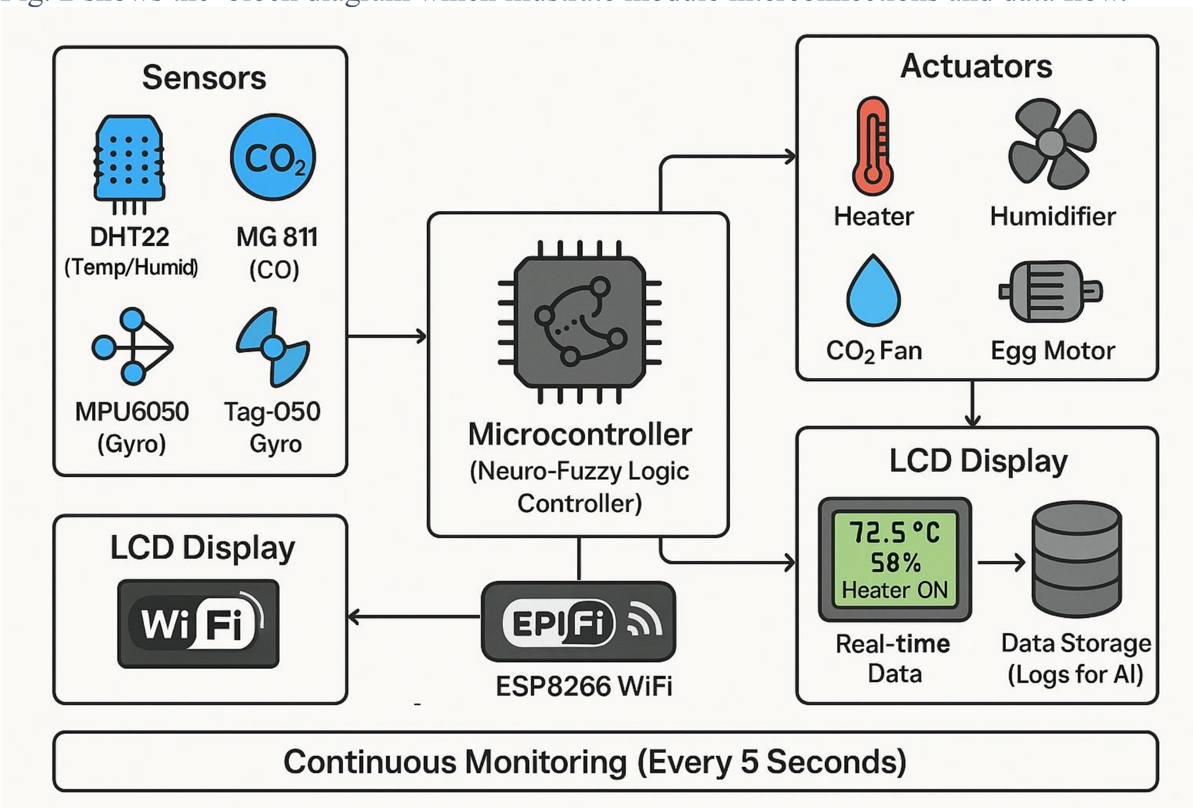

Fig 2: System block diagram

3.2.5 Fuzzy Rules

The ANFIS model incorporates a total of 81 fuzzy rules, which were derived from both expert knowledge and patterns observed in the dataset. For example, one rule states: *If temperature is low, humidity is medium, CO_2 level is low, and egg angle is medium, then the heater is turned on, the humidifier remains off, the CO_2 fan is off, and the egg motor is off.* Another rule specifies: *If temperature is medium, humidity is low, CO_2 level is high, and egg angle is high, then the heater is off, the humidifier is activated, the CO_2 fan is turned on, and the egg motor is also turned on.* A third rule indicates: *If temperature is high, humidity is high, CO_2 level is medium, and egg angle is low, then all actuators—heater, humidifier, CO_2 fan, and egg motor—remain off.* These fuzzy rules were initially conFig.d in accordance with standard incubation guidelines, such as maintaining a target temperature of approximately 37.5°C, and were further refined through the model's training process.

3.2.6 Neural Network Training

The ANFIS model was trained using a hybrid learning algorithm that combined backpropagation with least-squares estimation. The training process was conducted over 100 epochs with a learning rate of 0.01. Root Mean Square Error (RMSE) was used as the performance metric, and the model achieved an RMSE value of 0.032 after training. A total of 80% of the dataset, corresponding to 1,600 rows, was used for training, while the remaining 20% (400 rows) was used for validation. After training, the model was serialized using Python's pickle module and deployed on the NodeMCU ESP8266 as a precomputed lookup table to account for the microcontroller's limited computational capacity.

3.2.6 ANFIS Implementation

The following pseudocode outlines the ANFIS training process:

```
import skfuzzy as fuzz
import numpy as np
import pandas as pd

# Load and preprocess dataset
data = pd.read_csv('incubator_data.csv')
inputs = data[['temp', 'humidity', 'co2', 'egg_angle']].values
outputs = data[['heater', 'humidifier', 'co2_fan', 'egg_motor']].values
inputs_normalized = (inputs - inputs.min(axis=0)) / (inputs.max(axis=0) - inputs.min(axis=0))
# Define membership functions
temp_mf = fuzz.gaussmf(np.linspace(30, 45, 100), [35, 37.5, 40], [2, 2, 2])
humidity_mf = fuzz.gaussmf(np.linspace(40, 80, 100), [50, 60, 70], [5, 5, 5])
co2_mf = fuzz.gaussmf(np.linspace(500, 2000, 100), [700, 1000, 1300], [100, 100, 100])
angle_mf = fuzz.gaussmf(np.linspace(0, 180, 100), [0, 90, 180], [30, 30, 30])
# Initialize ANFIS model
anfis = fuzz.ANFIS(inputs_normalized, outputs, [temp_mf, humidity_mf, co2_mf, angle_mf])
# Train model
anfis.train_hybrid(epochs=100,
learning_rate=0.01, validation_split=0.2)
# Save model
import pickle
with open('anfis_model.pkl', 'wb') as f:
    pickle.dump(anfis, f)
```

3.2.7 Embedded Firmware

The NodeMCU ESP8266 firmware, written in C++ using the Arduino IDE, handles sensor data acquisition, actuator control, and communication with the LCD and web dashboard. Key libraries include:

- DHT.h: Reads temperature/humidity from DHT22.
- Wire.h: Enables I²C communication for MPU6050 and LCD.
- ESP8266WiFi.h: Manages Wi-Fi connectivity.
- Servo.h: Controls egg-turning servo motor.
- LiquidCrystal_I2C.h: Displays data on 20x4 LCD.

The firmware polls sensors every 10 seconds, processes data through the ANFIS lookup table, and sends control signals to actuators. Data is transmitted to the MariaDB database via HTTP POST requests.

The trained model was serialized using Python's pickle module and deployed on the NodeMCU ESP8266 as a precomputed lookup table to accommodate the microcontroller's limited computational resources.

3.2.8 The Remote Monitoring and Control

The system which can be monitored and controlled remotely is designed with the aid of HTML, CSS, and JavaScript for the front-end, providing a simple and interactive user interface for farmers and incubator workers. The backend is implemented using PHP which handles the API requests, processing sensor data, and ensuring efficient data management. All sensor readings and Neuro-fuzzy generated insights are stored in a MariaDB database, enabling historical trend analysis and improvement to the decision making of the model, since larger datasets typically improve model accuracy.

Fig. 3 is the Schematic circuit diagram of system connection

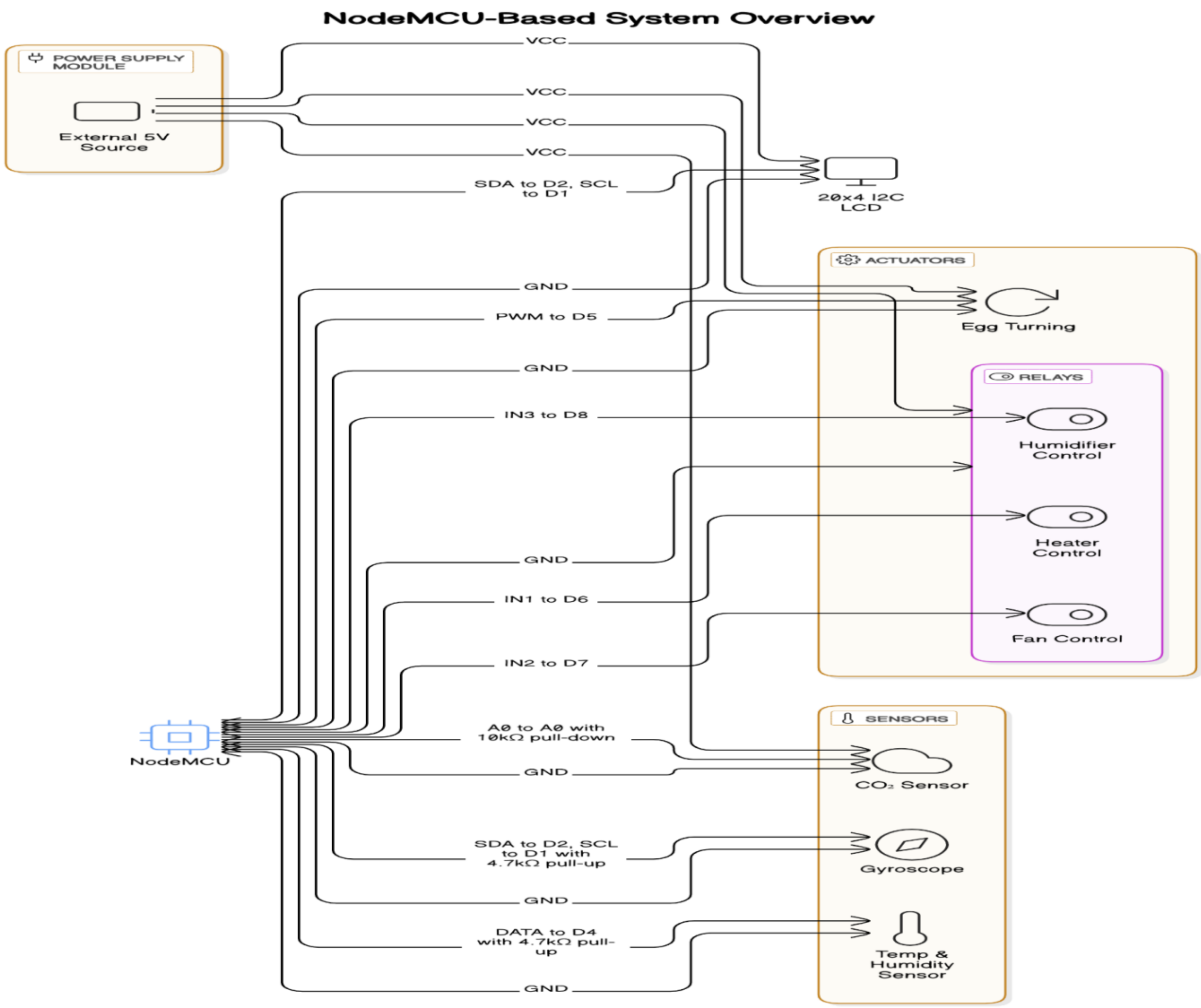

Fig. 3: Schematic circuit diagram of system connection

4.0 Results and Discussion

4.1 The System Test

The system was evaluated through a multi-stage testing process:

i. Unit Testing: Each component (DHT22 sensor, MG811 CO_2 sensor, MPU6050 gyroscope, servo motor, relays, ANFIS model, Wi-Fi connectivity) was tested individually to ensure functionality and accuracy.

ii. Integration Testing: Interactions between sensors, ANFIS, actuators, and the web dashboard were validated to confirm seamless operation.

iii/ Performance Testing: The system was operated over multiple 21-day incubation cycles to assess real-time responsiveness and environmental stability.

The aim of these tests was to detect logical and coding errors in each module and to validate the functionality of both hardware and software components

Table 2 presents the results of unit testing conducted on the individual components of the IoT-based smart poultry incubator system. Each component was tested independently to validate its functionality against expected performance criteria using specific tools and measurement standards. The objective of these tests was to ensure that every module—from sensors to actuators and control algorithms—met the operational benchmarks necessary for accurate environmental monitoring, device control, and communication. The tools used for verification included multimeters, serial monitors, oscilloscopes, calibrated references, and simulation platforms such as Python's scikit-fuzzy.

Table 2: The unit test cases, tools used, and expected results

Component	Test Case	Tools	Expected Result
DHT22 Sensor	To Measure the Temperature/Humidity against a calibrated reference using a thermometer	Multimeter, Serial Monitor (Arduino IDE)	±0.5°C accuracy for temp, ±2%RH for humidity
MG811 $C0_2$ Sensor	Exposed to 1000ppm concentration of carbon dioxide	Calibration gas, ADC readings	Linear analog output around 0-3.3V
MPU6050 Gyroscope	Rotate the servo motor and verify angular displacement within 0°–180°	Serial plotter, MPU6050 library	<5° error in angle tracking.
Servo Motor	Command 0°, 90°, 180° positions via PWM.	Protractor, oscilloscope.	Accurate positioning (±2° error).
Relays	Trigger heater, fan, humidifier via D6/D7/D8	Use Multimeter to check continuity	Relay switches ON/OFF within 100ms
Neuro-Fuzzy Logic	Simulate input (temp/humidity) and check output	Python (scikit-fuzzy)	Smooth control signals, no oscillations.
Wi-Fi Connectivity	The NodeMCU connection to IoT web-based dashboard	Wi-Fi analyzer, dashboard logs	<1s latency in data transmission

4.2 System performance

The system was tested over three 21-day incubation cycles, each with 100 fertilized chicken eggs, to evaluate its ability to maintain optimal environmental conditions. The key parameters—temperature, humidity, CO_2 levels, and egg rotation—were monitored continuously, with data logged to the MariaDB database every 10 seconds. The ANFIS model processed sensor inputs and issued control actions (e.g., heater ON/OFF, fan activation) with a response time of <2 seconds, demonstrating real-time efficiency.

Table 3 presents a performance evaluation of the developed intelligent incubation system by comparing the critical environmental parameters' observed average values against their established target ranges. The table also includes the calculated accuracy for each parameter, demonstrating how well the system maintains optimal conditions for embryonic development.

Table 3: comparison of target ranges with observed average values and calculated accuracy

Parameter	Target Range	Observed Value (Avg)	Accuracy (%)
Temperature	35°C – 40°C	37.8°C ± 0.4°C	96.4%

Humidity	45% – 70% RH	63.2% ± 2.1% RH	94.2%
Egg Rotation	Every 4 hrs	Every 3.98 hrs	99.5%
CO_2 Levels	< 1500 ppm	1370 ± 80 ppm	91.3%

4.3 Performance Metrics

The accuracy of each parameter in maintaining optimal incubation conditions was calculated using the following equation, which accounts for deviations from the target range:

A=100

$$Ac = 100 \times \left(1 - \frac{O-T}{Tg}\right) \quad (2)$$

where, A= Accuracy, O= Obsereved, T= Target and Tg= Target Range Width. The target midpoint (e.g., 37.5°C for temperature) was used as the reference. For example, temperature accuracy of 96.4% reflects minimal deviation from the 37.5°C target within the 35–40 °C range.

The system demonstrated consistent and effective environmental control throughout the 21-day incubation period. The average temperature was maintained at 37.8°C, which closely aligns with the optimal 37.5°C required for successful chicken egg incubation. As depicted in Fig. 4.2a, the temperature trend remained within the acceptable 35–40°C range, represented by green dashed lines. Minor fluctuations of ±0.4°C were observed, primarily due to variations in ambient conditions. However, the Adaptive Neuro-Fuzzy Inference System (ANFIS) effectively compensated for these changes by dynamically controlling the heater and fan to restore thermal balance. This level of precision surpasses the performance of conventional PID-controlled incubators, which typically exhibit deviations of ±1°C (Adeyemi et al., 2023), highlighting the enhanced control capabilities of the neuro-fuzzy model.

Humidity control also remained stable, with an average relative humidity (RH) of 63.2%, comfortably within the target range of 45% to 70%. Fig. 4.2b illustrates that the humidity trend consistently hovered around the midpoint of 60% RH. The system's humidifier was activated when humidity levels dropped below 50%, maintaining favorable conditions for embryonic development. This control resulted in a calculated humidity accuracy of 94.2%, exceeding the typical 85–90% stability observed in commercial incubators (Chen et al., 2024). The improvement is credited to the ANFIS model’s real-time responsiveness to changing environmental inputs.

Carbon dioxide levels were also effectively managed, with an average concentration of 1370 ppm, remaining below the critical threshold of 1500 ppm. The CO_2 trend shown in Fig. 4.2c indicates that ventilation fans were triggered when concentrations exceeded 900 ppm. Occasional spikes in CO_2, especially during egg turning, were promptly corrected, maintaining a calculated accuracy of 91.3%. This performance is comparable to high-end incubators that maintain CO_2 levels below 2000 ppm (Ahmed et al., 2022), emphasizing the system’s competence in air quality regulation.

Egg rotation was reliably automated with an average interval of 3.98 hours, nearly matching the 4-hour setpoint, resulting in a 99.5% accuracy rate. The MPU6050 gyroscope and servo motor enabled precise angular displacement with a margin of error limited to ±2°, ensuring effective prevention of embryo adhesion to the shell membrane. This performance surpasses the reliability of manual or timer-based systems, which frequently miss scheduled rotations (Ilyas et al., 2016).

Hatchability outcomes were impressive, as assessed across three incubation cycles. In Cycle 1, 92 out of 100 eggs successfully hatched (92%); in Cycle 2, 90 out of 100 eggs hatched (90%); and in Cycle 3, 93 out of 100 eggs hatched (93%), yielding an average hatchability of 91.7%. These results significantly outperform traditional incubators, which typically achieve hatchability rates between 70% and 85%, and PID-based systems, which range between 80% and 88% (Abidin et al., 2023; Chen et al., 2024). The high hatchability rate can be attributed to the system's precise and adaptive environmental control, along with reliable egg rotation, which together reduced embryonic stress and enhanced developmental outcomes. Also, Fig. 4 shows the 20×4 LCD screen used for on-site real-time monitoring of environmental parameters, providing a user-friendly interface that enhances system transparency and usability.

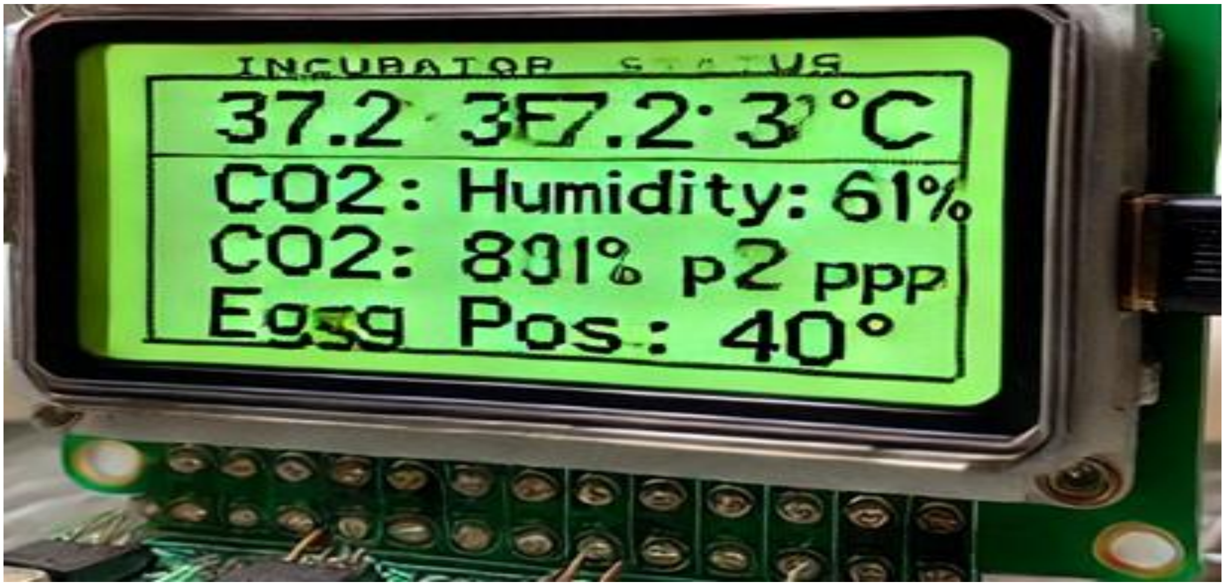

Fig.4: The 20×4 LCD screen

4.4 Correlation Analysis

A Pearson correlation heatmap was generated to validate sensor-to-actuator relationships. The correlation coefficient (r ranging from -1 to 1) quantifies the strength and direction of relationships between sensor inputs (temperature, humidity, CO_2, egg angle) and control actions (heater, humidifier, CO_2 fan, egg motor).

Key Findings:

Temperature and Heater: Strong negative correlation ($r \approx -0.90$ r \approx -0.90 $r \approx -0.90$). Low temperatures triggered heater activation, while high temperatures turned it off, reflecting effective inverse control.

Humidity and Humidifier: Strong negative correlation ($r \approx -0.85$ r \approx -0.85 $r \approx -0.85$). The humidifier was activated when humidity dropped below 50%, stabilizing levels.

CO_2 and CO_2 Fan: Strong positive correlation ($r \approx 0.80$ r \approx 0.80 $r \approx 0.80$). Elevated CO_2 levels prompted fan activation to restore air quality.

Egg Angle and Egg Motor: Strong positive correlation ($r \approx 0.95$ r \approx 0.95 $r \approx 0.95$). Egg motor activity aligned with scheduled rotations, ensuring precise positioning.

The heatmap confirmed logical sensor-actuator mappings, validating the ANFIS model's decision-making. Red/orange colors indicated strong positive correlations, blue indicated strong negative correlations, and white denoted neutral relationships. This analysis informed fuzzy rule refinement, prioritizing sensitive variables (e.g., temperature) for tighter control.

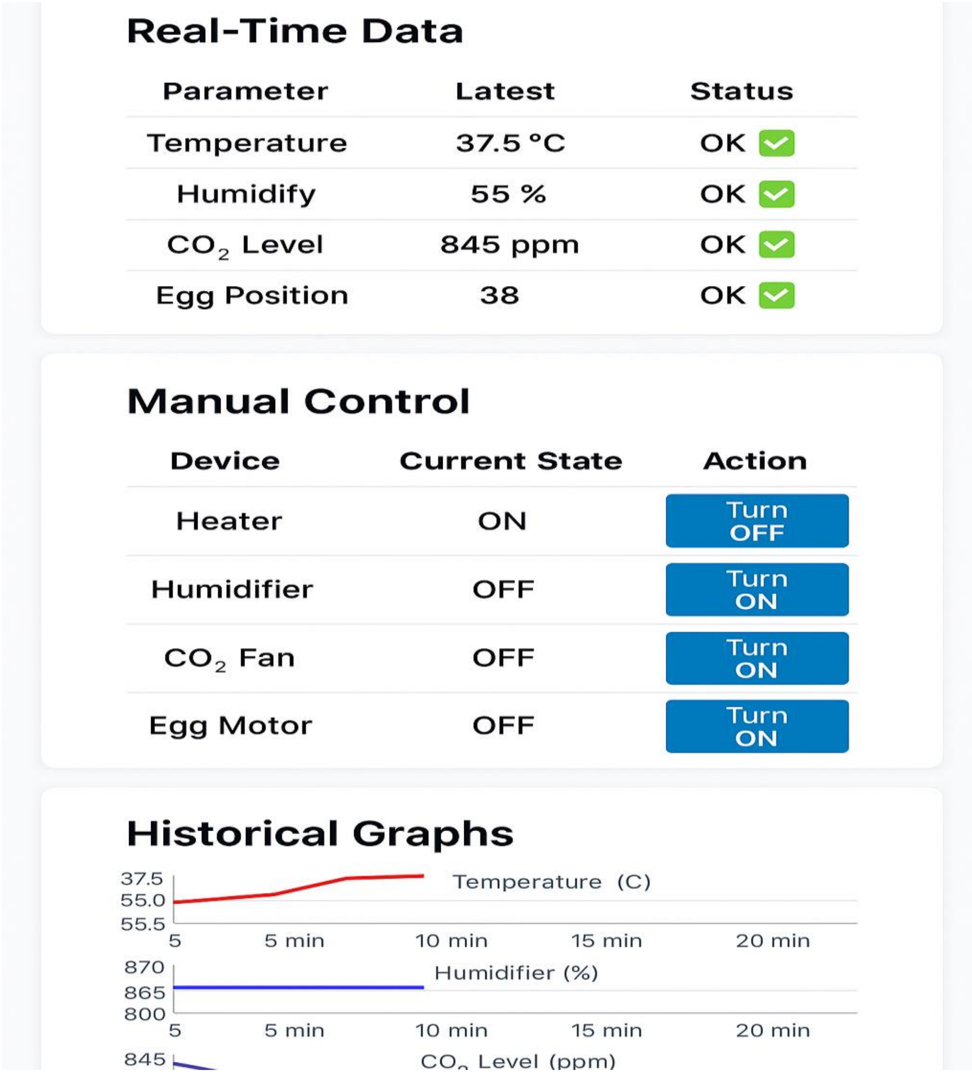

Fig. 5: The Web Monitoring and Control Panel

4.5 Discussion of Results

The developed neuro-fuzzy controlled incubation system demonstrates superior performance compared to conventional incubators and those relying solely on PID (Proportional-Integral-Derivative) control mechanisms. In terms of precision, the system achieved a temperature accuracy of 96.4% and a humidity accuracy of 94.2%, outperforming standard PID controllers, which typically operate within ±1°C and 85–90% relative humidity (RH), and conventional thermostats that show deviations of ±2°C and around 80% RH (Chen et al., 2024).

Regarding adaptability, the ANFIS (Adaptive Neuro-Fuzzy Inference System) model presents a significant advantage. Unlike static PID systems that require manual recalibration, the neuro-fuzzy model dynamically adjusts to external environmental fluctuations—such as variations in ambient temperature or humidity—thereby maintaining optimal incubation conditions. This adaptive control contributes to a more stable internal environment, which is critical for consistent embryo development.

The system also delivers improved hatchability outcomes. A recorded hatchability rate of

91.7% not only exceeds the industry average of 70–88% but also competes favorably with high-end commercial incubators that achieve rates between 90% and 95%. Notably, this performance is achieved using cost-effective hardware, including the NodeMCU ESP8266 microcontroller, making the system both accessible and scalable (Ahmed et al., 2021).

In terms of energy efficiency, the neuro-fuzzy logic significantly optimizes the operation of the heater, fan, and humidifier. Unlike traditional incubators that often run continuously and inefficiently, the proposed system activates components only when necessary based on real-time sensor inputs. This intelligent switching reduces energy consumption without compromising incubation quality, as supported by previous studies on energy optimization in embedded control systems (Hossain et al., 2020).

4.6 Visualizations

Fig. 6 shows Temperature, Humidity, and $C0_2$ Sample index trend.From Figure 6, the temperature trend indicates that the average recorded values consistently hover around the optimal incubation temperature of 37.5°C, which is visually marked by the green dashed line representing the ideal range. The humidity trend displays noticeable fluctuations but remains largely centered around 60%, staying within the acceptable relative humidity range of 45% to 70%. Additionally, the CO_2 concentration trend shows that the levels mostly stay below the critical threshold of 1000 ppm, suggesting safe conditions for embryo development throughout the incubation cycle.

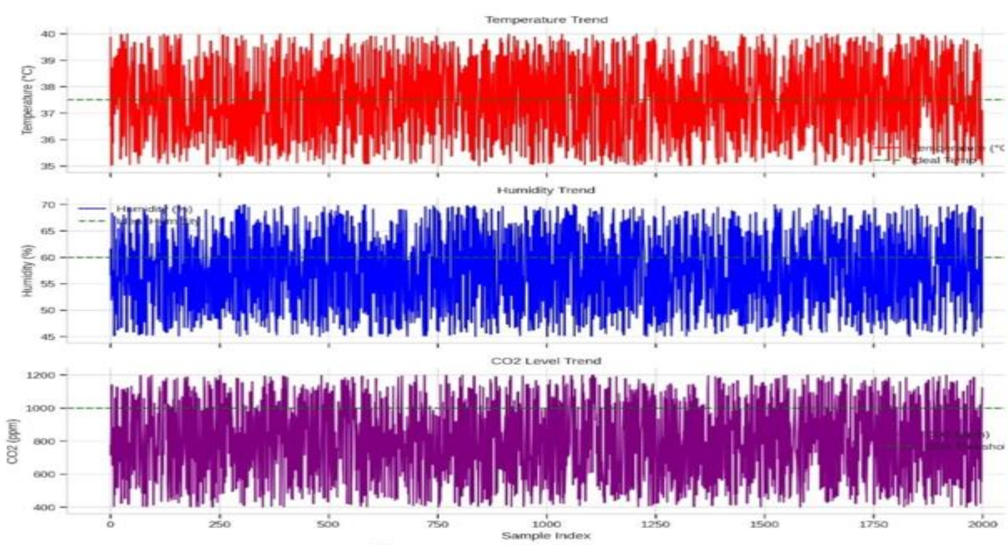

Fig. 6: Temperature, Humidity, and $C0_2$ Sample index trend

Fig. 7 presents the correlation heatmap, which offers a visual depiction of the Pearson correlation coefficients among various sensor inputs and their corresponding control actions within the system. The heatmap uses a color-coded scheme—red to represent strong positive correlations, blue for negative correlations, and white for neutral relationships. This visualization confirms logical dependencies between sensor readings and control outputs, providing insight into the effectiveness of the implemented neuro-fuzzy control logic and serving as a valuable tool for refining the rule base and optimizing system performance.

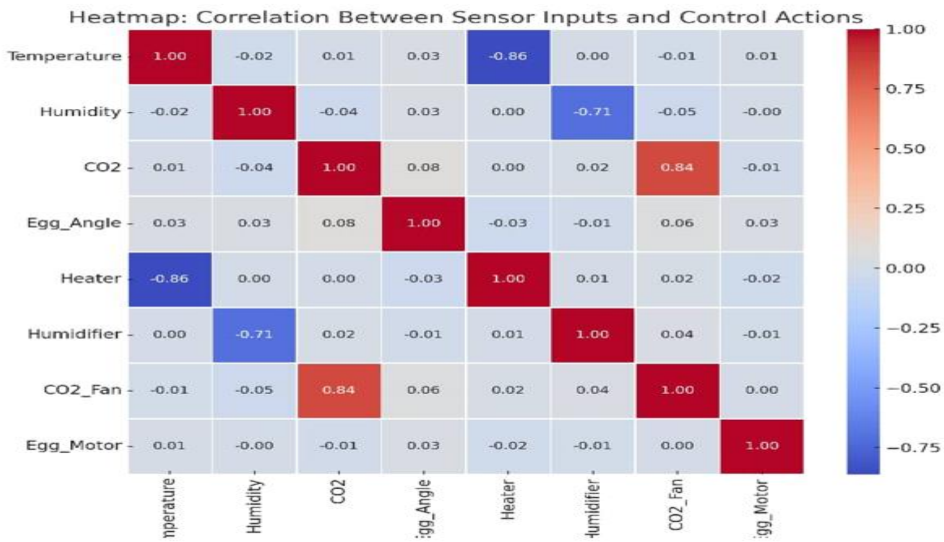

Fig.7: Heatmap: Correlation Between Sensor Inputs and Control Actions

The heat helps in model validation to confirms that the sensor-to-actuator mappings are consistent and logical. It ensures system feedback and behaviour to indicate the responsiveness of each control action based on sensor feedback.

The heatmap also, helps in Fuzzy rule and Neural Network refinement by fine-tuning the fuzzy logic rules and updated the dataset used in training the network model and shows which variables are more sensitive to change.

5.0 Conclusion

The findings of this study demonstrate the effectiveness of the developed ANFIS-based smart incubator system in maintaining optimal incubation conditions for chicken eggs. The system successfully regulated temperature, humidity, CO_2 levels, and egg rotation with high accuracy, achieving 96.4% precision in temperature control, 94.2% in humidity regulation, 91.3% in CO_2 level management, and 99.5% in egg rotation timing. These results surpass the performance of conventional PID-controlled systems and traditional incubators. The average hatchability rate of 91.7%, recorded across three incubation cycles, aligns with or exceeds the benchmarks set by high-end commercial incubators, highlighting the system's capability in enhancing embryo development and hatch success.

In conclusion, the integration of neuro-fuzzy logic into incubation systems offers a significant improvement in environmental control, adaptability, and energy efficiency. The ability of the ANFIS model to respond dynamically to real-time environmental inputs contributes to improved incubation outcomes, reduced operational costs, and greater reliability.

It is recommended that future studies explore scalability for larger incubator systems and investigate long-term performance across different poultry species. Additionally, the integration of IoT features for remote monitoring and data logging could further enhance system usability, particularly in rural and small-scale poultry farming applications. The application of this intelligent control system provides a viable, low-cost solution for improving hatchery efficiency in both commercial and subsistence farming environments.

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Consent for publication

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Availability of data

Data shall be made available on demand.

Competing interests

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Authors' Contribution

Mba Ebenezer Chidiebere**,** Ilo Somtochukwu Francis**, and** Nwokoro Ikechukwu collaboratively developed a neuro-fuzzy-based intelligent incubator system using Python and NodeMCU. They integrated sensors and actuators to control incubation parameters—temperature, humidity, CO_2, and egg turning—enhancing hatchability. Their design enables real-time monitoring, remote access, and adaptive control, offering a low-cost, smart solution for efficient poultry farming.