Engineering and Technology Journal e-ISSN: 2456-3358
Volume 11 Issue 01 January-2026, Page No.-8614-8621
DOI: 10.47191/etj/v11i01.23, I.F. – 8.482

Development of an Integrated Mushroom Cultivation System Based on Sensor Array and Machine Learning

Didit Rahmat Hartadi[1], Shabrina Choirunnisa[2], Tanti Kustiari[3], Denny Wijanarko[4], Khafidurrohman Agustianto[5], Prawidya Destarianto[6], Retno Sari Mahanani[7]
[1,2,4,5,6] Department of Information Technology, Politeknik Negeri Jember, East Java, Indonesia
[3,7] Department of Agribusiness Management, Politeknik Negeri Jember, East Java, Indonesia

ABSTRACT: The cultivation of oyster mushrooms (*Pleurotus ostreatus*) in Indonesia has expanded rapidly and has become one of the country's prominent horticultural commodities. According to the Directorate General of Horticulture, the demand for oyster mushrooms continues to increase for both domestic consumption and export. Oyster mushroom farming is highly promising for further development due to its economic value, environmental friendliness, and suitability for small- to medium-scale agribusiness. However, farmers often struggle to meet the growing demand because of inadequate infrastructure and limited environmental control technologies. A major challenge in oyster mushroom cultivation is the strict and highly sensitive microclimate requirements—particularly temperature, humidity, air circulation, and light exposure. Even minor deviations in these parameters can significantly affect yield, quality, and biological efficiency. To address these challenges, precision agriculture (PA) offers an effective solution through the integration of intelligent sensing technologies and automated environmental control systems. This study aims to develop an Integrated Mushroom Cultivation System that leverages sensor arrays and Machine Learning to optimize microclimate regulation. The system records environmental data—including light intensity, temperature, and humidity—in a big-data structure, enabling multi-sensor evaluation to generate more accurate environmental decisions. Field data collected from 1–25 August 2025 indicate that the microclimate within the cultivation chamber was relatively stable, with an average temperature around 24 °C. Humidity conditions remained within the Optimal Fruiting range at 80.44%. Meanwhile, peak light-intensity readings reached 55,000–60,000 lumens due to direct sensor exposure to the light source, rather than representing the actual illuminance at the substrate surface. To ensure reliable automated decision-making—particularly for misting and environmental adjustments—sensor calibration and anomaly detection mechanisms must be implemented, focusing especially on parameters that directly influence mushroom growth. The adoption of these recommendations is expected to enhance environmental stability within the cultivation chamber and improve production quality, supporting the development of adaptive systems for precision agriculture.

KEYWORDS: big data; machine learning; PID; neural network; array sensor, Pleurotus ostreatus

I. INTRODUCTION

The cultivation of oyster mushroom (*Pleurotus ostreatus*) in Indonesia has expanded rapidly in recent years and has become one of the country's leading horticultural commodities. According to data from the Directorate General of Horticulture, the demand for oyster mushrooms continues to rise for both domestic consumption and export markets [1]. Despite this increasing demand, farmers are often unable to meet market needs due to insufficient infrastructure and limited environmental control capabilities [2]. National oyster mushroom production in 2023 reached approximately 60,000 kg, with the majority originating from Java Island [3]. In 2024, production experienced a substantial increase, reaching 330 tons, with West Java (171 tons), East Java (87 tons), and Central Java (72 tons) recorded as the highest-producing provinces [4]. Nevertheless, per-capita consumption remains relatively low at only 0.15 kg, indicating a large untapped potential for market expansion. Oyster mushroom cultivation offers significant economic value and is considered environmentally sustainable, making it highly suitable for broader development across Indonesia [5]. However, a major challenge lies in maintaining the strict and consistent microclimate conditions required for optimal mushroom growth—particularly temperature, humidity, and air circulation. Even minor fluctuations in these parameters can markedly influence yield quantity and quality, underscoring the need for precision environmental management in commercial oyster mushroom production.

Oyster mushroom (*Pleurotus ostreatus*) cultivation requires highly specific environmental conditions, particularly a temperature range of 16–30 °C and relative humidity between 80–95%. However, most small-scale farmers in Indonesia still rely on manual environmental control through periodic water spraying [6]. This conventional method is labor-intensive, imprecise, and poses a risk of damaging the baglogs, often resulting in harvest yields reaching only about 50% of the potential capacity of the cultivation house. Previous studies have introduced Internet of Things (IoT)–based systems to automatically monitor temperature and humidity, yet the majority of these works focus solely on passive monitoring and lack adaptive, data-driven environmental control mechanisms.

To address these limitations, precision agriculture (PA) offers a promising solution through the integration of smart sensors and automated control systems. PA leverages smart sensing technologies, the Internet of Things (IoT), big data analytics, and artificial intelligence (AI) to optimize environmental management, resource utilization, and overall sustainability in agricultural production. In the context of oyster mushroom cultivation, PA enables precise and responsive environmental regulation that improves production efficiency and consistency. Therefore, this study proposes an integrated approach combining big data, machine learning, and a multi-sensor array to develop an automated and adaptive environmental control system tailored for oyster mushroom cultivation.

This study aims to develop an Integrated Mushroom Cultivation System based on Machine Learning and a multi-point Sensor Array. The system employs a Neural-Network–Assisted Proportional–Integral–Derivative (PID) controller [7], in which temperature and humidity measurements from multiple sensors are processed collectively as a sensor array [8–9]. All environmental data are stored as big data to ensure accuracy, continuity, and long-term integrity of the time-series records. By evaluating several sensor readings simultaneously, the system generates more robust and reliable microclimate estimations. These data are subsequently used as machine-learning input variables to determine automated control actions, particularly misting and ventilation, to maintain the target temperature and humidity levels. When the environmental conditions deviate from optimal thresholds, the system triggers corrective actions adaptively, enabling precise and intelligent microclimate regulation within the mushroom cultivation chamber.

II. RELATED WORK

Research on automation in oyster mushroom cultivation has grown substantially, with most studies concentrating on the regulation of temperature and humidity as the two most critical environmental variables. Waluyo et al. developed a microcontroller-based control system; however, their approach remained limited to simple binary actuation without adaptive or predictive capabilities [6]. To enhance system intelligence, subsequent studies adopted soft-computing methods. Amen and Villaverde, as well as Najmurrokhman et al., implemented fuzzy-logic controllers to stabilize temperature and humidity in real time within oyster mushroom growing houses [10–11]. These rule-based fuzzy systems demonstrated superior responsiveness to dynamic environmental changes compared with conventional control techniques, indicating the potential of intelligent algorithms for achieving more stable microclimate conditions in mushroom cultivation environments.

Another research, Fuady et al. compared the performance of Backpropagation Neural Networks (BPNN) and Extreme Learning Machines (ELM) for predicting and controlling microclimate variables in mushroom cultivation systems. Their results demonstrated that ELM achieves significantly faster convergence than BPNN, making it more suitable for deployment in microcontroller-based embedded systems with limited computational resources [12]. Beyond AI-driven controllers, substantial advancements have also been made in environmental monitoring technologies using Wireless Sensor Networks (WSN). For example, Cao et al. implemented ISFET microsensors integrated with mobile networks for real-time water-quality monitoring [13], while Perumal et al. developed an IoT-enabled environmental monitoring architecture supporting continuous data acquisition and remote analytics [14]. Although these systems were not designed specifically for mushroom cultivation, the WSN–IoT architectures presented in these studies offer a highly transferable foundation for real-time sensing, distributed data collection, and remote supervision within mushroom growth chambers.

Research directly related to mushroom cultivation within the context of wireless sensor networks (WSN) has been conducted by several scholars. Nakron et al. designed an automatic environmental control system for a greenhouse cultivating milky mushrooms, integrating environmental sensors and actuator control to maintain a stable microclimate [15]. Similarly, Kaewwiset and Yodkhad implemented a fuzzy-logic-based temperature and humidity control system for mushroom nurseries, demonstrating superior environmental stability compared to manual control methods [16]. These studies highlight the effectiveness of combining WSN architectures with intelligent control algorithms for microenvironment management. Nevertheless, most existing works continue to rely on rule-based control mechanisms and lack short-term predictive capabilities or optimization strategies driven by machine learning. Such predictive and adaptive features are crucial for anticipating dynamic daily fluctuations in temperature and humidity, particularly in oyster mushroom cultivation environments where small variations can significantly influence yield and quality.

Recent studies also show an emerging trend toward integrating Machine Learning and IoT Edge Computing in smart mushroom cultivation systems. Zhang et al. developed an LSTM-based predictive model for temperature and humidity regulation in greenhouse environments, demonstrating an improvement of up to 18% in forecasting accuracy compared to classical time-series approaches [17]. These studies indicate a paradigm shift from simple automation toward fully integrated monitoring–prediction–control frameworks driven by artificial intelligence. Nevertheless, the application of ML specifically to oyster mushroom cultivation remains limited, particularly in the use of multisensor arrays to construct predictive and adaptive water-misting control models capable of responding to dynamic microclimate fluctuations.

Accordingly, this study addresses a critical gap in the existing literature by integrating Wireless Sensor Networks (WSN), Internet of Things (IoT) technologies, temperature–humidity sensor arrays, and Machine Learning models to develop a smart cultivation system capable of adaptive and autonomous monitoring, prediction, and environmental control within oyster mushroom growing houses. Unlike previous studies that primarily relied on rule-based mechanisms or focused solely on monitoring, the proposed approach emphasizes a data-driven, predictive control framework. Furthermore, the study leverages high-resolution longitudinal data collected over 25 days at 10-minute intervals, providing a comprehensive microclimate dataset that has rarely been explored in prior research. This analytical depth enables the development of more robust predictive models and contributes to advancing precision agriculture practices for oyster mushroom cultivation.

III.METODOLOGY

The experiment was conducted from August 1 to August 25 at UKM Paramartha, located in Rambipuji Village, Jember Regency, Indonesia. A four-node sensor array was installed inside the mushroom cultivation house, with each node equipped to measure air temperature and relative humidity. Sensor readings were updated every 10 minutes to support the implementation of an adaptive control strategy aligned with precision agriculture principles. This high-resolution temporal sampling enables detailed characterization of the microclimate dynamics and provides sufficient granularity for training machine learning models for predictive control. The overall research methodology employed in this study is illustrated in Figure 1.

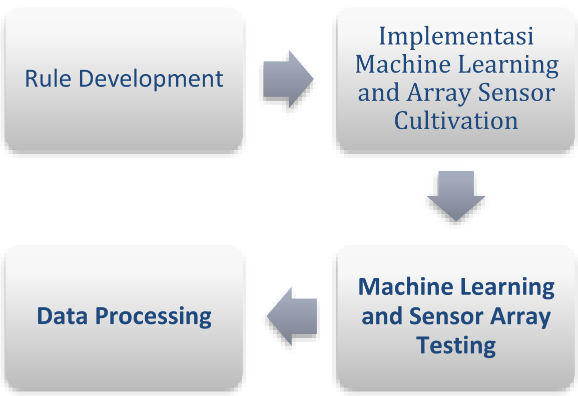


Figure 1. Method

A. Rule Development

The development of control rules constitutes a critical stage in this study, as multiple sensors are employed as environmental variables within the system. The readings obtained from the sensor array serve as the primary input for determining the appropriate water-spraying action required to maintain the optimal temperature and humidity conditions for the growth of *Pleurotus ostreatus*. These rules ensure that environmental adjustments—particularly misting intensity and duration—are carried out in accordance with the real-time microclimatic status of the cultivation chamber, thereby supporting an adaptive and precise environmental control strategy.

B. Implements Machine Learning and Array Sensor Cultivation

The rules derived in the previous stage were subsequently integrated into the Machine Learning framework and sensor-array architecture of the Integrated Mushroom Cultivation System. This implementation employs a neural network approach to enable more accurate and adaptive decision-making regarding environmental control. By processing multisensor inputs—comprising four distributed temperature and humidity nodes—the neural network learns patterns of microclimate fluctuations and maps them to the appropriate control actions, particularly the activation of the misting system.

The use of neural networks provides several advantages over conventional rule-based strategies, including improved robustness to sensor noise, better generalization under dynamic environmental conditions, and the ability to model nonlinear relationships between temperature, humidity, and optimal mushroom growth requirements. Through continuous learning from time-series data, the system is able to refine its prediction accuracy and enhance the responsiveness of environmental regulation. This ML–sensor-array integration forms the core of the adaptive smart cultivation model proposed in this study.

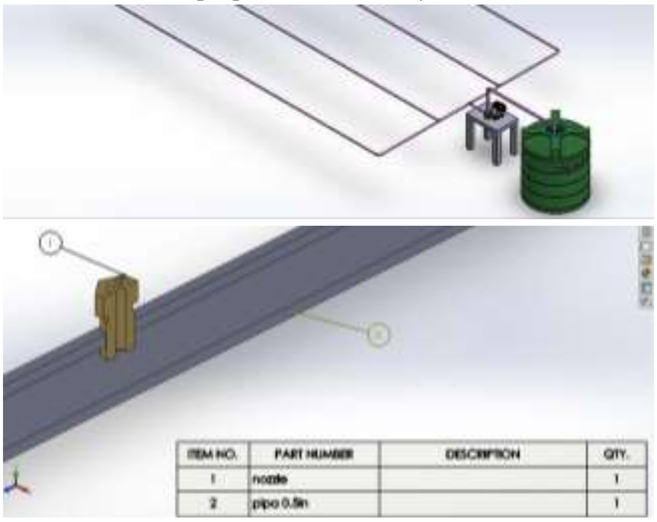


Figure 2. Initial Design of Integrated Mushroom Cultivation with Nozzle

C. Machine Learning and Sensor Array Testing

This stage involved validating the accuracy and reliability of the sensor array readings as processed by the machine learning model. Comprehensive testing was performed to evaluate end-to-end system performance, including data transmission from sensors to the base station, from the base station to the cloud database, and the subsequent database-level processing. The objective of this phase was to ensure that the entire data pipeline operates consistently and that the machine learning model accurately interprets real-time measurements. The results of this evaluation provide insights into system latency, data integrity, and the operational accuracy of environmental predictions and control decisions.

D. Data Processing of Sensor Array Measurements

The sensor data collected during the experimental phase were systematically processed and analyzed to evaluate the effectiveness of the implemented neural network algorithm. This data processing phase aimed to assess the model's ability to interpret microclimate conditions in the cultivation chamber—particularly temperature and humidity—and to determine whether the applied approach successfully enhances the precision of environmental evaluation. The processed time-series dataset also serves as a basis for further analysis, including performance benchmarking, anomaly detection, and refinement of environmental control strategies for adaptive mushroom cultivation.

IV. RESULT AND DISCUSSION

The results and discussion present the environmental parameters obtained from the multisensor array deployed in the integrated machine-learning–based mushroom cultivation system. The evaluated parameters include light intensity, temperature, and relative humidity, which were continuously recorded at 10-minute intervals over a 25-day period in August. Each dataset is subsequently interpreted and classified into environmental condition classes that correspond to the physiological requirements of *Pleurotus ostreatus* during its growth and fruiting phases.

A. Light Intensity Pattern

The two light-intensity graphs presented in Figure 3 illustrate the illumination dynamics inside the mushroom cultivation chamber over a 25-day monitoring period, with data captured at 10-minute intervals using the integrated Machine Learning–based sensor array system. The recorded light-intensity values exhibit a highly consistent diurnal cycle. Sharp peaks ranging from approximately **55,000 to 60,000 lumens** occur during the illuminated phase, followed by rapid decreases to near-zero values during the dark phase. This recurring pattern indicates that the illumination within the mushroom house is regulated in a scheduled manner—either as a result of controlled artificial lighting or periodic exposure to external light sources. Such consistency suggests that the system effectively simulates natural light rhythms or provides targeted illumination conditions required for specific physiological stages of *Pleurotus ostreatus* growth.

In addition to the dominant high–peak illumination cycles, the presence of several mid-level intensity spikes ranging from 20,000 to 30,000 lumens—which do not follow the primary light–dark rhythm—suggests the existence of auxiliary or unregulated light sources within or near the cultivation chamber. These sporadic peaks, observed around days 8–10 and 18–20, may be attributed to human activity (e.g., operators entering the facility with portable lighting), reflective glare from metallic surfaces, or incidental light leakage from the surrounding environment. Although such disturbances are relatively brief, their occurrence warrants close monitoring, particularly during the primordia initiation stage, as irregular or sudden changes in illumination can alter photomorphogenic responses in certain mushroom species.

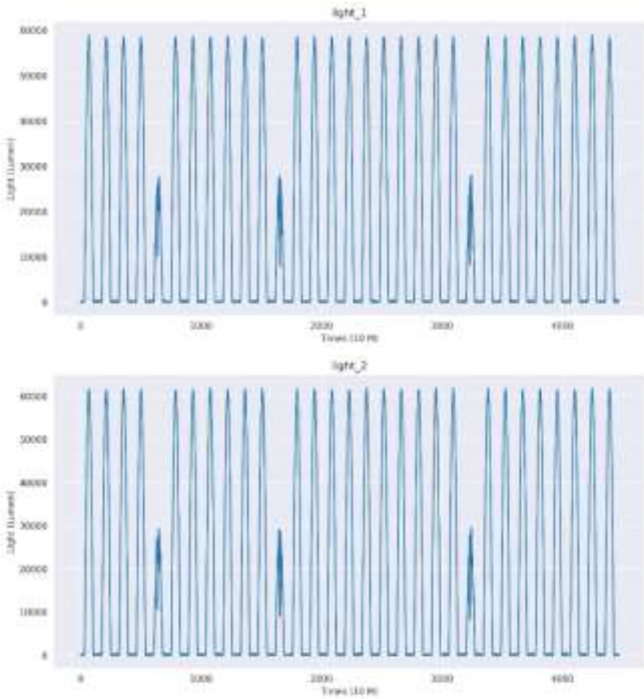


Figure 3. Light Intensity Pattern

From a physiological perspective, oyster mushrooms and most edible fungi require only **low-intensity light**, generally within the range of **200–1500 lux**, to trigger primordia formation, guide phototropic orientation, and support fruit body maturation [18–19]. Therefore, the exceedingly high intensity values recorded—far above the biological requirement—suggest that the sensors were likely detecting the **direct light source output** rather than the **effective illuminance at the growing surface**. This is consistent with known sensor limitations in enclosed environments where line-of-sight exposure to lamps can cause readings to overestimate actual luminance available to the crop. Consequently, while the system registered peaks of >55,000 lumens, the actual light received by the developing fruit bodies was likely much lower and still within or near biologically acceptable thresholds.

Tabel 1. Classification of light intensity for mushrooms

Class	Lux Range	Physiological Needs	Reference
Class 0	0–50	Inkubasi miselium	[20]
Class 1	50–200	Inisiasi primordia	[18]
Class 2	200–1500	Fruiting body growth	[21]

Class	Lux Range	Physiological Needs	Reference
Class 3	1500–5000	High light (not recommended)	[21]
Class 4	>5000	Overexposure – risks damaging the fruiting	[20]

Based on this classification, the measured peaks (>55,000 lumens) fall clearly into **Class 4 – Overexposure**. However, the interpretation must be nuanced. The high values are consistent with sensor detection of **direct beam intensity**, not the **incident illuminance** relevant for mushroom growth. In a typical cultivation house, racks, shading cloths, and wall structures significantly attenuate light before it reaches the substrate surface. Thus, although the sensor readings classify the environment as overexposed, the actual micro-illuminance experienced by the mushrooms may still fall within the **Class 2 optimal range**.

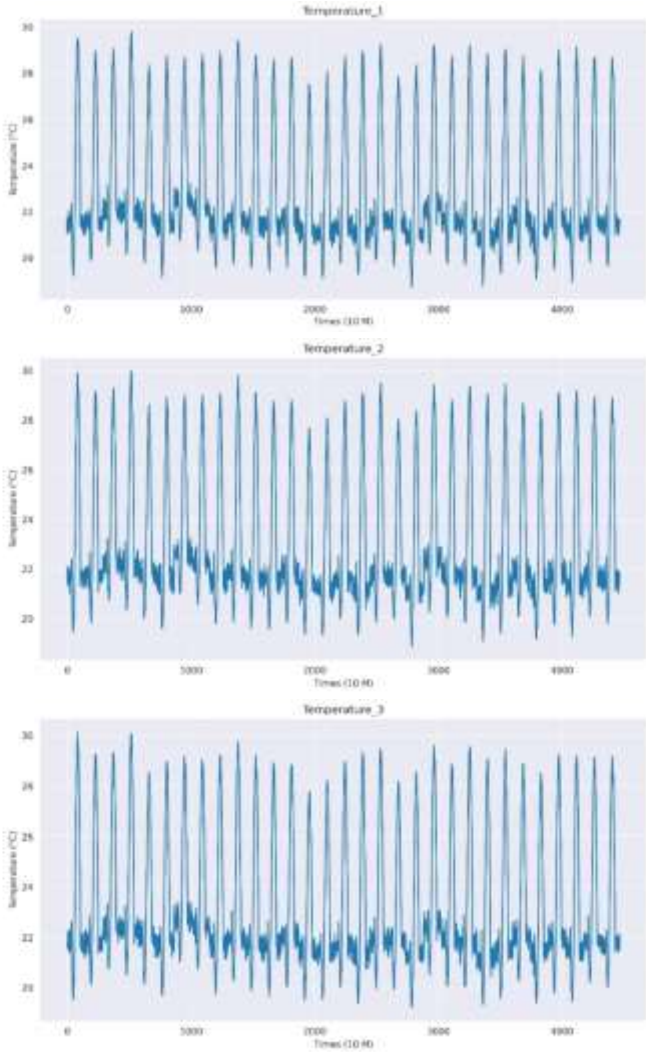
Sánchez et al. emphasize that oyster mushrooms and most edible fungi require only low-intensity illumination to trigger primordia formation and regulate fruiting body morphogenesis; thus, the extremely high light readings observed in this study are unlikely to represent the actual illuminance received by the mushroom beds. Such elevated values are most likely caused by the sensor's proximity to the artificial light source or by the device operating in a direct-beam detection mode, which captures the luminous intensity of the lamp rather than the diffused illuminance within the cultivation racks [18]. Within the Integrated Mushroom Cultivation system driven by Machine Learning, light intensity serves as an important environmental feature for several functional tasks: (i) predicting thermal increments induced by lighting-related heat load, (ii) adjusting the frequency and duration of water spraying to maintain humidity stability, (iii) detecting abnormal environmental conditions, and (iv) validating daily light–dark cycles as a baseline temporal pattern of the mushroom house environment.

During periods of peak illumination, ambient temperature is expected to rise, prompting the control system to increase misting duration or intensity to maintain humidity within the optimal 85–95% range for fruit body development [20]. Conversely, during dark phases the system reduces misting activity to avoid over-saturation and preserve a stable cultivation microclimate. Anomalies in light intensity—such as unexpected spikes or mid-range peaks—have the potential to trigger inaccurate control responses if misinterpreted as true environmental changes. Therefore, integrating an anomaly-detection module into the Machine Learning pipeline is essential to differentiate between technical disturbances (e.g., sensor noise, direct lamp exposure, or accidental shadows) and genuine environmental variations. This ensures that automated control decisions remain robust, accurate, and aligned with the physiological requirements of Pleurotus ostreatus throughout the production cycle.

B. *Temperature Profile*

The system employed four temperature sensors distributed across the mushroom house to capture the thermal dynamics of the cultivation environment. As shown in Figure 4, the average temperature recorded across all channels remained approximately 24 °C. Daily fluctuations exhibited a consistent pattern, with daytime temperature peaks reaching 28–30 °C and nighttime lows falling to 20–22 °C. This oscillatory thermal behavior—characterized by sharp and recurrent rises and drops—reflects the operation of mechanical environmental controls, such as cyclic ventilation or intermittent cooling mechanisms, which regulate heat dissipation throughout the day.

Superimposed on this diurnal pattern is a series of micro-fluctuations appearing as high-frequency noise around the baseline temperature. These variations arise from localized thermal conduction effects involving the walls, substrate racks, and surrounding structural elements. The presence of such micro-scale fluctuations indicates that, although the macro-level temperature control operates consistently, the microclimate remains influenced by inherent spatial and material thermal dynamics that are difficult to suppress entirely.



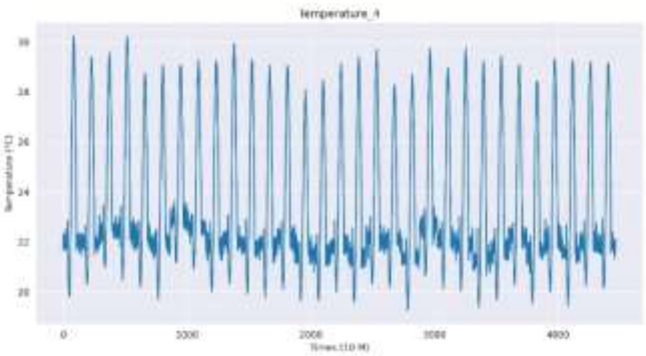


Figure 4. Temperature Profiles from the Four Sensor Channels

The consistency of the patterns observed across all temperature sensors indicates that the horizontal distribution of heat within the mushroom house is relatively homogeneous. This high degree of uniformity suggests that the air circulation system functions effectively in equalizing thermal conditions throughout the cultivation chamber. Such homogeneity is essential for oyster mushroom production, as uneven temperature gradients are known to influence mycelial colonization rates and lead to heterogeneity in fruiting body development. A stable and uniformly distributed temperature profile therefore supports more synchronized growth and contributes to overall production consistency and quality.

Table 2. Temperature Profile Classification for Mushroom Cultivation Rooms

Class	Temp range (°C)	Meaning	Reference
Class 0	< 20 °C	**Suboptimal Cold Zone**	[19-20]
Class 1	20–23 °C	**Lower Fruiting Threshold**	[18]
Class 2	24–26 °C	**Optimal Fruiting Zone**	[22]
Class 3	27–29 °C	**High Temperature Stress**	[18-19]
Class 4	> 30 °C	**Overheat / Critical Zone**	[20]

The temperature-class analysis presented in Table 2 indicates that the average thermal conditions within the cultivation chamber remain within the ideal range of 24–26 °C, which is widely recognized as the optimal microclimate for mycelial development and fruiting of *Pleurotus ostreatus*. Nevertheless, maintaining this range consistently requires an adaptive and precise response, particularly during periods of thermal stress such as midday heating or nighttime cooling. Without appropriate corrective action, deviations from the optimal band may disrupt metabolic activity, reduce primordia formation, and ultimately impact yield uniformity. Therefore, a responsive control mechanism—capable of anticipating thermal fluctuations and adjusting actuators in real time—is essential to sustain stable, biologically favorable temperature conditions throughout the cultivation cycle.

C. *Humidity*

The humidity data presented in Figure 5 exhibit considerably greater variability compared to both light intensity and temperature profiles. The two humidity sensors recorded an average relative humidity of 80.44%, with values ranging from 56.5% to 98.5% throughout the 25-day observation period. Maximum humidity levels (≥90%) consistently occurred during nighttime, whereas daytime values dropped to approximately 56–65%, reflecting the combined influence of elevated daytime temperatures and natural evaporative processes within the cultivation room. These fluctuations also display short-cycle oscillatory patterns that correspond to the activation of the automatic misting system. Each misting event produces a sharp rise in relative humidity toward near-saturation levels, followed by a gradual decline as moisture dissipates through convection and evaporation. This cyclic behaviour indicates that the microclimate is dynamically regulated yet remains susceptible to rapid environmental shifts, thereby requiring an adaptive control mechanism to maintain humidity within the optimal fruiting range.

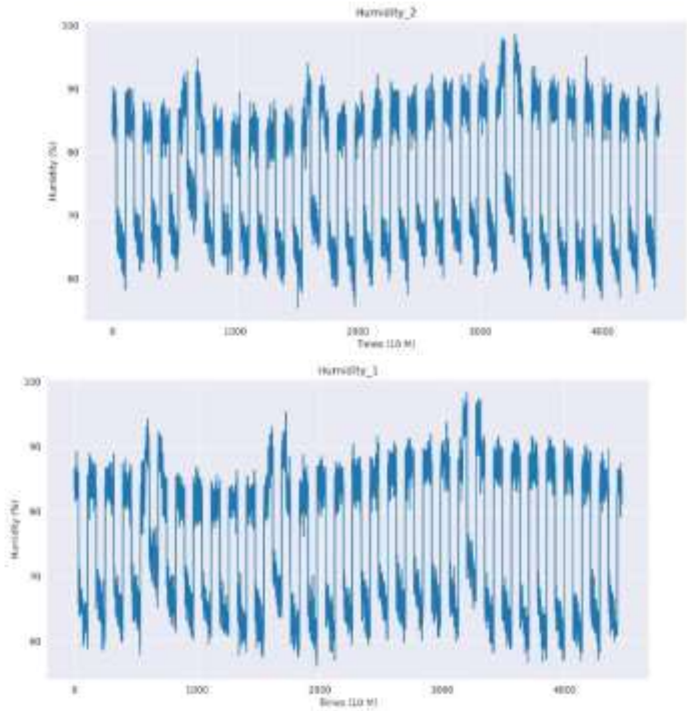


Figure 5. Humidity Sensor 1 and Sensor 2

The data presented in Figure 5 demonstrate that humidity exhibits far greater variability compared to light intensity and temperature profiles. The two humidity sensors recorded an average relative humidity of 80.44%, with values ranging from 56.5% to 98.5%. Peak humidity levels (≥90%) generally occurred during nighttime, while daytime readings consistently dropped to 56–65%. These fluctuations form short, repetitive cycles that reflect the operation of the automated humidification system. Each activation of the misting unit causes humidity to rise sharply toward saturation, followed by a gradual decline driven by natural evaporation processes.

Certain segments from both sensors also show prolonged periods of high humidity. Such intervals typically indicate that the humidification system is operating more intensively to maintain elevated moisture levels during specific developmental stages of the mushroom that require high relative humidity. However, sustained saturation phases may also signal reduced ventilation efficiency, for example, a decrease in air exchange rates that allows water vapor to accumulate within the cultivation chamber.

Differences in amplitude and pattern characteristics between Humidity Sensor 1 and Sensor 2, as illustrated in Figure 5, indicate that moisture distribution inside the cultivation room is not entirely uniform. Sensors positioned closer to the misting nozzles captured sharper and higher humidity peaks, whereas those located in airflow-dominant zones recorded smoother and more moderate variations. Such heterogeneity is typical of humid environments with active ventilation systems. Nevertheless, spatial inconsistencies in humidity warrant attention, as uneven moisture distribution may lead to non-uniform fruiting body development and variability in overall mushroom growth performance.

Table 3. Humidity Classification for Mushroom Cultivation

Kelas	Humidity range (%)	Meaning	Reference
Class 0	< 70 %	**Critical Dry Zone**	[18]
Class 1	70–80 %	**Suboptimal Low RH**	[21]
Class 2	80–90 %	**Optimal Fruiting RH**	[19]
Class 3	95–98 %	**High Humidity Zone**	[22]
Class 4	> 98 %	**Over-humid / Condensation Zone**	[20]

Relative humidity is the most critical environmental variable in mushroom cultivation, and the findings indicate that the average humidity of 80.44% falls within the ideal range of 80–90% for the fruiting stage. However, the substantial daily fluctuations—particularly the significant drop to 56.5% during daytime—may inhibit primordia formation and lead to surface dehydration of the fruiting bodies, ultimately affecting mushroom size, texture, and overall quality [18–19]. These conditions underscore the necessity of an adaptive control mechanism equipped with anomaly detection, enabling rapid and precise responses to humidity decreases to maintain a stable microclimate conducive to optimal mushroom development.

CONCLUSIONS

Data collected from 1–25 August 2025 reveal the microclimatic characteristics of the mushroom cultivation chamber. The average temperature remained relatively stable at approximately 24 °C, although additional control is required to prevent transient thermal spikes during daytime periods. Relative humidity was found to be within the Optimal Fruiting range, with an average of 80.44%, yet the system still requires more consistent humidity regulation to avoid excessive fluctuations that may disrupt primordia formation. Meanwhile, the recorded peak light intensities—approximately 55,000–60,000 lumens—were identified as measurements of the light source rather than the actual illuminance at the substrate surface. This highlights the need for sensor calibration to ensure that illuminance readings reflect biologically relevant exposure levels. To guarantee accurate autonomous decision-making—particularly for misting and microclimate correction—an integrated anomaly detection module is essential, focusing on identifying sensor drift, noise, or environmental disturbances. Implementing these recommendations is expected to enhance the environmental stability of the cultivation chamber and improve overall yield quality, thereby supporting the development of adaptive, data-driven precision agriculture systems for oyster mushroom production.

ACKNOWLEDGMENT

The author would like to acknowledge the finansial support of this work by grants from PNBP Politeknik Negeri Jember. The author also thanked the P3M Politeknik Negeri Jember which has provided support and assistance in completing this research.

REFERENCES

1. Direktorat Jenderal Holtikultura Kementerian Pertanian. 2023. Budidaya Jamur Punya Potensi Ekspor Tinggi, Permintaan Terus Meningkat [internet]. [cited 2025 nov 20]. Available from: https://hortikultura.pertanian.go.id/budidaya-jamur-punya-potensi-ekspor-tinggi-permintaan-terus-meningkat/
2. Bisnis Jamur Tiram Tetap Eksis di Tengah Pandemi - Pusat Sosial Ekonomi dan Kebijakan Pertanian [Internet]. [cited 2025 Sept 27]. Available from: https://pse.litbang.pertanian.go.id/ind/index.php/covid-19/berita-covid19/471-bisnis-jamur-tiram-tetap-eksis-di-tengah-pandemi.
3. GoodStat. Produksi Jamur Indonesia Didominasi Jawa [Internet]. 2023. Available from: https://data.goodstats.id/statistic/produksi-jamur-indonesia-didominasi-jawa-M7ZHT

4. BPS. Produksi Tanaman Sayuran Jamur [Internet]. 2025. Available from: https://www.bps.go.id/
5. Saskiawan I. LIPI Galakkan Budidaya Jamur Oangan di Indonesia [Internet]. 2017. Available from: http://lipi.go.id/berita/single/LIPI-Galakkan-Budidaya-Jamur-Pangan-di-Indonesia/19346.
6. Waluyo S, Wahyono RE, Lanya B, Telaumbanua M. Pengendalian Temperatur dan Kelembaban dalam Kumbung Jamur Tiram (Pleurotus sp) Secara Otomatis Berbasis Mikrokontroler. agriTECH. 2019;38(3):282.
7. Muhlasin, Budiman, Ali M, Parwanti A, Firdaus AA, Iswinarti. Optimization of Water Level Control Systems Using ANFIS and Fuzzy-PID Model. Proceeding - 2020 3rd Int Conf Vocat Educ Electr Eng Strength Framew Soc 50 through Innov Educ Electr Eng Informatics Eng ICVEE 2020.
8. Dakulagi V, Member JH. Improved Direction-of-Arrival Estimation for Modified Symmetric Sensor Array. IEEE Sens J [Internet]. 2021;21(4):5213–20. Available from: https://ieeexplore.ieee.org/document/9225069.
9. Hossain A, Thomson B, Debnath R, M A, Rao M V. Nanowire-based Sensor Array for Detection of Cross-sensitive Gases Using PCA and Machine Learning Algorithms. IEEE Sens J. 2020;20(11):6020–8.
10. Amen JC del, Villaverde JF. Fuzzy Logic-based Controlled Environment for the Production of Oyster Mushroom. In: 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM) [Internet]. Laoag, Philippines; 2019. Available from: https://ieeexplore.ieee.org/document/9072902.
11. Najmurrokhman A, Daelami A, Kusnandar, Adiputra F, Komarudin U. Design and Implementation of Temperature and Humidity Control System in Oyster Mushroom Cultivation using Fuzzy Logic Controller. In: 2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA). IEEE; 2019. p. 146–50.
12. Fuady GM, Turoobi AH, Majdi MN, Syaiin M, Adhitya RY, Rachman I, et al. Extreme learning machine and back propagation neural network comparison for temperature and humidity control of oyster mushroom based on microcontroller. In: 2017 International Symposium on Electronics and Smart Devices, ISESD 2017. 2018. p. 46–50.
13. Cao F, Jiang F, Liu Z, Chen B, Yang Z. Application of ISFET Microsensors with Mobile Network to Build IoT for Water Environment Monitoring. In: Proceedings - 2014 International Conference on Intelligent Environments, IE 2014. 2014. p. 207–10.
14. Perumal T, Sulaiman N, Leong CY. Internet of Things (IoT) Enabled Water Monitoring System. In: 2015 IEEE 4th Global Conference on Consumer Electronics (GCCE) Internet. 2015. p. 86–7.
15. Nakron P, Nakron P, Nakron P, Nakron P, Nakron P. Design of Automatic Control System within the Greenhouse to Maintain the Weather to be Appropriate for the Growth of the Milky Mushroom. In: International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON) [Internet]. Pattaya, Thailand; 2020. p. 3–6. Available from: https://ieeexplore.ieee.org/document/8955127.
16. Kaewwiset T, Yodkhad P. Automatic temperature and humidity control system by using Fuzzy Logic algorithm for mushroom nursery. 2nd Jt Int Conf Digit Arts, Media Technol 2017 Digit Econ Sustain Growth, ICDAMT 2017. 2017;396–9.
17. Zhang, J., Zheng, C., & Liu, H. (2021). Intelligent environmental monitoring and control systems for mushroom cultivation. *Sensors*, 21(11), 3771
18. Sánchez, C. (2010). Cultivation of *Pleurotus ostreatus* and other edible mushrooms. *Applied Microbiology and Biotechnology*, 85(5), 1321–1337
19. Royse, D. J., Baars, J., & Tan, Q. (2017). Current overview of mushroom production worldwide. In *Edible and Medicinal Mushrooms* (pp. 5–13). Wiley
20. S. T. Chang dan P. G. Miles, *Mushrooms: Cultivation, Nutritional Value, Medicinal Effect, and Environmental Impact*. Boca Raton, FL: CRC Press, 2004.
21. Moonmoon, M. et al. (2010). Effect of light on the growth of oyster mushroom. *Bangladesh J. Mushroom Science*, 4(1), 61–70
22. Oei, P. (2003). *Mushroom Cultivation: Appropriate Technology for Mushroom Growers*. CTA