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Real-Time Environmental Monitoring and Growth Analysis of Labisia Pumila in Indoor Conditions Using IoT

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ABSTRACT

Labisia pumila (Kacip Fatimah) is a traditional Malaysian herb widely used for women's health, particularly in alleviating postmenopausal symptoms and aiding childbirth. Indoor cultivation allows precise environmental control, improving growth performance. Environmental data were compiled into a database and analyzed using Principal Component Analysis to identify key growth factors. Light intensity and soil moisture were found to be the dominant parameters influencing leaf development. Optimal growth occurred at 28.56 °C, 85.82 % relative humidity, 974.57 lux, and 88.17 % soil moisture, offering insights for optimized Labisia pumila cultivation.

Keywords: Growth Performance, Indoor Plant, Internet of Things, Labisia pumila, Sensors

INTRODUCTION

Kacip Fatimah (Labisia pumila, family Primulaceae) is a well-known herbaceous plant native to the tropical rainforests of Southeast Asia and widely recognized for its diverse benefits to women's health. Traditionally, it has been extensively used in herbal medicine to treat various ailments, including dysentery, bloating, dysmenorrhea, and gonorrhoea. It is also valued for its role in postpartum care, particularly in promoting uterine contraction, alleviating postnatal fatigue, and regulating menstrual disorders in women [1-3]. Accumulating scientific evidence indicates that Labisia pumila exhibits diverse pharmacological effects, notably antioxidant, antibacterial, anti-estrogenic, and anti-aging activities [1, 3-5]. Labisia pumila naturally thrives in forested environments, but its indoor cultivation presents a promising approach for sustainable production. Nevertheless, maintaining optimal growth conditions in controlled indoor settings remains challenging due to the need to precisely regulate temperature, humidity, light intensity, and soil moisture [3, 6].

With the growing recognition of Labisia pumila as a potential source of medicinal compounds and the increasing demand for herbal products, the need for its raw materials has risen substantially. However, large-scale outdoor

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cultivation of Labisia pumila remains challenging. Conventional farming methods depend heavily on natural environmental conditions, which are often unpredictable and difficult to regulate, resulting in inconsistent growth performance and variable yields [2, 3]. Indoor cultivation of Labisia pumila offers a viable alternative to overcome the limitations of outdoor farming. However, it requires accurate, real-time monitoring of key environmental parameters such as temperature, humidity, light intensity, and soil moisture. The integration of Internet of Things (IoT)-based sensors enables continuous monitoring and automated control of these variables, allowing for a precisely regulated environment that supports efficient and consistent plant growth [7-10]. The implementation of IoT-based smart planting systems provides an effective approach to optimize environmental conditions for plant growth. At the same time, integrating data analytics enables the generation of accurate and reliable insights to support informed decision-making and further optimization of cultivation processes [10-13].

In recent years, the application of big data has expanded significantly across multiple industries, such as agriculture, finance, transportation, healthcare, and tourism. In agriculture, agricultural big data serves crop cultivation, intelligent control, meteorological analysis and agricultural production decision-making, improving agricultural production efficiency, and promoting the transformation of agriculture towards data-driven intelligent production methods [7, 9-11, 14-16]. Collecting data on plant growth status and corresponding growth data and quantitatively analysing the relationship between plant growth status and environmental factors to determine which plant is suitable for planting or which type of plant is suitable for growing in which environment will have great theoretical significance and practical value. Labisia pumila usually grows in shady lowland forests where there is ambient light, temperature, humidity and humus-rich soil. The suitable shading rate of Labisia pumila is about 50 - 70% and open sunlight can be harmful to its establishment and growth. In its natural habitat, Labisia pumila grows on humus-rich soil where the soil moisture is 60 – 70 %, relative humidity between 70 – 80 %, and the temperature is around 25~30 °C [1, 2]. Thus, in cultivating Labisia pumila indoor, it is important to try to mimic the natural forest habitat for the plant's survival.

In the agricultural context, IoT-based systems can significantly enhance productivity, resource management, and sustainability by providing continuous, data-driven insights and enabling timely responses to environmental changes [10, 17]. Among the components of IoT systems, sensors are particularly crucial, as they gather essential environmental data that underpin the system's functionality. With ongoing advancements in sensor technology, these components have become increasingly compact and efficient, enabling their seamless integration into various devices and everyday applications.

The ability to use these data to predict future parameters allows farmers to better plan production management and the consequent distribution and sales [17]. Agriculture is one of the domains that will be influenced by the IoT, and specifically indoor agriculture [18]. Indoor planting protects the plants by climate control, which obtains optimal conditions for growth and photosynthesis, and also from the greenhouse effect phenomenon, which contributes to the good growth of the plant. An IoT-driven agricultural production system integrates environmental sensors and predictive models to analyse crop environments, optimize decision-making processes, and forecast agricultural yields [19]. IoT is used in a drip irrigation monitoring framework for mustard leaf planting experiments, enabling precise irrigation control to improve plant growth and to enhance Indian oyster mushroom cultivation, achieving a significant yield increase from 4.118 kg to 5.306 kg compared to traditional methods [15, 19]. Kirci et al. [13] constructed a prototype of a small smart greenhouse that utilizes Arduino microcontrollers, sensors, and actuators to monitor and control environmental parameters such as temperature, humidity, soil moisture, and lighting. They planted flowers and three types of vegetables (chilli peppers, tomatoes, and cucumbers) in smart greenhouses and outdoor flowerpots, and compared their growth. The findings indicated that plants grown in the smart greenhouse exhibited healthier growth and stronger leaves compared to those in conventional conditions, with the exception of cucumbers.

Despite the rapid progress and proven commercial as well as pharmaceutical significance of IoT-based agricultural systems, their application in the indoor cultivation of Labisia pumila remains largely unexplored. This research gap underscores the need for further studies to demonstrate how IoT technologies can optimize the growth performance and yield of this valuable medicinal plant. This study investigates the integration of IoT technology in the cultivation of Labisia pumila, a species for which limited research exists in this area. By employing sensors that monitor temperature, humidity, soil moisture, and light intensity, key environmental factors are continuously tracked in real time. The collected data are transmitted via wireless networks to an online platform, allowing for efficient monitoring, analysis, and control. This approach not only provides a scientific foundation for improving Labisia pumila cultivation but also illustrates the transformative role of IoT in advancing precision agriculture and sustainable indoor farming practices.

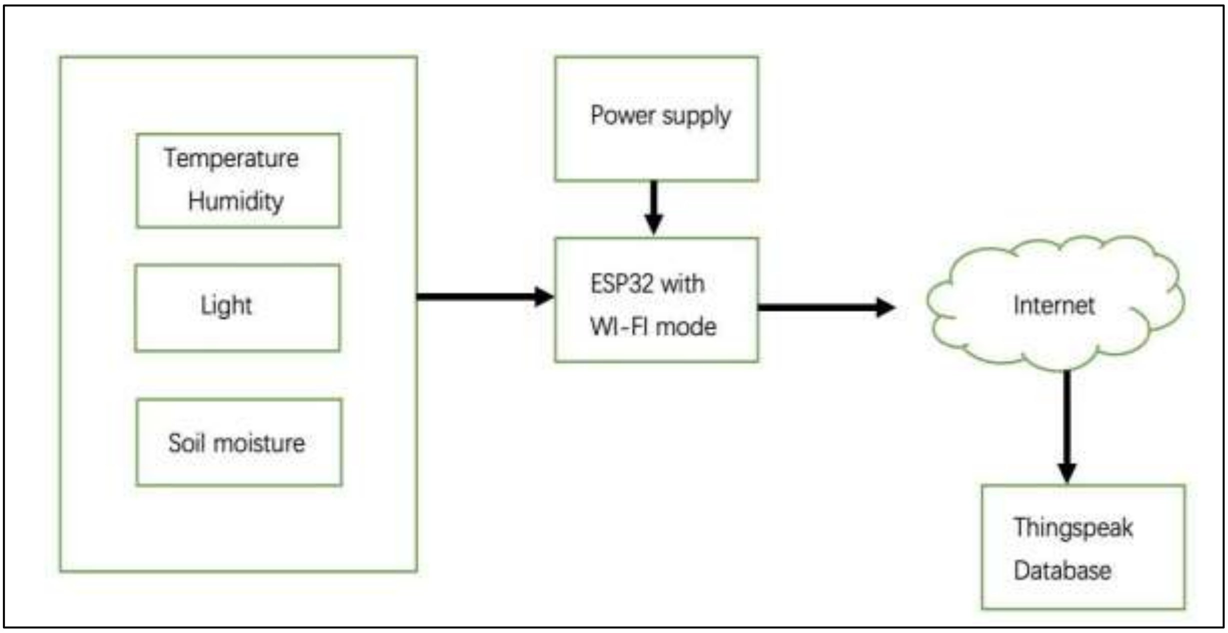
Combining agricultural IoT in the cultivation of medicinal plants like Labisia pumila under uncontrolled indoor environments has the potential to revolutionize the production of high-value nutraceutical and pharmaceutical products. This research contributes to the advancement of smart farming technology and provides a model for sustainable indoor farming practices for other medicinal plants. The overall objective of this research is to investigate the potential of a smart, multi-sensor, IoT-based system for plant growth environment monitoring under indoor conditions. The optimal environmental conditions, such as temperature, humidity, light, and soil moisture, for Labisia pumila indoor plant growth will be obtained through the statistical analysis. In this study, the dependent variables for analysis will encompass both morphological and physiological traits. These include leaf length, width, area, and perimeter, along with the average values of photosynthetic rates, stomatal conductance, and transpiration rates. By integrating these diverse variables, the study aims to provide a holistic understanding of the environmental factors governing the growth dynamics of Labisia pumila.

METHODOLOGY

Experimental Design

This study investigated the indoor growth of the forest medicinal plant Labisia pumila at Department of Physics, Universiti Malaya. An environmental monitoring system utilizing an ESP32 microcontroller was developed to continuously record temperature, humidity, light intensity, and soil moisture in real time. The collected data were wirelessly transmitted to the ThingSpeak platform for visualization and analysis (**Figure 1**).

Figure 1: IoT-Based Sensor System for Monitoring Labisia pumila Growth



Sensor Integration

The indoor monitoring stations were established and strategically positioned to ensure optimal sensor coverage and facilitate future system scalability. Each station employed an ESP32 development board for data acquisition and wireless transmission. The system (**Figure 2**) incorporated several sensors: a DHT22 for measuring temperature and humidity, an LM393 sensor for detecting light intensity, and a soil moisture sensor. The ESP32 microcontroller was programmed using the Arduino IDE, while its built-in Wi-Fi module enabled seamless real-time data transmission to the designated cloud platform. Frequent updates are achieved by uploading sensor data every 15 minutes, calculating hourly averages, and sending these to the ThingSpeak platform for visualization and monitoring. All sensors were experimentally calibrated to enhance measurement accuracy and maintain error

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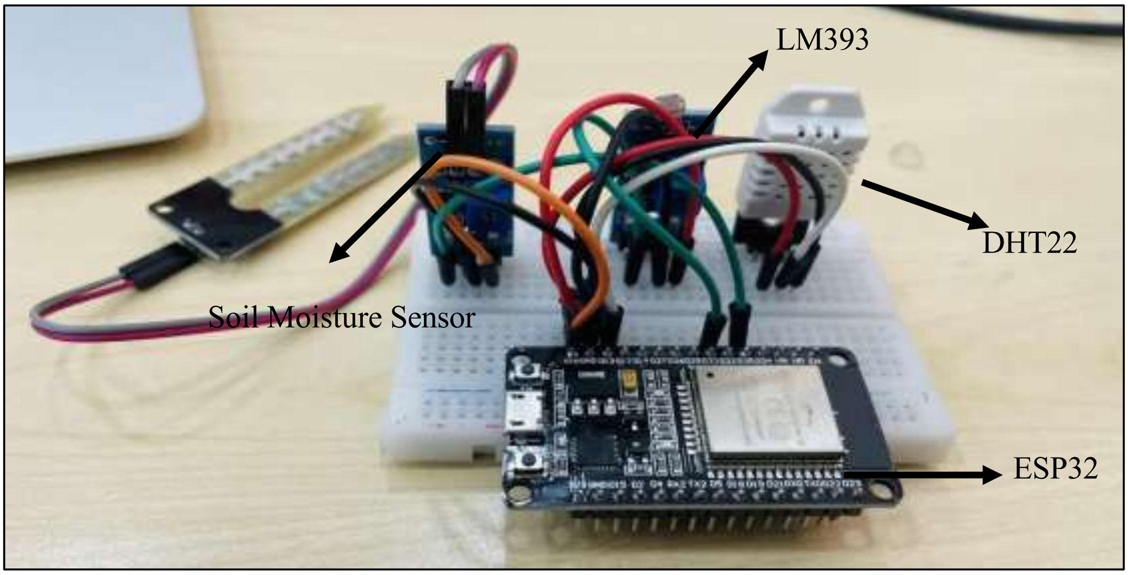
margins within acceptable ranges. Accuracy was then verified through manual tests by comparing sensor outputs with manually measured values. Data were collected and analyzed by this system for three months.

Figure 2: Hardware connection setup



Plant Growth Measurement

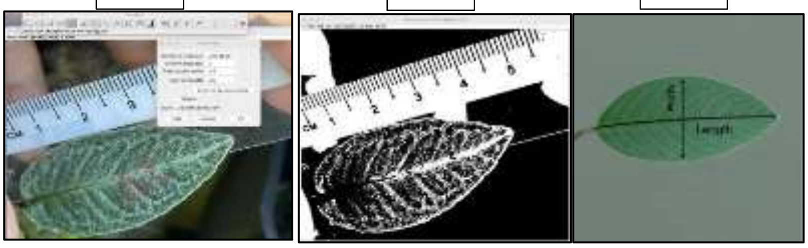
In this system, it is necessary to measure the growth changes of plants. To align the environmental factors data with plant growth measurements, the noon time window (12 to 1 PM) was chosen as the representative data point because it corresponds to a peak in physiological activity, such as photosynthesis and transpiration, giving a constant and accurate dataset for assessing the relationship between plant growth performance and environmental conditions.

Leaf Size

Leaf size measurements were conducted monthly over three months, specifically in August, September, and October of 2024. Seven groups of plants, with a total of 105 fully expanded leaves were chosen and ImageJ 1.8.0 was used to measure the length, width, area, and circumference of leaves. ImageJ is designed to handle various types of image data across many computing platforms and has been widely adopted for its utility and ease of use. Photos of the plant leaves were taken and samples of all leaves were numbered. A ruler was placed next to the leaf to provide a dimensional reference. At the same time, the leaves and the camera were kept as parallel to each other during shooting to ensure the accuracy of the test. The sampling diagram is shown in **Figure 3(a)-(c)**. The selected size in this system is measured in centimetres, and the size was re-determined for each photo. Then, the size of the leaves was measured using free-hand drawing tools. Grayscale processing of leaves was used to better highlight the outline of the leaves and improve the accuracy of testing.

Figure 3: (a) Leaf sample, (b) & (c) Determination of plant leaf size using ImageJ (Grayscale processing) based on the reference.

(a) **(b)** **(c)**



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Photosynthetic Rate, Transpiration Rate and Stomatal Conductance

Similarly, the photosynthetic rate, transpiration rate, and stomatal conductance were measured in August, September, and October of 2024 using a portable photosynthesis system (Li6400XT, LICOR, USA) in an open system mode between 1200 hr and 1300 hr. Ambient CO2 (Ca) was set at 400 ppm, while the temperature and Photosynthetically Active Radiation (PAR) were set according to the ambience in the leaf chamber, respectively. Additionally, the infra-red gas analyzer (IRGA) was zeroed after each measurement was taken.

Statistical Data Analysis

Principal Component Analysis (PCA) was used to identify the primary environmental factors influencing plant growth. The raw data comprises four environmental variables such as temperature, humidity, light intensity, and soil moisture. The analysis included calculating the principal components and visualizing the results with a biplot, which illustrates the relationships between the variables and the principal components. By evaluating the contributions of each variable to the principal components, the key environmental factors impacting plant growth were identified. This preliminary analysis provides valuable insights into the dominant factors affecting growth under varying conditions. Meanwhile, Pearson Correlation Coefficient (PCC) was employed to analyse relationships between environmental factors (temperature, humidity, light intensity, and soil moisture) and leaf growth indicators (area, length, perimeter). Higher correlation coefficients indicate stronger influences of specific environmental factors on plant growth, offering valuable insights for optimizing environmental conditions to enhance plant growth.

RESULTS AND DISCUSSION

Sensor Calibration

Although sensors are initially tested and calibrated individually during manufacturing, practical applications involving simultaneous sensor operation often produce measurement errors. Secondary testing and calibration are necessary to minimize these errors and enhance accuracy. This study tested and calibrated DHT22 temperature and humidity sensors within laboratory conditions. Two monitoring systems using ESP32 boards were simultaneously evaluated, and sensor outputs were visualized through ThingSpeak. Real-time temperature and humidity data were plotted in **Figure 4(a) & Figure 4(b)**, illustrating fluctuations and trends clearly over time. Additionally, manual tests verified sensor accuracy by comparing sensor outputs with manually measured values (**Figure 5**). **Figure 5(a)** shows that the orange dots represent sensor temperature data, the red dashed line represents the linear fitting line, and its equation is $y = 1.02x - 0.46$. The green solid line is the ideal line $y = x$. The blue dots in **Figure 5(b)** represent the humidity data of the sensor, the red dashed line represents the linear fitting line, and its equation is $y = 1.00x + 0.24$. The green solid line is the ideal line $y = x$. Results indicated a strong linear relationship and close alignment between sensor measurements and true values, confirming high sensor accuracy. Despite minor deviations, the data demonstrated reliability, validating the sensors' effectiveness in accurately monitoring environmental conditions.

Figure 4: (a) Temperature monitoring and (b) Humidity monitoring data captured by DHT22 in the ThingSpeak Channel.

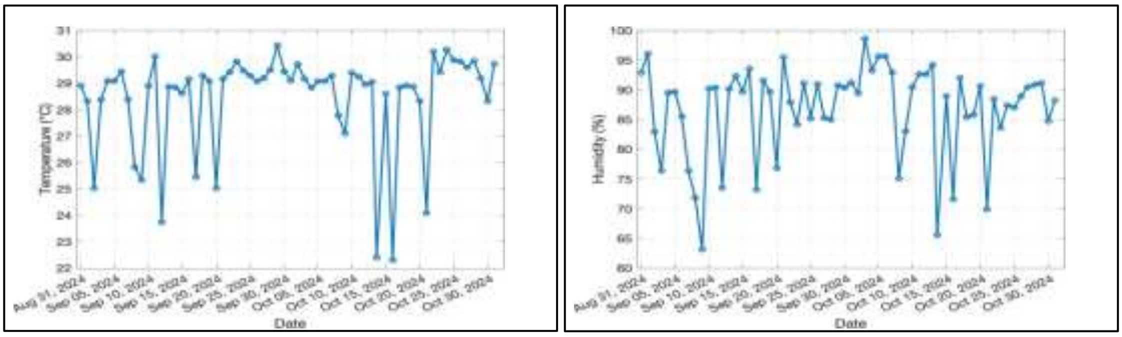

Figure 5: Linear Fitting Line between the true value and sensing value of (a) Temperature and (b) Humidity.

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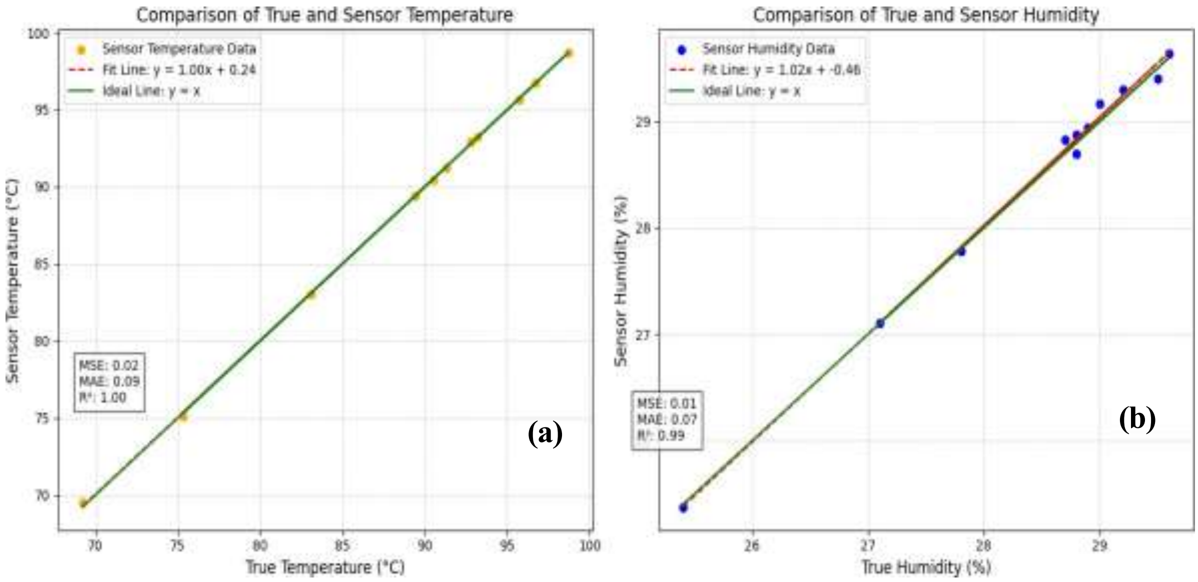

The light sensor used in this system is LM393. As LM393 is a universal comparator, its output signal is a digital signal (high or low), which can only represent the comparison result between the input signal and the set threshold and cannot directly provide the illumination value. Therefore, to meet the system design requirements of outputting light values in lux units, further processing of the output signal is required. **Figure 6(a)** shows the real-time test values of LM393.

Figure 6: (a) Light intensity monitoring data captured by LM393 and (b) Linear Fitting Line between the true value and sensing value of the light sensor.

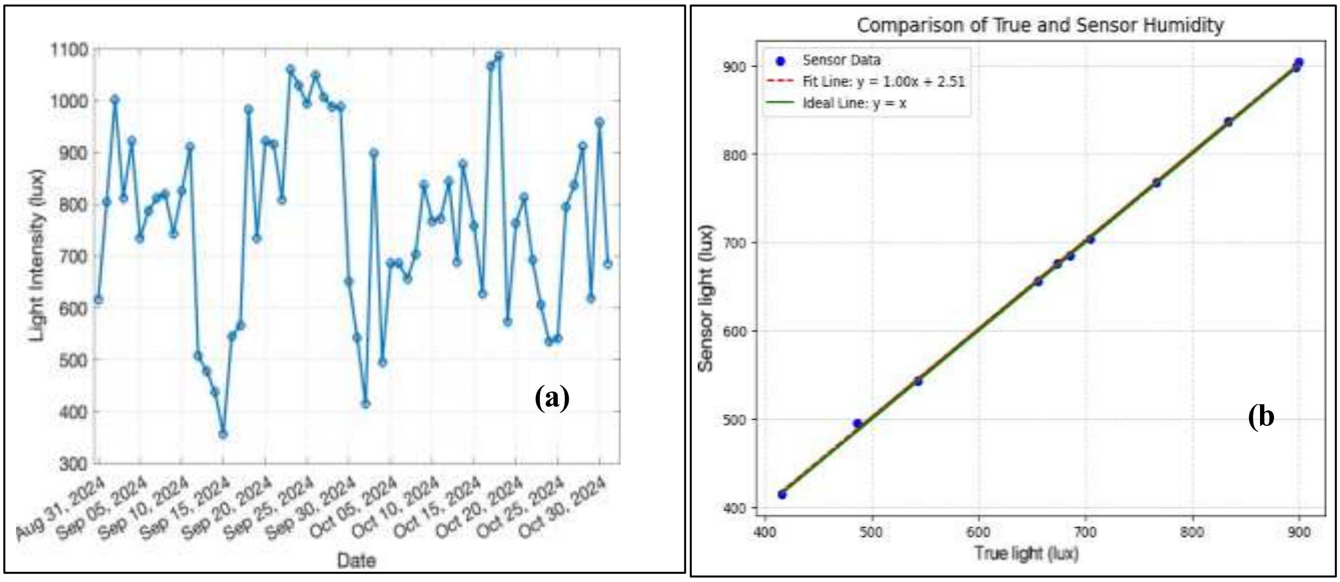

Figure 6(b) shows the comparison between the actual light values obtained through manual testing and the light values obtained through sensor testing. The blue dots in the figure represent the light values measured by the sensor under different real lights, and the red dashed line is the fitting line obtained by linear fitting based on the sensor data, with the equation $y = 1.00x + 2.51$. The ideal green line represents the straight line where the data point should fall if the sensor measurement is completely accurate, according to the equation $y = x$. From the graph, the height overlaps between the red fitting line and the green ideal line indicate a good linear relationship between the light values measured by the sensor and the true light values measured manually, with minimal deviation. Specifically, the slope of the fitted line is very close to the ideal slope, indicating that the light value measured by the sensor is highly consistent with the true value change. The intercept of the fitted line (2.51) indicates that there is a small constant deviation in the sensor, which can be used for calibration in practical applications. The blue dots in the figure are closely distributed around the red fitting line, indicating that the stability of the sensor measurement results is high, and the deviation is small.

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Figure 7: (a) Soil Moisture monitoring data and (b) Linear Fitting Line between the true value and sensing value of the soil moisture sensor.

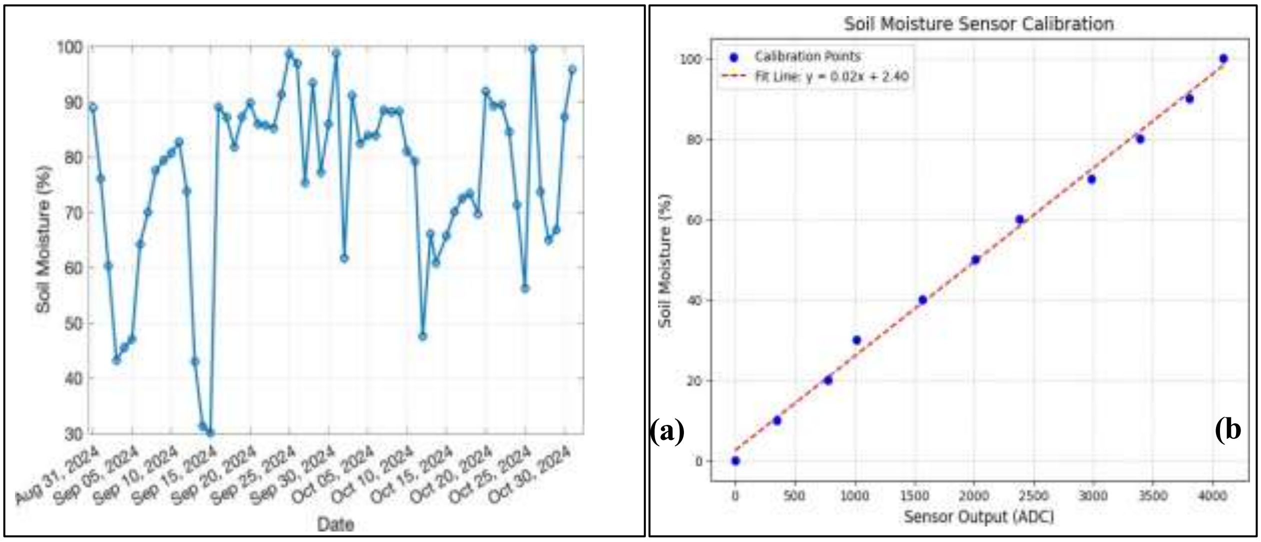


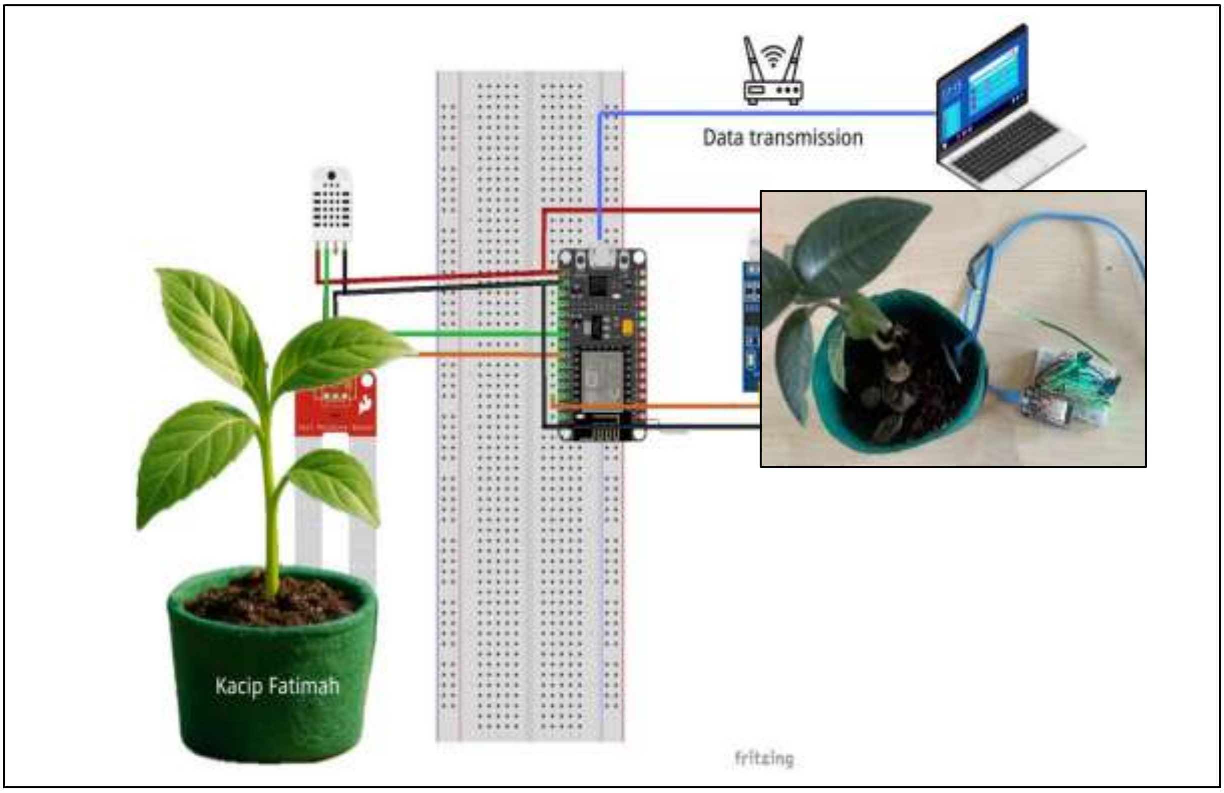
Figure 7(a) illustrates the real-time test values recorded by the soil moisture sensor, providing a detailed representation of its performance and accuracy during the testing process. To verify the reliability of the soil moisture sensor, the extreme value calibration method was used to test the output of the sensor under 0% and 100% humidity conditions. Specifically, fully exposing the sensor to dry air simulates a completely dry soil state, corresponding to a humidity of 0%. Immerse the sensor completely in water and simulate the saturated water-holding state of the soil, corresponding to a humidity of 100%. By recording the output values of the sensor under these two extreme conditions and collecting intermediate output data of the sensor under different humidity conditions, a mapping relationship between humidity percentage and sensor output is generated. Subsequently, linear fitting was performed on the collected data, as shown in **Figure 7(b)**. This graph indicates a clear linear relationship between sensor output values and actual soil moisture, which provides a basis for us to use sensor test values. Although there is a certain deviation between the calibration point and the fitting line, the overall fitting degree is good, indicating that the sensor can reliably reflect changes in soil moisture within the tested range. Therefore, the sensor test value can be used and has a certain degree of reliability. In the figure, the horizontal axis represents the analog-to-digital converter (ADC) value output by the sensor, and the vertical axis represents the actual measured soil moisture percentage. The blue dots represent calibration points, and the red dashed lines are the straight lines obtained by linear fitting of these points, with the equation $y = 0.02x + 2.40$.

Sensor Network Testing

Figure 8 illustrates the experimental setup used for monitoring the growth of Labisia pumila plants indoors. The soil moisture probe is inserted into the soil to measure the moisture levels, which are crucial for assessing the plant's hydration needs. The probe is connected to an IoT device on a breadboard, which consists of an ESP32 microcontroller, a temperature and humidity sensor, a light sensor, a soil moisture sensor, and additional wiring. This IoT device collects real-time indoor environment data and transmits it wirelessly for further analysis. The setup highlights the integration of sensor technology with IoT for efficient plant monitoring, enabling precise environmental control. The data is sent to the computer terminal by the ESP32 every hour. The results indicate that the data can be tested and sent according to the settings, the node networking is successful, and the data can be transmitted normally.

The findings indicated that when multiple sensors operate simultaneously, signal interference occurred, particularly between the two soil moisture sensors included in this system. Testing revealed that when the light sensor, temperature and humidity sensor, and one soil moisture sensor work together, the measurements remain consistent with the values obtained when the sensors operate individually. However, when both soil moisture sensors operate simultaneously, signal interference prevents accurate testing and also disrupts the power supply to the temperature and humidity sensor. To address these issues, a time interval of 200 ms is set for two soil moisture sensors to reduce interference, improve measurement accuracy, enhance data independence, and improve system processing efficiency. The temperature and humidity sensor is connected to a 5 V power supply. By changing the power supply voltage of the temperature and humidity sensor from 3.3 V to 5 V, the problems of unstable power supply voltage, insufficient current, and weak signal were resolved. This improves the operational reliability of DHT22 and avoids interference when multiple sensors are running simultaneously.

Figure 8: Sensor hardware connection setup for the growth rate monitoring of Labisia pumila.



Plant Growth Data Testing

By manually measuring and confirming the test results and comparing the data, it can be concluded that the average data obtained through ImageJ testing is the same as the actual data obtained, and the collected results have high accuracy (**Table 1**). The collected data can accurately provide the length and width of the leaves.

Table 1: Comparison of leaf size measurements

Group	Manual length(cm)	ImageJ length(cm)	Manual width(cm)	ImageJ width (cm)	Length difference(cm)	Width difference(cm)
1	3.6	3.606	1.8	1.846	0.006	0.046
2	3.2	3.190	1.8	1.820	-0.01	0.020
3	4.1	4.102	2.3	2.226	0.002	-0.074
4	4.5	4.443	2.4	2.413	-0.057	0.013
5	6.2	6.127	2.7	2.686	0.027	-0.014
6	7.8	7.861	3.6	3.632	0.061	0.032
7	6.2	6.200	3.6	3.580	0.000	-0.020

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In addition to the growth data collected by the system design, including length and width, three variables, photosynthetic rate, stomatal conductance, and transpiration rate, are also added as dependent variables for analysis. The data of photosynthetic rate, stomatal conductance, and transpiration rate were measured and theaverage values were presented in **Table 2**. All the data entered after sorting is shown in the table, and the data is entered in units of months.

Table 2: Data collected and analyzed by the IoT system

Variables	August	September	October
Temperature (°C)	28.04	28.56	28.17
Humidity (%)	85.82	86.52	88.63
Light (lux)	952.47	974.57	945.09
Soil Moisture (%)	75.34	88.17	77.9
Leaf Length (cm)	3.32	4.58	5.01
Leaf Width (cm)	2.14	2.46	2.77
Leaf Area (cm^2)	4.63	9.58	11.55
Leaf Perimeter (cm)	9.97	11.51	12.66
Photosynthetic Rate ($\mu molCO_2m^{-2}s^{-1}$)	10.73	22.19	23.14
Stomatal Conductance ($molH_2Om^{-2}s^{-1}$)	0	0.00086	0.00682
Transpiration Rate ($mmolH_2Om^{-2}s^{-1}$)	0	0.02386	0.21323

The biplot of principal component analysis (PCA) is shown in **Figure 9**. The characteristic values and contribution rates of each principal component are shown in **Table 3**, and the explained variance ratio of each principal component group is shown in **Table 4**. According to **Table 4**, PC1 explains 92 % of the total variance, indicating that almost all changes in variables can be explained by PC1. PC2 explained 7.8 % of the total variance, and its contribution is relatively small, which may describe some subtle changes between variables. PC1 and PC2 together explained 99.8 % of the total variance, indicating that the PCA model effectively captures the main variability in the data. Meanwhile, in this model, PC1 is the main direction of data changes. According to **Table 3**, the main contribution characteristics of PC1 are soil moisture and light intensity, followed by temperature, and finally, humidity. The contribution rates are 73.70 %, 62.85 %, 24.30 %, and -5.36 %, respectively. The contribution rate of soil moisture and light to PC1 is the highest, while the contribution rate of humidity to PC1 is the lowest, compared to soil moisture and light intensity. Although temperature has a smaller contribution to PC1, it still has a positive effect. The main contribution characteristics of PC2 are humidity and soil moisture, followed by temperature and light intensity. The contribution rates are 66.14 %, 45.95 %, 19.76 %, and -55.89 %, respectively. Overall, PC1 alone explains most of the data changes, and almost all the main patterns of change can be identified through PC1 analysis. Among them, light (load of 0.6285) and soil moisture (load of 0.7370) are the factors that contribute the most to PC1, which directly indicates the dominant role of these two environmental factors. That is to say, from the macro perspective of overall data changes, soil moisture and light intensity are the main driving factors affecting leaf growth. However, this does not mean that they are the sole cause of plant growth changes, and other potential environmental factors and interactions also need to be considered. Thus, correlation analysis was used to explore the relationship between the independent and dependent variables.

Figure 9: Principal Component Analysis Chart

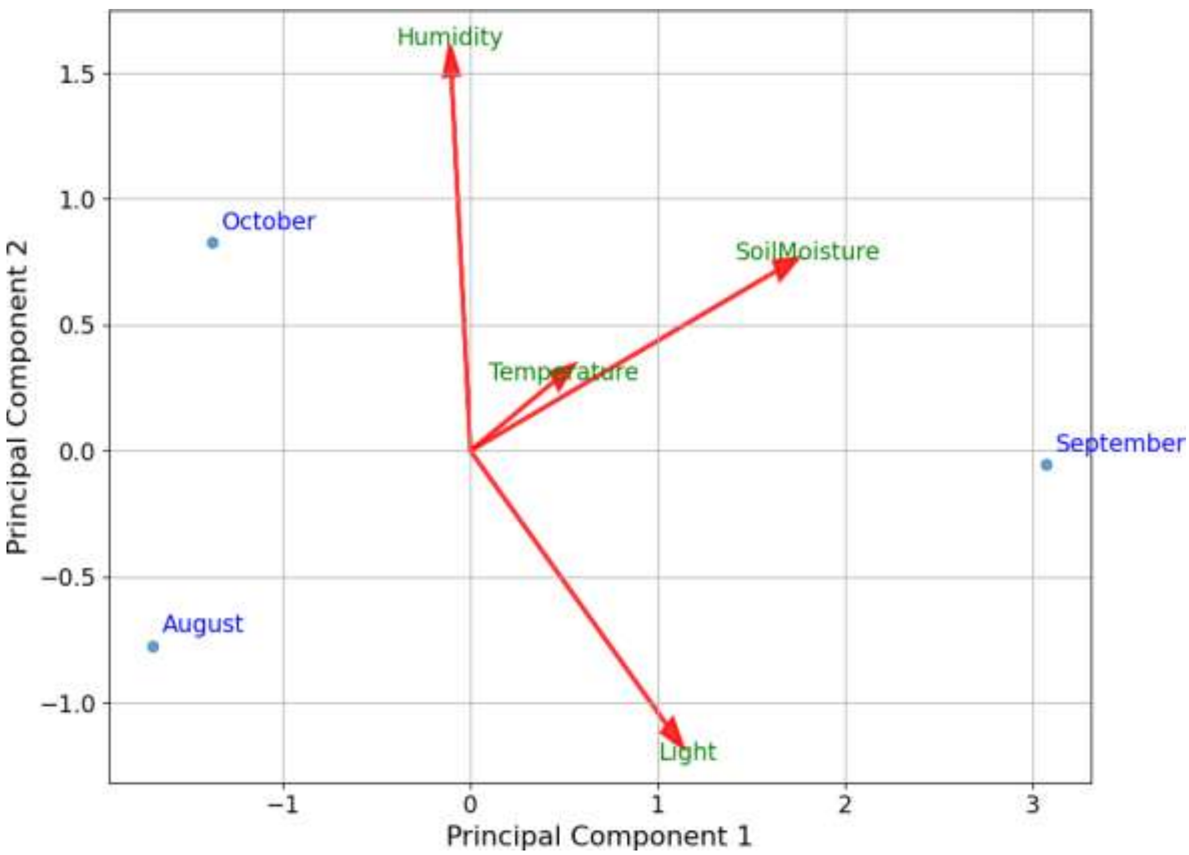

Table 3: Principal component characteristic values and contribution rate

Principal component	**PC1 contribution rate**	**PC2 contribution rate**
Temperature	0.2430	0.1976
Humidity	-0.0536	0.6614
Light	0.6285	-0.5589
Soil Moisture	0.7370	0.4595

Table 4: Explained Variance Ratio

Principal component group	**Explained Variance Ratio**
PC1	0.920
PC2	0.078

The Pearson correlation analysis results show a strong interaction between the independent and dependent variables (**Table 5**). Analysis of the above results shows that humidity has a strong correlation among multiple growth indicators, especially width, area, and perimeter. However, this result does not conflict with the results obtained from PCA analysis. Correlation analysis emphasizes the direct impact of environmental factors on individual growth indicators and is the result obtained from micro-level analysis. That is to say, humidity may show a strong correlation in certain growth indicators, but it does not dominate the overall trend and only has a strong impact on individual growth indicators. Meanwhile, we can infer that the high correlation between humidity and width and area may be the reason for the high humidity load on PC2 in PCA.

Table 5: Pearson Correlation Coefficient

	Temperature	Humidity	Soil Moisture	Light
Length	0.8559	0.5504	0.8821	0.9983
Width	0.1782	0.9903	0.2300	0.6168
Area	0.4673	0.8650	0.4199	0.1800
Perimeter	0.3203	0.9339	0.2698	0.1587
Photosynthetic Rate	0.6422	0.7407	0.6007	0.2103
Stomatal Conductance	0.1643	0.9921	0.2162	0.6056
Transpiration Rate	0.1778	0.9903	0.6165	0.2296

Growth Index

Data standardization has been applied to independent variables (temperature, humidity, light intensity, and soil moisture) and dependent variables (length, width, etc.) (**Table 6** & **Table 7**) and a new PCA was performed to identify underlying patterns and reduce dimensionality.

Table 6: Standardized dependent variables

Month	Length	Width	Area	Perimeter	Photosynthetic Rate	Stomatal Conductance	Transpiration Rate
August	-1.371	-1.231	-1.359	-1.279	-1.411	-0.844	-0.828
September	0.386	0.012	0.341	0.118	0.621	-0.561	-0.578
October	0.985	1.218	1.018	0.161	0.790	1.405	1.407

Table 7: Standardized independent variables

Month	Temperature	Humidity	Light	Soil Moisture
August	-0.981	-0.980	-0.392	-0.925
September	1.373	-0.394	1.373	1.389
October	-0.392	1.373	-0.981	-0.464

This analysis extracted three primary principal components (PC1, PC2, and PC3), which collectively explain the majority of the variance in the combined data. These principal components offer a consolidated perspective on the relationships between environmental factors and plant growth metrics. Among them, PC1 explained 67.49 % of the total variance of the data, which is mainly composed of dependent variables such as length, width, and photosynthetic rate. Therefore, PC1 is defined as a comprehensive growth indicator to measure the overall growth status of plants. PC2 explained 32.47 % of the total variance, mainly contributed by the independent variables (light, soil moisture, and temperature), representing the comprehensive impact of environmental conditions on plant growth. The contribution rate of PC3 is extremely low (approximately 0.04), indicating that its impact on the overall model can be ignored. The cumulative interpretation rate of PC1 and PC2 reached 99.96 %, indicating that PC1 and PC2 can effectively summarize the information of the original data.

Table 8: Principal component load value

	PC1	PC2	PC3
Temperature	0.1033	0.5074	0.0739
Humidity	0.3479	-0.1687	0.3051
Light	-0.0730	0.5182	0.3051
Soil Moisture	0.0845	0.5146	0.3051
Length	0.3570	0.1224	0.0201
Width	0.3668	-0.0177	0.3150
Area	0.3596	0.1056	-0.2770
Perimeter	0.3667	0.0216	-0.3771
Photosynthetic Rate	0.3663	0.2118	-0.3127
Stomatal Conductance	0.3304	-0.2301	0.2214
Transpiration Rate	0.3282	-0.2366	-0.1878

In PC1, the load values of width, perimeter, area, and photosynthetic are relatively high. In PC2, the load values of light, soil moisture, and temperature are relatively high, especially light and soil moisture, indicating that these variables have a significant impact on plant growth in different months. The analysis results are consistent with separate analyses of environmental factors. In PC3, the humidity load value dominates, indicating that it has a certain degree of independence, but its contribution to the comprehensive index is relatively small. Finally, the system uses PCA analysis to calculate the growth index and identify the optimal growth environment. The comprehensive growth rate is defined as the score of the first PC1. Because PC1 explains most of the variance, and PC1 is more dominated by the dependent variable of leaf growth changes, it is reasonable to choose PC1 for analyzing growth rate. Combining **Table 6, Table 7 and Table 8**, standardized values and simultaneously standardized values can be obtained according to formula (1.0):

$$PC1 = w_1 \cdot Z_1 + w_2 \cdot Z_2 + \cdots + w_p \cdot Z_p \qquad (1.0)$$

Where, $w_1, w_2 \ldots w_p$ is the principal component loading value of the corresponding variable.

$Z_1,\ Z_2\ \ldots\ Z_p$ is the standardized variable value. In this way, the comprehensive growth rate for each month can be obtained. In this analysis, the environmental conditions in September were considered the most suitable for plant growth. Through further optimization analysis, we have identified the optimal environmental conditions shown in **Figure 9**.

Table 9: Optimal indoor environmental conditions for the growth of Labisia pumila

Temperature	28.56 ℃
Humidity	85.82 %
Light	974.57 lux
Soil Moisture	88.17 %

CONCLUSIONS

This study investigated the suitable indoor growth environment for Labisia pumila using a self-designed monitoring and analysis system. A multi-sensor system based on the ESP32 microcontroller was developed to enable comprehensive environmental monitoring. The system collected real-time data and transmitted it via Wi-Fi to the ThingSpeak IoT platform, forming a stable cloud-based framework. Statistical and computational analyses verified the system's accuracy, confirming its feasibility. A measurement system tailored for small potted plants was constructed, integrating sensor acquisition nodes, wireless communication, and PC-based monitoring software. The system automatically collected, stored, and processed environmental data, uploading it periodically for further analysis. Integrated temperature, humidity, light, and soil moisture sensors were calibrated to ensure reliable measurements, enhancing precision and stability. Experimental results showed that soil moisture and light intensity were the dominant factors influencing leaf growth, while temperature and humidity had secondary yet measurable effects. Optimal growth conditions for Labisia pumila were determined at 28.56 °C, 85.82 % relative humidity, 974.57 lux light intensity, and 88.17 % soil moisture. These findings demonstrate the system's potential for real-time environmental monitoring and support practical applications in smart indoor agriculture.

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Competing and Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article. There is no conflict of interest to disclose.

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