

Solar Drying System Based on Multi-Parameter AI Model

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ABSTRACT

Agricultural drying strongly affects post-harvest product quality and storage stability. This study develops a smart solar drying system integrating multi-parameter sensing, electrical storage, water-based thermal storage, an Industrial IoT V-box, and a Siemens S7-1200 PLC. Temperature, relative humidity, solar irradiance, airflow, and CO₂ concentration were monitored to characterize the drying environment. A hierarchical Random Forest framework was developed to estimate the chamber temperature, relative humidity, and coffee moisture content. Leave-one-day-out validation yielded pooled R² values of 0.909 and 0.890 for indoor temperature and relative humidity, respectively. The moisture model achieved R²=0.882, MAE = 0.472 percentage points, and RMSE = 0.740 percentage points against the sensor reference. The Random Forest models were executed on the V-box, while the PLC acquired sensor data and controlled the actuators. The results demonstrate the feasibility of integrating data-driven estimation with PLC-based supervision for solar coffee drying.

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1. INTRODUCTION

Agricultural drying is a critical post-harvest process that directly affects product quality, storage stability, and economic value [1], [2]. Fundamental studies on drying technology emphasize the role of heat and mass transfer mechanisms as well as drying kinetics in system design [3]. However, in practice, many small-scale and semi-industrial agricultural drying systems are still developed based on empirical experience, leading to unstable drying performance and limited adaptability to varying environmental conditions.

To improve drying stability, several solar drying systems with automatic temperature and humidity control have been proposed, including PID-based, ON–OFF [4], and hybrid control approaches [5], [6]. Although these methods can enhance local stability of temperature or humidity, they generally focus on one or two variables and do not adequately consider multi-parameter interactions or drying kinetics [7], [8]. In parallel, the use of electrical or fossil-fuel-based heat sources has been reported to shorten drying time [9], but at the cost of increased energy consumption, operational expenses, and reduced sustainability [10].

Solar-powered drying systems, particularly greenhouse-type dryers, have emerged as a sustainable alternative by exploiting the greenhouse effect to enhance drying temperature [11], [12], [13]. Nevertheless, many of these systems still operate in passive or semi-automatic modes, lacking real-time monitoring of key environmental parameters such as temperature, humidity, solar radiation, and airflow [14], [15]. As a result, evaluating energy efficiency and drying quality under fluctuating climatic conditions remains challenging [16], [17].

Recent advances in IoT, sensing technologies, and data acquisition systems have enabled real-time monitoring in post-harvest and drying applications [18]. However, most implementations remain at the experimental level and are not fully integrated with industrial control platforms, limiting their long-term

applicability [19]. Moreover, despite growing interest in data-driven and AI-based approaches for post-harvest processes [20], [21], agricultural drying systems still predominantly rely on threshold-based or rule-based control strategies [22], [23]. Advanced predictive control methods, such as MPC and deep-learning-based frameworks, have been reported, but their computational complexity and modeling requirements hinder practical deployment in small-scale solar dryers [24], [25].

Existing solar drying studies have extensively investigated ON–OFF, PID, fuzzy, and rule-based control methods for regulating temperature and relative humidity. Therefore, the contribution of this study does not lie in proposing a fundamentally new control theory. Instead, the research addresses the practical integration gap between multi-parameter environmental monitoring, data-driven prediction, renewable-energy utilization, and industrial control implementation. In addition to temperature and relative humidity, the proposed system simultaneously monitors solar irradiance, outdoor wind velocity, indoor CO₂ concentration, and product moisture content. In particular, CO₂ is used as an auxiliary indicator of product respiration, air exchange, and ventilation conditions inside the drying chamber.

2. RESEARCH METHOD

2.1. Theoretical Basis and Energy Balance–Based Design

Agricultural drying systems are designed to reduce product moisture to safe storage levels while minimizing degradation of sensory and nutritional quality. For common grains such as rice, maize, and legumes, a safe drying temperature typically ranges from 40 to 55 °C, ensuring an adequate drying rate with limited thermal damage, which is particularly suitable for solar greenhouse-based dryers [26].

To maintain effective moisture transfer without excessive surface drying, the relative humidity inside the drying chamber is commonly controlled within 40–60%. The target final moisture content, typically 13–14% for grain products, is a key indicator of drying effectiveness and long-term storability [27].

Solar drying systems are generally designed to complete the drying process within a single day by maximizing solar energy utilization and minimizing auxiliary energy consumption, which is activated only under unfavorable conditions. In this context, the coordinated design of the drying chamber and ventilation system is critical for maintaining thermal–moisture balance and achieving high energy efficiency.

The thermal energy used in the drying process is primarily consumed for evaporating the moisture that must be removed from the agricultural product. The energy required for the drying process can be expressed as [3]:

$$Q_{total} = Q_{evap} + Q_{loss} = m_w \times r + Q_{loss} \quad (1)$$

Where: m_w (kg) is the mass of water that needs to be removed from the agricultural product, r (kJ/kg) is the latent heat of vaporization of water, Q_{loss} (kJ) is the energy loss.

$$Q_{loss} = U \times A \times (T_{in} - T_{out}) \quad (2)$$

With U (W/m²·K) is being the overall heat transfer coefficient, T_{in} , T_{out} are the temperatures inside and outside the drying chamber, respectively. The greenhouse effect allows solar radiation to be converted into thermal energy inside the drying chamber, thereby increasing the internal air temperature. The heat gained from solar radiation can be expressed as [12]:

$$Q_{solar} = G \times A \times \eta \quad (3)$$

Where G (W/m²) is the solar radiation intensity, A (m²) is the radiation collection area, and η is the overall heat collection efficiency of the drying chamber [28].

2.2. Effect of Multiple Environmental Parameters on the Drying Process

Effect of Ambient Temperature on the Drying Process: The internal temperature T_{in} directly affects the evaporation of moisture from the material surface by controlling the saturation vapor pressure. Higher drying temperatures increase the vapor pressure at the material surface, thereby enhancing the moisture diffusion rate.

The drying rate can be expressed in a simplified form as [26]:

$$\frac{dM}{dt} = -k_T \left(\frac{p_{vs}(T_{in})}{p_{v,air}} - 1 \right) \quad (4)$$

Where M is the moisture content of the material, k_T is the temperature-dependent drying coefficient, $p_{vs}(T_{in})$ is the saturation vapor pressure at the internal drying temperature, and $p_{v,air}$ is the partial vapor pressure of water in the drying air.

Effect of Ambient Humidity on the Drying Process: To relate relative humidity to absolute humidity, the following expression is used:

$$w = 0.622 \times \frac{RH \times p_{vs}(T)}{p_{atm} - RH \times p_{vs}(T)} \quad (5)$$

Where RH is the relative humidity, $p_{vs}(T)$ is the saturation vapor pressure at temperature T , and p_{atm} is the atmospheric pressure.

The moisture removal process can be described using a simplified first-order drying kinetics model:

$$\frac{dM}{dt} = -k_h D w \quad (6)$$

Where: k_h is the effective mass transfer coefficient, which depends on airflow conditions and drying chamber configuration. For practical drying system analysis, the above relationship can be approximated as:

$$\frac{dM}{dt} = -C(\omega_{in} - \omega_{out}) \quad (7)$$

Where ω_{in} and ω_{out} are the absolute humidity of the air inside and outside the drying chamber, C is a lumped parameter reflecting the combined effects of airflow rate, turbulence, and material properties.

Effect of Ambient Wind Speed on the Drying Process: During the drying process, the moisture reduction of the material is influenced simultaneously by the convective airflow inside the drying chamber and the ambient wind speed outside. These two factors determine the intensity of moisture exchange between the material surface and the surrounding air. The moisture reduction process of the material can be described by the following expression:

$$\frac{dM}{dt} = -k(v_{in}, v_{out})(M - M_e) \quad (8)$$

M_e is the equilibrium moisture content, v_{in} is the internal convective air velocity, v_{out} is the ambient wind speed, and k is the overall mass transfer coefficient that depends on both factors. As v_{in} and v_{out} increase, the coefficient k increases accordingly, resulting in a higher moisture reduction rate and significantly improved drying efficiency.

Effect of CO₂ Generated by Agricultural Products on the Drying Process: During the drying process, fresh agricultural products continue to undergo respiration and biological decomposition, generating CO₂ that alters the air composition inside the drying chamber. The accumulation of CO₂ reduces the vapor pressure gradient and the oxygen (O₂) concentration, thereby weakening convective airflow and slowing the moisture diffusion rate. Therefore, controlling and removing CO₂ through ventilation or fan control is necessary to maintain drying efficiency and product quality. The moisture reduction process, considering the effect of CO₂, can be generally expressed as:

$$\frac{dM}{dt} = -k(C_{CO_2})(M - M_e) \quad (9)$$

Where C_{CO_2} is the CO₂ concentration inside the drying chamber, and k is the mass transfer coefficient that depends on the ventilation condition and the gas composition.

2.3. Development of a Multi-Parameter Model for the Drying Process

From a methodological perspective, this study does not propose a new Random Forest algorithm. The main contribution lies in the development of a two-layer Random Forest model integrated with multi-parameter experimental data. The first layer predicts the drying chamber microclimate from the outdoor environmental conditions, while the second layer uses the predicted microclimate to estimate the moisture content of the agricultural product. This hierarchical structure improves the interpretability of the model and provides a clearer understanding of the relationship between environmental factors and the drying process.

Before model training, the one-minute sensor records were chronologically ordered and screened for missing, duplicate, non-numeric, and physically invalid values. The resulting datasets contained 6,196 environmental records collected from 25–29 January 2026 and 1,432 product-moisture records collected on 28 January 2026. The Random Forest regressors used 200 trees, a maximum depth of 10, bootstrap sampling, and a fixed random seed of 42. Feature scaling was not applied because tree-based models are insensitive to differences in input scales. The moisture-model inputs comprised indoor temperature, indoor relative humidity, and elapsed drying time. Model performance was evaluated using R², MAE, and RMSE.

The drying process can be regarded as a multiple-input–single-output (MISO) system, in which the output is the moisture reduction rate:

$$\frac{dM}{dt} = f(T_{in}, T_{out}, G_s, RH_{in}, RH_{out}, v_{in}, v_{out}, C_{CO_2}) \quad (10)$$

Converted into a dynamic (kinetic) form:

$$\frac{dM}{dt} = k_{eff}(t) \left(M(t) - M_e(t) \right) \quad (11)$$

$$\text{Where: } k_{eff} = k_0 \frac{\left(\frac{T_{in}}{T_{ref}} \right)^{\frac{a}{b}} \left(\frac{G_s}{G_{ref}} \right)^{\frac{b}{c}} \left(\frac{v_{in}}{v_{ref}} \right)^{\frac{c}{d}}}{\left(\frac{T_{in}}{T_{ref}} \right)^{\frac{a}{b}} \left(\frac{G_s}{G_{ref}} \right)^{\frac{b}{c}} \left(\frac{v_{in}}{v_{ref}} \right)^{\frac{c}{d}}} - \frac{RH_{in}}{100} \exp(-hC_{CO2})$$

Integrated Control Law (Applied to the Automatic Drying System):

$$u(t) = w_1(T_{in} - T_{ref}) + w_2(RH_{ref} - RH_{in}) + w_3(v_{in}) - w_4C_{CO2} \quad (12)$$

Where $u(t)$ is the control signal for the circulation fan, exhaust fan, and auxiliary heater, and w is the weighting coefficient. The AI model used to predict the moisture reduction rate is based on the Random Forest algorithm.

The agricultural drying process is simultaneously influenced by multiple environmental parameters and can be modeled as a multiple-input–single-output system. The input vector of the model includes:

$$X = [T_{in}, T_{out}, G_s, RH_{in}, RH_{out}, v_{in}, v_{out}, C_{CO2}] \quad (13)$$

Where the output of the system is the moisture reduction rate of the agricultural product:

$$y = \frac{dM}{dt} \quad (14)$$

Random Forest is an ensemble machine learning algorithm that consists of multiple decision trees trained in parallel on different subsets of the data. Each decision tree produces a prediction, and the final output is obtained by averaging the predictions of all trees.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(X) \quad (15)$$

Where $T_i(X)$ denotes the i -th decision tree and N is the total number of trees in the forest.

The performance of the models is evaluated using the $RMSE$, MAE , and the coefficient of determination R^2 . The root mean square error (RMSE) is defined as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (16)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (17)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (18)$$

Where: $\hat{y}$ is the predicted value of the moisture reduction rate, y_i is the experimentally measured moisture reduction rate, and $\bar{y}$ is the experimental mean value.

In this study, the Random Forest model is not only used for environmental prediction but also integrated into an AI-assisted monitoring and supervisory control framework. Based on the predicted internal temperature and humidity, control actions are selected to ensure drying quality while minimizing auxiliary energy consumption.

To reduce temporal leakage, the indoor-environment model was evaluated using leave-one-day-out cross-validation on 6,196 records collected from 25–29 January 2026. For product-moisture evaluation, 1,432 synchronized records collected on 28 January 2026 were used to compare the model-calculated moisture content M with the sensor-measured value M_I . This evaluation represents within-batch model–sensor agreement rather than independent temporal or external validation.

2.4. Control Law for the Smart Solar Drying System

The control objective of the proposed solar-assisted agricultural drying system is to maintain appropriate drying conditions while minimizing auxiliary electrical energy consumption. Due to the strong variability of solar radiation and ambient environmental conditions, the control strategy is designed to be simple, robust, and suitable for implementation on a PLC platform, while still exploiting predictive information from data-driven models. The Siemens S7-1200 PLC collects real-time sensor data and transmits them to the Industrial IoT V-box through the industrial communication network. The trained Random Forest model is

deployed on the V-box to process the data, perform real-time predictions, and calculate the appropriate control commands. These commands are then transmitted back to the PLC to control the circulation fans, exhaust fan, circulation pump, ventilation system, and auxiliary heaters. To improve operational reliability under unexpected weather conditions, the Industrial IoT V-box checks whether the measured environmental inputs remain within the ranges represented in the training dataset. If an input is outside the validated range or the Random Forest prediction is unavailable, the predictive command is rejected, and the Siemens S7-1200 PLC switches to a conventional threshold-based control mode.

The drying process is influenced by multiple environmental parameters and can be represented by the following discrete-time dynamic model:

$$M(k+1) = f(M(k), x(k), u(k)) \quad (19)$$

Where $M(k)$ is the moisture content of the agricultural product,

$x(k) = [T_{out}, RH_{out}, G, v_{out}, C_{CO2}]^T$ is the vector of environmental inputs,

$u(k)$ is the control action applied at time step k , including circulation fan speed, exhaust fan operation, ventilation state, and auxiliary heating.

Based on the outputs of the hierarchical Random Forest models, an optimal control-oriented formulation is introduced to describe the future development of the supervisory control system. In this formulation, the control vector u represents the operating states of the circulation fan, exhaust fan, water pump, and auxiliary heater. The objective is to select an appropriate control action that drives the predicted moisture content toward the target value while limiting auxiliary energy consumption. At the present stage, this formulation provides a mathematical direction for optimizing the control input u ; it has not yet been implemented as a complete online optimization algorithm. A Random Forest model is employed to approximate the nonlinear mapping:

$$(M_{pred}(k+1|k, u) = \hat{f}_{RF}(M(k), x(k), u(k)) \quad (20)$$

The control vector $u(k)$ is based on the minimization of a cost function that balances drying accuracy and energy efficiency

$$u^*(k) = \underset{u}{\operatorname{argmin}} [(M_{pred}(k+1|k, u) - M_f)^2 + \alpha E_{aux}(u)] \quad (21)$$

$$W = \{u(k) | 0 \leq s_{cir}, s_{ex}, s_{pump} \leq 1, z_{heat} \in \{0, 1\}, 40^\circ \text{C} \leq T_{in} \leq 55^\circ \text{C}, 45\% \leq RH_{in} \leq 55\%\}. \quad (22)$$

Where: $u(k) = [s_{cir}, s_{ex}, s_{pump}, z_{heat}]^T$, s_{cir} , s_{ex} , and s_{pump} are normalized control commands for the circulation fan, exhaust fan, and circulation pump, respectively, while z_{heat} is the auxiliary-heater state. The admissible control set is defined as. $M_{pred}(k+1|k, u)$ is the predicted moisture content of the agricultural product at time $k+1$, obtained from the Random Forest model combined with the drying kinetics model, taking into account the effect of the control action $u(k)$. M_f is the target moisture content after drying; $E_{aux}(u)$ is the auxiliary electrical energy consumption associated with the control action; and α is the weighting coefficient that balances drying quality and energy consumption.

At each control interval, the Siemens S7-1200 PLC collects real-time sensor data and transmits them to the Industrial IoT V-box through the industrial communication network. In the present implementation, the Random Forest models are executed on the Industrial IoT V-box to estimate the chamber conditions and product moisture content. The PLC acquires sensor data and operates the actuators according to predefined supervisory rules. Equations (20)–(22) provide a basis for future online optimization and were not solved during the reported experiment.

3. RESULTS AND DISCUSSION

3.1 Experimental Drying System Calculation

A solar-powered agricultural drying system based on the greenhouse effect is designed, incorporating both solar electrical energy storage and thermal (water-based) energy storage, and tailored to the climatic conditions of Gia Lai, Vietnam, in order to ensure drying quality and optimal energy efficiency.

The design parameters include a fresh agricultural product mass of $m=200$ kg, an initial moisture content of $M_0=25\%$, and a target final moisture content of $M_f=14\%$. The average ambient temperature is $T_{out}=25^\circ\text{C}$, while the ambient relative humidity varies from 20% to 98% throughout the day.

The selected design coefficients are as follows: the heat radiation transfer correction factor $\alpha=1.2$ (polycarbonate material), the convection-enhanced moisture transfer factor $\beta=1.05$ (forced-air drying with fans), and the baseline moisture transfer coefficient $k_0=0.05$ (grain-type agricultural products).

The target operating conditions inside the drying chamber are an internal temperature of $T_{in} = 40\text{--}55^\circ\text{C}$ and an internal air relative humidity of 45%–55%, which are suitable for grain products.

Based on these data, the authors designed and calculated the following drying system:

The drying chamber has dimensions of length $L=2.5$ m, width $W=2.0$ m, and height $H=2.5$ m. The structure is made of transparent polycarbonate covering all side walls and the roof (Figure 1).

The solar power system is equipped with a 5 kWh battery storage, ensuring continuous operation for up to 12 hours under no-sun conditions.

A 300-liter water-based thermal storage tank is used, providing sufficient thermal energy to support the drying system for 12 hours during nighttime operation.

External measured parameters include ambient temperature, relative humidity, wind speed, and solar radiation.

The continuously measured internal variables include temperature, relative humidity, CO_2 concentration, and sensor-based product moisture content M_t .

The control cabinet consists of an inverter, a 4G WiFi module, an industrial IoT V-box, a Siemens S7-1200 PLC, and switching/protection devices.

Control devices inside the drying system include a circulation pump and heat exchanger for the thermal storage tank, a dehumidifying exhaust fan, circulation fans, and infrared heating lamps.



Figure 1. Experimental Drying System

3.2 Experimental Results of the Multi-Parameter Effects on the Moisture Reduction Rate

The trial involved a single batch of coffee sourced from Dak Doa, Gia Lai, during which the system demonstrated stable operational performance.

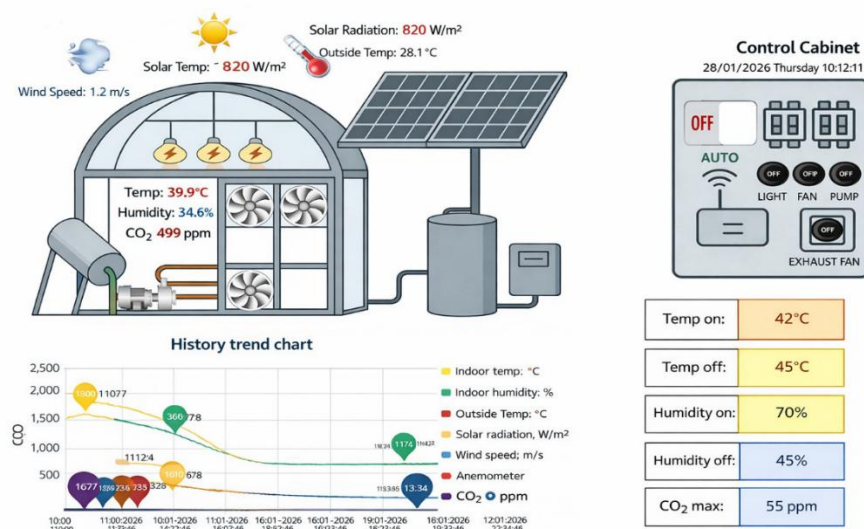


Figure 2. Remote monitoring dashboard using Industrial Internet of Things (IIoT)

The experiment was conducted on a single 200 kg coffee batch monitored from 25 to 29 January 2026 at approximately one-minute intervals. Because the daily records originated from the same batch, they were temporally correlated and were not treated as independent experimental replicates. The data from 28 January were selected for moisture analysis because they contained 1,432 complete synchronized records of T_{in} , RH_{in} , sensor-measured moisture content M_I , and model-calculated moisture content M . These data represent within-batch temporal evaluation rather than independent external validation.

The influence of multiple environmental parameters (T_{out} , G , RH_{out} , V_{out}) on the indoor temperature T_{in} : The variation in internal temperature T_{in} was analyzed as a function of multiple environmental parameters, specifically ambient temperature T_{out} , solar irradiance G , outdoor relative humidity RH_{out} , and air velocity V_{out} .

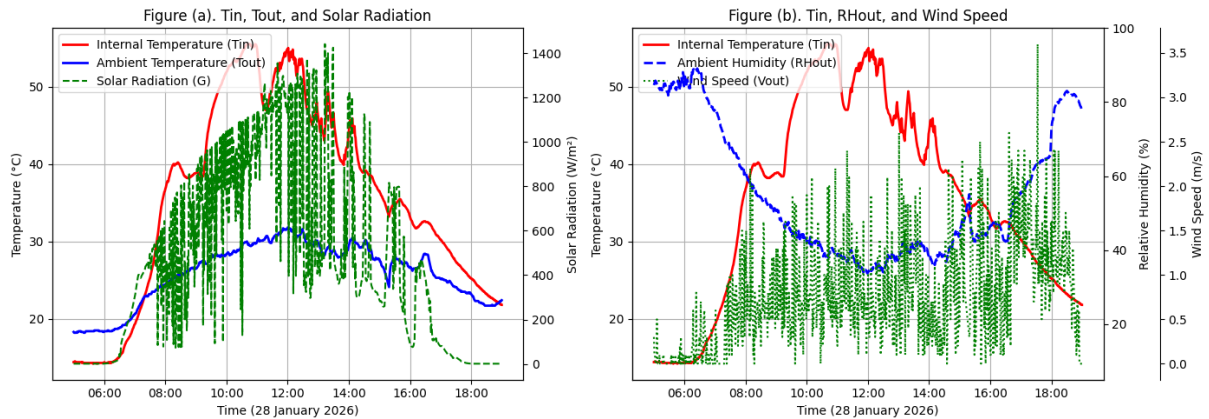


Figure 3. Effects of external factors on internal temperature

The combined results presented in Figure 3 provide a comprehensive view of the influence of ambient environmental conditions on the internal thermal and drying behavior of the system. The left figure demonstrates that the internal temperature closely follows the variation of solar radiation and remains significantly higher than the ambient temperature throughout the drying period, confirming the dominant role of radiative heat input and the effectiveness of the greenhouse effect. In contrast, the right figure indicates that ambient humidity and wind speed primarily affect the convective and mass transfer conditions rather than directly governing the internal temperature dynamics. Together, these observations are consistent with the multi-parameter drying model proposed in Section 2.3, in which solar radiation determines the thermal driving force, while ambient humidity and wind speed modulate moisture removal efficiency.

The internal temperature T_{in} of the drying system is significantly influenced by a multiparameter set of environmental factors, specifically ambient temperature T_{out} , solar irradiance G , outdoor relative humidity RH_{out} , and wind velocity V_{out} . The correlation coefficient between T_{in} and solar radiation reached 0.91 during peak drying hours.

The results indicate that the internal relative humidity is strongly influenced by solar radiation through its effect on air temperature, leading to a rapid decrease in RH_{in} during periods of high irradiance. In addition, ambient humidity directly affects the internal moisture level via ventilation-driven mass transfer, while wind speed mainly enhances convective exchange without governing the overall trend. These observations are consistent with the coupled heat and mass transfer model described in Section 2.3.

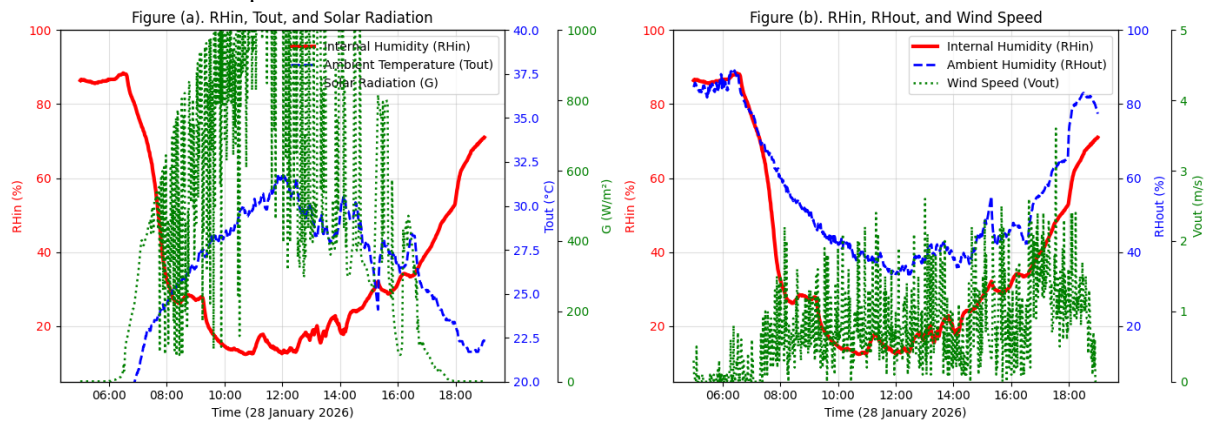


Figure 4. Effects of external factors on internal humidity

Investigation of the influence of CO_2 concentration on the internal microclimate parameters, specifically T_{in} and RH_{in}

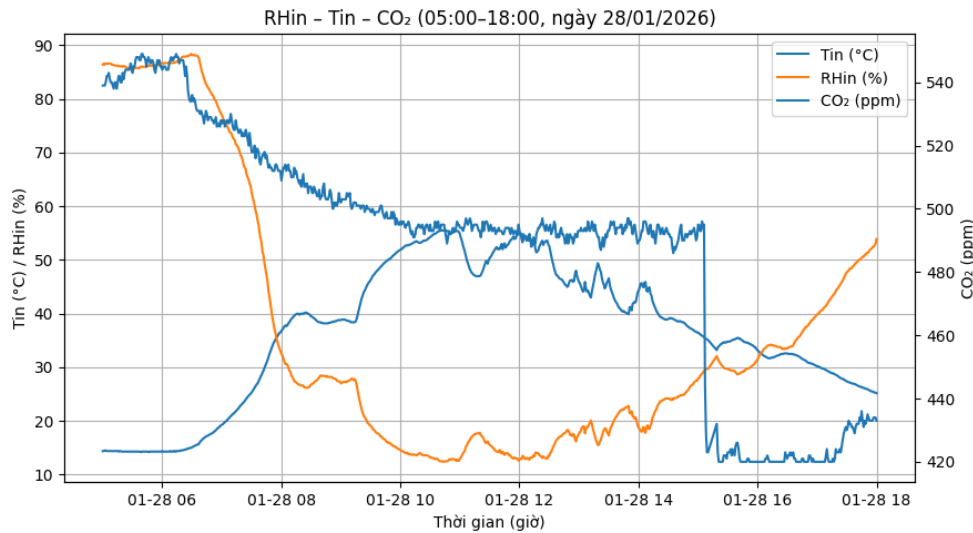


Figure 5. Effects of external factors on internal CO_2 concentration

The results indicate a clear relationship between indoor CO_2 concentration, temperature, and relative humidity. An increase in CO_2 concentration, typically associated with reduced ventilation, is accompanied by a rise in indoor temperature due to heat accumulation. In the initial stage, higher CO_2 levels also coincide with increased relative humidity; however, as temperature continues to increase, RH_{in} decreases as a result of enhanced moisture-holding capacity of warm air. Conversely, a reduction in CO_2 concentration leads to a decrease in both temperature and humidity, highlighting CO_2 as an effective indicator of indoor air exchange and thermal moisture conditions.

3.3. Experimental Modeling of the Drying System

An AI-based two-layer prediction model is developed to estimate the internal environmental conditions and the moisture content of agricultural products. In the first layer, outdoor environmental variables, including outdoor relative humidity (RH_{out}), outdoor temperature (T_{out}), solar radiation (G), CO_2 concentration, and ventilation velocity (V_{out}), are used as input features [24]. The outputs of the first layer are the indoor temperature (T_{in}) and indoor relative humidity (RH_{in}).

In the second layer, the predicted T_{in} , RH_{in} , and elapsed drying time are used to calculate the product moisture content M . This hierarchical modeling structure enables the separation of environmental prediction and product-level moisture estimation, improving model interpretability and overall prediction accuracy.

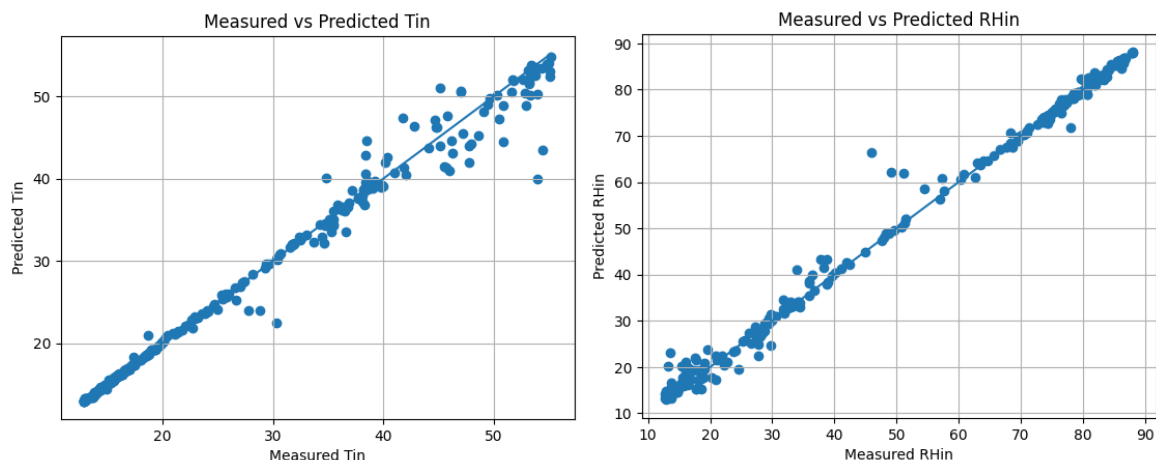


Figure 6. Results of the Random Forest

We consider an AI-based model with two directly measured output variables: the indoor temperature T_{in} and the indoor relative humidity RH_{in} of the drying system. These two variables play a decisive role in the *Solar Drying System Based on Multi-Parameter AI Model (Do Van Can et al)*

moisture reduction process of coffee. The input variables include the outdoor temperature T_{out} , outdoor relative humidity RH_{out} , solar radiation G , wind speed v_{out} , and CO_2 concentration.

$$T_{in} = f_{AI}(T_{out}, RH_{out}, G, v_{out}, CO_2) \quad (23)$$

$$RH_{in} = f_{AI}(T_{out}, RH_{out}, G, v_{out}, CO_2) \quad (24)$$

The figure 6 shows a very strong correlation between the measured temperature values and those predicted by the Random Forest model. The data points are closely clustered along the ideal line $y = x$, indicating a small prediction error and the model's ability to accurately capture the nonlinear relationship between the internal temperature and the environmental input variables. Minor deviations can be observed in the high-temperature range; however, they do not significantly affect the overall predictive accuracy of the model.

For the internal relative humidity, the Random Forest model demonstrates very high accuracy, as the data points almost perfectly overlap with the $y = x$ line across the entire value range. This confirms that the model not only predicts the variation trend of RH_{in} effectively but also maintains strong stability, reflecting its capability to learn efficiently from experimental data and its suitability for humidity prediction in enclosed environments.

The results of the analysis of the influence level of the input variables and the corresponding index evaluation are presented as follows.

Table 1. Feature importance and prediction accuracy of the Random Forest model for indoor environmental variables

Feature Importance (%)		Output variable	R ²	MAE	RMSE
Feature	Importance (%)	T_{in}	0.909	2.795°C	3.750 °C
RH_{out}	49.46%	RH_{in}	0.890	6.224%	8.472%.
T_{out}	46.46%				
G (Solar radiation)	2.00%				
CO_2	1.82%				
V_{out}	0.27%				

RH_{out} and T_{out} are the two most dominant factors governing the indoor variables T_{in} and RH_{in} . Solar radiation (G) and CO_2 have secondary effects, reflecting their role in microclimate regulation and ventilation intensity. V_{out} shows only a minor influence in this dataset, indicating that the ventilation system is not yet a primary controlling factor.

A multi-output Random Forest regressor was trained using T_{out} , CO_2 concentration, outdoor humidity, ventilation velocity, and solar radiation as inputs to predict T_{in} and RH_{in} . To provide a more reliable assessment and reduce temporal leakage between adjacent one-minute observations, the model was evaluated using leave-one-day-out cross-validation. The fold-wise results are presented in Table 2. The pooled evaluation achieved $R^2 = 0.909$, $MAE = 2.795$ °C, and $RMSE = 3.750$ °C for T_{in} . For RH_{in} , the corresponding values were $R^2 = 0.890$, $MAE = 6.224\%$, and $RMSE = 8.472\%$. The lower performance on 29 January was mainly associated with the limited partial-day dataset of 544 observations.

Table 2. Leave-one-day-out cross-validation results for indoor temperature and relative humidity prediction

Fold/day	n	T R ²	T MAE	T RMSE	RH R ²	RH MAE	RH RMSE
2026-01-25	1439	0.932	2.505	3.168	0.878	6.290	8.310
2026-01-26	1438	0.925	2.399	3.638	0.971	3.544	4.840
2026-01-27	1343	0.898	2.653	3.249	0.883	6.195	7.369
2026-01-28	1432	0.901	2.994	4.246	0.864	6.953	10.298
2026-01-29	544	0.585	4.436	5.007	0.431	11.285	12.637
Pooled	6196	0.909	2.795	3.750	0.890	6.224	8.472

In Layer 2, the objective is to model and predict the moisture content of agricultural products based on the internal drying conditions. To ensure physical consistency and academic rigor, a physics-based surrogate model is developed to describe the moisture evolution as a function of temperature, relative humidity, and drying time.

A Random Forest regressor is trained to learn the nonlinear mapping

$$[T_{in}(k), RH_{in}(k), t(k)] \otimes M(k) \quad (25)$$

$$M = M_f + (M_0 - M_f)^{(-a(T_{in} - T_0) + b(RH_{in} - RH_0))} \quad (26)$$

Where: a is the coefficient representing the effect of T_{in} , b is the coefficient representing the effect of RH_{in}

The influence of internal humidity and temperature on the moisture content of agricultural products

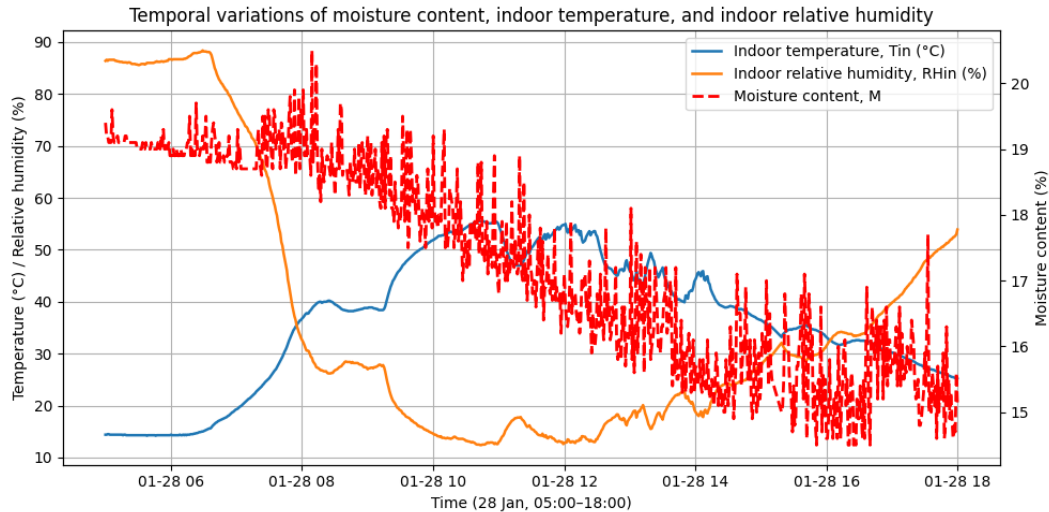


Figure 7. Temporal variation of indoor temperature, indoor relative humidity, and model-calculated coffee moisture content on 28 January 2026

The results clearly indicate that the moisture content (M) of the agricultural product is strongly influenced by the coupled variation of indoor air temperature (T_{in}) and indoor relative humidity (RH_{in}). As T_{in} increases during the daytime, the saturation vapor pressure of air rises, enhancing the moisture-holding capacity of the drying air. Consequently, RH_{in} decreases significantly, leading to a larger vapor pressure gradient between the product surface and the surrounding air. This condition accelerates moisture diffusion and evaporation, resulting in a rapid reduction of moisture content.

During the period of peak solar radiation (approximately 09:00–14:00), the drying chamber exhibits high T_{in} and low RH_{in} , which corresponds to the highest moisture removal rate. In contrast, during the early morning and late afternoon, lower T_{in} combined with higher RH_{in} reduces the driving force for mass transfer, causing a slower decrease in moisture content. These observations confirm that T_{in} and RH_{in} jointly govern the drying kinetics, and their interaction plays a decisive role in determining the overall moisture reduction behavior of the system.

The model was evaluated using blocked temporal cross-validation to reduce information leakage between adjacent one-minute observations.

Table 3. Feature importance and performance evaluation of the Random Forest model for moisture content prediction

Reference variable	Calculated variable	n	R ²	MAE	RMSE	Correlation
M_1 , sensor measured	M , model calculated	1,432	0.882	0.472%	0.740%	0.963

The model-calculated moisture content M was evaluated against the sensor-measured value M_1 . For the 1,432 synchronized records, the resulting R², MAE, RMSE, and Pearson correlation coefficient were 0.882, 0.472%, 0.740%, and 0.963, respectively. These results indicate good agreement within the investigated batch but do not constitute independent batch-level validation. respectively, demonstrating a low prediction error despite the presence of experimental noise [25].

The leave-one-day-out evaluation produced pooled R², MAE, and RMSE values of 0.909, 2.795 °C, and 3.750 °C, respectively, for indoor-temperature prediction. For indoor relative humidity, the corresponding values were 0.890, 6.224%, and 8.472%. These blocked-validation results are lower than the values obtained from the original random 80/20 split, indicating that random partitioning of adjacent one-minute observations produced an optimistic estimate. The revised results therefore provide a more conservative assessment of

performance on an unseen day. The model-calculated moisture content M was evaluated against the sensor-measured value M_1 , achieving $R^2 = 0.882$, $MAE = 0.472\%$, and $RMSE = 0.740\%$. These results demonstrate agreement within the investigated coffee batch but do not constitute independent batch-level validation. Further experiments using multiple coffee batches and independently verified moisture references are required.

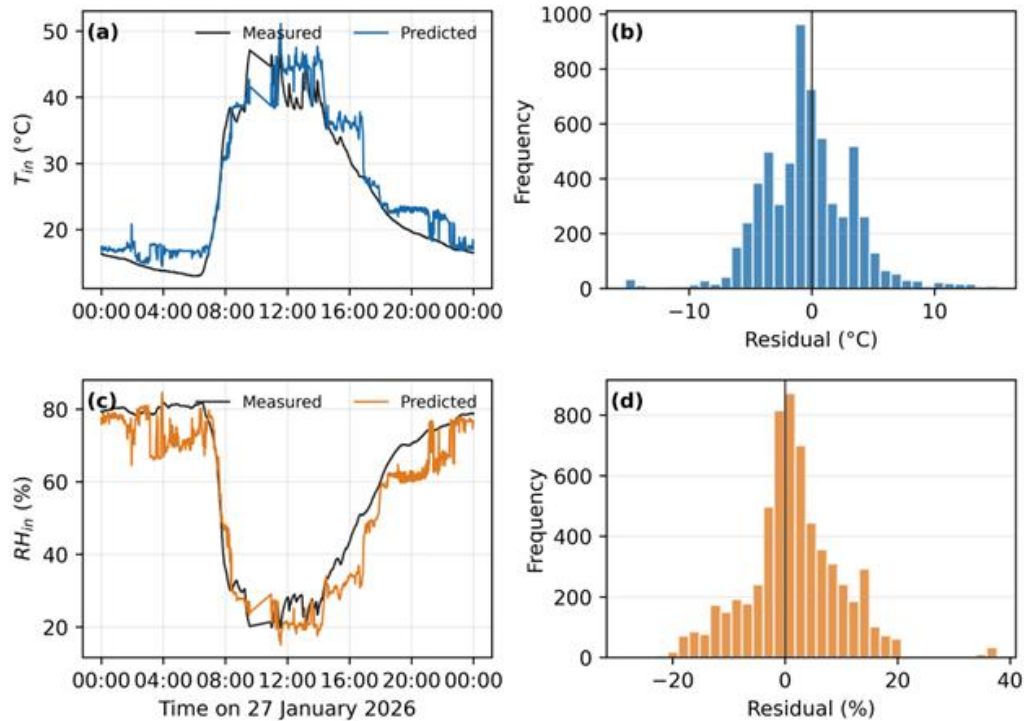


Figure 8. Leave-one-day-out predictions and residual distributions for indoor temperature and relative humidity

3.4. Comparison with Conventional Control Strategies

The Random Forest model was trained using data collected during a five-day experimental period and may therefore be sensitive to climatic conditions outside the observed range. Abrupt variations in solar irradiance, temperature, humidity, or wind velocity may reduce prediction accuracy. Consequently, the present results demonstrate performance only within the investigated climatic range and do not establish seasonal robustness.

A percentage-based comparison with conventional rule-based control strategies reported in the literature is used to evaluate the performance of the proposed AI-based approach.

Table 4. Qualitative comparison of agricultural drying approaches

Criterion	Rule-based [29]	PID/Fuzzy [8]	MPC/Deep learning [25]	Proposed system
Operating principle	Fixed thresholds	Feedback control	Predictive optimization	RF-assisted supervision PLC
Monitored variables	Mainly temperature and RH	Temperature and RH	Multiple variables	Temperature, RH, irradiance, wind, CO ₂ , and moisture
Moisture estimation	Usually unavailable	Usually unavailable	Sometimes available	Included and experimentally evaluated
Industrial integration	Limited	Moderate	Implementation-dependent	S7-1200 PLC and IIoT V-box
Computational demand	Low	Low-moderate	Moderate-high	Moderate
Validation	Operating response	Set-point tracking	Mainly simulation/laboratory	Five-day coffee-drying data with blocked validation

Table 4 qualitatively compares the proposed system with existing drying approaches. Unlike conventional rule-based and PID/fuzzy methods, the proposed system integrates multi-parameter sensing, hierarchical Random Forest estimation, and PLC-based supervision. It also estimates product moisture and was evaluated using five-day coffee-drying data. However, because alternative controllers were not tested under identical conditions, the comparison does not demonstrate direct quantitative superiority in drying time or energy consumption.

Although the comparison is based on literature-reported results under similar climatic conditions, slight variations in experimental setups may exist. The comparison results indicate that the proposed AI-based predictive control significantly reduces auxiliary energy consumption while maintaining stable drying conditions. Compared to conventional threshold-based control, the proposed method achieves lower temperature fluctuations and shorter drying time, demonstrating its suitability for small-scale smart drying systems.

4. CONCLUSION

This study proposed an energy-efficient smart solar agricultural drying system based on multi-parameter analysis and AI-assisted control. By exploiting the greenhouse effect and integrating thermal and electrical energy storage, the system ensures stable operation under variable climatic conditions. Experimental results confirm that solar radiation governs the internal temperature, while relative humidity, airflow, and CO₂ concentration jointly influence moisture removal efficiency. A hierarchical Random Forest-based model accurately predicts indoor conditions and moisture content, achieving $R^2=0.882$, MAE =0.472%, and RMSE =0.740%. Future work will extend the dataset across multiple seasons and weather conditions, incorporate model-drift detection, and periodically retrain the Random Forest model to improve robustness under unexpected climatic variations. Compared with conventional rule-based control strategies reported in the literature, the proposed AI-based approach provides improved drying stability, reduced auxiliary energy consumption, and shorter drying time, demonstrating its suitability for small-scale smart solar drying applications.

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REFERENCES

- [1] M. Faisal *et al.*, “Recent Advances in Technologies for Preserving Fresh-Cut Fruits and Vegetables,” *Foods*, vol. 14, no. 16, pp. 1–26, 2025, doi: 10.3390/foods14162769.
- [2] S. Shankar, A. K. Mohanty, J. R. DeEll, K. Carter, R. Lenz, and M. Misra, “Advances in antimicrobial techniques to reduce postharvest loss of fresh fruit by microbial reduction,” *npj Sustain. Agric.*, vol. 2, no. 1, 2024, doi: 10.1038/s44264-024-00029-x.
- [3] Trần Văn Phú, “Công nghệ sấy và bảo quản nông sản,” in *NXB Khoa học & Kỹ thuật*, NXB Khoa học & Kỹ thuật, 2018, p. 278.
- [4] M. A. Arifin, P. Pangaribuan, B. A. Pramudita, and P. Megantoro, “Controlling temperature using proportional integral and derivative control algorithm for hybrid forced convection solar dryer,” vol. 14, no. 1, pp. 239–247, 2024, doi: 10.11591/ijece.v14i1.pp239-247.
- [5] L. A. Alkahdery, A. V. Yurchenko, J. A. K. Mohammed, and Y. G. Neshina, “Automated Temperature and Humidity Control and Monitoring System for Improving the Performance in Drying System,” *Eurasian Phys. Tech. J.*, vol. 20, no. 2–44, pp. 32–40, 2023, doi: 10.31489/2023No2/32-40.
- [6] T. . Shikhare, Y. . Bhange, and A. . . Vibhute, “Review of Temperature Conditioning for Solar Dryer,” *Int. Res. J. Eng. Technol.*, vol. 05, no. 04, pp. 5–7, 2018.
- [7] S. C. S. N, V. K. Kaushik, S. Saha, and S. M, “Solar-Powered Crop Drying with Automated Temperature and Humidity Control: A Comprehensive Analysis,” *Int. J. Adv. Trends Eng. Manag.*, pp. 25–34, 2025.
- [8] N. Abdenouri, A. Zoukit, I. Salhi, and S. Doubabi, “Model identification and fuzzy control of the temperature inside an active hybrid solar indirect dryer,” *Sol. Energy*, vol. 231, no. April 2021, pp. 328–342, 2022, doi: 10.1016/j.solener.2021.11.026.
- [9] Nguyễn Xuân Trung, Đinh Vương Hùng, “Thiết bị sấy nông sản bằng năng lượng mặt trời tại việt nam,” *Khoa học công nghệ*, vol. Số 11, no. NXB Khoa học & Kỹ thuật, 2018., pp. 4–8, 2013.
- [10] L. Labrot-Rhodes, E. Campo, and P. Poujaud, “Review of monitoring systems for stored grains in a modified atmosphere,” *Heliyon*, vol. 11, no. 3, p. e42347, 2025, doi: 10.1016/j.heliyon.2025.e42347.
- [11] H. Chouikhi and B. M. A. Amer, “Performance Evaluation of an Indirect-Mode Forced Convection Solar Dryer Equipped with a PV/T Air Collector for Drying Tomato Slices,” *Sustain.*, vol. 15, no. 6, 2023.
- [12] Arjoo, YADvikA2 and Y.k. YADAv, “Performance Evaluation of a Solar Tunnel Dryer For Around the Year Use,” *Curr. Agric. Res. J.*, vol. 5, no. 3, pp. 414–421, 2017.
- [13] N. V. N. Van Thi Thuy Trang, Hoang Thi Hang, Pham Quynh Nhi, Nguyen Thanh Trung, Nhat-Le Bui Dang, Thanh-Lieu Thi Le, Le Thi Cam Nhung, Do Van Can, Hao Van Bui, and N. and L. Le Thi, “Enhancement of

- Photothermal Conversion by TiN Nanoparticles Embedded Black Paint and Applications in Solar Drying,” *MDPI, Mater. Artic.*, vol. 17, no. 4393, pp. 1–15, 2024.
- [14] L. Protopappas, D. Bechtsis, and N. Tsotsolas, “IoT Services for Monitoring Food Supply Chains,” *Appl. Sci.*, vol. 15, no. 13, pp. 1–17, 2025, doi: 10.3390/app15137602.
- [15] T. Miller, G. Mikiciuk, I. Durlik, M. Mikiciuk, A. Łobodzińska, and M. Śnieg, “The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies,” *Sensors*, vol. 25, no. 12, pp. 1–32, 2025, doi: 10.3390/s25123583.
- [16] B. B. Sharma *et al.*, “Enhancing post-harvest sustainability in temperate crops through smart IoT-integrated indirect solar dryer,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–15, 2025, doi: 10.1038/s41598-025-13499-x.
- [17] D. Schmidt, L. F. Casagrande, M. A. Butturi, and M. A. Sellitto, “Digital Technologies, Sustainability, and Efficiency in Grain Post-Harvest Activities: A Bibliometric Analysis,” *Sustain.*, vol. 16, no. 3, 2024, doi: 10.3390/su16031244.
- [18] N. E. Mansour *et al.*, “Effect of Drying Conditions on Kinetics, Modeling, and Thermodynamic Behavior of Marjoram Leaves in an IoT-Controlled Vacuum Dryer,” *Sustain.*, vol. 17, no. 13, pp. 1–33, 2025, doi: 10.3390/su17135980.
- [19] W. R. G. Gomez, “Web-Based SCADA: Data Acquisition, Control and Energy Monitoring of Dryers,” *Mindanao J. Sci. Technol.*, vol. 23, no. 2, pp. 226–250, 2025, doi: 10.61310/mjst.v23i2.2497.
- [20] D. M. Rodrigues, P. C. Coradi, L. P. R. Teodoro, P. E. Teodoro, R. dos S. Moraes, and M. M. Leal, “Monitoring and predicting corn grain quality on the transport and post-harvest operations in storage units using sensors and machine learning models,” *Sci. Rep.*, vol. 14, no. 1, pp. 1–23, 2024,
- [21] T. G. Hoffmann *et al.*, “Challenges and future perspectives in postharvest cold storage: technological review on sustainable and efficient cold storage of fresh produce,” *Food Res. Int.*, vol. 221, no. P3, p. 117406, 2025, doi: 10.1016/j.foodres.2025.117406.
- [22] A. Boulemtafes-Boukadoum and A. Benzaoui, “Energy and exergy analysis of solar drying process of mint,” *Energy Procedia*, vol. 6, pp. 583–591, 2011, doi: 10.1016/j.egypro.2011.05.067.
- [23] K. Usmanov, N. Yakubova, S. Sultanova, and Z. Turakulov, “Fuzzy-Logic-Based Intelligent Control of a Cabinet Solar Dryer for Plantago major Leaves Under Real Climatic Conditions in Tashkent †,” pp. 1–14, 2025.
- [24] T. Anukiruthika and D. S. Jayas, “AI-driven grain storage solutions: Exploring current technologies, applications, and future trends,” *J. Stored Prod. Res.*, vol. 111, no. May, 2025,
- [25] I. M. C. Paddy and D. Process, “Deep-Learning-Based Model Predictive Control of an,” *MPI foods*, vol. 13, no. 43, pp. 1–21, 2024, doi: 10.3390/foods13010043.
- [26] C. Kumar, M. A. Karim, and M. U. H. Joardder, “Intermittent drying of food products : A critical review,” *J. Food Eng.*, vol. 121, pp. 48–57, 2014, doi: 10.1016/j.jfoodeng.2013.08.014.
- [27] M. Saif and H. Ahmed, “Effect of Storage Temperature and Periods on Some Characteristics of Wheat Flour Quality,” no. September, pp. 1148–1159, 2015.
- [28] Arun S. Mujumdar, “Handbook of Industrial Drying,” in *CRC Press is an imprint of Taylor & Francis Group*, CRC Press., 2014, p. CRC Press is an Impr. Taylor Fr. Gr.
- [29] M. A. Tawfik, K. M. Oweda, M. K. Abd El-Wahab, and W. E. Abd Allah, “A New Mode of a Natural Convection Solar Greenhouse Dryer for Domestic Usage: Performance Assessment for Grape Drying,” *Agric.*, vol. 13, no. 5, 2023,

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