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IoT Enabled Mushroom Farm Automation with Machine Learning

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ABSTRACT

Mushroom farming has gained prominence due to its significant contribution to the global market. One major challenge for mushroom cultivation is maintaining optimal environmental conditions, specifically temperature and humidity. Traditional farming methods, prevalent in many parts of the world, lack precise control over these parameters, often leading to poor yield. This paper presents an innovative approach combining the Internet of Things (IoT) and Machine Learning (ML) for mushroom farm automation. The proposed system employs the ESP8266 microcontroller with specific agricultural sensors for smart monitoring. To regulate the farm's environmental conditions, ML algorithms predict mushroom farm weather states: mild, normal, and hot. The ensemble ML model, comprising five classifiers – Decision Tree, Logistic Regression, K-nearest neighbor, Support Vector Machine, and Random Forest – delivers a commendable accuracy of 100% when combining predictions, surpassing the performance of individual classifiers. This integrated IoT and ML approach promises to revolutionize real-time automation and cultivation practices in the mushroom industry.

Keywords: IoT, Ensemble Algorithm, Machine Learning

1. INTRODUCTION

Mushrooms, commonly mistaken as vegetables, are in fact, fungi. Their increased consumption is attributed to their nutritional benefits, including protection against diseases like diabetes and heart disorders [1]. Modern cultivation methods, such as vertical farming, offer controlled environments suitable for consistent mushroom production. However, optimal temperature and humidity remain paramount for their growth. Many mushroom cultivators are still entrenched in traditional methods, particularly in remote regions. These methods, lacking precise environmental control, often lead to challenges such as decreased yields and pest infestations, especially in structures like thatched mud houses.

For countries like Malaysia, where the ideal mushroom cultivation climate is restricted between October and February due to beneficial rainy seasons, this becomes particularly challenging [2]. The dry seasons from March to September offer less than ideal-conditions for mushroom growth [3]. Conventional systems using devices like the ESP8266 board and DHT11 sensor are based on fixed thresholds, which might not be adaptive or comprehensive enough.

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Enter the Internet of Things (IoT). As a solution, IoT provides an interconnected network of devices, facilitating data exchange without human intervention. It can assist farmers in agriculture with negligible environmental impact; coupled with Machine Learning (ML), which can predict farm conditions using real-time data, these technologies can revolutionize mushroom farming. Bhandari and Kimothi [4] emphasized the stringent need for proper humidity, temperature, and light management in mushroom farming. By integrating these advanced techniques, farmers can autonomously predict and manage farm conditions, ensuring optimal mushroom growth and addressing concerns raised by Anindya, Yuliana, & Samsono Hadi [5].

The overarching objective of this project is twofold: developing an IoT-based system for precise cultivation parameter monitoring and crafting an ML model to predict and control these conditions. This endeavor aims to maximize productivity, enhance mushroom quality, and ensure a consistent food supply.

2. LITERATURE REVIEW

Mushroom cultivation requires precision in controlling environmental parameters like temperature, humidity, and lighting. Several studies have explored technological solutions to optimize these conditions. Sihombing et al. [6] emphasized the importance of automating temperature and humidity controls, creating a tool using Arduino Uno for such purposes. This tool, controlled via an Android smartphone, maintained oyster mushroom cultivation room conditions within specified optimal ranges. Rahman et al. [7] identified the potential dangers of traditional farming leading to harmful mushroom growth. They proposed an IoT and ML-integrated system using an ESP32 micro-controller, achieving an impressive 100% accuracy in edible mushroom classification. Velliangiri et al. [8] introduced machine learning with prediction analysis (MLPA) using Dht22 sensors and IoT for predicting mushroom diseases, while Singh & Anand [9]focused on reducing human intervention, utilizing a Raspberry Pi 3B+ with ESP8266 sensing nodes for real-time data monitoring.

Furthermore, Chong et al. [10] proposed using unmanned aerial vehicles (UAVs) and ground cameras to enhance data gathering, aiming for improved efficiency in mushroom harvesting. They incorporated machine learning algorithms to process the data collected, enabling insights like production predictions. Surige et al. [11] demonstrated high accuracy levels in different mushroom farming tasks using a combination of LSTM and CNN models, emphasizing their system's potential to increase yields. Subedi et al. [12] highlighted the challenges faced by Nepali mushroom growers, who utilized IoT sensing and mobile technologies, employing platforms like ThingSpeak and Blynk for data visualization and remote monitoring.

In light of the literature reviewed, our proposed methodology seeks to synergize the Internet of Things (IoT) capabilities with advanced machine learning algorithms. Additionally, we aim to introduce a user-friendly web interface that empowers users to both monitor and adjust environmental parameters seamlessly. This approach not only facilitates remote accessibility but also ensures meticulous monitoring and control.

3. METHODOLOGY

In the rapidly evolving era of smart devices and connected systems, real-time environmental monitoring and control have become pivotal. Understanding and adapting to environmental parameters can greatly influence efficiency, safety, and user comfort. The core of our methodology revolves around developing a system that not only comprehensively monitors the environment but also effectively controls it using a blend of hardware integration and algorithmic decision-making. This section delves into the intricate details of our proposed real-time environmental monitoring and control system. We introduce data collection, processing, and decision-making using machine learning models. Figure 1 shows the overall block diagram of the system.

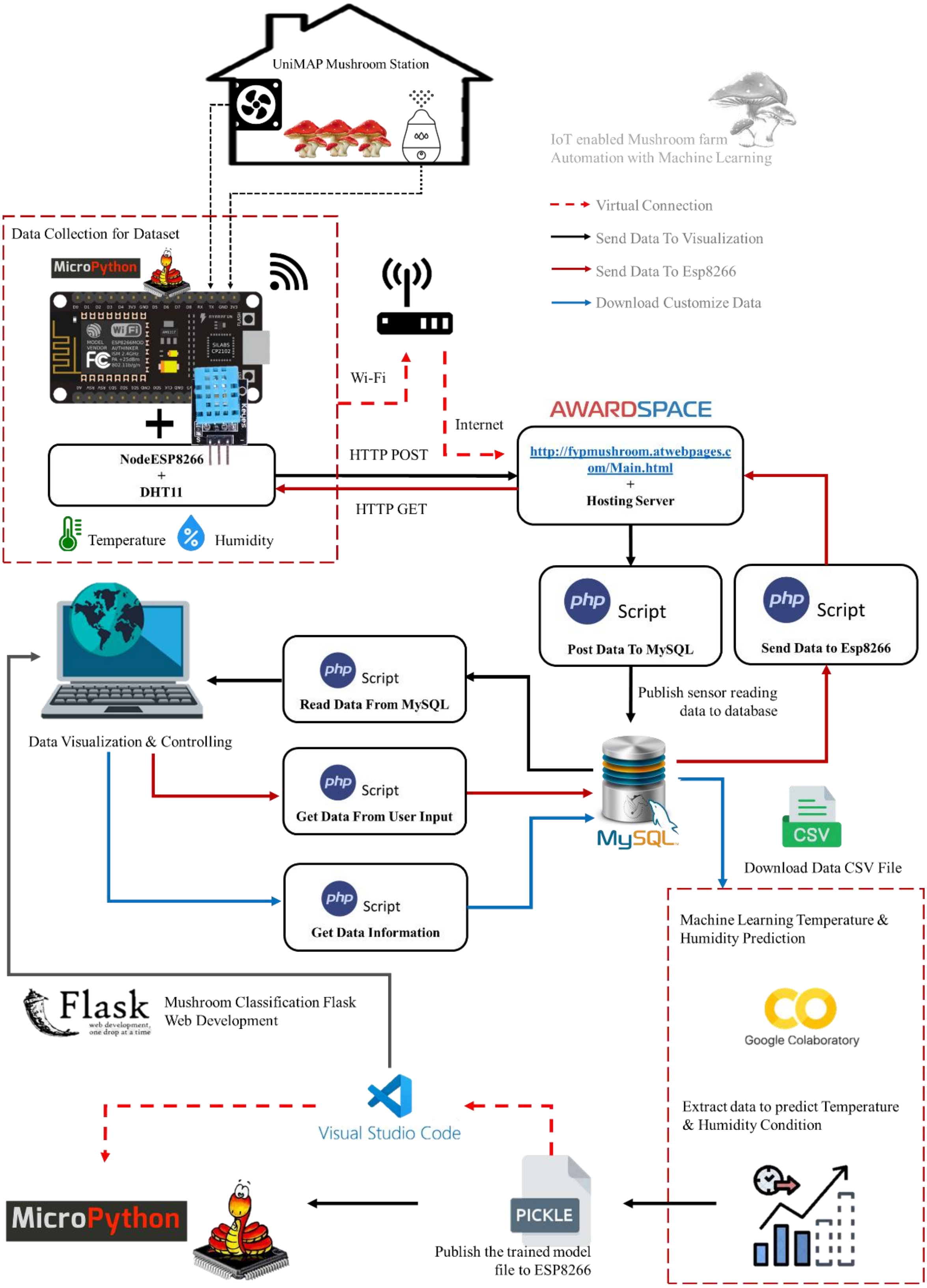

Figure 1: Overall process of the system.

3.1 Data Collection

As shown in Figure 1, the data collection was managed by ESP8266, and the sensors were connected to it. DHT11 Sensor was connected to ESP8266. DHT11 sensor measures temperature and humidity, critical parameters for maintaining optimal growing conditions on a mushroom farm.

3.2 Data Processing

The ESP8266, after collecting data from the DHT11 sensor—a digital temperature and humidity device begins the data transmission and storage process. The DHT11, equipped with capacitive humidity and thermistor components, measures the environment and converts these readings into a digital format using the One-Wire protocol.

Once prepared, the ESP8266 connects to Wi-Fi and transmits the data to a web hosting service in a JSON format. This service quickly processes and inserts the data into the MySQL database, a reliable and efficient relational database system. Data is extracted and displayed in a web browser to facilitate real-time monitoring, ensuring users have continuous access to the latest readings.

Furthermore, a tailored script allows users to retrieve specific data based on criteria like date, time range, or location. The resulting data is then available in a CSV format labeled "Data.csv," for users to download. Parallelly, user interactions, such as toggling settings, are processed and communicated seamlessly to the ESP8266, ensuring the dynamic adaptability of the system.

3.3 Machine Learning with Decision Making

The machine learning procedure kicks off with essential data manipulations using relevant libraries. Data sourced from a CSV file undergoes preprocessing: features like temperature and humidity are distinguished from the target variable, which describes environmental conditions (e.g., hot, mild, normal). This target undergoes numerical encoding, streamlining the subsequent model training.

Utilizing a strategic data split, a variety of models—such as Logistic Regression, Decision Tree, Random Forest, SVM, and KNN—are trained. Their performance is gauged on unseen data, with accuracy scores being a primary metric. Table 1 shows the machine learning model used in our model.

Table 1: Machine Learning Model Algorithm.

Model	Description
Decision Tree	Uses a tree structure. Nodes represent features, branches signify decision rules, and leaves denote outcomes.
Logistic Regression	A classification algorithm for binary outcomes. It fits data using a linear equation.
K-Nearest Neighbour	Assumes similarities between new and existing data. Classifications are based on the nearest data points.
Support Vector Machine	Classifies data by determining the best decision boundary. In complex scenarios, the kernel trick increases dimensionality for easier data separation.
Random Forest	An ensemble approach using multiple decision trees. It offers higher accuracy by averaging the outcomes of various trees.

Once the model is trained using the stored data, it is deployed to the ESP8266. Here, real-time decisions are made based on the model's classifications of the environmental conditions. For instance, a "hot" classification triggers the fan, and a "mild" classification triggers the humidifier, whereas "normal" might turn off both the fan and humidifier. This integration enables the ESP8266 to provide immediate and intelligent responses to varying environmental conditions.

4. RESULTS AND DISCUSSION

Our proposed system had undergone three experiments in a local mushroom farm, proving its usability. The first experiment compares the system with the previous traditional manual system. The results are shown in Table 2 below.

Table 2: Error Calculation on Temperature and Humidity Reading.

Date	**Temperature (Cº)**		**Error (%)** $\frac{Previous\ System - Proposed\ System}{Proposed\ System} X\ 100\%$
	Data Collected by Previous System	Data Collected by Proposed System	
26th Jun 2023	31.6	31.8	0.62
27th Jun 2023	23	22.7	1.32
28th Jun 2023	25.9	25.5	1.56
Average Error Calculation			1.17
Date	**Humidity (%)**		**Error (%)** $\frac{Previous\ System - Proposed\ System}{Proposed\ System} X\ 100\%$
	Data Collected by Previous System	Data Collected by Proposed System	
26th Jun 2023	78	78	0
27th Jun 2023	80	81	1.23
28th Jun 2023	70	70	0
Average Error Calculation			0.41

The test was carried out for a week. The table results showed that the data collected by the system has a small deviation when compared to manual data collected by the farmer. The results show that the system is highly accurate in monitoring temperature and humidity in the farm environment.

The next experiment is about feasibility tests. The system's effectiveness is gauged by its response to temperature and humidity changes, as shown in Table 3. Tests for the fan and humidifier indicated that if the temperature doesn't decrease after the fan runs for 25 minutes or humidity doesn't increase after using the humidifier; there might be sensor or equipment malfunctions. Proper function is confirmed if the desired temperature and humidity adjustments are observed. The test shows that the system was able to function well.

Table 3: Feasibility study on our system.

System	No. Test	Run Time	Temperature /Humidity	Effect On Temperature/Humidity	System Function Check
Fan System	1	15min	34 Cº	-2 ºC	Functioning Well
	2	23min	31 Cº	-3 ºC	Functioning Well
	3	5min	30 Cº	-1 ºC	Functioning Well
	4	25min	30 Cº	0 ºC	DHT11 Sensor fail
Humidifier System	1	30min	60%	+20%	Functioning Well
	2	25min	70%	+5%	DHT11 Sensor fail
	3	10min	78%	+3%	Functioning Well
	4	8min	75%	+5%	Functioning Well

The third test is the machine learning model test. In this test, a dataset fetched from historical data was used. The dataset contains 7335 instances, categorized into three classes: Hot, Mild, and Normal. These data fit into the model listed in Table 1. The results are shown in Figure 2 below.

	precision	recall	f1-score	support
h	1.00	1.00	1.00	1313
m	1.00	1.00	1.00	404
n	1.00	1.00	1.00	484
accuracy			1.00	2201
macro avg	1.00	1.00	1.00	2201
weighted avg	1.00	1.00	1.00	2201

Randon Forest Accuracy: 1.0

	precision	recall	f1-score	support
h	1.00	1.00	1.00	1313
m	1.00	1.00	1.00	404
n	1.00	1.00	1.00	484
accuracy			1.00	2201
macro avg	1.00	1.00	1.00	2201
weighted avg	1.00	1.00	1.00	2201

Decision Tree Accuracy: 1.0

	precision	recall	f1-score	support
h	1.00	1.00	1.00	1313
m	1.00	1.00	1.00	404
n	1.00	1.00	1.00	484
accuracy			1.00	2201
macro avg	1.00	1.00	1.00	2201
weighted avg	1.00	1.00	1.00	2201

Logistic Regression Accuracy: 1.0

	precision	recall	f1-score	support
h	0.98	0.98	0.98	1313
m	0.81	0.98	0.89	404
n	0.92	0.75	0.83	484
accuracy			0.93	2201
macro avg	0.90	0.90	0.90	2201
weighted avg	0.93	0.93	0.93	2201

Support Vector Machines Accuracy: 0.9304861426624261

	precision	recall	f1-score	support
h	1.00	1.00	1.00	1313
m	0.99	1.00	1.00	404
n	1.00	0.99	0.99	484
accuracy			1.00	2201
macro avg	1.00	0.99	1.00	2201
weighted avg	1.00	1.00	1.00	2201

K-Nearest Neighbors Accuracy: 0.9963652885052249

Figure 2: Model performance.

As the majority of the classifier algorithm shows 100% accuracy, we used the computation time for the algorithm to complete the classification as the chosen model. The decision tree algorithm has the shortest execution time compared to the other algorithms. Thus, the Decision Tree algorithm was chosen as the primary algorithm. Table 4 shows the time taken for each algorithm to execute.

Table 4: Time taken for each algorithm execute.

Algorithm	Time Taken (S)
K-Nearest Neighbors (KNN)	2
Random Forest (RF)	5
Support Vector Machine (SVM)	32
Decision Tree (DT)	3
Logistic Regression (LR)	5

4.1 Comparison proposed system with previous work

Our proposed system incorporates Decision Trees (DT), Logistic Regression (LR), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF) techniques, attaining a comparable accuracy of 100%. Table 5 shows the comparison between previous research and our method.

By comparing the existing systems with our proposed system, it is evident that our system achieves comparable accuracy while offering a custom web-based dashboard and database integration. This combination enhances the system's flexibility, scalability, and usability, making it an effective and advanced solution for mushroom farm automation.

Table 5: A comparison between existing systems and our proposed system.

Ref. No.	IoT Technique	AI Technique	Highest Accuracy	Mushroom Farm Automation	Control Environment Technique	Database used
[6]	Yes	No	N/A	Yes	Predefined	No
[13]	Yes	No	N/A	Yes	Predefined	No
[8]	Yes	DT	97.3%	Yes	MLPA	No
[9]	Yes	No	N/A	Yes	Predefined	Yes
[11]	Yes	LSTM + CNN	99%	Yes	Predefined	No
[7]	Yes	SVM +DT +LR+NB+KNN+RF	100%	Yes	Predefined	No
[10]	Yes	Not Mentioned	N/A	Yes	Predefined	No
Proposed System	Yes	DT + LR + KNN + SVM + RF	100%	Yes	Classification	Yes

4.2 Proposed System Prototype

The system prototype was built and deployed at UniMAP Mushroom Farm in Unimap Agrotechnology, Sungai Chuchuh Padang Besar. Figure 3 shows the prototype while Figure 4 shows the web interface of the system.

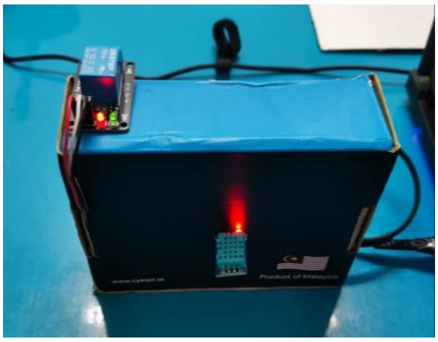

Figure 3: System prototype.

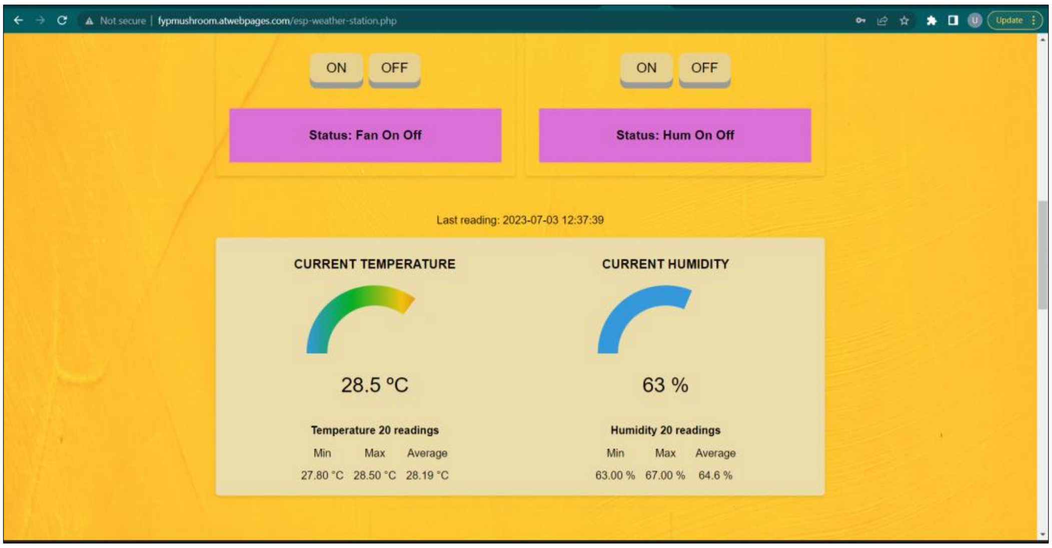

Figure 4: Web interface for the system.

5. CONCLUSION

Mushroom farming, traditionally anchored in conventional methods, is experiencing a global paradigm shift, underscored by the pressing need for advanced automation given environmental inconsistencies. This research presents a transformative approach with an IoT-enabled mushroom farm automation system enhanced by machine learning. The system prioritizes real-time monitoring using the DHT11 sensor to track temperature and humidity, ensuring optimal farm conditions consistently. The automation's strength is further amplified through an ensemble of machine learning classifiers, with Decision Tree (DT), Logistic Regression (LR), and Random Forest (RF) achieving a remarkable 100% accuracy rate. DT stood out for its time efficiency, making it the model of choice for real-time farm management. Looking forward, there is immense potential in integrating more comprehensive sensors to capture a wider spectrum of environmental factors and leveraging predictive analytics. Such advancements can offer real-time alerts, allow for predictive growth trajectories, and optimize resource allocation, pushing the boundaries of efficiency and productivity in mushroom farming.

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