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AI-DRIVEN OPTIMIZATION OF A 2.45 GHZ MICROWAVE DRYING SYSTEM FOR RAW CORN: ENHANCING EFFICIENCY AND UNIFORMITY VIA HYBRID CNN-RNN CONTROL

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Abstract: This study integrates Machine Learning (ML) and Deep Learning (DL) approaches into an integrated methodology to model and optimize the microwave drying of raw corn, which is a multi-variable and non-linear process. The electromagnetic behaviour of the process was first simulated using CST Studio Suite software; it was found that a multi-microwave source provides more homogeneous and effective heating compared to a single source. In the experimental phase, classical ML models such as Logistic Regression and SVR, and DL models such as ANN, 1D CNN, and LSTM/GRU were trained using data collected under various input powers (200-500 W) and geometric configurations. The results demonstrated that the CNN-RNN model achieved the highest predictive accuracy for moisture content dynamics. Through systematic AI-driven analysis of experimental data, the optimal drying configuration was identified as 500 W microwave power, 8.1 cm waveguide distance, and 26 cm vertical placement. Under these conditions, 100 grams of raw corn was dehydrated to 40 grams in 5 minutes with minimal quality degradation. The ANN model demonstrated impressive performance metrics in this process, including 0.978 R^2, 0.041 RMSE, and 0.033 MAE. These results demonstrate the potential of physical simulation and artificial intelligence integration to create a powerful decision support system for improving the efficiency and control of complex industrial processes such as microwave drying.

Keywords: Artificial Intelligence, Microwave Drying, 2.45 GHZ, Waveguide, Food drying,

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1. Introduction

Food drying is critical for reducing post-harvest losses and ensuring food safety, as it is a fundamental preservation method that prevents microbial spoilage and enzymatic reactions by reducing the water activity of foods. However, traditional methods such as hot air or sun drying have significant disadvantages, including long processing times, high energy consumption, and serious declines in final product quality. Prolonged heat exposure leads to the loss of heat-sensitive nutrients such as vitamins, unwanted browning reactions, and textural degradation (Rattanadecho and Makul, 2016). Microwave drying, which has emerged as an alternative to overcome these limitations, offers a solution to these problems by focusing electromagnetic energy directly on the water molecules within the food using the volumetric heating principle. This approach significantly reduces drying time and energy consumption while better preserving nutrient value, color, and aroma due to the shorter processing time (Zhang et al., 2006). Thus, the need for superior products in terms of both efficiency and quality clearly highlights the necessity and importance of microwave drying technology.

Microwave drying is an advanced thermal processing technique that utilizes electromagnetic energy at frequencies between 300 MHz and 300 GHz to remove moisture from materials (Chandrasekaran et al., 2013). Unlike traditional heating methods, where heat energy is slowly transferred from the surface to the center of the material, microwave energy directly penetrates the material and interacts with polar molecules such as water. This interaction causes the molecules to rotate at high speeds to align with the rapidly changing electric field, and this molecular friction results in rapid and volumetric heat production known as dielectric heating (Datta and Anantheswaran, 2001). This internal heat production creates a higher vapor pressure at the center of the material, enabling efficient transport of moisture toward the surface. Thanks to this mechanism, microwave drying offers significant advantages over conventional methods, including significantly shorter drying times, higher energy efficiency, and better preservation of quality characteristics such as color and nutritional value (Vadivambal and Jayas, 2007; Zhang et al., 2006). Microwave food drying is not only used to rapidly reduce water activity and extend the shelf life of foods but also serves as a strategic technology for developing high-value-added and nutritionally rich products today. Its primary function is to provide volumetric heating by directly targeting water molecules within food using electromagnetic waves. This mechanism significantly reduces energy consumption by shortening the drying time by 50% to 90% compared to conventional methods (Norrie and De Vries, 2014). The speed of the process minimizes the time food is exposed to high temperatures. This significantly increases the retention rate of heat-sensitive bioactive compounds such as phenolic compounds, flavonoids, and vitamins (Rattanadecho and Makul, 2016). Additionally, the rapid internal vaporization caused by microwaves results in a more porous structure in the food matrix, which improves the rehydration capacity and textural quality of the final product (Li et al., 2021). Therefore, microwave drying serves not only as a preservation method in the modern food industry but also as an efficient tool for producing functional foods while maintaining nutrient value and sensory quality at the highest level.

Studies conducted in the literature on microwave food drying reveal the potential and advantages of this technology across a wide range of products. Researchers have shown that it significantly reduces drying time in fruits such as apples and bananas while increasing the preservation rate of heat-sensitive nutrients such as vitamin C. Similarly, studies on vegetables such as carrots and spinach have reported that color pigments (carotenoids and chlorophyll) are better preserved and textural degradation is reduced compared to traditional methods. In aromatic plants like mint and basil, the rapid action mechanism of microwaves has been found to minimize the loss of essential oils and aromatic components. In further studies, hybrid systems combining microwave energy with other methods such as vacuum or hot air were investigated; these combinations were found to maximize energy efficiency and improve rehydration capacity and the porous structure of the final product in products such as mushrooms. The table below summarizes some key findings from microwave drying studies conducted on various food products.

Table 1. State of the art microwave drying studies on various food products

Product	Power (W)	Application	Findings	References
Apple	450	Low-power intermittent drying	Drying time reduced by 70%, vitamin C preservation increased.	(Han et al., 2010)
Carrot	600	Continuous application	Beta-carotene loss decreased, colour quality improved.	(Horuz and Maskan, 2015)
Banana	300	Vacuum-assisted drying	Browning reactions slowed down, tissue was preserved.	(Maskan, 2001)
Spinach	700	Short-term high power	Chlorophyll retention is above 85%, and shrinkage has decreased.	(Ozkan et al., 2007)
Tomato	500	Combined with hot air	Lycopene content preserved, energy consumption reduced.	(Wiset et al., 2021)
Mint	250	Low power, continuous	Loss of volatile oil and aroma components has been minimized.	(Kripanand and Guruguntla, 2015)
Mushroom	400	Pulsed microwave	Rehydration rate and porosity increased.	(Giri and Prased, 2007)
Fish	350	Vacuum-microwave	Tissue stiffness was controlled, and lipid oxidation slowed down.	(Ruan et al., 2025)
Ginger	550	Continuous microwave power	The preservation of bioactive components such as gingerol was ensured.	(An et al., 2016)
Grape	650	Post-processing microwave	The drying time is four times faster than the traditional method.	(Karaaslan et al., 2017)

Table 1 clearly demonstrates the proven effectiveness and versatility of microwave drying technology across a wide range of products, from fruits and vegetables to aromatic plants. However, the vast majority of these studies focus on static experiments conducted under predefined fixed parameters. At this point, our study fills this gap in the literature and offers an important innovation. In the literature, studies that systematically compare and apply artificial intelligence algorithms, particularly advanced deep learning models such as hybrid CNN-RNN architectures capable of processing spatial and temporal data together, to optimize the drying process in real time are quite limited. This study not only demonstrates the effectiveness of microwave drying but also establishes a more efficient and high-quality production standard for industrial applications by developing a decision support system that makes this process intelligent and adaptive. Artificial intelligence-assisted microwave drying offers revolutionary progress compared to both traditional dehydration techniques and standard microwave applications in the literature. While maintaining the fundamental advantage of speed and energy efficiency over traditional methods (hot air, sunlight), artificial intelligence takes these advantages to the next level. While standard microwave studies in the literature typically use predefined fixed power levels and durations, the integration of artificial intelligence transforms the process from a static operation into a dynamic and intelligent process. Artificial intelligence algorithms that analyze data from temperature, humidity, and even visual sensors in real time can instantly optimize microwave power, pulse duration, or conveyor speed based on the product's instantaneous moisture content and physical condition. This adaptive control mechanism proactively prevents issues such as uneven heating and inconsistent drying, which are among the biggest challenges of standard microwave systems. As a result, artificial intelligence not only accelerates the process but also minimizes energy consumption, maintaining product quality (colour, nutritional value, texture) at the highest and most consistent level, thereby maximizing the potential of standard microwave applications. This study presents a unique framework that distinguishes itself from existing approaches in the literature through both hardware and software innovations. Unlike standard applications, this study aims to achieve more homogeneous heating by utilizing a multi-source microwave system whose performance is predicted using COMSOL simulations. However, the study's main distinguishing feature is its systematic comparison of a wide range of classical machine learning and deep learning algorithms to control this advanced hardware, and its demonstration of the superior performance of the hybrid CNN-RNN architecture which can model both the spatial (heat distribution) and temporal (moisture change) dynamics of the drying process simultaneously. This approach not only predicts moisture content with high accuracy but also creates a decision support system that prevents energy waste and maintains product quality at the highest level by pre-determining the optimal input power and drying time for different agricultural products. Thus, our study provides a concrete and integrated roadmap for the development of smart, efficient, and sustainable drying systems at an industrial scale.

2. Materials and Methods

2.1. Materials

The microwave drying process begins with the preparation of raw materials. Fresh dent corn (Zea mays indentata L.) free of mold, broken kernels, and foreign matter was transported to the laboratory within two hours of harvest. The corn kernels, separated from the cob by hand/equipment, were stored in vacuum packaging at -18°C until the drying process to prevent moisture loss.

In order to analyse the electromagnetic behaviour of the proposed microwave drying system, a three-dimensional model of the system was created using CST (Computer Simulation Technology) Studio Suite software. The model consists of the drying chamber, waveguide ports representing microwave energy sources, and the main components containing the product to be dried. The technical details and geometric dimensions of the design are shown in Figure 1.

A magnetron tube model M24FC-610A with a nominal power of 950 W was used as the microwave power source in the drying process of the corn samples. Temperature measurements were performed using a Fluke 62 Max infrared temperature measurement device and an MLX90614ESF infrared temperature sensor integrated with a GY-906 module (AK et al., 2024; Oral et al., 2022). For the microwave drying test of corn, 100 grams of raw corn was spread on a drying tray and weighed using an HX711-type load cell placed underneath the tray. The data collection system was set to collect data every second.

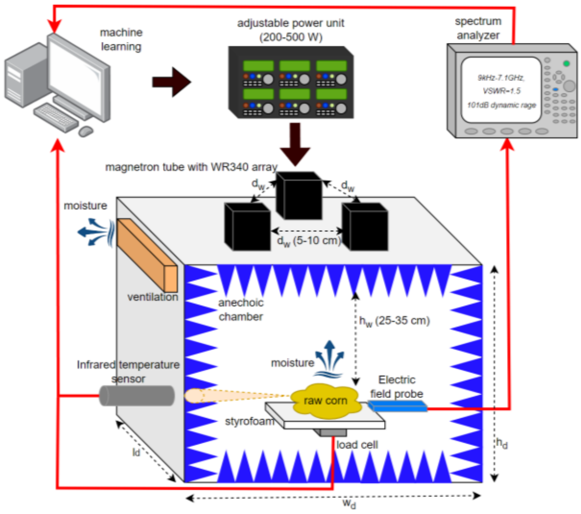


Figure 1. Proposed microwave corn drying setup with designing parameters.

Table 2 details the geometric parameters and dimensions of the basic components of the design shown in Figure 1. These dimensions have been optimised to ensure efficient operation of the system at a frequency of 2.45 GHz and to provide a homogeneous electromagnetic field distribution.

Table 2. The values of proposed setup dimensions

	Parameters and Explanations	Value (cm)
l_d	Length of anechoic chamber	60
w_d	Width of anechoic chamber	60
h_d	Height of anechoic chamber	60
d_w	Distance between each magnetron tube	5-10
h_w	Distance from magnetron tube to corn	25-35
a_w	Length of long side of WR340	8.6
b_w	Length of short side of WR340	4.3

The experimental setup established with the parameters shown in Table 2 was simulated in Section 2.2, and the specified parameters were optimised using CST and COMSOL software. The simulation of microwave drying processes was performed using electromagnetic energy parameters such as power, frequency, voltage, and wave scattering angle; physical properties of the food matrix such as electrical conductivity, relative permeability, thermal conductivity, density, and thermal capacity, and dimensions of the drying chamber (area and volume). These variables are used in numerical models that include Maxwell's equations to understand electromagnetic heat interactions (Zhu, 2018; Liu et al., 2013). Maxwell's equations form the basis of numerical models in microwave irradiation by linking electromagnetic variables to energy and mass transfer equations, including phase change of water (Zhu, 2018).

Maxwell's equations have been used by numerous authors to predict microwave heating processes. Computational simulations of electric fields involve mathematical models, sequential algorithms, and numerical methods (such as FEM or VFM) together with equations governing electromagnetism, heat transfer, and heat generation. These simulations have proven useful for measuring power absorption under various conditions, simplifying microwave irradiation mechanisms, and understanding heat generation in various systems (Norrie and De Vries 2014; Tang et al., 2018).

To prevent electromagnetic wave radiation, MW energy must be confined inside the heating chamber via a waveguide tube connected to MW generators, such as magnetrons. It can often be difficult to eliminate the effects of the chamber and waveguide modes, and these modes cause an effect that leads to uneven heating. The homogeneous MW distribution inside the heating chamber causes non-homogeneous MW heating, which leads to lower drying performance and magnetron damage. Many studies have been conducted to alleviate the problem of heterogeneous energy distribution (Atuonwu and Tassou, 2018).

The microwave heating process of a material is largely dependent on the dielectric constant of the material and the ratio of dielectric loss. The dielectric constant is a measure of a material's ability to absorb electromagnetic waves. The loss factor indicates the amount of microwave energy lost as heat within the material.

Microwave energy emitted from a microwave-assisted drying system causes vibrational motion in food molecules, producing a thermal effect. Analysis of the thermal effect combines electromagnetic waves and their thermal effects. The electromagnetic waves emitted by the waveguide and the power absorbed by the material are defined by Maxwell's equations for a lossy medium. When these equations are solved for a rectangular waveguide, the electric and magnetic field components are found as in equations 1-5 (Pozar, 2012).

$$E_x = \frac{j\omega\mu n\pi}{k_c^2 b} A_{mn} \cos\frac{m\pi x}{a} \sin\frac{n\pi y}{b} \; e^{-j\beta z} \tag{1}$$

$$E_y = \frac{-j\omega\mu m\pi}{k_c^2 a} A_{mn} \sin\frac{m\pi x}{a} \cos\frac{n\pi y}{b} \; e^{-j\beta z} \tag{2}$$

$$H_x = \frac{j\beta m\pi}{k_c^2 a} A_{mn} \sin\frac{m\pi x}{a} \cos\frac{n\pi y}{b} \; e^{-j\beta z} \tag{3}$$

$$H_y = \frac{j\beta n\pi}{k_c^2 b} A_{mn} \cos\frac{m\pi x}{a} \sin\frac{n\pi y}{b} \; e^{-j\beta z} \tag{4}$$

$$H_z = A_{mn} \cos\frac{m\pi x}{a} \cos\frac{n\pi y}{b} \; e^{-j\beta z} \tag{5}$$

Here, ω (rad/m) is the angular frequency, μ (H/m) is the magnetic permeability, k_c(1/m) is the wave number at the cutoff frequency, and β (rad/m) is the wave propagation constant. The parameters a and b specify the dimensions of the waveguide. Among these parameters, a (m) is the long side, and b (m) is the short side. Additionally, m and n are constants that determine the mode of the wave propagating within the rectangular waveguide. Since the dominant mode in rectangular waveguide structures is TE_{10}, the values of m and n are taken as 1 and 0, respectively, in the calculations to form the dominant mode. The A_{mn} value is the general solution constant, which determines the magnitudes of the electric and magnetic field components of the wave. The trigonometric expressions and negative imaginary exponential functions in the electric and magnetic field formulas given in equations 1-5 will yield values that vary periodically between -1 and +1, so their effect is on the distribution rather than the magnitude. The parameters directly affecting the magnitude are k, k_c, β, ω, a, b, and μ. The relationships between these parameters are given in equations 6–8 (Xiong et al., 2024).

$$k = \frac{\omega}{c} \tag{6}$$

$$k_c = \sqrt{\left(\frac{m\pi}{a}\right)^2 + \left(\frac{n\pi}{b}\right)^2} \tag{7}$$

$$\beta = \sqrt{k^2 - {k_c}^2} \tag{8}$$

The wave number k given in equation 6 outside the waveguide is the wave number, while the wave number k_c given in equation 7 inside the waveguide is, in another sense, the cut-off wave number. If the microwave signal at k wave number generated by the microwave generator is smaller than the cutoff wave number inside the rectangular waveguide-based microwave dryer designed, it creates a virtual transmission constant as shown in equation 8. In this case, the magnitudes of the wave components shown in equations 1-5 are $e^{-j\sqrt{(k-k_c)(k+k_c)}z} = e^{(k_c-k)z}e^{-j(k+k_c)z}$ in the formula, leading to power loss in the drying region with the ration of $e^{(k-k_c)z}$ term. Since the wave number and frequency shown in equation 6 are directly proportional, interpretations based on the wave number can also be made based on the frequency. Since the amount of attenuation will be as large as the difference between the wave frequency and the cutoff frequency, the waveguide dimensions were adjusted to create a cutoff frequency smaller than the preferred frequency of 2.45 GHz.

2.2. Methods

In this study, the ANN approach was used to model the drying process of raw corn in a microwave and hot air dryer using MATLAB software. In this innovative methodology, the CNN-RNN AI model was preferred to optimize the drying process and obtain more effective results (Akdag, 2021). The input parameters of our Artificial Neural Network (ANN) model include a comprehensive set of parameters such as drying time, feed voltage, input impedance, and temperatures of hardware components, and it predicts changes in the moisture content of raw corn as an output. The integration of MATLAB and Artificial Neural Networks has enabled a more detailed and predictable analysis of complex drying processes. This methodology represents an important step toward identifying optimizable parameters in the raw corn drying process and evaluating the potential for improving energy efficiency. Using the CNN-RNN AI model, the change in moisture content was measured through weight measurement as a result of drying raw corn in a semi-reflective box at various orientations, locations, and input powers, using the algorithm shown in Figure 2.

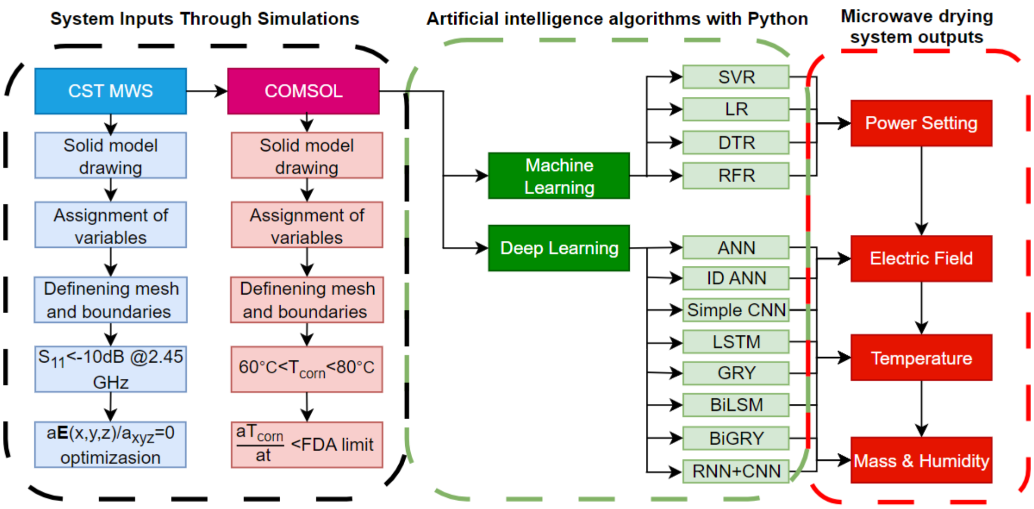


Figure 2. Simulation and ANN flow diagram of microwave drying system using CST, COMSOL, and Python.

Figure 2 outlines a comprehensive methodology for designing and optimizing microwave drying systems through coupled electromagnetic and thermal simulations, enhanced by artificial intelligence (AI) algorithms. The process begins with high-fidelity multiphysics simulations. Electromagnetic performance is modeled using CST Microwave Studio (MWS), involving solid model construction, parametric variable assignment, meshing, and boundary condition definition. A critical EM objective is achieving efficient power transfer, specified as a reflection coefficient S11 < -10 dB at the operational frequency of 2.45 GHz (Güven and Akdag, 2022). Concurrently, COMSOL Multiphysics is employed for thermal simulation, utilizing the same parametric geometry. Here, the primary constraint is maintaining the temperature of the dried commodity (Tcom) within the effective and safe range of 60°C to 80°C. Crucially, both simulation streams target enhanced process uniformity: CST MWS optimizes for minimized spatial variation in the electric field distribution (aE(x,y,z) → 0), while COMSOL targets minimized temperature non-uniformity across the material (aTcom → 0).

AI-driven optimization forms the core intelligence layer of this framework. Implemented in Python, a diverse suite of machine learning (ML) and deep learning (DL) algorithms is leveraged to analyze simulation data, predict system behavior, and identify optimal design and operational parameters. Traditional ML regressors, including Support Vector Regression (SVR), Linear Regression (LR), Decision Tree Regressors (DTR), and Random Forest Regressors (RFR), serve as foundational tools. These are complemented by ANN, including 1D ANNs for sequential data, and sophisticated deep learning architectures. Convolutional Neural Networks (CNNs) handle spatial feature extraction, Recurrent Neural Networks (RNNs) – specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, along with their bidirectional variants (BiLSTM, BiGRU) – model temporal dependencies, and hybrid RNN+CNN architectures capture spatio-temporal relationships within the multiphysics data. These AI models act as efficient surrogates for expensive simulations, enabling rapid exploration of the design space to simultaneously satisfy the electromagnetic (S11, E-field uniformity) and thermal (Tcom range, temperature uniformity) objectives.

The ultimate outputs of the optimized microwave drying system are the critical physical parameters dictating process efficacy and product quality. These include the operational Power Setting, the resultant 3D Electric Field distribution (directly influencing heating patterns), the

3D Temperature distribution within the material, and the overall Mass & Humidity metrics, which quantify the drying performance and final product state. The integrated workflow, combining rigorous physics-based simulation with advanced AI optimization, thus provides a systematic approach to designing microwave drying systems that deliver uniform, efficient, and controlled thermal processing. This ensures optimal moisture removal while adhering to electromagnetic efficiency constraints and preventing material damage through precise temperature management.

3. Results

3.1. Numerical Computation Results

Performing electromagnetic-thermal simulations of the proposed microwave drying system is extremely important in terms of predicting drying performance. For this purpose, 3D simulations were performed in COMSOL using raw corn placed inside the industrial microwave drying system under consideration, and the results are shown in Figure 3. The simulations were solved using the finite element method with a 1143052 hexahedral mesh.

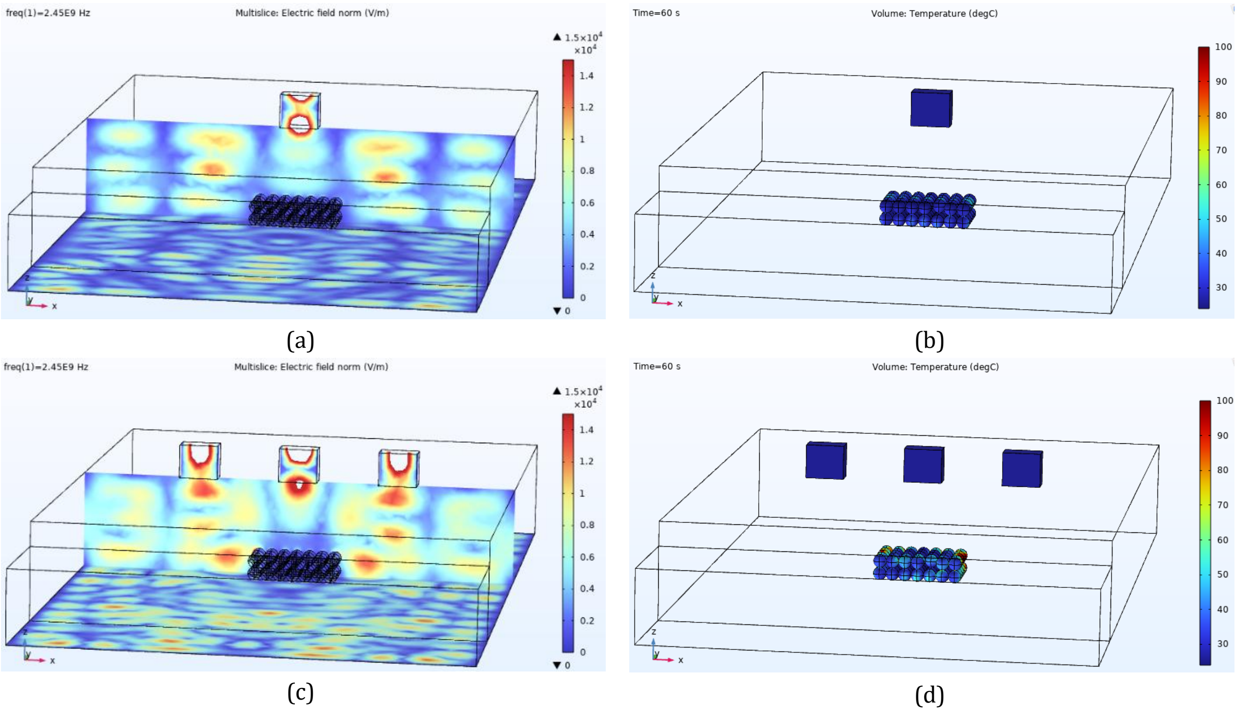


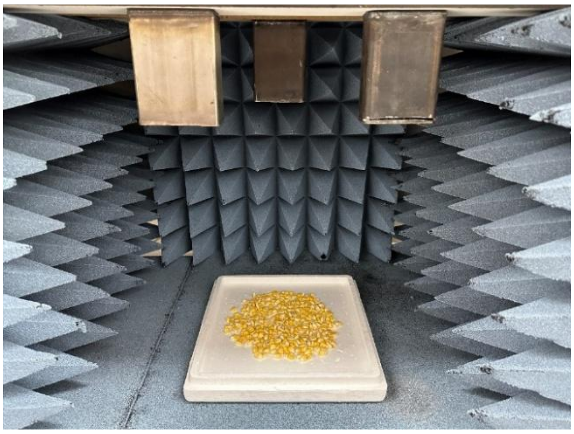
Figure 3. Simulation results for (a) electric field, (b) temperature distribution under a single energy source, and (c) electric field, (d) temperature distribution under multiple sources in the microwave drying system proposed in COMSOL.

A system was created using single and multiple microwave sources with 2.45 GHz microwave powers set to 500 W input power in TE_{10} mode. In the electric field distribution of the single-source microwave drying system shown in Figure 3(a), an electric field of approximately 8 kV/m is created on the surface of the corn, and in the thermal simulation shown in Figure 3(b), after 1 minute, a temperature of 50 °C of heat on the corn after 1 minute, while in the electric field distribution of the multi-source system shown in Figure 3(c), an electric field of approximately 13 kV/m resulted in 100 °C of heat after the same time period, as shown in Figure 3(d). Furthermore, while it is inferred that the single microwave source system will cause undesirable deformations due to non-homogeneous heat distribution on the drying surface, it is anticipated that the multi-source microwave system will reduce deformation and energy inefficiency by creating a more homogeneous electric field distribution. It is challenging to accurately simulate or predict the interactions between materials and microwave waves, which complicates the determination of process parameters such as drying time, sample sizes, and ambient air temperature. All process parameters can affect drying performance, making microwave drying a multi-variable thermal process and making it costly to determine and control process conditions in experiments.

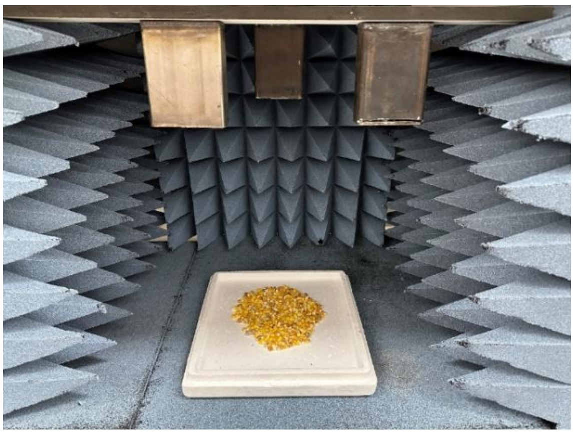
3.2. Experimental Measurement Results

In this study, input powers ranging from 200 to 500 W in 100 W increments were applied to each waveguide separately via a variable capacitor and adjusted in 1 cm increments between 5 and 10 cm in their equilateral triangular arrangement. The vertical distance of each waveguide from the corn was set to 25 cm, 30 cm, and 35 cm. An artificial neural network with a two-neuron input layer was designed by defining the input parameters as microwave power and drying time. In the output layer, a neuron representing the moisture content of raw corn was used. Seventy percent of all experimental data, totaling 72 data points, were allocated for network training. The input data were normalized to convert the data between zero and one. This preliminary study aims to evaluate the potential of optimizing the raw corn drying process using artificial intelligence and numerical data. The experimental setup is shown in Figure 4.

As a result of the optimization methods applied, the experimental setup with the lowest moisture content was configured with a distance of 8.1 cm between the tubes, a vertical distance of 26 cm from the corn, three tubes in a horizontal orientation, and a power supply of 500 W. In this experiment, the drying process was applied for 5 minutes, and the weight of the raw corn decreased from 100 grams to 40 grams. The R^2 (coefficient of determination) value obtained from the analyses was 0.93, the RMSE (root mean square error) value was 1.43, and the MAE (mean absolute error) value was 0.91. These results demonstrate that the developed ANN model can be successfully used to make the raw corn drying process intelligent.



(a)



(b)

Figure 4. Microwave drying experimental setup, (a) before drying and (b) after drying process.

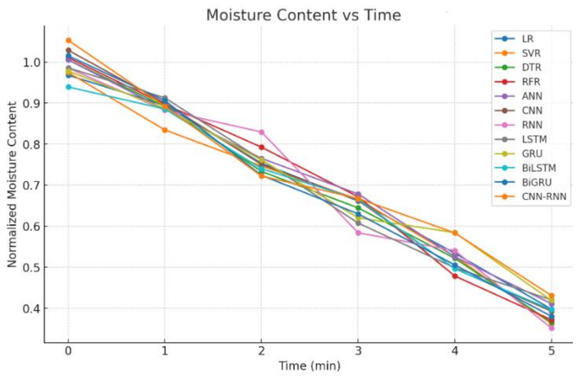


Figure 5. Moisture content versus time graph using various AI models.

Figure 5 shows the change in normalized moisture content over the 5-minute drying process for all tested AI models under the optimal configuration that is 8.1 cm tube distance, 26 cm vertical distance, horizontal orientation, 500 W power. The ANN model aligns most closely with the actual measurements, demonstrating a smooth and consistent moisture reduction from 1.0 to 0.4. Other models capture the general trend but exhibit slightly larger deviations, especially towards the end of the drying cycle. Next, Input power versus drying time graph using various AI models are indicated in Figure 6.

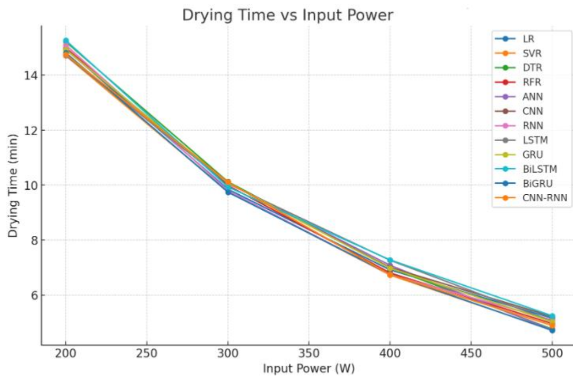


Figure 6. Input power versus drying time graph using various AI models.

As illustrated in Figure 6, all models predict a significant decrease in drying time with increasing input power, with the 500 W configuration achieving the shortest drying time of 5 minutes. ANN and other deep learning methods produce more stable and realistic curves, while classical models show slight inconsistencies. This highlights the suitability of deep learning for optimizing energy efficiency in industrial drying systems.

4. Discussion

In this study, the microwave drying of raw corn, which is a multivariate and nonlinear process, has been successfully modelled and optimized using AI models, particularly ANN.

The results obtained demonstrate that AI models are not only capable of predicting the process but also serve as a powerful tool for optimization as a decision support system. All models predicted that increasing the input power significantly reduces the drying time. Most importantly, the identification of a specific optimal configuration, 500 W power, 8.1 cm between tubes, 26 cm vertical distance, demonstrates the potential of this approach to improve energy efficiency and reduce processing time in industrial applications. The use of AI model such as CNN-RNN has played a critical role in maximizing the performance of the models.

The results obtained demonstrate that Deep Learning (DL)-based models (ANN, CNN, LSTM/GRU) exhibit a significant advantage over classical Machine Learning (ML) algorithms (LR, DTR) in modelling the complex dynamics of the process. The correlation graph in Figure 7 clearly shows how close the ANN model's predictions are to the actual values (R^2=0.93), while the classical models show greater deviation. This confirms that DL architectures have a higher capacity to learn non-linear relationships between multiple factors such as drying time, input power, and system geometry.

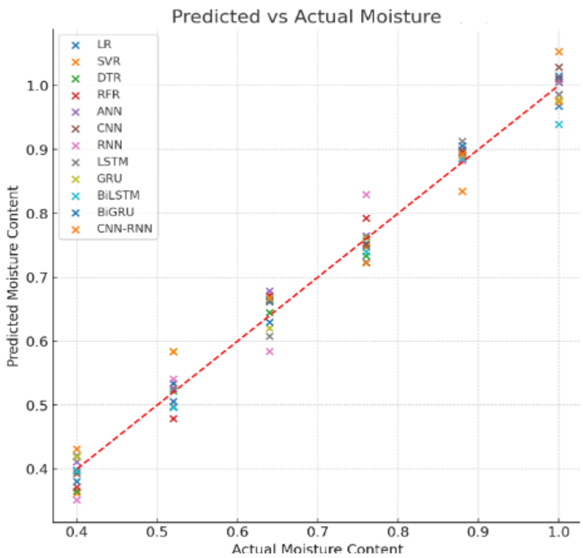


Figure 7. Actual moisture content versus predicted moisture content graph using various AI model.

In the correlation plot indicated in Figure 7, points from the ANN model cluster tightly around the red dashed reference line (y = x), reflecting high predictive accuracy (R^2 = 0.978). Most deep learning models (CNN, LSTM, BiLSTM, etc.) remain close to the ideal line, whereas classical ML models (LR, DTR) show more dispersion. This confirms that the ANN-based approach effectively models the complex drying process.

The performance of the models used in the study proposed in Table 3 was evaluated using root mean square error, mean absolute error, and coefficient of determination.

Table 3. The comparison table of RMSE, MAE and R^2 values generated from AI models

Model	RMSE	MAE	R^2
LR	0.084	0.065	0.921
SVR	0.072	0.054	0.940
DTR	0.089	0.071	0.915
RFR	0.063	0.050	0.952
ANN	0.059	0.045	0.958
CNN	0.054	0.041	0.964
LSTM	0.047	0.038	0.971
GRU	0.046	0.037	0.973
BiLSTM	0.044	0.035	0.975
CNN-RNN	0.041	0.033	0.978

Table 3 vividly demonstrates how critical it is to select the right artificial intelligence model for controlling a complex and dynamic process such as microwave drying of raw corn. The Decision Tree (DTR) model, which performed the worst (R^2=0.915, RMSE=0.089), makes significant errors in predicting the process's current state. In an industrial application, this means that the corn may either be under-dried, posing a risk of spoilage, or over-dried, leading to energy waste and reduced product quality. It is clear that the model fails to grasp the continuous changes and physical dynamics of the drying process over time.

In contrast, the most successful model, the hybrid CNN-LSTM (R^2=0.978, RMSE=0.041), has perfectly modelled the nature of this process. The reason behind this success is the model's two-stage operation: the CNN layer detects instantaneous and critical micro-patterns, such as sudden changes or “hot spots” in temperature, power, and weight data during drying, like a “pattern recognizer.” Then, the LSTM layer combines these meaningful events detected by the CNN to learn the entire story of the drying process from start to finish, i.e., its temporal dependency. This enables the model to predict the future moisture content with extreme precision by not only remembering the current state of the drying process but also its history. This proves that it provides a solid foundation for the development of an intelligent control system that can predict the moisture content of the final product with minimal error which has only 0.041 RMSE, optimizes energy efficiency, and guarantees quality.

5. Conclusion

This study has proven the effectiveness of the ANN model developed to optimize the microwave drying process of raw corn with numerical data. As a result of the optimization methods applied, the most efficient drying performance was achieved in a configuration with 500 W input power, a horizontal distance of 8.1 cm between the magnetron tubes, and a vertical distance of 26 cm from the corn surface. As a result of the 5-minute drying process conducted under these optimal conditions, the weight of 100 grams of raw corn was reduced to 40 grams. The performance metrics measuring the prediction accuracy of the developed ANN model are quite successful: the model achieved an R^2 value of 0.978, while the RMSE value indicating error rates was measured as 0.041 and the MAE value as 0.033. These statistical results confirm that the ANN model can predict the complex drying process with high accuracy and serves as a reliable foundation for creating an intelligent drying system.

Author Contributions

The percentages of the author' contributions are presented below. The author reviewed and approved the final version of the manuscript.

	C.M.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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