

Article

Design and Evaluation of Wheat Moisture Content Detection Device Based on a Stripline

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Abstract: The detection of the moisture content of wheat is an important index used to measure the quality and preservation of wheat. In order to rapidly and non-destructively detect the moisture content of wheat, in this study, we designed a stripline detection device that measures 151 frequency points in the 50–200 MHz frequency range with a vector network analyzer. Random forest (RF), extreme learning machine (ELM), and BP neural network prediction models were established, using the frequency, temperature, volume density and dielectric constant as input and the water content as output. It was shown that, in the frequency range 50–200 MHz, the permittivity of wheat decreases as the frequency increases, and that this is negatively correlated. The dielectric constant of wheat increases as the moisture content, temperature, and bulk density increase, and these are positively correlated. The random forest (RF) prediction model, which uses the frequency, temperature, effective dielectric constant ϵ_{eff} and volume density as inputs and the wheat moisture content as the output, demonstrates the best performance. The determination coefficient (R^2) = 0.99977, the mean absolute error (MAE) = 0.044368, the mean square error (MAE) = 0.0053011, and the root mean square error (RMSE) = 0.072809. This study provides a new device and method for the detection of the moisture content of wheat. The device is small and is not easily disturbed by the external environment. It can be measured in a variety of conditions and is important for the development of low-cost, high-precision, and portable devices for the detection of the moisture content of wheat.

Keywords: dielectric constant; stripline; wheat; moisture content



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1. Introduction

Wheat is one of the main food crops in China. It plays an important role in agricultural production, accounting for more than 20% of the total grain output [1]. The moisture content of wheat determines the safety of wheat storage. A moisture content that is too high can make it difficult to store wheat grain germination. A low moisture content makes the wheat cortex brittle and prone to loss and wastage during processing and transportation. After wheat harvest, rapid and accurate measurements of the moisture content can guide farmers in choosing appropriate storage methods and measures to ensure the quality and safe storage of wheat.

At present, the methods employed to measure the moisture content of wheat mainly include the capacitance method [2,3], coaxial probe method, resonant cavity method [4], free space method [5–8], and so on. These methods have their limitations when performing actual detection [9–13]. Among them, the coaxial probe method has a limited measurement accuracy compared with the transmission line method and the resonant cavity method. The resonant cavity method can only perform measurements at one or several frequency points, and it requires the use of a special resonant cavity-measuring instrument, which is expensive. The propagation and interaction of electromagnetic waves in a substance are influenced by factors such as the substance's properties and water content. Mykola Karpenko

and collaborators [14] utilized piezoelectric micro-vibration testing and frequency analysis to evaluate the properties of tire materials. Their results demonstrated the applicability of the frequency response optimization method in the numerical simulation of composite tires. Therefore, conducting tests at different frequencies can offer a more comprehensive and precise understanding of the internal properties and moisture content of grain samples. Trabelsi and collaborators [15] utilized the free space method combined with the NRW (Nicolson–Ross–Weir) algorithm to measure the dielectric constant of shelled and unshelled peanuts at 23 °C over the frequency range of 2–18 GHz, obtaining dielectric constants close to the actual values. However, using the NRW algorithm leads to phase ambiguity. In addition, the free-space approach requires a large measurement space, and the propagation of electromagnetic waves is susceptible to environmental interference, which requires the measurements to be performed in microwave anechoic chambers. Guo and collaborators [16] used the concentric capacitance method to detect the moisture content of oats at 103–106 Hz. The effect of the temperature, bulk density, and test frequency on the dielectric constant of wheat was studied at 12–21% moisture content. A linear regression model was used to model the prediction of the oat moisture content. In this frequency band, the relaxation effect of polar molecules in oats is dominated by interfacial polarization, resulting in a low measurement accuracy. LI [17] used hyperspectral measurements to detect the moisture content of soybeans. The ELM model was fused with the feature bands extracted from SPA and RF, and the regression model achieved a correlation coefficient of 0.90536. Because the hyperspectral sorter can only extract the surface information of soybean samples, the measurement accuracy was low.

The precise determination of wheat moisture content is important not only for agricultural producers but also for wheat processors, food manufacturers, and logistics operators in the context of academic research. This article presents a device that was designed to detect the moisture content of wheat using a strip transmission line. The device is a specially designed transmission line that can be used to transmit electromagnetic wave signals and facilitate interaction with wheat samples. The moisture content of the wheat is reflected by measuring the attenuation of the electromagnetic wave signals as they pass through the wheat sample. Based on this device, the influence of the signal frequency (50–200 MHz), temperature (5–40 °C), moisture content (8.99–22.22%) and volume density (low and high) on the dielectric constant of the wheat is measured, and then a prediction model of the moisture content of wheat is established. The device is small in size and is not easily disturbed by the external environment. It can be measured in a variety of conditions, providing a basis for low-cost, high-precision portable online small-grain detection devices.

2. Materials and Methods

2.1. Design and Simulation of Wheat Moisture Content Detection Devices

2.1.1. Structural Design of Wheat Moisture Content Detection Devices

A stripline is a microwave transmission component that consists of a signal transmission strip embedded between two grounding layers. It exhibits excellent shielding properties and low loss characteristics. The schematic diagram is shown in Figure 1. In Figure 1, the blue portion represents the dielectric filling area. During measurements, coupling occurs between the wheat crop medium and the stripline. As the electromagnetic wave propagates from one end of the stripline to the other, the presence of wheat affects the propagation velocity and propagation loss of the electromagnetic wave. Additionally, the impact of the wheat moisture content on the propagation velocity and propagation loss varies. The wheat moisture content is predicted by measuring the reflection coefficient at the port of the stripline. The internal impedance of the vector network analyzer is 50 Ω . To minimize the reflection coefficient of the test unit, a detection device was fabricated using a 50 Ω characteristic impedance stripline. The characteristic impedance value of the stripline was determined by the four parameters outlined in Figure 1: the width of the W driving electrode, the thickness of the t driving electrode, the plate spacing of the h two driving

electrodes, and the dielectric constant ϵ of the medium [18]. The formula used to calculate the impedance is shown in Equations (1) and (2).

$$Z = \frac{30\pi}{\sqrt{\epsilon}} \frac{h}{w_e + 0.441h} \quad (1)$$

$$\frac{W_e}{h} = \frac{w}{h} - \begin{cases} 0 & \frac{W}{h} > 0.35 \\ (0.35 - \frac{W}{h})^2 & \frac{W}{h} < 0.35 \end{cases} \quad (2)$$

where W_e is the effective width of the central conductor.

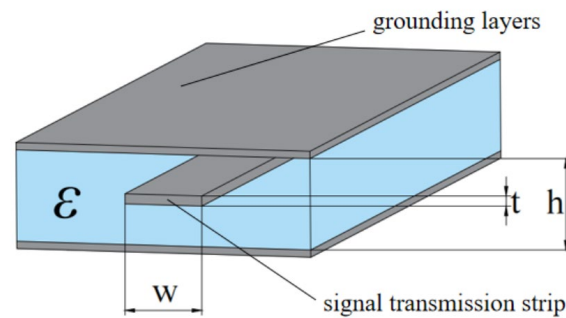


Figure 1. Stripline structure.

An air stripline with a characteristic impedance of 50Ω was designed via the use of the Calculate analytical Line Impedance function in the CST Studio Suite. The structural parameters of the stripline are shown in Table 1.

Table 1. Stripline structure parameters.

Serial Number	Parameter	Numerical Value
1	W	76 mm
2	t	4 mm
3	h	58 mm
4	ϵ	1.00053

The structural diagram of the stripline detection device is shown in Figure 2. During the industrial processing of the stripline detection device, aluminum plates were used for both the signal transmission strip and the two grounding layers. The two ends of the detection device comprise two aluminum plates fixed on the grounding layers. On each side of the aluminum plates, an SMA-KFD female connector was installed to connect the device with the vector network analyzer. The detection device was divided into three sections using four polytetrafluoroethylene (PTFE) boards, with the middle section serving as the grain-filled region. The air transmission line boundaries on both sides of the grain-filled region are designed so that modes other than the Transverse Electromagnetic (TEM) mode are prevented from exerting an influence on the detection. From Figure 2, it can be observed that the wheat-filled region is the area between the three parallel plates, facilitating the rapid filling of wheat during measurements.

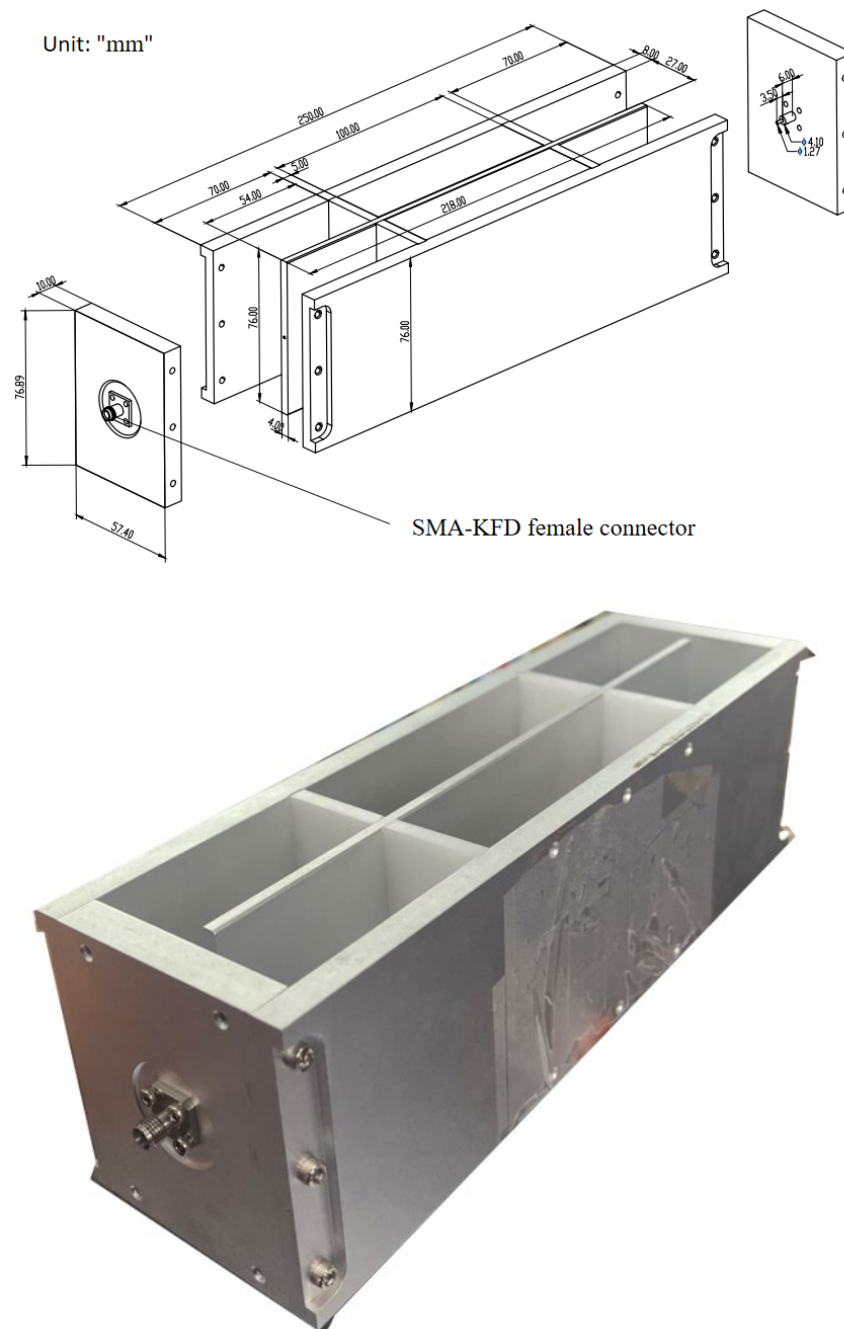


Figure 2. Drawing and physical drawing of the stripline testing device size structure.

2.1.2. Principle of Dielectric Constant Measurement

A stripline with the same dielectric can be equivalent to a two-port network. According to transmission line theory, the structural properties of transmission lines in the same medium can be described by a transmission matrix. The transmission matrix T of the transmission line with a length of l is shown in Equation (3), and the equivalent diagram of the stripline detection device is shown in Figure 3. Among them, T_{con} is the coaxial line part, T_{pin} is the coaxial line and driving electrode connection part, T_{air} is the air transmission line part, T_p is the PTFE partition part, and T_g is the wheat sample filling part. Z_E is the terminal resistance (50Ω) on one side of the detection device. The detection device was divided into 9 units for analysis [19]. By employing the electromagnetic simulation software CST Studio Suite, the detection device was modeled in 3D, and the excitation was set on each unit. The characteristic impedance (Z) of each unit and the attenuation α caused by the loss

mechanism of the transmission line itself were obtained via simulation analysis, and the transmission matrix of each unit was further obtained [20–22]. The simulation parameters are shown in Table 2.

$$T = \begin{pmatrix} A & B \\ C & D \end{pmatrix} = \begin{pmatrix} \cosh(\gamma l) & Z \cdot \sinh(\gamma l) \\ \frac{\sinh(\gamma l)}{Z} & \cosh(\gamma l) \end{pmatrix} \quad (3)$$

Different stripline media lead to complex propagation constants γ and changes in the characteristic impedance Z . The relationship between effective dielectric constant, characteristic impedance, and complex propagation constant is shown in Equations (4) and (5).

$$\gamma = \sqrt{\varepsilon} \cdot \frac{2\pi f}{c} \cdot j + \alpha \quad (4)$$

$$Z = \frac{Z_0}{\sqrt{\varepsilon}} \quad (5)$$

where A, B, C, D are the elements of the matrix; ε is the effective dielectric constant of the transmission line medium; f is the frequency; c is the speed of light; j is an imaginary unit; α is the attenuation due to the loss mechanism of the transmission line itself; and $Z_0 = 50 \Omega$.

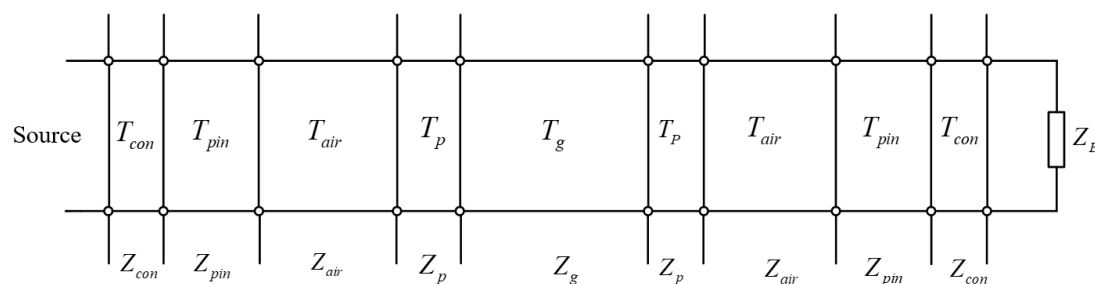


Figure 3. Equivalent diagram of the stripline detection device.

According to the cascading characteristics of the transmission line, the transmission matrix of the entire network is the product of each transmission matrix, as shown in Equation (6). The relationship between the port scattering parameter S_{11} and the transmission matrix $T(ABCD)$ of the stripline detection device is shown in Equation (7). The reflection coefficient S_{11} of the stripline is measured using the vector network analyzer, and then the dielectric constant of the wheat to be measured is calculated.

$$T(ABCD) = T_{con} \cdot T_{pin} \cdot T_{air} \cdot T_p \cdot T_g \cdot T_p \cdot T_{air} \cdot T_{pin} \cdot T_{con} \quad (6)$$

$$S_{11} = \frac{A + B/Z_0 - C \cdot Z_0 - D}{A + B/Z_0 + C \cdot Z_0 + D} \quad (7)$$

Table 2. Attenuation caused by the characteristic impedance of each unit of the stripline and the loss mechanism of the transmission line itself.

Serial Number	Name	Numerical Value
1	Source impedance	50 Ω
2	Coaxial connector impedance (Z_{con})	50.1059 Ω
3	Impedance of the connection section between the coaxial line and the central plate (Z_{pin})	222.674 Ω
4	Impedance of air filling section (Z_{air})	50.0514 Ω
5	Impedance of polytetrafluoroethylene filling section (Z_p)	28.2927 Ω
6	The attenuation caused by the loss mechanism of the transmission line itself	0.001

2.1.3. Calibration of Dielectric Constant

Using CST Studio Suite, the grain filling section was set to a medium with a dielectric constant ranging from 1 to 7, with an increment of 1. The reflection coefficient S_{11} of the port of the stripline was obtained via finite element simulation, and the dielectric constant of the grain filling part was solved reversely by using the solution principle outlined in Section 2.1.2. The results obtained when setting the dielectric constant ϵ_r and inverting the dielectric constant ϵ_{mea} are shown in Figure 4. As can be seen from Figure 4, the dielectric constant of the inversion calculation remains essentially constant at frequencies between 50 and 200 MHz. For the quantitative detection of solid-state humidity, the directional polarization of water in this band is prominent and stable, which leads to a good signal-to-noise ratio for the measurements; in addition, the measurements in this band are repeatable. Therefore, this frequency band was chosen in order to measure the moisture content of wheat. At the same time, it can be seen from Figure 4 that when the set dielectric constant is 1, the calculated dielectric constant is close to 1. As the set dielectric constant increases, the calculated dielectric constant is smaller than the set dielectric constant, which is due to the propagation of some electromagnetic waves in the outer region of the plate. By using Equation (8) to calibrate the dielectric constant of the inversion calculation, the effective dielectric constant value ϵ_{eff} was obtained.

$$\epsilon_{eff} = a \cdot \epsilon_{mea} + b \quad (8)$$

where a and b are the calibration coefficients.

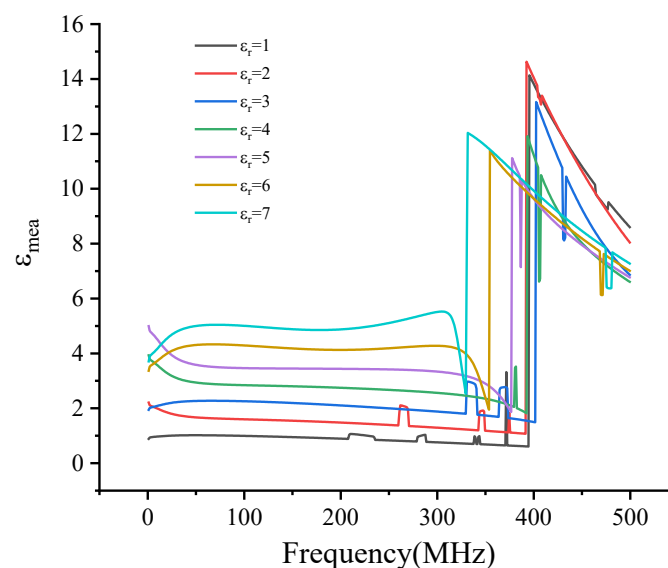


Figure 4. Diagram of the corresponding relationship between the dielectric constant ϵ_r and inversion calculation dielectric constant ϵ_{mea} .

2.2. Principle of Measurement

By using transmission line technology, the dielectric constant of the wheat was calculated by measuring the reflection coefficient of the electromagnetic waves passing through the wheat, and then the moisture content of the wheat was evaluated. The experimental device is shown in Figure 5. The experimental equipment consisted of the following components: aluminum strip detection device, Keysight P9371 A USB VNA (Keysight, Santa Rosa, CA, USA), and computer. The stripline is primarily used for the loading of the object to be measured and the propagation of the electromagnetic wave signal; the Keysight P9371 A USB VNA measures the reflection coefficient of the wheat samples under different frequency conditions in real time by connecting to a computer and storing the results.

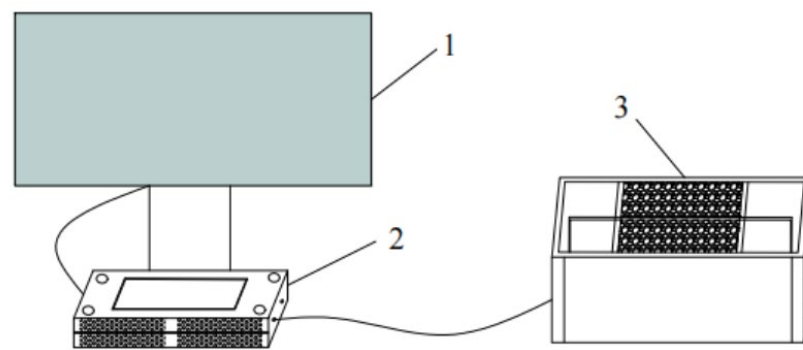


Figure 5. Experimental detection device showing a computer (1); a Keysight P9371A USB VNA (2); and the Stripline 200 detection device (Keysight, Santa Rosa, CA, USA) (3).

2.3. Test Equipment

An MB45 Halogen Moisture Analyzer (Shanghai Ohaus Instruments Ltd., Shanghai, China), YH electronic balance (Shanghai Yingheng Weighing Co., Ltd., Shanghai, China), LK-80G high- and low-temperature test chamber (Dongguan Qinzhuo Environmental Testing Equipment Co., Ltd., Dongguan, China), 3310 laboratory grinder (Botong Ruihua Scientific Instruments (Beijing) Co., Ltd., Beijing, China), 34972A Data Acquisition Switch Unit (Keysight, Santa Rosa, CA, USA), Refrigerator (Qingdao haier Co., Ltd., Qingdao, China), and other auxiliary equipment, such as a thermocouple, sealing bag, spray pot, aluminum tray, and scraper, were used to conduct the experiments performed in this study.

2.4. Sample Preparation

The sample used in this experiment comprised Shandong Pingdu winter wheat. Before the experiment, any impurities and broken grains in the wheat were removed using a sieve, and the wheat with full shape and full grain was selected as a sample. In order to obtain a gradient distribution of the moisture content of the wheat samples, it was necessary to spray distilled water to adjust the moisture content of the samples. The wheat was ground into powder by the 3310 laboratory grinder (Botong Ruihua Scientific Instruments (Beijing) Co., Ltd., Beijing, China), and the initial moisture content of wheat was determined by the MB45 halogen moisture analyzer. Three measurements were taken, and the average value obtained was 8.51%, representing the initial moisture content. Then, 14 portions of 1000 g of wheat were weighed with the YH electronic balance and sealed in a bag for storage. According to the initial moisture content, the distilled water spray adjusted the moisture content of the sample between 9% and 22%, with an approximate 1% gradient distribution [23]; the weight of the sprayed distilled water was calculated using Equation (9).

$$G = \frac{(M_2 - M_1)G_1}{1 - M_2} \quad (9)$$

where G is the quantity of the distilled water to be sprayed on the wheat sample, grams; G_1 is the weight of the wheat sample, grams; M_1 is the initial moisture content of the wheat sample, %; and M_2 is the wheat sample needed to match the moisture content, %.

The sample was prepared by spraying distilled water while shaking the sample; for the preparation of samples with a high water content, spraying was performed only a few times. After spraying, the experimental samples were stored in double-sealed bags and kept in an environment void of light at a temperature of 23 °C for 48 h. During this period, the samples were gently shaken every 3 h to ensure that the wheat absorbed moisture uniformly. After the completion of water absorption, the samples were placed horizontally in a refrigerator at 4 °C for 7 days, so that the water distribution was balanced across the whole bag of test samples. After equilibrating the distribution of water in the wheat samples, the moisture content of each bag of samples was measured using the drying method. The average moisture content of each bag of samples was measured three times.

The moisture content of the 14 bags of samples was 8.99%, 10.11%, 11.05%, 12.36%, 13.02%, 14.18%, 15.05%, 16.1%, 17.3%, 18.09%, 19.99%, 20.36%, and 22.22%.

2.5. Experimental Design

In this experiment, the bulk density, moisture content, temperature, and detection frequency of the wheat samples were used as independent variables to explore their effects on the dielectric constant of wheat. Before each test, the wheat sample was taken out of the refrigerator and brought to room temperature. The samples were then placed in the LK-80G high and low-temperature test chamber and thermocouples were inserted into the samples. The data acquisition switch was connected to a thermocouple to obtain the sample temperature. When the sample temperature was 5 °C, the sample was loaded into the stripline detection device in a free-falling manner. The excess sample was hung with a scraper in the shape of a 'Z' so that the sample was flush with the upper edge of the measurement tank. At frequencies ranging from 50 MHz to 200 MHz, the reflection coefficient S_{11} was measured at 151 discrete integer frequency points, and the average value was taken as the result of 3 measurements. After the measurement, the mass of the measured sample was weighed using an electronic balance and the volume density of the sample was calculated. Subsequently, the temperature of the high- and low-temperature experimental box was set to 5, 10, 15, 20, 25, 30, 35, and 40 °C in turn, and the above operation was repeated. Based on the low-volume-density measurements described above, the mass of the wheat sample in the container was varied according to vibration and pressure to obtain a high-volume-density wheat sample, which was measured following the procedure described above. A total of 224 sets of test samples were obtained.

2.6. Prediction Model

In this study, random forest (RF), extreme learning machine (ELM), and BP neural network prediction models were established with frequency, temperature, volume density, and dielectric constant as input and water content as output. The mathematical principles of each prediction model are shown below.

2.6.1. Random Forest Algorithm

The RF algorithm combines randomly formed decision trees to form a powerful classifier with a more stable prediction performance [24,25]. Finally, the prediction results of all decision trees are combined to determine the output value. The decision tree is constructed using the CART algorithm; that is, starting from the nodes, the optimal attribute is selected according to the principle of the minimum Gini index, and then the attribute is split using a binary recursive method and the nodes are constructed until the condition is satisfied. Then, the splitting is halted and a leaf node is formed. The prediction of the decision tree is based on the path from the root node to the leaf node. Because the input data travel through different paths, the predictions are different. The algorithm flow of the RF algorithm is as follows:

1. n groups of training sample sets are randomly generated via the self-help sampling method, and a decision tree model is constructed based on each group of new samples.
2. When selecting attributes in each internal node (non-leaf node), several attributes are randomly selected from all attributes of the sample set to be used as the attribute set of the node; then, the optimal attributes are selected according to the evaluation rules of the CART algorithm and are split until the decision tree is fully grown. As the decision tree grows, no pruning is performed.
3. When entering the test sample set, each decision tree is computed to generate a prediction value. Based on all the predicted values, the final results are obtained. For the regression problem, the weighted average of the predicted values of all decision trees is taken as the final result.

2.6.2. Extreme Learning Machine

ELM is a forward network with a single hidden layer that is based on generalized inverse matrix theory; it exhibits excellent performance [26,27]. Compared to conventional neural networks, the output weights of the proposed network can be resolved with only one computational step, which has a strong nonlinear fitting capability.

For N arbitrary samples with the same part (x_n, y_n) , where $x_n = [x_{n1}, x_{n2}, \dots, x_{ni}]^T \in R^i$, $y_n = [y_{n1}, y_{n2}, \dots, y_{nj}]^T \in R^j$. Then, for a node with L hidden layers, the activation function is $g(x)$. The output of the feed-forward neural network can be expressed as Equation (10):

$$f_L(x) = \sum_{n=1}^L \beta_n G(a_n \cdot x_n + b_n), x_n \in R^i, a_n \in R^i, \beta_n = R^j \quad (10)$$

where $a_n = [a_{n1}, a_{n2}, \dots, a_{ni}]^T$ represents the input weight from the input layer to the first hidden layer node; b_n is the deviation of the i hidden layer node; $\beta_n = [\beta_{n1}, \beta_{n2}, \dots, \beta_{nj}]^T$ represents the output weight connecting the i hidden layer node; and $a_n \cdot x_n$ denotes the inner product of vectors a_n and x_n . The activation function $g(x)$ can be selected as 'Sigmoid', 'RBF', etc. The activation function selected in this study is 'Sigmoid'.

If a feed-forward neural network with L hidden layer nodes can approximate N samples with zero error, then there exists a_n, b_n, β_n , such that the following is relevant:

$$f_L(x) = \sum_{n=1}^L \beta_n G(a_n \cdot x_n + b_n) = y_n, \quad n = 1, 2, \dots, L, \quad (11)$$

Equation (11) is simplified as follows:

$$H\beta = Y$$

Here, H is the hidden layer output matrix of the network. In the extreme learning machine algorithm, the output weights and biases can be given randomly, and the hidden layer matrix H becomes a deterministic matrix. Thus, the training of a feed-forward neural network can be transformed into a problem that requires the least-squares solution of the output weight matrix to be solved. Only the least-squares solution of the input weight is required to complete the training of the network, and the output weight matrix β can be obtained using Equation (12).

$$\tilde{\beta} = H^+ Y \quad (12)$$

where H^+ represents the generalized inverse matrix of the hidden layer output matrix H .

2.6.3. BP Neural Network

The BP neural network is a multi-layer feed-forward neural network [28–30]. The neurons of the proposed algorithm can be divided into three layers: input layer, hidden layer, and output layer. The neuron state of each layer only affects the neuron state of the next layer. The network structure is shown in Figure 6. The main features of the network are signal forward propagation, error back propagation, and by back propagation; the weights and thresholds of the network are continuously adjusted so that the sum of the squared errors of the neural network is minimized. The proposed algorithm is highly nonlinear and capable of mapping any complex nonlinear relationship; it is also very robust and adaptive.

Each layer of the network contains one or more neurons, and the neurons between the layers are connected to each other. The number of neurons in the hidden layer are generally determined according to the empirical Equation (13). In this research, the number of neurons in the hidden layer was determined to be 5. In order to remove the effect of dimensionality between metrics, the data need to be normalized before the network is trained.

$$L = \sqrt{m + n} + a \quad (13)$$

where L is the number of hidden layer nodes; m is the number of output layer nodes; n is the number of input layer nodes; and a is a constant between 1 and 10.

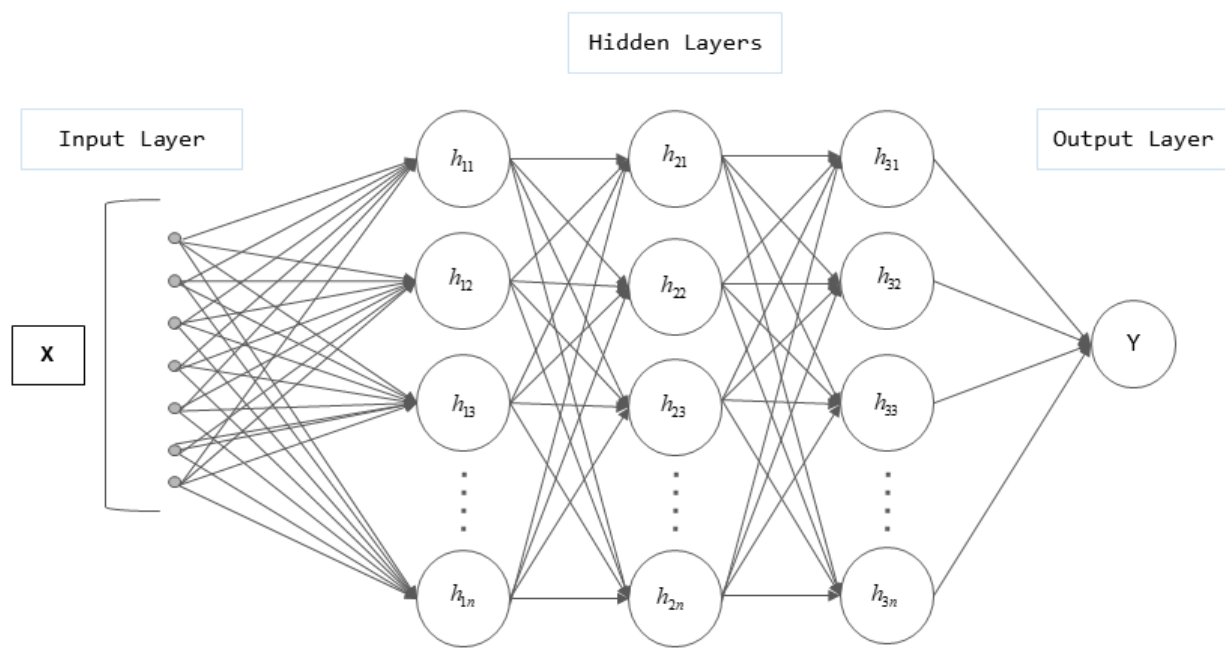


Figure 6. BP neural network structure.

3. Results and Analysis

3.1. Frequency Effect on Wheat Dielectric Constant

Figure 7 shows the curve depicting the influence of frequency on the dielectric constant of wheat with different moisture contents at 5 °C and 20 °C under a low bulk density. Based on Figure 7, within the frequency range of 50–200 MHz and at a temperature of 5 °C, the wheat moisture content ranged from 8.99% to 22.22%, while the corresponding dielectric constant of wheat varied approximately between 2.6 and 4.7. Additionally, at a temperature of 20 °C, the dielectric constant of the wheat was approximately in the range of 2.71 to 4.9. Within the frequency range of 50–200 MHz, at the same temperature, the dielectric constant of the wheat decreased as the frequency increased for the same moisture content. The variation in the dielectric constant of the wheat relative to the frequency was caused by the Maxwell–Wagner effect and the electric dipole polarization effect. When the frequency was low, the period of the field change was extensive and the charge accumulated in time at the boundary of the conducting region. However, water molecules are also typical electric dipoles. At low frequencies, the electric dipole energy can vary with the electric field. Therefore, the dielectric constant is larger at lower frequencies. As the frequency increases, the electric field variation period becomes shorter, the charge cannot accumulate and the electric dipole cannot change with the electric field. As a result, the dielectric constant of wheat decreases with as the measurement frequency increases. The increase in the moisture content did not affect the decrease in the dielectric constant of wheat as the frequency increased.

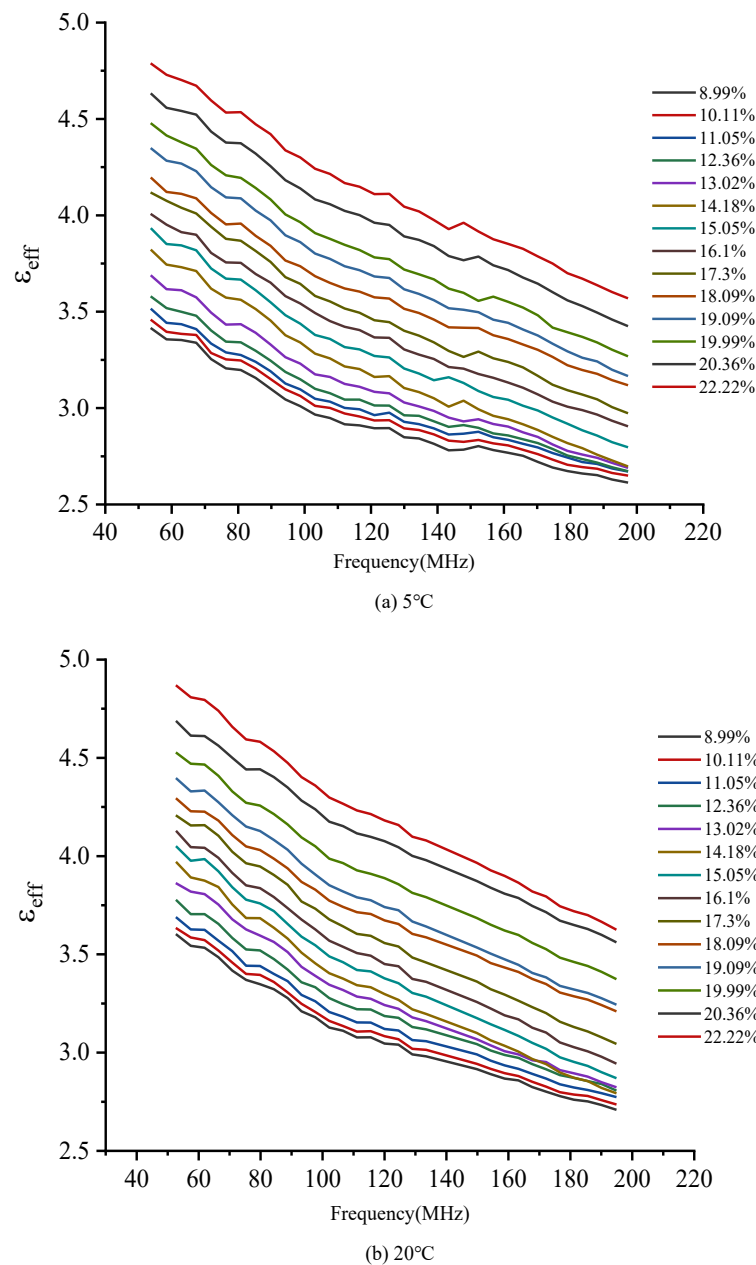


Figure 7. Effect of frequency on dielectric constant of wheat under different water content.

3.2. Effect of Temperature on Dielectric Constant of Wheat

Figure 8 shows the curve depicting the influence of temperature on the dielectric constant of wheat with different moisture contents at 50 MHz and 100 MHz under a low bulk density. Based on Figure 8, within the moisture content range of 8.99% to 22.22% and the temperature range of 5 °C to 40 °C, at a frequency of 50 MHz, the dielectric constant of the wheat varied approximately between 3.4 and 5.1. Furthermore, at a frequency of 100 MHz, the dielectric constant of the wheat varied between 3.18 to 4.72. At the same frequency, the dielectric constant of wheat with the same moisture content increased as the temperature increased. This is because the free water that was observed in the sample is a polar molecule. At higher temperatures, polar molecules are more active, leading to an increase in the number of polar molecules. At the same time, an increase in temperature also accelerates the Brownian motion of free water. Therefore, the higher the temperature, the larger the dielectric constant. At the same time, changing the moisture content and frequency did not affect the trend observed in the dielectric constant of the wheat, which

increased relative to the temperature. From Figure 8, it can be seen that, at the same moisture content, with each 5 °C increase in temperature, the slope of the wheat dielectric constant curve is different. This is due to the use of the free-falling loading method, which causes the bulk density to fluctuate, thus affecting the slope of the curve of the wheat dielectric constant.

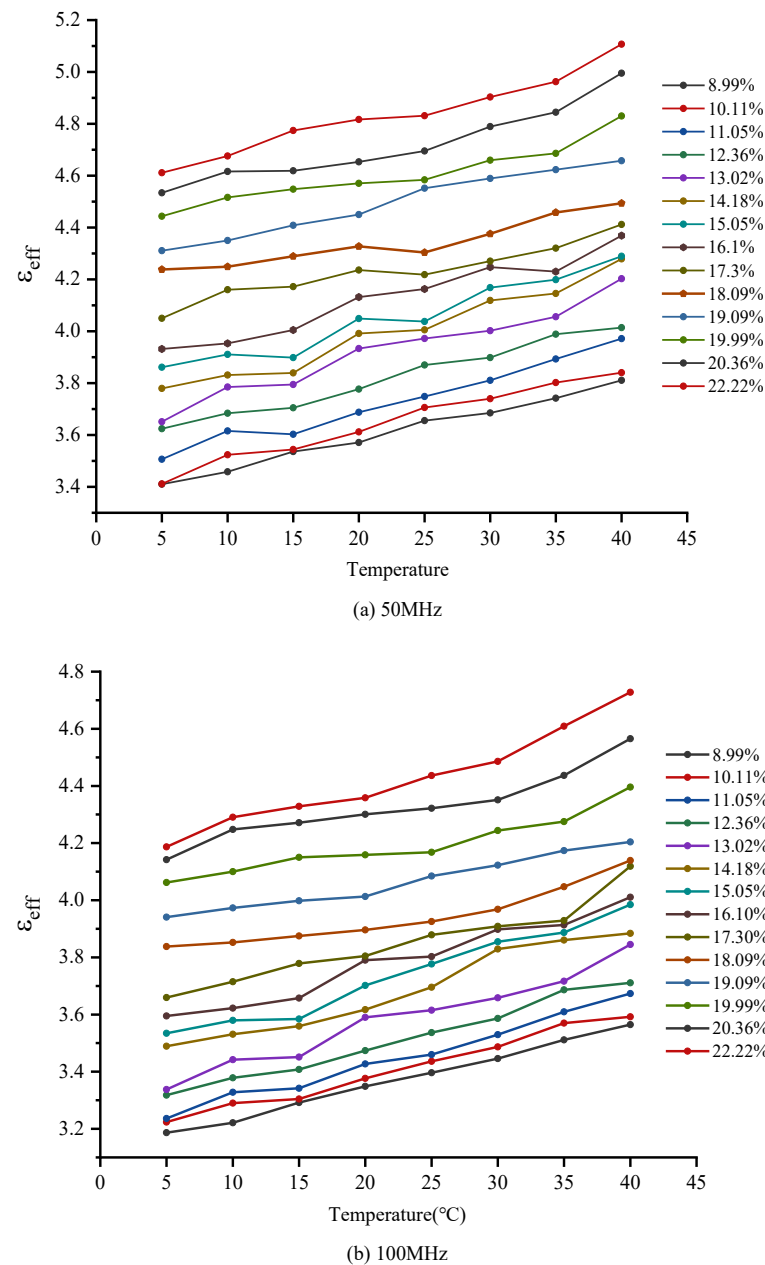


Figure 8. Effect of temperature on dielectric constant of wheat under different moisture contents.

3.3. Effect of Volume Density on Dielectric Constant of Wheat

Figure 9 shows the curve depicting the influence of the volume density on the dielectric constant of wheat with different moisture contents at 5 °C and frequencies of 50 MHz and 150 MHz. Based on Figure 9, within the moisture content range of 8.99% to 22.22%, at a frequency of 50 MHz, the dielectric constant of the wheat varied between 3.41 and 5.2 for different bulk densities. Additionally, at a frequency of 150 MHz, the dielectric constant of the wheat varied between 2.85 and 4.3. At the same frequency, the dielectric constant of the wheat with the same moisture content increased as the bulk density increased. As the bulk

density increased, the medium in the stripline increased. When an electric field is applied to the stripline, a larger quantity of electric field energy can be stored per unit volume, resulting in an increase in the dielectric constant with an increase in the bulk density. From Figure 9, it can also be observed that, at the same frequency, the decrease in the bulk density is smaller for wheat with a low moisture content than for that with a high bulk density. This is because the wheat bran becomes smoother upon the absorption of water, causing the grains to expand slightly.

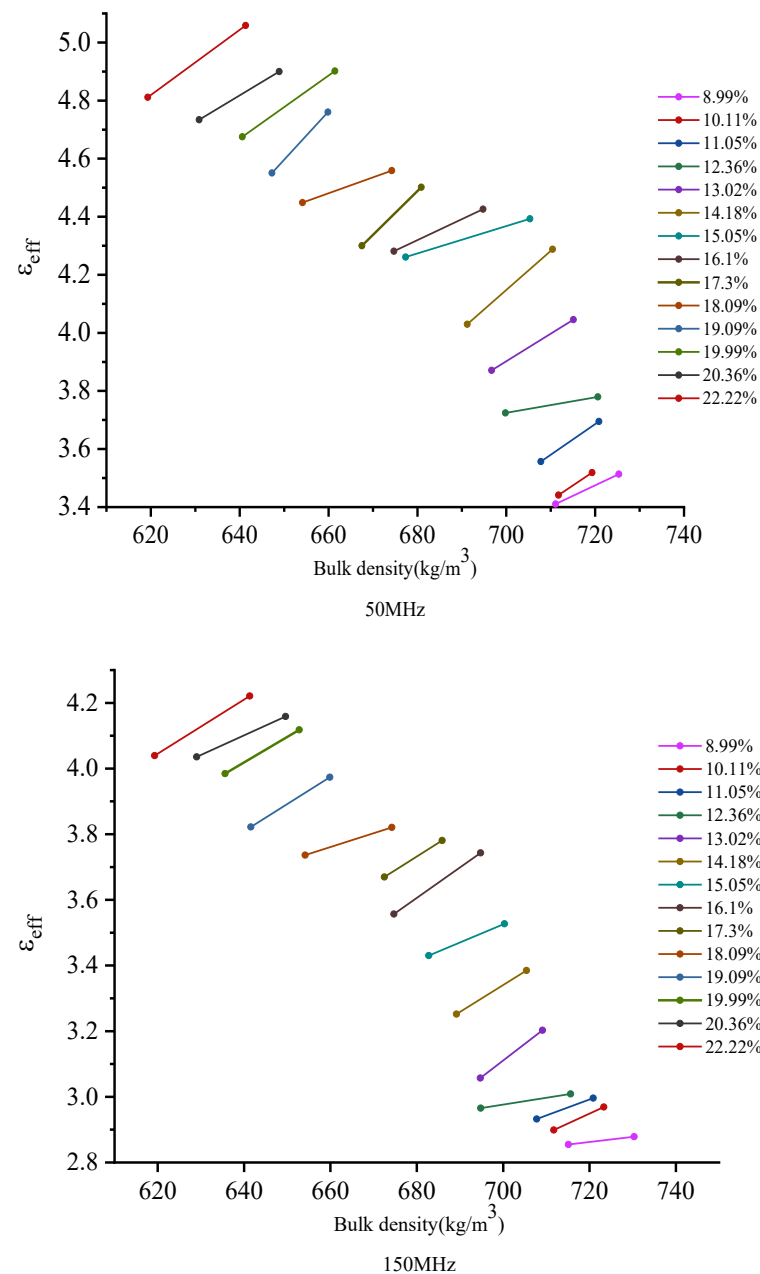


Figure 9. Effect of bulk density on the dielectric constant of wheat under different moisture contents.

3.4. Effect of Moisture Content on Dielectric Constant of Wheat

Figure 10 illustrates the variation trend observed in the dielectric constant of wheat with respect to the moisture content at different temperatures, specifically at frequencies of 150 MHz and 200 MHz, under low-bulk-density conditions. Based on Figure 10, within the moisture content range of 8.99% to 22.22% and under low-bulk-density conditions, at a frequency of 150 MHz, the dielectric constant of the wheat varied between 2.9 and

4.22. Additionally, at a frequency of 200 MHz, the dielectric constant of the wheat varied in the range of 2.58 to 3.76. Under the same measurement frequency and temperature, the dielectric constant of the wheat tended to increase as the moisture content increased. This is because, with an increase in the water content, the free water content of wheat increases. With an increase in the free water content, the number of electric dipoles increases, and the wheat's capacity for energy storage increases when the electric field is applied. Therefore, the dielectric constant of wheat increases as the water content increases.

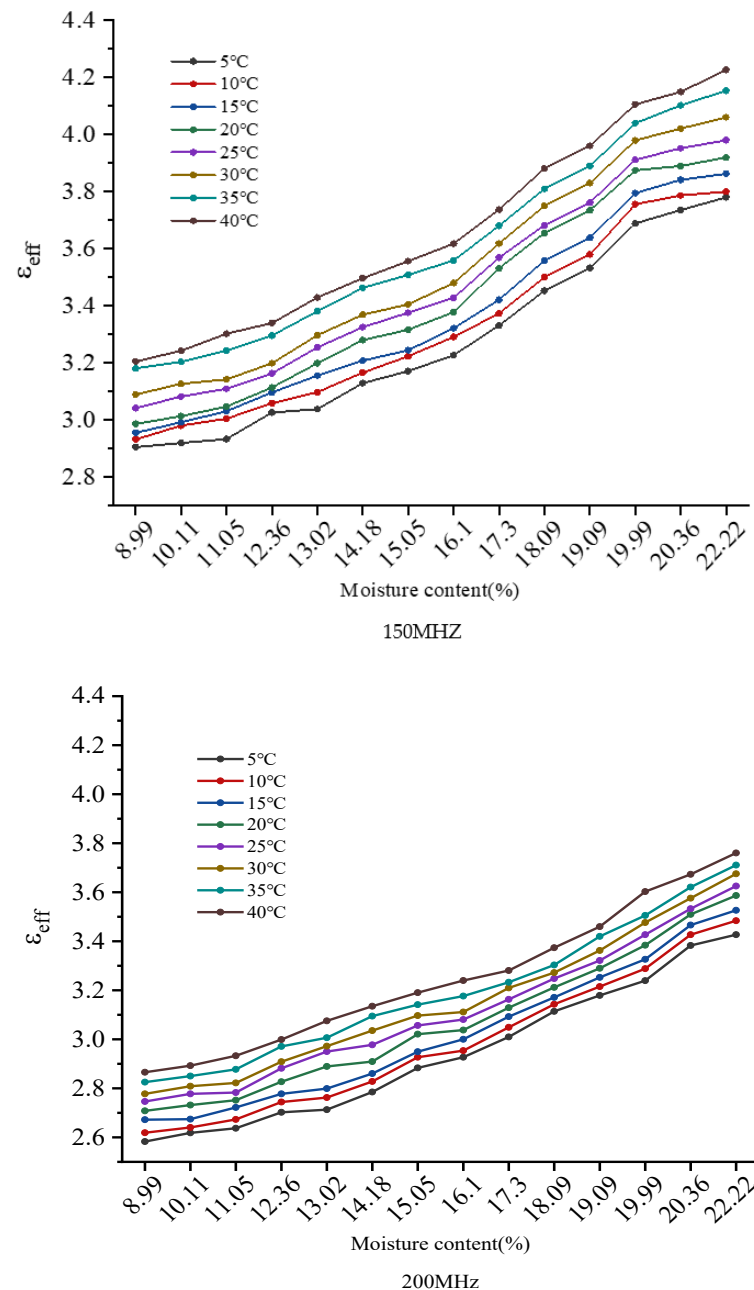


Figure 10. Effect of moisture content on the dielectric constant of wheat at different temperatures.

3.5. Effects of Variables on Wheat Moisture Content

In this section, the correlation between the measurement frequency, dielectric constant, temperature, bulk density, and wheat moisture content is analyzed using the Pearson correlation coefficient and significance analysis (with a significance level of 0.05). From Table 3, it can be observed that the significance of the impact of temperature and bulk density on

the wheat moisture content is less than 0.05, indicating a certain level of correlation. The dielectric constant exhibits the greatest influence on the wheat moisture content, with a more significant correlation.

Table 3. The correlation and significance of each factor with the wheat moisture content.

Feature	Correlation Coefficient	Significance
Frequency	0	1
Dielectric constant	0.698	0.000
Temperature	0.009	0.02
Bulk density	−0.271	0.000

4. Establishing a Model for Wheat Moisture Content Prediction

Establishment of a Model for Wheat Moisture Content Prediction

The measured dielectric constant of wheat varies with the volume density. In order to eliminate the influence of volume density on the measured dielectric constant of wheat, Equation (14) is used to calibrate the effective dielectric constant [31].

$$\varepsilon_{corr} = \left[\left(\varepsilon_{eff}^{\frac{1}{3}} - 1 \right) \cdot \frac{\rho_{ave}}{\rho_{sam}} + 1 \right]^3 \quad (14)$$

where ε_{corr} is the density-calibrated value of the permittivity; ε_{eff} is the effective dielectric constant value; ρ_{ave} is the average volume density of the wheat sample to be measured in the measuring device; and ρ_{sam} is the volume density of the sample to be tested.

In order to eliminate the influence of bulk density on the dielectric constant of wheat, this study uses the calibration function of the prediction model itself. First, the bulk density is taken as the input variable, and the moisture content of the wheat under different bulk densities is predicted via the iterative learning of the prediction model. Therefore, in order to accurately predict the moisture content of wheat under different measurement conditions, two independent variable input methods were used to build the prediction model. It can be seen from Table 4 that the prediction model is built using the following two independent variable input methods: Method 1: frequency, temperature, density calibration dielectric constant ε_{corr} ; Method 2: frequency, temperature, volume density, effective dielectric constant.

Table 4. Comparative analysis of wheat moisture prediction models.

Input Parameter	Model	R ²	MAE	MSE	RMSE
Frequency, Temperature, ε_{corr}	RF	0.96198	0.73596	0.87905	0.93758
	ELM	0.94482	0.65408	0.86697	0.93111
	BP	0.95603	0.63757	0.69833	0.83566
Frequency, Temperature, Bulk density, ε_{eff}	RF	0.99977	0.044386	0.0053011	0.072809
	ELM	0.92938	0.81584	0.114	1.0554
	BP	0.97275	0.51944	0.4299	0.65567

The first method involves the construction of RF, ELM, and BP neural network models that are capable of performing a dynamic prediction of the wheat moisture content, with the measured frequency, temperature, and density-calibrated permittivity ε_{eff} used as inputs, and the wheat moisture content used as output. The 14 sets of measured moisture contents and 16,800 sets of data were divided into training and test set input models according to an 8:2 ratio for training.

Method 2: The RF, ELM, and BP neural network dynamic models designed for the prediction of the wheat moisture content are built by using the frequency, temperature, effective permittivity ε_{eff} , and volume density measurements as inputs, and using the wheat moisture content as output. The 14 sets of measured moisture contents and 33,600

sets of data were divided into training and test set input models according to an 8:2 ratio for training.

The determination coefficient R^2 , mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE) were used as measures to select the optimal prediction model. Figure 11 displays the R^2 coefficients of determination for the prediction results of the test set. All R^2 coefficients exceeded 0.92, with the highest reaching 0.99977. These results indicate that the prediction model is capable of determining the wheat water content. The RF and BP models input the variables outlined in method 2 significantly more than those outlined in method 1, and the ELM model inputs the variables outlined in method 1 significantly more than those outlined in method 2. A comprehensive comparison revealed that when the variables described in method 2 are utilized as inputs, the RF (random forest) model yields the most accurate predictions, as evidenced by the determination coefficients $R^2 = 0.99977$, $MAE = 0.044386$, $MSE = 0.0053011$, and $RMSE = 0.072809$.

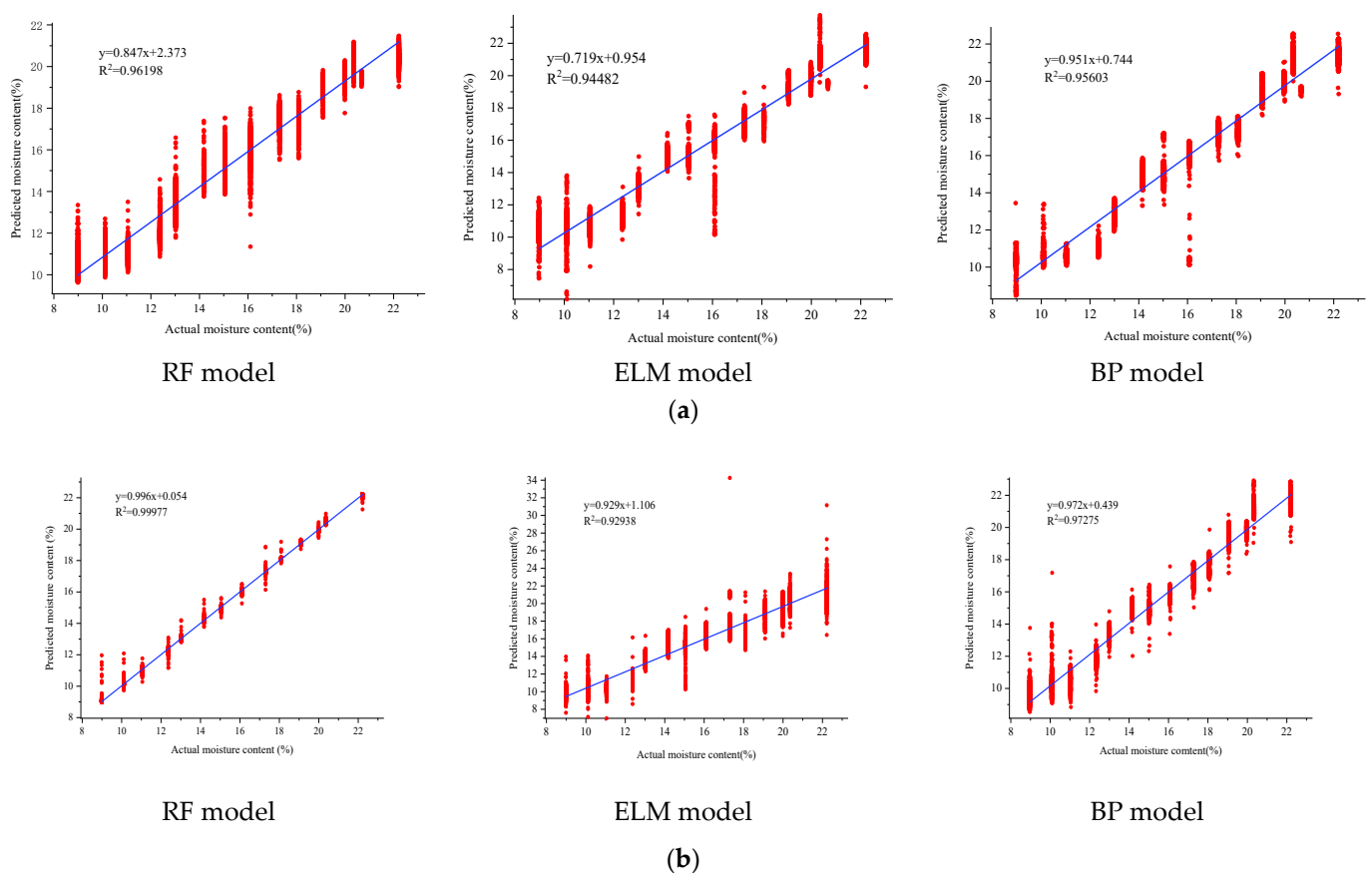


Figure 11. Test set results for RF, ELM, and BP models with different input patterns: (a) Use of frequency, temperature, and ε_{corr} as input, and wheat moisture content as output, with different model prediction results. (b) Use of frequency, temperature, bulk density, and ε_{corr} as input, and wheat moisture content as the output, with different model prediction results.

Table 5 lists several nondestructive testing methods that have been employed in recent years; compared to them, the method described in this study exhibits higher measurement accuracy. The free-space method achieves a similar level of precision, but it requires a larger measurement device and necessitates interference suppression measures. Hyperspectral and near-infrared methods can only detect information from the surface of grains, resulting in lower measurement accuracy, and the instruments are costly and relatively complex to operate. In contrast, the measurement process outlined in this study is simpler, resulting in higher interference resistance.

Table 5. Comparison of different methods used for measuring moisture content.

Method	R ²	Reference
Free-space	0.992	[8]
Hyperspectral	0.874	[17]
Near-infrared	0.989	[32]
Stripline	0.99977	This study

5. Conclusions

In this study, a device based on a ribbon line was designed to measure the water content of wheat. The impact of frequency, temperature, bulk density, and water content on the dielectric constant of wheat was analyzed via dielectric constant measurements. RF, ELM, and BP prediction models were employed to evaluate the moisture content of the wheat, based on methods 1 and 2. The main research conclusions are as follows:

- (1) The stripline detection device was verified via a CST Studio Suite simulation. It has a good signal-to-noise ratio and is able to probe the permittivity of wheat in the 50–200 MHz range.
- (2) In the frequency range of 50–200 MHz, the dielectric constant of wheat decreases as the frequency increases, showing a negative correlation. The dielectric constant of wheat increases as the moisture content, temperature, and bulk density increase, and these are positively correlated.
- (3) The RF model, ELM model, and BP neural network model were used to model the dynamics of water content prediction. The determination coefficients R² and the error analysis of various prediction results revealed that the RF prediction model, which utilizes the frequency, temperature, volume density, and effective dielectric constant A as inputs and the wheat moisture content as the output, exhibited superior predictive performance. Notably, the RF model achieved an exceptional R² value of 0.99977. The detection method is characterized by its small size and strong anti-jamming capability. By considering the known sample when predicting the moisture content of other samples, the method is simple and can be used for the detection of small grains.

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