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Design and Evaluation of a Smart Poultry Farm Device Integrating Internet of Things and Machine Learning for Monitoring Temperature and Humidity

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ABSTRACT

Rising global temperatures and humidity are significantly impacting birds' welfare, productivity, and mortality rates, leading to economic losses and inefficiencies in poultry farm management. This research aims to design and implement an Internet of Things (IoT) device integrated with Machine Learning (ML) models to forecast temperature and humidity values in a poultry farm. This study designed a prototype of an IoT device consisting of DHT11 sensors connected to an ESP32 microcontroller to collect real-time temperature and humidity data from a poultry farm. The collected data are used to train ML models, namely: Auto-Regressive Integrated Moving Average (ARIMA), Random Forest (RF) and Support Vector Machine (SVM) to forecast future temperature and humidity values. The measured and predicted data are displayed on an LCD screen connected to the ESP32 microcontroller, enhancing proactive decision-making. Simulation testing was carried out on Python software to compare and analyse the measured and predicted temperature and humidity values. The performance of the ML models was evaluated in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). The results show that RF predicted data gave a close fit to the actual data, SVM provided a tendency toward lower predicted value and ARIMA model showed the most accurate predictions, providing lowest RMSE (1.56) and MAE (0.34) at highest R^2 (88%) than RF and SVM. This approach demonstrates that ARIMA model offers effective solution than other ML models in poultry farming through real-time monitoring and predictive analysis.

1. INTRODUCTION

Over the years, poultry industry has seen significant growth, mainly due to the increasing demand for healthy affordable sources of protein [1] . Chicken meat and eggs are widely consumed across the world because they offer excellent nutrition and are rich in protein and generally lower in cholesterol. By 2050, demand for poultry meat is expected to be more than double and egg consumption to increase by about 40% compared to 2005 levels [2,3]. This growing demand highlights the importance of improving farming methods. Technological methods such as precision farming have been employed to boost productivity, cut costs, and reduce environmental impact [4,5]. These innovations help tackle challenges that come with higher demand, but environmental conditions in poultry houses are crucial for bird health and performance. Poultry production is influenced not just by genetics but also significantly by the environment [6]. Factors affecting production include feeding, management, disease control, and heat stress. Consequently, heat stress is recognized as one of the most serious challenging factor affecting poultry production [7].

In reducing heat stress traditional poultry farmers often rely on manual observation and simple control mechanism, which has slow respond when environmental conditions fluctuate [8-10]. Thus, failures in timely environmental control mechanism has led to higher mortality, poorer meat quality, and economic

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losses. The fundamental problem, then, is the absence of a cost-effective, system to continuously track temperature and humidity and alert operators when heat stress is present [11]. With advanced technologies to detect early sicknesses, the Internet of Things (IoT) and Artificial Intelligence (AI) have now come together to provide solution to even the smallest farms [12-13]. IoT sensors are the eyes and ears of the poultry house, scanning around the clock and picking up even the slightest changes that human eyes would not detect [14-15]. While AL systems interpret the data gathered by these sensors to pick up even the most subtle patterns and problems [16-17]. In recent year various research have been proposed to reduce heat stress in poultry farming. For instance, [18] developed a prototype broiler house system that incorporated an Arduino Due and DHT11 temperature-humidity sensors to automatically read cage conditions in real-time. This was supported by an Android app and web-based interface to display readings. In early detection of disease in poultry, [15] developed an IoT-based predictive system that utilizes wearable sensors to gather data. The work applied machine learning methods, including Generative Adversarial Networks, to compensate for limited datasets, ultimately achieving an impressive 97% accuracy in distinguishing between healthy and infected chickens. However, the study's focus solely on behavioural indicators, with no consideration on environmental factors such as temperature or air quality. Therefore, lack of consideration on environmental factors limits the comprehensiveness of the framework.

In [19] designed an ESP32-based monitoring system for poultry farms. This system combined DHT11 temperature-humidity, PIR sensor, MQ135 gas sensors, buzzer and controllable lighting. The proposed work was capable of sensing air quality and motion, alerting the farmer via Wi-Fi notifications, and adjusting a lamp to regulate temperature. The authors tested the designed project in a small poultry house and discovered that the system effectively maintained target conditions and enhanced bird nurturing. The authors in [20] applied machine learning to poultry environment management. The authors recorded ventilated duck house internal air temperature and humidity time series data and trained Recurrent Neural Networks (RNNs) to forecast the data levels. This study demonstrated the feasibility of IoT and predictive analytics in facilitating more adaptive poultry farming system.

The study in [21] reviewed the literature of machine learning and IoT integration in the management of poultry health. The review indicated that AI-based systems could potentially be harnessed to monitor disease outbreaks, resource management, and production efficiency optimization. The review also indicated there

Authors in [22] explored the potential of artificial intelligence in reducing heat stress among livestock. The research focused on developing AI-driven tools for real-time monitoring and informed decision-making. These tools enabled the detection of key heat stress indicators, including animal behaviour, physiological responses, and overall health status. Additionally, the system provided early warnings of disease outbreaks, helping to minimize productivity losses. The study highlighted the importance of AI applications in promoting sustainable livestock management. However, it did not incorporate the use of IoT-based temperature and humidity sensors, which are essential for comprehensive environmental monitoring.

In [23] presented a conceptual Wi-Fi sensor network for poultry houses. The authors demonstrated how a distributed IoT system can regulate four key parameters: temperature, humidity, CO_2, and ammonia through automated actuation and a user dashboard to manage ventilation and heat.

The reviewed work reveal that IoT and machine learning have been used in controlling heat stress in poultry farming, but most existing work treat environmental control separately, managing temperature, ventilation or feeding independently and rarely offer a unified interface for the farmer. In particular, there are few work that combines real-time IoT data with machine learning to predict temperature and humidity value in poultry farm. Although, CO_2, and ammonia have been identified in the literature as important parameters in poultry farm management, however, this study only focuses on temperature and humidity monitoring and prediction. Therefore, this work aim to design and implement an IoT-based measuring device that also uses ML model to predict future temperature and humidity value enabling proactive control mechanism. In doing so, the system can alert farmers to actuate cooling measures ahead of time, rather than responding after high temperature and humidity.

This paper is structure as follows. Section 2 provide the method. The results and discussion are presented in section 3. Section 4 conclude the study.

2. METHODOLOGY

2.1 System Approach

This section describe the system approach employed as illustrated in Figure 1. The temperature-humidity sensor DHT11 on the IoT device measure real-time poultry farm temperature and humidity data for thirty days. The ESP32 microcontroller module, handles all of the computing and information processing. Custom applications built on the ESP32 microcontroller module are used to offer a Wi-Fi access point and web server hosting operations to view and store real-time data. The recorded data from the web database as shown in Figure 2 are downloaded and stored as .CSV file. In order to control the temperature and humidity in the environment, relay module connected to the microcontroller are used to switch On and OFF the fan automatically based on a predefine value. Also, for the IoT to be able to forecast future temperature and humidity, ML algorithms are integrated to predict future values based on the real-time recorded data from the web server database. The predicted value from the ML algorithms are displayed along with the measured value on an LCD screen. For training and testing of ML models, set of data gather only during the afternoon particular between 12 noon and 3 pm were used for 30 days. This period was employed to capture daily temperature, which is the best for fan and actuator control. Consequently, performance of the ML model used were evaluated in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). In the following sub-section, component selection is discussed, the second section presents IoT device hardware functional definitions and the third section explain the ML algorithm applications.

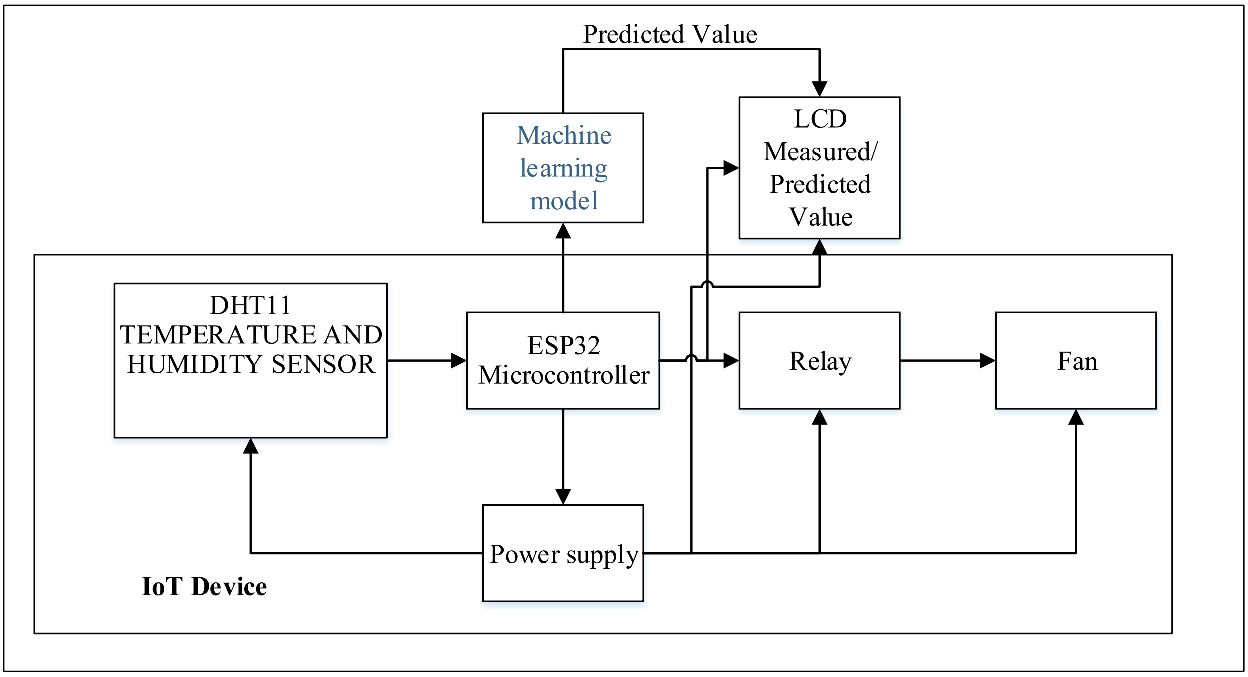

Fig. 1. Block Diagram of the System Approach

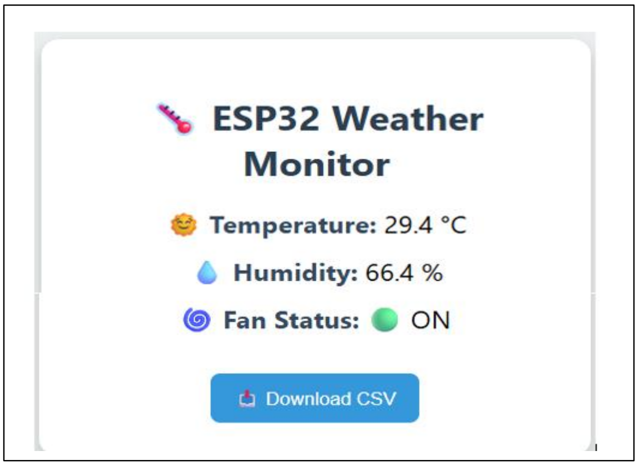

Fig. 2. Web view of IOT Temperature and Humidity Monitoring System

2.2 Component Selection

Each hardware component was evaluated for its operating voltage, current draw, and corresponding power consumption to ensure adequate power supply dimensioning. The ESP32, operating from a 5V external USB supply, consumes approximately 0.8 W during Wi-Fi activity, with internal regulation down to 3.3V for logic operations. The DHT11 sensor, powered at 3.3V, requires ~2.5 mA during active period, yielding a negligible power demand of 0.008 W. The I^2C 16×2 LCD screen, also operating at 3.3V with an average current draw of 20 mA, consumes 0.066 W. The relay module, driven at 5V with a coil current of 70 mA, contributes an additional 0.35 W, while the 12V DC fan, powered directly from a 12V adapter draws approximately 250 mA, corresponding to 3 W.

a) *ESP32 Microcontroller:* Modern IoT solutions often use small ESP32 microcontroller boards with built-in wireless capabilities as shown in Figure 3. The ESP32 is an inexpensive, low-power chip that combines a dual-core processor with integrated Wi-Fi and Bluetooth radios. It can read sensor values and send the data over Wi-Fi to a cloud server or dashboard without any additional networking module. ESP32 boards typically run at 3.3 V, have analogue-to-digital converters, I^2C/SPI ports, and can interface with many sensors and relays enabling real-time data logging and remote monitoring and control in IoT environments [19].

General specification [19]

i. Support Wi-Fi 802.11
ii. GPIO pins from 17 to 36, and 16 additional PWM channels
iii. 4 MB of external flash memory
iv. 240 MHZ Frequency
v. Operating Voltage: 5V
vi. Power Input via VIN Pin: 5V
vii. Operating Current (Wi-Fi active): ~160mA
viii. Power Consumption: 0.8W
ix. The ESP32 was powered via a 5V external USB supply and regulates internally to 3.3V for internal operations.

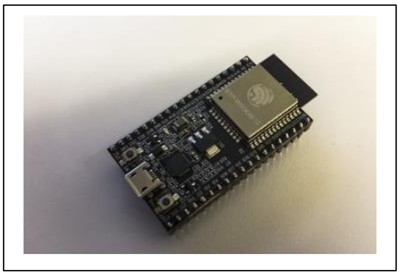

Fig. 3. Esp32 Microcontroller Chip (Wi-Fi module)

b) *Digital Humidity and Temperature Sensor:* The Digital Humidity and Temperature sensor (DHT11) in Figure 4 is a widely-used temperature and humidity sensor module. Internally it has a thermistor for temperature and a capacitive humidity element. Because of its simple interface and low cost, the DHT11 is often used in small-scale poultry monitoring systems to provide real-time temperature-humidity data to a microcontroller in an IoT system [24].

General specification [25]

i. Operating Voltage:5-3.3V
ii. Current Consumption during active read: ~2.5mA
iii. 16-bit resolution
iv. Low-cost module
v. Good for 20-80% humidity reading with $\pm 5\%$ accuracy
vi. Good for 0-$50^0 C$ temperature readings $\pm 2^0 C$ accuracy
vii. No more than 1 Hz sampling rate once every second

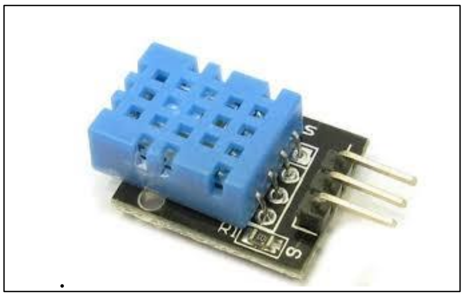

Fig. 4. Digital Temperature and Humidity Sensor (DH11)

c) *Actuators:* Actuators is a ventilation fans that help in regulating the temperature and humidity of the farm when they are above certain threshold. In this work, the ESP32 controller connected to a DHT11 turns on the 12 V Direct Current (DC) actuator fan in Figure 5 via a relay when the temperature exceeded above 24°C and Off when it fell below that threshold.

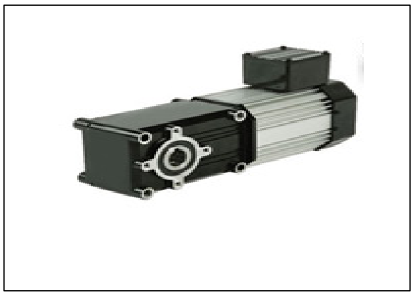

Fig. 5. Actuator Fan

d) *Liquid Crystal Display:* The Liquid Crystal Display (LCD) module in Figure 6 shows live data like temperature, humidity, and system status, which helps farmers make quick decisions without the need for extra devices like smartphones or computers. A (16x2) i^2c LCD with 3.3 Voltage, ~20MA current rating was used for this project since it does not consume much power and works well with the ESP32. Besides just monitoring, the LCD also acts as a backup by quickly alerting farmers to any issues or errors, so they can take action right away.

General specification
Operating Voltage: 3.3V
Current Consumption during: ~20mA

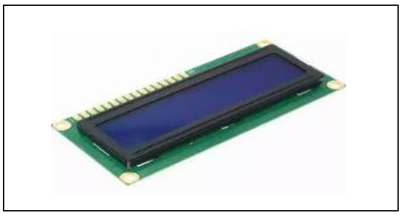

Fig. 6. Liquid Crystal Display (LCD)

2.3 IoT Device Development and Functional Description

In this section, the hardware development, and functional description of the created IoT temperature and humidity measurement device prototype was discussed. Prior to the development of the prototype, circuit design and testing was carried out on Proteus software as shown in Figure 7 to confirm the operation of the device. After the design and testing all the hardware components namely: ESP32 microcontroller, DHT11 sensor, relay, 12V DC cooling fan and 16×2 I^2C LCD were assembled and soldered on a Vero board as shown in Figure 8 (a-b). The ESP32 microcontroller code was written with Lua programming language. Lua programming language was used in the prototype to allow for fast code modification of temperature thresholds logging interval during field experiment preventing change in parameter. ESP32 serves as the central processing unit for data acquisition, fan actuation, data display, and web hosting. DHT11 sensor connected to ESP32 microcontroller GPIO D23 pin provides periodic measurements of temperature and humidity value. The relay connected to GPIO D19 of the microcontroller switches the 12V DC cooling fan ON if the temperature is greater than 24^0C. The fan operates independently from the ESP32 power supply, drawing current directly from a 12V adapter to ensure stable operation. For user interaction, a 16×2 I^2C LCD connected via SDA–D21 and SCL–D22 of the microcontroller presents real-time measured values of temperature, and humidity. The experiment was carried out for 30 days and all measured values during the day were recorded and stored as a .CSV file. However, power distribution is achieved using a regulated 5V DC adapter, with the ESP32 internal power regulating down to 3.3V. Peripheral components are powered from the ESP32's 3.3V and 5V pins, with all devices sharing a common ground. The functional distribution flowchart of the IoT device is show in Figure 9.

2.4 Machine Learning Model for Temperature and Humidity Prediction

Machine Learning Model such as Auto-Regressive Integrated Moving Average (ARIMA), Rain Forest (RF) and Support Vector Machine (SVM) were used to predict temperature and humidity as depicted in Figure 10. The data collected from the IoT device through the ESP32 microcontroller were used to train the ML models. This dataset is divided into 30% and 70%, for testing and training respective.

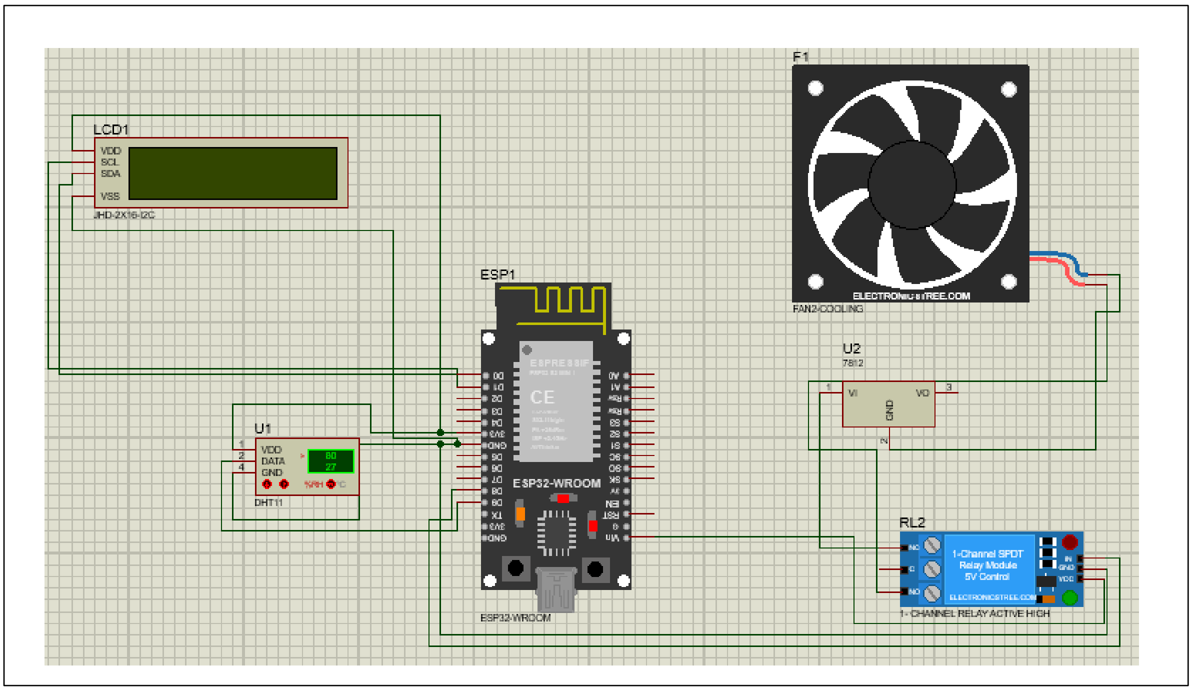

Fig. 7. Circuit diagram of IOT Temperature and Humidity measuring System

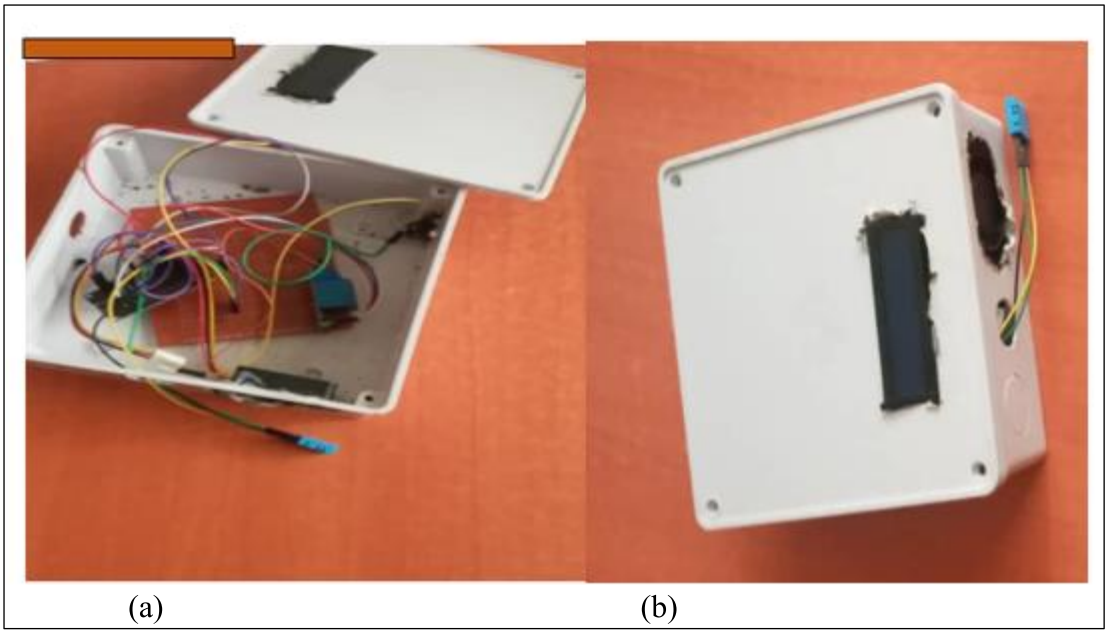

Fig. 8. Prototype of IOT temperature and humidity measuring device

Tensor flow in Python 3 with Keras Library is used to design all the ARIMA, RF and SVM models. After the training, analysis testing is performed. MAE, RMSE and R^2 are used to evaluate the performance of the ARIMA, RF and SVM models.

The formulae used for MAE, RMSE and R^2 is given as [26]:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i| \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{m}} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\overline{Y} - Y_i)^2} \quad (3)$$

$$\overline{Y} = \frac{1}{m}\sum_{i=1}^{m} Y_i \quad (4)$$

Where:
m denotes number of observations
X_i denotes predicted ith value
Y_i denotes actual ith value
$\overline{Y}$ denotes the mean of the actual value

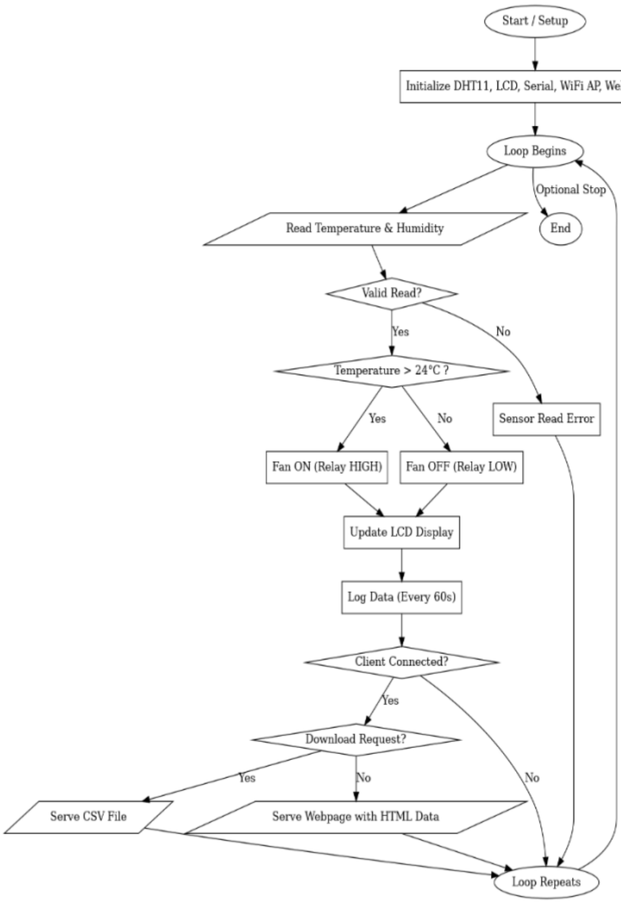

Fig. 9. Flow chart of the functional description of the IoT device

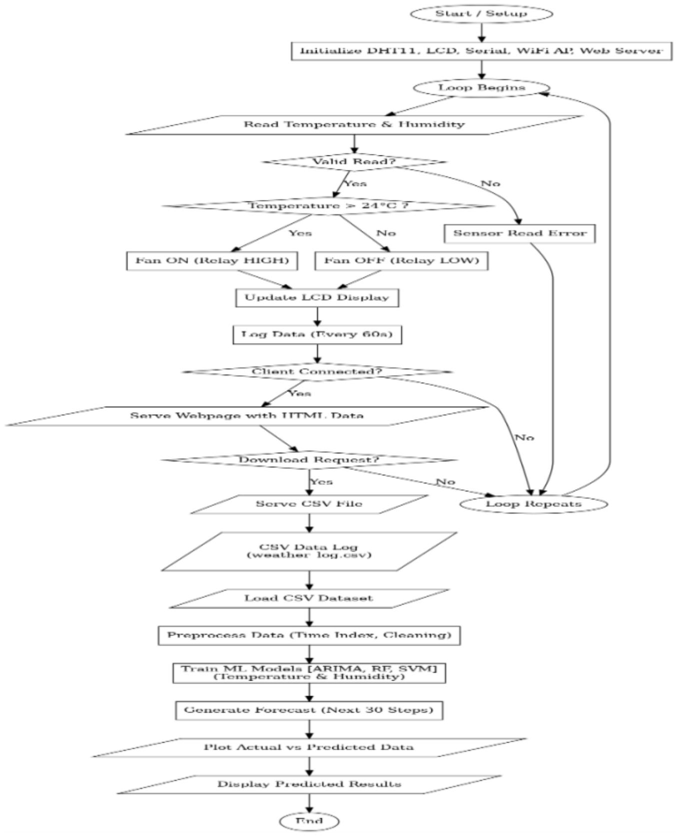

Fig. 10. Machine learning models for Temperature and Humidity Prediction

3. RESULT AND DISCUSSION

Simulation testing was carried out on python3 software to compare and analysis the measured and predicted temperature and humidity values. Figure 11 and 12 shows the difference between the predicted and actual temperature and humidity forecast value over a period of 90 hours respectively. The temperature forecast graph in Figure 11 depict that, the temperature range in the dataset is between 14.9-38.95°C for the predicted and actual temperature value. Also, the humidity graph in Figure 12 shows that, the predicted and actual humidity value dataset ranges from 52.9-86.8 %. However, the graphs in Figure 11 and 12 shows that RF models almost follows the trend of the actual data obtained from the IoT device, but ARIMA graph shows higher data prediction while SVM gave the lowest predicted value. The result illustrates that, RF model was not able to capture some particular data because it is best at solving non-linear association, while ARIMA is targeting upward trend that RF or SVM is trying to smooth. Hence, the results from the temperature and humidity forecast graph illustrate that each models observe the data through different perspective.

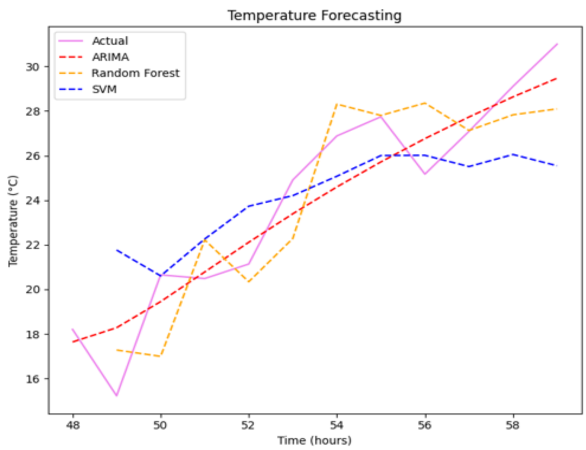

Fig. 11. Graph comparing the actual and predicted temperature model

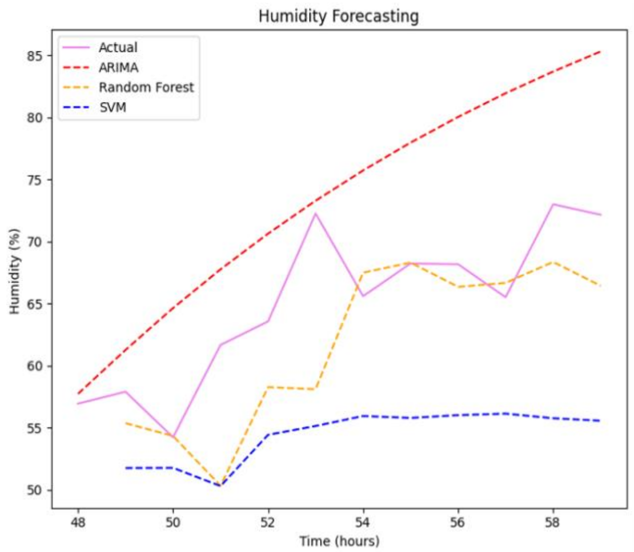

Fig. 12. Graph Comparing the Actual and Predicted Humidity Model

The performance of the three machine learning models was evaluated and compared based on RMSE, MAE and R^2 as shown in Fig. 13, 14 and 15 to determine effective model for temperature and humidity prediction. Fig. 13 shows low RMSE value in temperature for all the models, but ARIMA gave the lowest RMSE value of 1.56. While for humidity models, RF provides the lowest RMSE with highest value in SVM model as 6.21 and 12.07 respectively. The MAE temperature model evaluation in Fig. 14 show that, ARIMA gave the lowest MAE value of 1.34 followed by RF then SVM at a value of 1.796 and 2.38 respectively, while RF gave the lowest MAE of 4.43 for humidity followed by ARIMA then SVM at a value of 8.39 and 11.23 respectively. The results in Fig. 13 and 14 indicates that, for temperature models, ARIMA provides better magnitude of prediction errors, therefore, it performance is better than RF and SVM model. While in humidity model, RF is better than ARIMA when compared with SVM. Also, R^2 in Fig. 15 present that the temperature models, ARIMA, RF and SVM gave positive value of 0.88, 0.78 and 0.53 respectively. While the humidity models yielded negative values (-1.55 for ARIMA, -0.17 for RF, -3.42 for SVM), indicating the model performed worse than temperature models performance. Hence this device is not suitable for forecasting humidity in poultry farm, due to sensor precision limits of ±5% and high atmospheric volatility within 12 noon and 3 pm causing noise on the training data.

The summary of temperature and humidity prediction performance comparison for ARIMA, RF and SVM is as shown in Table 1 and 2.

Table 1. Summary of Temperature prediction performance evaluation for ARIMA, RF and SVM models

Model	RMSE	MAE	R^2
ARIMA Temp	1.564312	1.344312	0.884312
RF Temp	2.140580	1.796701	0.775928
SVM Temp	3.041915	2.376743	0.527306

Table 2. Summary of Humidity Prediction performance evaluation for ARIMA, RF and SVM models

Model	RMSE	MAE	R^2
ARIMA	9.583849	8.389338	-1.549286
RF	6.216805	4.425559	-0.171779
SVM	12.068367	11.232061	-3.415788

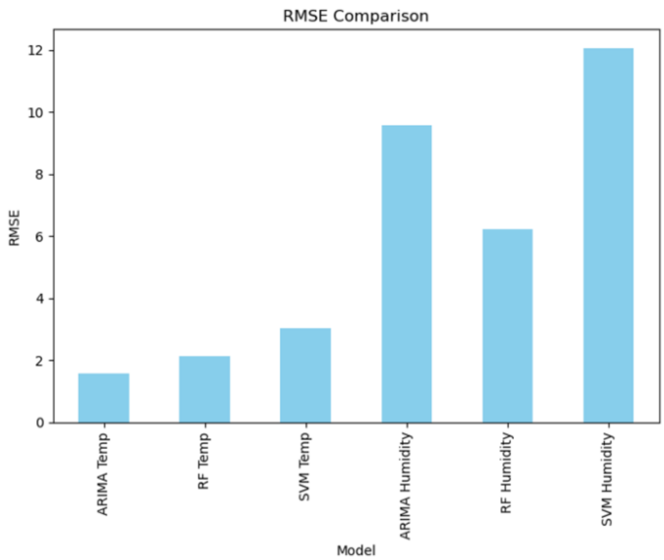

Fig. 13. Graph Showing RMSE Comparison of ARIMA, RF and SVM Models

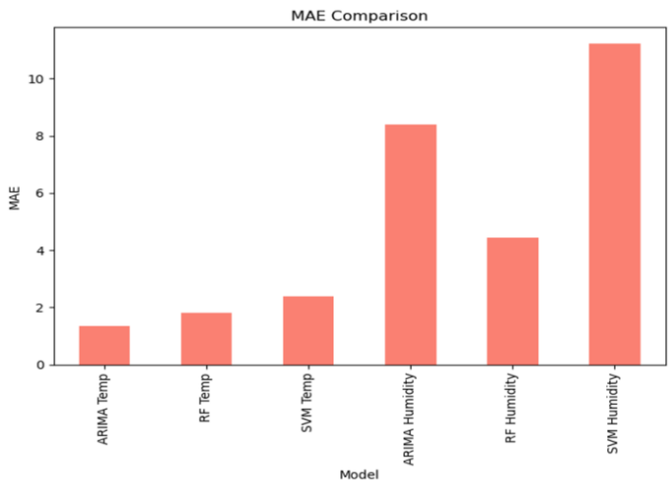

Fig. 14. Graph Showing MAE Comparison of ARIMA, RF and SVM Models

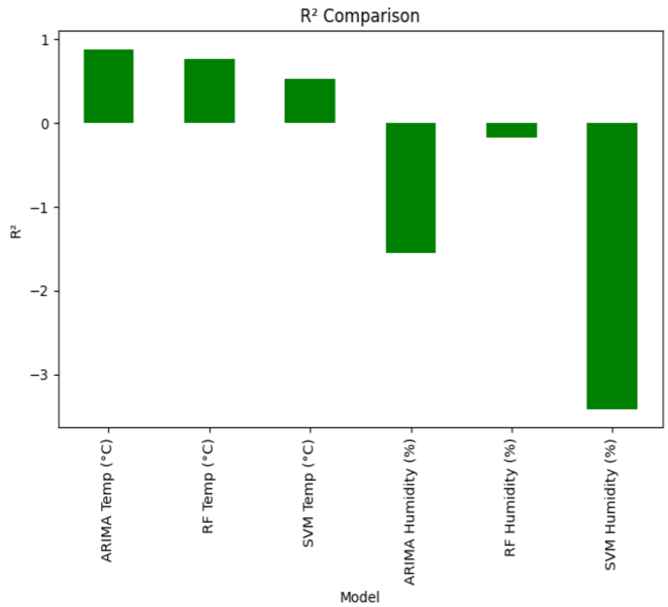

Fig. 15. Graph Showing R^2 Comparison of ARIMA, RF and SVM Models

4. CONCLUSION

The smart poultry farming system described in this article makes use of IoT device and ML structure. This study design and implemented an IoT device prototype consisting of a DH11 sensor, ESP32 microcontroller, relay and LCD screen integrated with machine learning models to forecast temperature and humidity value of a poultry farm. The aim of the device is to measure the expected value and predict future temperature and humidity value in order to inform farmers ahead and make them to provide preventive measure. Testing and analysis are done on different ML models namely: ARIMA, RF and SVM model to determine the most efficient model for prediction. To verify the propose model's accuracy, the models were evaluated based on RMSE, MAR, and R^2. The result shows that, ARIMA model gave the lowest error in temperature prediction and highest R^2 than other ML models. while RF model provide close fit between actual and predicted values than SVM and ARIMA Model. Hence, ARIMA model provides the most robust tool for temperature prediction in poultry farming. However, the result for humidity prediction shows that the device is not suitable for forecasting humidity in poultry farm, because of sensor precision limits of $\pm 5\%$ and high atmospheric volatility within 12 noon and 3 pm causing noise on the training data. These findings have major impact for poultry farm management as they permit proactive decision making and quick risk mitigation measures by providing efficient measuring, timely identification of critical situations and prompt response.

In future, CO_2, and ammonia sensors will be integrated to help in improving the air qualities in poultry farm. Cost effective analysis and comparison can be investigated to determine capital and operational cost under different farming condition. Also, hybrid ML model can be implemented and evaluated to determine it performance and effectiveness in temperature and humidity prediction.

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