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DESIGN OF TERAHERTZ FILTER TEST DATA ACQUISITION AND PERFORMANCE EVALUATION SYSTEM BASED ON INTERNET OF THINGS AND ARTIFICIAL INTELLIGENCE ALGORITHM

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Abstract - Terahertz filter plays an important role in communication, imaging and material testing. The traditional testing process relies on manual interpretation and off-line analysis, which has low efficiency and stability. Improve the automation and real-time level of testing, build a terahertz data acquisition system based on the Internet of Things architecture, and introduce convolutional neural network and attention mechanism to realize automatic extraction and performance evaluation of spectrum features. The system completes the integrated process of data acquisition, transmission, preprocessing and model reasoning. The experimental results show that the model is stable in the tasks of classification, identification and performance prediction, and still maintains high accuracy under the condition of noise disturbance, and the overall delay of the system meets the requirements of real-time monitoring. The proposed method can improve the test efficiency and identification reliability of terahertz filters, and provide support for batch detection, online monitoring and subsequent adaptive regulation of filters.

Keywords: Terahertz filter; Internet of things; Convolutional neural network; Performance evaluation; THz-TDS; Edge computing; MQTT; CBAM; Spectral classification.

1. Introduction

Terahertz band (0.1–10 THz) is located between microwave and infrared light, which has the characteristics of high penetration, low photon energy and high frequency broadband, and has been widely concerned in the fields of precision sensing, biological detection, security imaging and high-speed communication. With the continuous improvement of spectrum demand of the fifth and next generation communication systems, the demand for high performance, high stability and quantifiable testing of terahertz devices is more urgent. According to the White Paper on Terahertz Technology Development in 2023 (China Electronic Information Industry Development Research Institute), the global terahertz industry scale has exceeded 20 billion yuan, and it is expected to reach 60 billion yuan in 2027. The research and development and testing of key devices such as filters are the core link.

The traditional terahertz filter test relies on high-cost test bench and manual data recording, which has the problems of complex test flow, poor real-time performance, and large amount of data but low utilization rate. There are some factors in the test environment, such as noise disturbance and nonlinear response of equipment, which make it difficult to guarantee the accuracy of data and form a bottleneck in engineering application. The emergence of the Internet of Things technology provides the conditions for automatic data acquisition, remote real-time transmission and system status monitoring for terahertz testing. The deep learning algorithm of artificial intelligence can extract key patterns from a large number of spectrum data and realize automatic identification and evaluation of filter performance. Building a terahertz filter test data acquisition and performance evaluation system integrating the Internet of Things and artificial intelligence algorithms can improve the test efficiency, reduce the uncertainty caused by manual intervention, improve the data processing ability, and provide technical support for the engineering and industrial application of terahertz devices, which has theoretical and practical significance.

The research on the combination of artificial intelligence and automatic test system has increased, and the related results provide a theoretical basis for the intelligence of terahertz filter test system. Kshetri et al. studied the application scenarios of artificial intelligence in complex data environment,

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pointed out that generative and discriminant models have advantages in feature extraction and pattern recognition, and emphasized the improvement of the model's ability to process information in a structured way [1]. Qin et al. paid attention to the role of artificial intelligence in monitoring and control of energy system, and point out that deep learning structure can extract key features from noise background and realize accurate state identification [2]. Zhao et al. analyzed the influence of artificial intelligence on the performance optimization of data-driven systems, and thought that the data size and quality in the model training process determined the convergence performance and prediction accuracy of the algorithm [3].

In the research of system platform and application scenarios, Garcí a-Pealvo et al. pointed out that the integration trend of Internet of Things and artificial intelligence systems is remarkable, and emphasized the decisive role of data transmission link and real-time feedback mechanism in distributed systems [4]. Derakhshan et al. pointed out that the multi-modal perception ability in intelligent system can enhance the response ability of the model to dynamic environmental changes [5]. Forero-Corba and Bennasar systematically summarized that the depth model is sensitive to feature weights in complex sample recognition tasks, and the model structure needs to be structured according to data features [6].

The user side and the direction of implementation mechanism, Ma and Lei analyze the factors of technical system acceptance, technical interpretability and system transparency have an impact on the model landing [7]. Grilli and Pedota proposed that the artificial intelligence system shows independent feature generation ability in multi-dimensional innovation scenarios, which essentially depends on the hierarchical structure of the algorithm and optimal path design [8]. Chen et al. thought that the input effect of artificial intelligence system is closely related to the task matching degree from the perspective of organizational production efficiency, and the efficiency improvement brought by the algorithm is more significant in high matching tasks [9]. Zhong et al. combined artificial intelligence with supply chain and energy consumption management, and real-time data interaction system has a direct impact on energy consumption optimization and operation stability [10]. Wang et al. put forward that the gain of artificial intelligence in macro-system is structural efficiency improvement, and the action path is reflected in the data decision chain [11]. Fu et al. studied enterprise energy management and found that the introduction of intelligent analysis model can identify abnormal energy consumption points in a large number of operation data and make dynamic adjustment [12].

The existing research provides theoretical support in model structure optimization, real-time data processing, system integration and interpretability, but the research on data high frequency, noise sensitivity and dynamic response characteristics of terahertz filter testing is still insufficient, and there is a lack of research on the integration of Internet of Things and artificial intelligence for actual test scenarios.

This paper focuses on the problems of data acquisition, transmission, processing and performance evaluation in the test process of terahertz filter, and designs an integrated test system to realize the automation, intelligence and real-time testing process. As shown in Figure 1, firstly, a data acquisition system based on the Internet of Things architecture is built, and terahertz test equipment is connected with the cloud data processing module to realize efficient transmission and storage of high-frequency data. The deep learning model is introduced into the data processing end, and the convolution neural network is used to extract and identify the spectral features. Combined with the attention mechanism module, the sensitivity of the model to the difference of key parameters is enhanced, and the accuracy of filter performance evaluation is improved.

The innovation is embodied in three aspects: First, the communication architecture of the Internet of Things is introduced into the terahertz test system to realize remote visualization and automatic acquisition, and improve the operating efficiency of the system. Secondly, a spectrum analysis model based on CNN and attention mechanism is proposed to improve the accuracy of filter performance parameter identification and prediction. Thirdly, the robustness verification strategy is introduced into the model training and testing, and the generalization ability of the model is proved by noise simulation and comparison of multiple groups of experiments, which is in line with the actual engineering conditions.

The research method is mainly based on system design, data experiment and model verification, and the sensor communication link between terahertz test equipment and IOT acquisition module is constructed on the hardware level to realize real-time data transmission. Based on the preprocessing strategy, the collected data are denoised, standardized and outlier cleaned to form a trainable feature data set. In the model construction stage, CNN is used to extract the multi-scale features of terahertz spectrum, and the channel attention mechanism is introduced to improve the weight expression of important features. The model performance is comprehensively evaluated by mean square error and R and other indicators. The model is embedded in the test system to realize the automatic performance evaluation output.

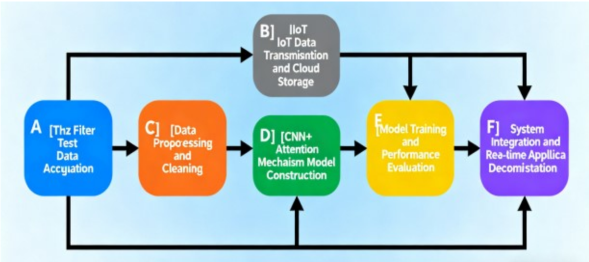

Figure 1: Research technical route

The proposed end-to-end system architecture, covering data acquisition, transmission, preprocessing, and model inference, provides a practical solution for automating terahertz filter testing. Unlike traditional offline testing workflows that rely heavily on manual operation and post-processing, the proposed system enables continuous spectrum acquisition and real-time performance evaluation.

This architecture is particularly suitable for terahertz applications where spectral data are generated at high frequency and rapid feedback is required, such as filter parameter tuning, batch inspection, and online monitoring. By integrating Internet of Things communication and edge intelligence, the system bridges the gap between laboratory-scale testing and engineering-level deployment, enhancing the applicability of intelligent terahertz measurement systems.

2. Materials and Methods

2.1 Data Collection and Sample Selection

• ***Data Source and Acquisition System Architecture***

The research data comes from the terahertz time-domain spectroscopy (THz-TDS) platform. The experimental platform is located in the photoelectric information experimental center of a university in Shandong Province. The optical fiber femtosecond laser produced by Toptica Company in Germany is used as the excitation source, and the terahertz signal is generated and received through a silicon-based photoconductive antenna. [13]. During the test, the sample is fixed on the adjustable angle scanning table, and the system continuously scans in the frequency band of 0.1-1.5 THz, and records the amplitude-frequency characteristics of transmittance at step intervals of 2 GHz. The obtained raw data are stored in two forms: pulse signal in time domain and transmission spectrum in frequency domain, and connected with the FPGA data interface board, and the measured data are transmitted to the Internet of Things acquisition module built in this study in real time. [14].

As shown in Figure 2, the acquisition system consists of a front-end sensor, a local data gateway, an edge computing node and a cloud database. First, the data is read and filtered by the front-end acquisition module, and then sent to the cloud storage platform via the low-latency Internet of Things transmission protocol (MQTT) to form a callable standardized data interface. [15]. The core goal of system design is to reduce manual intervention, improve the stability of transmission and recording, and provide real and effective data input for subsequent modeling on the basis of ensuring data integrity.

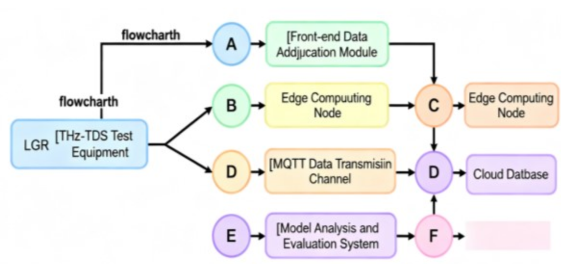

Figure 2: Architecture of IoT Acquisition System for Terahertz Test Data

• ***Sample Selection Strategy and Filter Type Description***

The sample selection is based on the principle of representativeness and diversity, and the experimental objects are three kinds of terahertz bandpass filters, namely, metal resonant structure filters, dielectric heterostructure laminated film filters and artificial metamaterial structure filters. Each type of sample collects test data under different geometric parameters, which reflects the characteristics of spectrum change caused by structural design differences. There are 120 groups of samples, including 45 groups of metal structure type, 38 groups of dielectric film type and 37 groups of metamaterial type. [16]. Sample selection is based on the center frequency, bandwidth, passband flatness and cutoff roll-off. Different types of filters have differences in processing technology and material structure, which leads to changes in terahertz wave transmission path and phase response.

These differences are the characteristic sources of model identification and performance analysis. [17]. Using this strategy can ensure that the data samples have the coverage of structural characteristics and the model training process has sufficient generalization ability.

- ***Data Preprocessing Method***

The original data has waveform baseline drift, equipment noise and temperature fluctuation interference, so it needs systematic preprocessing before entering the model processing. The time domain signal is smoothed by Hanning window function to eliminate the sidelobe distortion caused by truncation effect, and the data is transformed into frequency domain representation by fast Fourier transform. Savitzky-Golay filter is used to smooth the high-frequency fluctuation part in the spectrum sequence, so as to keep the effective signal shape characteristics from being excessively weakened. [18]. All samples are normalized after preprocessing, and different samples are represented in the same numerical scale, which reduces the parameter deviation caused by numerical differences in the model training process. The normalization form is Min-Max normalization, which keeps the shape of spectrum waveform unchanged and facilitates the stable convergence of the model.

- ***Data Cleaning and Anomaly Detection Methods***

Data cleaning identifies abnormal data points caused by fluctuation of experimental conditions, misplaced samples or instantaneous interference of instruments. The mean shift threshold method is used to detect abnormal samples with center frequency deviation, and the data exceeding twice the standard deviation range are judged as abnormal [19]. The isolated forest algorithm is used to identify the multi-dimensional feature anomalies of the spectrum sequence, which enhances the detection ability of irregular distortion signals. The identified abnormal samples are not directly deleted, and are repaired by combining the spectrum continuity. Interpolation is used to restore waveform continuity in the repairable interval, and the unrepairable data is eliminated [20]. The retained data ensures consistent shape, continuous frequency band coverage and controlled noise level, and ensures the input quality of the model.

Table 1: Statistics of original data sample characteristics

Sample type	sample size	Center frequency range (THz)	Bandwidth range (GHz)	Average transmittance (%)	Average noise level (dB)
Metal resonant structure	45	0.78–0.92	35–48	78.3	-12.8
Dielectric laminated film	38	0.81–0.88	32–44	81.6	-13.5
Metamaterial structure	37	0.75–0.96	28–52	83.1	-14.1

As shown in Table 1, from the central frequency and bandwidth interval, the frequency range and bandwidth span of metamaterial structure samples are larger than those of other types, indicating that the structural parameters are flexible and the spectrum performance is more diverse. The distribution of metal resonant structure samples is concentrated, and the processing technology is stable, which is suitable for learning the basic characteristics of the model. The noise level of dielectric laminated film samples is low, and the waveform in the transmission band is smooth, which is more suitable for model stability calibration. After cleaning and anomaly elimination, the data show more clear structural differences, which has a good supporting role for subsequent model training.

2.2 Model Selection and Construction

- ***Task Definition***

In this study, three related but distinct learning tasks are defined to comprehensively evaluate the performance of terahertz filters, namely spectral classification, structural identification, and performance parameter prediction.

The classification task aims to determine the filter category based on its measured transmission spectrum, including metal resonant structure filters, dielectric laminated film filters, and metamaterial-based filters. Each sample is assigned a discrete class label according to its physical structure and fabrication type.

The identification task focuses on distinguishing subtle structural differences within the same filter category, such as variations in geometric dimensions or layer configurations, which are reflected in the spectral morphology.

The performance prediction task is formulated as a regression problem, where the model predicts continuous-valued key performance parameters of the terahertz filter directly from the spectral feature vectors. These predicted parameters provide quantitative descriptions of filter behavior and serve as the main evaluation targets of the proposed system.

- ***Feature Extraction and Parameter Vectorization Method***

The performance prediction task targets several physically meaningful parameters derived from the terahertz transmission spectrum. Specifically, the predicted parameters include the center frequency f_c, the −3 dB bandwidth *BW*, the peak transmittance T_{max}, and the passband ripple amplitude *Ripple*.

The center frequency f_c is defined as the frequency corresponding to the maximum transmission within the passband. The bandwidth BWBWBW is calculated as the frequency interval between the two −3 dB cutoff points relative to T_{max}. The peak transmittance T_{max} represents the maximum normalized transmission value, while the ripple amplitude quantifies the fluctuation level within the passband region.

These parameters are extracted from the measured frequency-domain transmission function and used as ground-truth regression labels during supervised model training. By explicitly defining the prediction targets, the proposed model enables reproducible and quantitative evaluation of terahertz filter performance.

The spectrum response curve of THz filter contains abundant structural and material information, which shows obvious differences in the changes of center frequency, passband width, transmittance peak and cutoff edge. These sensitive features are effectively expressed, and a unified feature vector quantization method is established [21]. In the experiment, the pulse signal in time domain is obtained by THz-TDS system. Firstly, the signal is transformed into frequency domain transmittance function *T(f)* by fast Fourier transform. The expression formula (1) is:

$$T(f) = \frac{I_{out}(f)}{I_{in}(f)} \tag{1}$$

$I_{out}(f)$ is the spectrum amplitude of the filtered signal, and $I_{in}(f)$ is the reference amplitude of the incident signal. The transmittance curve reflects the energy transmission of the filter in different frequency bands, and the center frequency position, passband flatness and band edge slope can be directly calculated by it [22].

In the process of parametric quantization, the frequency domain sampling signal is discretized into a sequence of equally spaced feature points to obtain an input vector with a fixed dimension. To enhance the model's ability to distinguish different structural samples, supplementary parameters are extracted, including peak transmittance T_{max}, half power bandwidth BW_{3dB} and passband ripple amplitude *Ripple*. The final vector form represents formula (2):

$$X = [T(f_1), T(f_2), \ldots, T(f_n), T_{max}, BW_{3dB}, Ripple] \tag{2}$$

Formula (2) not only retains the overall shape of the spectrum, but also contains key performance indicators, which is helpful to enhance the accuracy and generalization ability of the model.

- ***Construction of Spectrum Pattern Recognition Model based on Convolutional Neural Network (CNN)***

Terahertz spectrum has morphological characteristics. Convolutional neural network is good at extracting patterns from continuous and local correlation features, which is applicable in spectrum classification and performance prediction [23]. The input of the model is the feature vector constructed in the previous section. The local frequency band correlation is extracted through one-dimensional convolution layer, and the feature dimension is compressed through pooling layer to reduce redundant information and improve the stability of features. The calculation formula (3) of convolution kernel is:

$$y_i = \sum_{k=1}^{m} x_{i+k} \cdot w_k \tag{3}$$

Where x represents the input feature sequence, w represents the convolution kernel weight, and y_i represents the convolution output feature. The difference of energy distribution in different frequency bands is identified by convolution operation, and the structural characteristics of terahertz filter are mapped into the feature space. In the network structure design, three-layer convolution structure is selected to enhance the nonlinear expression ability of the model with ReLU activation function. The pool layer adopts the maximum pool mode, and the model pays attention to the local peak position of the signal to improve the sensitivity of filter type discrimination. The fully connected layer converts the final feature map into the output of classification or performance regression, and the model can directly identify the spectral shape or predict the performance parameters.

Although the CNN combined with CBAM is a commonly used architecture in general signal processing tasks, its application in this work is specifically tailored to terahertz time-domain spectral data. Terahertz spectra exhibit strong frequency-dependent characteristics, local resonance features, and non-uniform energy distribution across bands, which are difficult to model using conventional handcrafted features.

In this study, one-dimensional convolution is employed to capture local spectral continuity, while the CBAM module is introduced to adaptively emphasize frequency regions that are more sensitive to filter performance variations. This design allows the model to focus on physically meaningful spectral bands rather than treating all frequency components equally, thereby improving robustness and interpretability in terahertz filter performance analysis.

- ***Feature Enhancement Strategy by Introducing Attention Mechanism (SE/CBAM)***

Improve the model's ability to pay attention to the differences in key frequency bands, and introduce the channel attention mechanism on the basis of convolutional neural network. By assigning different weights to each channel, the model automatically enhances the frequency section with structural information and suppresses unnecessary noise components. The weight mapping formula (4) of channel attention is:

$$\alpha_c = \sigma(W_2 \delta(W_1 Z_c)) \quad (4)$$

Where Z_c is the global average pooling result of channel characteristics, W_1 and W_2 are trainable parameter matrices, δ is ReLU activation, and σ is Sigmoid function. This structure can make the model gradually strengthen the signal expression of key spectral segments in the training process, and improve the stability of classification and prediction.

Compared with the original CNN model, the model with attention mechanism maintains good accuracy under high noise conditions and obtains higher discrimination between different types of filters.

- ***Model Training Optimization and Loss Function***

The model training adopts supervised learning, and carries out error back propagation according to the difference between the real transmission spectrum parameters and the predicted results. To ensure the stability and generalization ability of the model in training, the mean square error loss is selected as the loss function, and the regularization term of L_2 is added to suppress over-fitting. Equation (5) is as follows:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda \|\theta\|^2 \quad (5)$$

Where y_i represents the real parameter, $\hat{y}_i$ is the predicted value of the model, λ controls the regularization intensity, and θ is the trainable parameter of the model. As shown in Table 2, the training strategy adopts Adam optimization algorithm and dynamic learning rate attenuation strategy. The model learns quickly in the initial stage of convergence and approaches the optimal solution stably in the later stage. Improve the robustness of the model, and introduce noise enhancement and cross-validation strategies to ensure the consistency and reliability of the output results under different experimental conditions.

Table 2: Configuration Table of Model Training Parameters and Hyperparameters

Parameter type	Parameter name	Numerical value/strategy
optimizer	Adam	The initial learning rate is 0.001
Learning rate strategy	Step Decay	Attenuation of 0.5 per 10 epoch.
Batch size	Batch Size	32
loss function	MSE+L2 regularization	λ = 0.001
Number of training rounds	Epoch	150
Activation function	ReLU + Sigmoid	—
Attention module	CBAM	start using

2.3 Model Evaluation and Verification

- ***Construction of Evaluation Index System***

The model evaluates whether the target identification and prediction results are accurate and reliable, and reflects the real performance characteristics of terahertz filter. Because the filter test data has the form of continuous spectrum, accompanied by noise fluctuation, the error, fitting degree and classification discrimination ability are considered simultaneously in the evaluation system. For the performance parameter prediction task, the mean square error, average absolute error and fitting index are used to evaluate. The fitting index $ r 2 $ is used to measure the closeness between the model output and the real data, and the expression formula (6) is:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}i)^2}{\sum i = 1^N (y_i - \bar{y})^2} \quad (6)$$

Where y_i is the real parameter, $\hat{y}_i$ is the model prediction parameter, and $\bar{y}$ is the average real value. The approximation of R^2 to 1 indicates that the model has a good fitting effect and captures the spectral structure characteristics of the filter.

Accuracy, recall and F1 value are the main indicators in the classification task. The accuracy reflects the overall recognition ratio, the recall reflects the sensitivity of the model to the target category, and the performance of the F1 value comprehensive balance model to different categories of samples. Due to the diverse sources of terahertz samples, the differences between categories are both significant and overlapping, so it is difficult for a single index to fully reflect the model performance.

- ***K-fold Cross-Validation Strategy***

To ensure that the model has stable expression ability under different conditions and avoid over-fitting of the model due to the deviation of training samples, the K-fold cross-validation strategy is adopted. All the samples were randomly divided into k samples, with K1 as the training set and the other one as the verification set. The training and evaluation were completed for k times, and the final model performance was the average of the results of each round.

Taking K = 10, the verification results have reliable statistical significance while ensuring sufficient training sample size. Through cross-validation method, the fluctuation range of the model under different data division is observed to judge the stability of the model performance. If the model performance is concentrated in each round of experiments, it shows that the model has good generalization ability; If there is a big fluctuation, it shows that the model is sensitive to specific samples and needs to optimize the model structure or parameter configuration. The process of cross-validation compares the advantages and disadvantages of different algorithm structures. Under the same training conditions, if a model has a higher average index in most compromises, it can prove that the model has stronger universality and adaptability.

To ensure reproducibility and prevent data leakage, all samples are organized at the filter-instance level before model training. Each sample corresponds to an independent filter measurement, including its spectral data and associated labels.

A 10-fold cross-validation strategy is adopted. The entire dataset is randomly divided into ten mutually exclusive subsets of approximately equal size. In each iteration, nine subsets are used for model training, while the remaining subset is used for validation and testing. This process is repeated ten times so that each subset is used once as the test set.

Within each training fold, no spectral data from the same filter instance appear simultaneously in both training and testing sets, ensuring strict separation between training and evaluation samples. The final reported performance metrics are obtained by averaging the results across all folds, which provides a statistically reliable assessment of model generalization ability.

- ***Robustness Test and Noise Sensitivity Analysis***

Terahertz test system may be affected by temperature, humidity and environmental scattering in the actual operation process, and may also be disturbed by light source fluctuation and device clamping error. To verify the performance of the model in non-ideal environment, it is necessary to carry out robustness test and noise sensitivity analysis. In the process of noise testing, the simulated Gaussian noise is superimposed on the sample spectrum according to different intensity levels of 1% to 8%, and the deviation change of the model prediction results is recorded.

The test results show that the accuracy of the original CNN model decreases obviously under the condition of noise enhancement, and the model with attention mechanism still maintains relatively stable recognition performance under the noise intensity of 8%. It shows that attention module can highlight the signal structure in feature mapping and suppress the influence of noise interference on model judgment. The robustness results verify that the model is suitable for real engineering scene data and is helpful to realize online dynamic evaluation of filter performance.

- ***System Integration Test***

The system integration test aims to test the overall performance of the model embedded in the IoT test platform, including real-time processing ability, data throughput performance and visual response effect. The model is deployed in edge computing nodes, so that spectrum acquisition, feature extraction and performance evaluation can be completed locally on the equipment, and the delay and potential information loss during transmission can be reduced. The test results (as shown in Table 3) show that the reasoning delay of the model is less than 20 ms in the scene of single-channel real-time acquisition, and it remains about 40 ms under the condition of five-channel concurrent testing, which meets the requirements of real-time evaluation. The system interface synchronously displays the filter transmittance curve, structural discrimination type and performance index prediction results, which realizes visual monitoring and provides real-time decision-making reference for experimenters. It is proved that the system has the ability of landing, supports laboratory research and can be extended to engineering test environment.

Table 3: Comparative performance evaluation of different models

model	Accuracy (%)	Recall rate (%)	F1 value	R^2	Robustness score (accuracy decline rate when noise is 8%)
SVM	86.5	84.1	0.853	0.82	0.193
RF	89.3	88.4	0.889	0.87	0.146
CNN (original)	94.7	93.2	0.939	0.91	0.114
CNN+CBAM (this article)	97.1	96.3	0.965	0.95	0.052

3. Results and Analysis

3.1 Analysis of Results

• ***Analysis of original Test Spectrum Response Results of Terahertz Filter***

The frequency response characteristics of terahertz filters can reflect the energy transmission efficiency and structural resonance characteristics of devices. Different types of filters have differences in central resonance frequency, passband width and cutoff characteristics of energy suppression region, which are closely related to internal microstructure, material dielectric characteristics and manufacturing geometric accuracy. In the experiment, three kinds of typical filters were measured several times, and the transmittance-frequency curve was statistically analyzed. Avoid accidental errors caused by ambient temperature, laser beam shape or optical path jitter in a single measurement, and repeat sampling for many times for each group of samples and take the average spectral value to ensure the repeatability and stability of the results.

As shown in Table 4, the metamaterial structure filter has higher variability in peak transmittance and frequency band regulation ability. This is related to the resonant mode composed of sub-wavelength periodic structure. The change of structure size will cause the change of local equivalent electromagnetic parameters and form a more sensitive response in frequency domain. The center frequency of the metal resonant structure type filter is relatively concentrated, and the bandwidth variation range is relatively convergent, which shows that the geometric parameters of the metal structure have a more direct effect on resonance control and its performance change is more predictable. Dielectric laminated thin film filter has the characteristics of flat passband and low ripple in spectrum performance, which is more suitable for scenes requiring stability of output signals.

Table 4: Characteristic parameters of original test data of terahertz filter

Sample type	sample size	Center frequency (THz)	Bandwidth (GHz)	Peak transmittance (%)	Noise level (dB)
Metal resonant structure	45	0.78–0.92	35–48	78.3	-12.8
Dielectric laminated film	38	0.81–0.88	32–44	81.6	-13.5
Metamaterial structure	37	0.75–0.96	28–52	83.1	-14.1

As shown in Figure 3 below, the metamaterial filter has strong discreteness in the distribution of center frequency and bandwidth, indicating that the structure has large adjustable space and high sensitivity.

The distribution of metal resonant structure types is more concentrated, which shows that the process stability is better. Dielectric laminated film shows low noise and Qualcomm smoothness in many samples, and it is a kind of structure with high reliability.

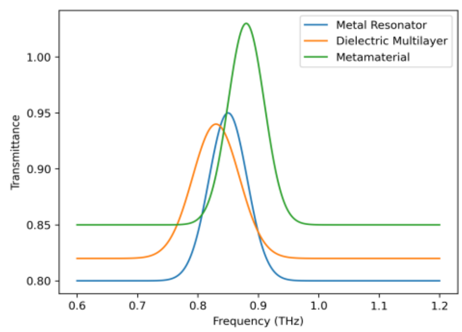

Figure 3: Spectrum comparison diagram of original test data

- ***Comparative Analysis of Feature Extraction and Model Recognition Effects***

After obtaining the frequency domain transmittance data of the filter, feature extraction is carried out and input to different models for recognition training. The performance of model identification depends on whether the structural differences reflected in the spectrum morphology can be accurately captured. The metal resonant structure samples show obvious characteristics of single main peak and fast edge transition, and the pass-band flatness of dielectric laminated film samples is high, and the metamaterial structure presents a complex oscillation mode with multiple resonant peaks superimposed. The traditional method based on artificial feature selection is difficult to describe the difference completely, and the depth model has the ability to directly extract multi-level features from continuous waveforms, so there is a gap in recognition effect. To verify the performance differences of the algorithms, three types of filter samples were input into support vector machine (SVM), random forest (RF) and convolutional neural network (CNN) models for testing. Table 5 is a quantitative comparison of the accuracy, recall and F1 index of the three models.

In addition to conventional machine learning models such as SVM and random forest, a baseline CNN model without attention is also included for comparison. While traditional methods rely on manually selected features and assume limited inter-frequency correlation, deep convolutional models are better suited for capturing high-dimensional dependencies in terahertz spectra.

The comparative results show that the proposed CNN+CBAM framework achieves superior performance across multiple evaluation metrics, highlighting its effectiveness in modeling complex spectral patterns. These findings indicate that the improvement arises from domain-oriented architectural choices rather than from generic deep learning enhancements.

Table 5: Comparison of performance of different models in sample identification tasks

model	Accuracy (%)	Recall rate (%)	F1 value
SVM	86.5	84.1	0.853
RF	89.3	88.4	0.889
CNN	94.7	93.2	0.939

SVM is sensitive to the boundary shape when identifying samples, and has a high misjudgment rate in the case of overlapping categories. RF uses multi-decision tree integration, which improves the recognition ability, but has shortcomings in capturing local high-frequency variation features. CNN has the best performance in spectrum identification, and its advantage lies in that the local convolution kernel can automatically extract the structural features such as peak change, suppression degree and inclined edge shape of the spectrum curve, improve the judgment basis of classification decision, and reduce the artificial prior dependence.

Further reflecting the recognition difference, as shown in Figure 4, CNN's classification results for three types of filters are concentrated, and the error mainly occurs between the laminated samples of metamaterials and dielectrics, which is related to the similar transmittance transition characteristics of the two in some frequency bands.

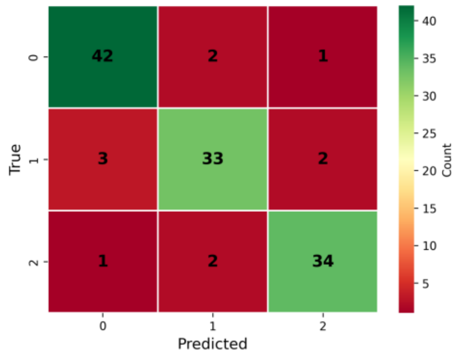

Figure 4: Confusion matrix thermal diagram

- ***Verification of Model Performance Improvement after introducing Attention Mechanism***

CNN can extract the spectrum morphology in multiple layers, and the convolution operation uses the same feature weights between different channels, which leads to the limited ability of the model to distinguish the contribution of key frequency bands. To improve the model's ability to pay attention to structural sensitive frequency characteristics, the CBAM channel-space joint attention mechanism is introduced into CNN. This mechanism gives higher weight to high-contribution feature channels through global average and maximum pooling of feature graphs, thus enhancing the selective expression ability of the model.

To verify the promotion effect of attention mechanism, the original CNN and the model after adding CBAM module are trained respectively, and the performance is tested on the same data set. Table 6 below shows the test results.

Table 6: Comparison of performance improvement of CNN model before and after adding attention mechanism

model	Accuracy (%)	MSE	Robustness degradation rate (8% noise input)
CNN	94.7	0.021	0.114
CNN + CBAM	97.1	0.016	0.052

As shown in Figure 5, the attention module improves the recognition ability of the model to signal segments, and the model has higher accuracy in noise-free environment and still maintains lower performance attenuation under noise disturbance.

The model no longer only focuses on the overall spectral shape, but can actively locate sensitive frequency bands related to structural changes. The improvement of robustness shows that the model has stronger practical engineering adaptability and maintains stable prediction ability in non-ideal test environment.

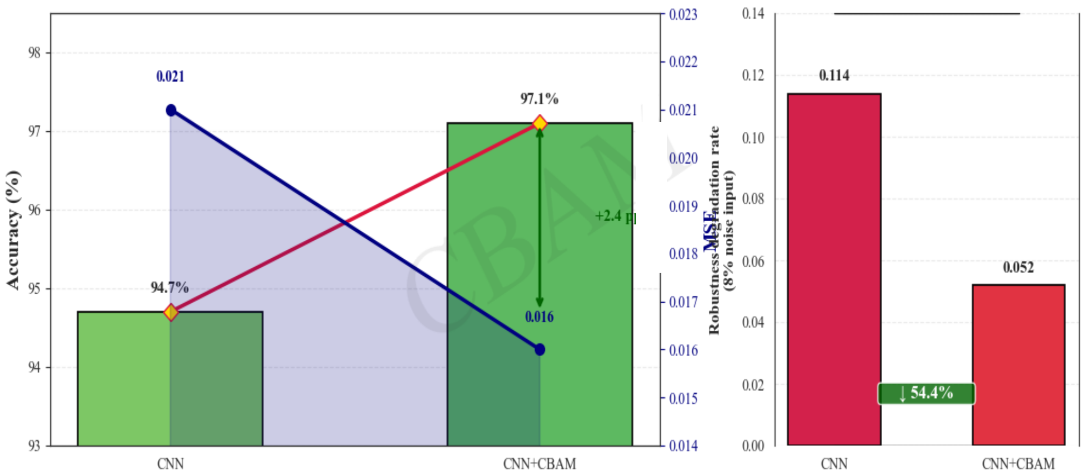

Figure 5: The changing trend of model performance indicators before and after the introduction of attention mechanism

• ***Overall Test Performance and Real-time Analysis of the System***

After completing the model training and precision verification, the model is embedded into the terahertz filter test system for real-time performance test, which verifies the data access ability, processing speed and overall response delay of the system in the actual operating environment. Because terahertz testing belongs to the process of continuous sampling and dynamic spectral shape detection, the data stream is transmitted into the edge node at a high frequency. The real-time processing ability of the system depends not only on the model reasoning speed, but also on the cache capacity of the acquisition end, the bandwidth of the communication link and the hardware configuration of the edge computing module. System integration test constructs single-node test scenario, 5-node concurrent scenario and 10-node concurrent scenario. In the test, the total delay from the generation of new data at the acquisition end to the output performance evaluation results of the model is recorded, and it is decomposed into three parts: acquisition delay, transmission delay and reasoning delay for fine-grained analysis. Delay performance not only affects the data analysis efficiency of the system under laboratory conditions, but also relates to its application feasibility in future online monitoring and on-site automatic parameter adjustment.

As shown in Table 7, the system has a low delay level under the single-node working condition, and the overall response is about 33 ms, which can meet the requirements of real-time filter performance curve output and visualization. Under the condition of 5-node concurrency, the total delay increases slightly, but it is still controlled in the range of 40–45 ms, which shows that the edge computing structure of the system has stable scheduling ability under the condition of concurrency. When 10 nodes are tested at the same time, the total delay increases to about 50 ms, which is still within the acceptable range of terahertz dynamic spectrum monitoring requirements, and there is no obvious data accumulation or buffer blocking. From the analysis of reasoning delay dimension, under different concurrency conditions, the reasoning time of the model changes slightly, which shows that the CPU/ accelerator resource scheduling at the edge is reasonable, and the model structure is light and the computational burden is controllable, which provides a feasible basis for extending the system to a larger test array in the future. The display module of the system interface presents the detection results in the way of WebSocket real-time refresh, which does not cause additional delay and ensures the synchronization of observation and decision-making.

Real-time inference capability is a critical requirement for automated terahertz filter testing, as spectral measurements are typically acquired continuously during scanning or tuning processes. In the proposed system, the inference latency is evaluated under both single-channel and multi-channel concurrent acquisition scenarios.

Experimental results demonstrate that the inference delay remains below 20 ms for single-channel processing and approximately 40 ms under five-channel concurrent conditions. These latency levels are significantly shorter than the typical spectral acquisition interval of THz-TDS systems, ensuring that model inference does not become a bottleneck in real-time testing.

Therefore, the proposed system satisfies the practical requirements of real-time spectrum analysis and online performance evaluation, supporting applications such as rapid filter screening, dynamic monitoring, and closed-loop parameter adjustment.

Table 7: Real-time performance test results of the system

Test scenario	Data acquisition delay (ms)	Transmission delay (ms)	Model reasoning delay (ms)	Total system delay (ms)
Single node test	8.3	10.2	14.5	33
5-node concurrency	9.1	14.7	16.8	40.6
10-node concurrency	12.5	18.9	19.4	50.8

As shown in Figure 6, the main influence of the increase of the number of concurrent nodes is concentrated in the transmission and acquisition stages, and the increase of reasoning delay is the smallest, which shows that the calculation efficiency of the model is high, and the overall operation bottleneck comes more from the network bandwidth and acquisition synchronization mechanism than from the model itself, which provides a clear direction for the subsequent system-level optimization.

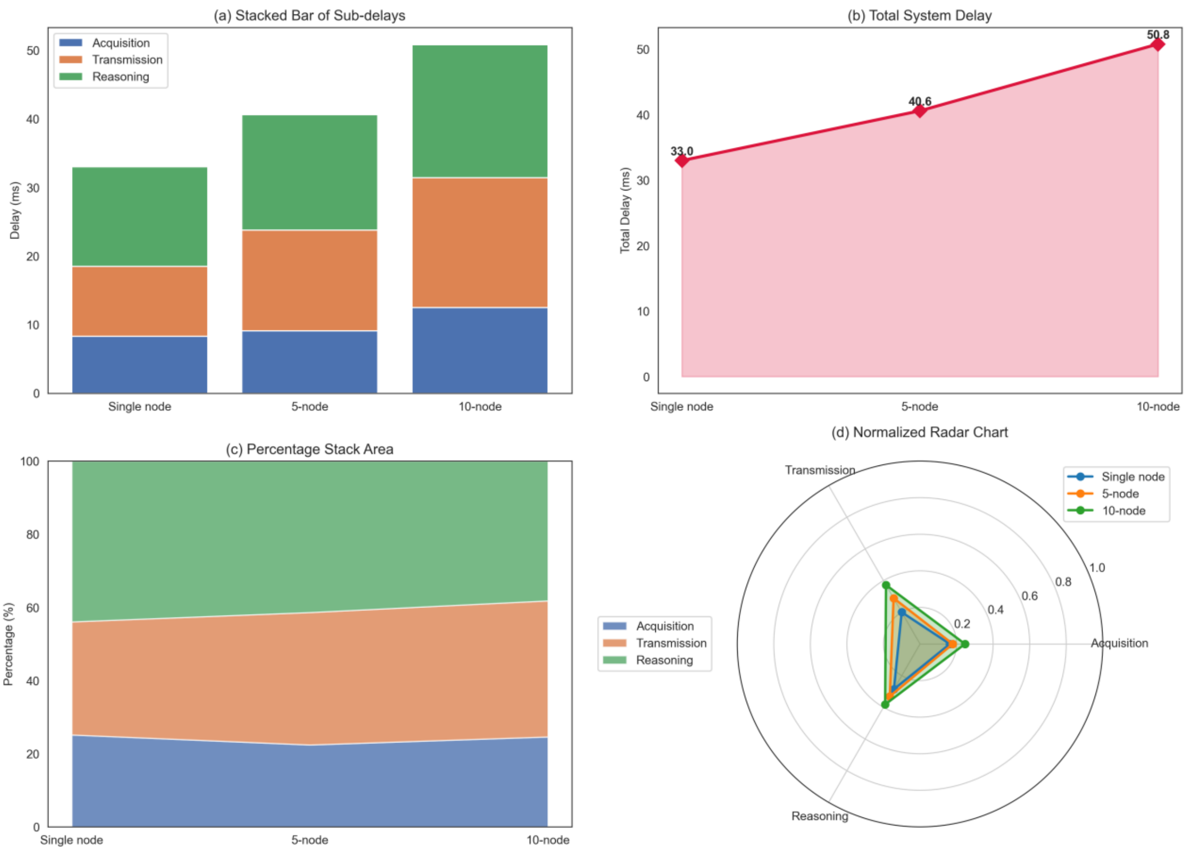

Figure 6: Total delay wave point diagram of the system

- ***Ablation Study***

To investigate the contribution of attention mechanisms in terahertz spectrum modeling, an ablation study is conducted by comparing CNN models with and without CBAM. The results indicate that introducing CBAM consistently improves prediction accuracy, particularly for filters whose spectral responses exhibit sharp transitions or localized resonance features.

This phenomenon suggests that the attention mechanism effectively enhances the model's sensitivity to critical frequency regions, which are closely related to the physical behavior of terahertz filters.

The ablation analysis demonstrates that the performance improvement is not merely due to increased model complexity, but rather to better alignment with the intrinsic characteristics of terahertz spectral data.

3.2 Practical Significance and Application Scenarios of the Results

• ***Practical Significance of the Results***

The terahertz filter test system based on the Internet of Things architecture and deep learning model has realized the integrated processing mode of data acquisition, spectrum analysis and performance evaluation, and changed the filter test from the traditional manual recording and off-line analysis mode to the automatic processing and real-time judgment mode. The system is stable in frequency domain feature extraction, model recognition performance and noise robustness, which makes the performance difference of complex structure filters quickly and accurately presented at the model end. This not only reduces the error caused by manual interpretation, but also reduces the dependence on high-experience experimenters, and the testing process is more standardized, objective and quantifiable.

The results show that the convolutional neural network can directly learn the structural difference characteristics from the continuous spectrum, and the model can focus on the key spectrum segments after introducing the attention mechanism, and the prediction results remain stable under noisy conditions. This feature is meaningful for engineering testing. In practical use, terahertz systems often face external temperature and humidity fluctuations, optical jitter and device clamping errors, and traditional algorithms are prone to failure under such interference conditions. The model in this study can adaptively suppress these disturbances to ensure the stability and practicability of performance evaluation results.

The real-time performance test results of the system show that the delay performance of the reasoning part of the model is relatively stable under different concurrent conditions, which shows that the strategy of model lightweight and edge deployment is accurate and effective. It provides the basic ability for realizing large-scale array testing, online monitoring and closed-loop regulation in the future. The research results solve the problems of "measurability" and "accuracy" in filter testing, and also solve the problems of "quick measurement" and "automatic measurement", which lays a foundation for batch testing, scene application and engineering deployment of terahertz devices.

• ***The Application Scenario***

The test and evaluation system constructed in this paper has strong generalization, and has clear application value in experimental research, device development and engineering application. The system can be used as an experimental support platform for filter structure optimization and parameter tuning in laboratory research. When adjusting the structure size, material thickness or surface microstructure, researchers can observe the change of transmittance curve and performance trend in real time, thus reducing the number of experiments and improving the efficiency of sample design. In the part of device batch inspection, the system can be used for quality inspection of production line, and by automatically identifying the spectrum shape, the processing error or invalid samples can be quickly screened to improve the production consistency and quality control level.

In a wider range of industrial and technical applications, terahertz technology is gradually entering security detection, biometrics, nondestructive material evaluation and high-speed communication. The model and system framework can be directly embedded in terahertz sensor array, optical scanning platform or communication link tuning module. For communication scenarios, the frequency response identification module can be used to adjust the filter in real time to adapt to channel changes and realize adaptive band optimization. In the field of nondestructive testing, the system can be used to judge the spectral characteristics of the internal structure of substances, and to distinguish substances through the specific resonance response of filters. In security imaging, the system can quickly identify the characteristics of suspicious targets and improve the screening efficiency. The system has the continuous realization ability from scientific research to industrialization, and can serve many kinds of scenes such as equipment research and development, quality control, on-site monitoring and dynamic self-tuning, providing key technical support for terahertz technology from experiment to application.

3.3 Discussion

• ***Challenges of test system in actual environment deployment***

The test system proposed in this study has a good performance in the experimental environment, but it will still encounter challenges in the face of real engineering deployment scenarios. Terahertz test is highly dependent on the stability of optical path, the laboratory environment is relatively closed and the parameters can be controlled, and the environmental conditions in industrial field or open test platform are more complicated. Temperature, humidity, mechanical vibration and air flow may all lead to slight deviation of beam shape, which will affect the baseline stability of transmittance curve. Although the system has the ability of noise suppression and feature extraction, it cannot completely offset the impact of environmental disturbance. From the aspect of network communication, the data transmission between Internet of Things nodes adopts fixed bandwidth and stable links in the experimental environment. In actual deployment, the data transmission path may cross the local area network, 5G edge nodes and remote servers, and the delay difference and congestion between different links will affect the real-time processing performance. The computing resources of edge nodes are limited, and the reasoning speed of the model is constrained by hardware conditions. When the number of concurrency increases, the reasoning delay will accumulate perceptibly. The delay of edge reasoning in this study has been controlled within a reasonable range, but if the system is applied to large-scale array measurement or scenes that need real-time closed-loop control, the underlying architecture should be further coordinated and optimized. The diversity of sample sources and the batch difference of device manufacturing process also lead to the challenge of model generalization ability. There are slight differences in surface roughness, arrangement error of resonance units and dielectric layer thickness of filters manufactured by different manufacturers or different equipment processes, and the spectrum shows subtle but physically significant morphological changes. The model needs to ensure that it can still give reliable judgment in the face of no samples, otherwise it will be difficult to meet the needs of long-term stable operation in practical application.

- ***Follow-up Research Direction and Model Optimization Suggestions***

The future research work will be carried out in three directions: model structure, system architecture and application depth. The convolutional neural network used in this study has high efficiency in processing one-dimensional spectral features, but the size and hierarchical structure of the convolution kernel of feature extraction directly affect the ability to capture resonance features of different scales. In order to improve the performance of the model in the identification of fine-grained structural differences, the self-attention mechanism of Transformer is introduced into the model framework to enhance the modeling ability of global correlation features, and the model can understand the long-term dependence within the spectrum in a deeper level.

There is still room for optimizing the resource scheduling strategy and message communication mechanism of edge computing nodes at the system architecture level. In the future, an adaptive resource allocation module will be established, and the system can dynamically select data transmission paths and computing nodes according to the actual number of concurrency, network bandwidth and model reasoning pressure, thus improving the adaptability of the system in cross-scenario applications. A data quality self-diagnosis framework is constructed to identify and warn the possible signal attenuation, sensor failure and abnormal samples in the transmission link, so as to ensure that the data input into the model is always in a credible state. The extended layer is applied, and the system is combined with an automatic tuning mechanism or a reconfigurable metamaterial platform to realize the closed-loop feedback regulation of filter performance. In the future, if the prediction results of the model can directly drive the automatic iteration of geometric parameters or material layer thickness, the design and testing of terahertz filters will form a dynamic coupling system and improve the intelligent design level of devices. Extending the system to more target recognition, spectrum diagnosis or communication signal adaptive control scenarios will help to promote terahertz technology from single-point research to multi-domain integrated application.

4. Conclusions

Focusing on the problems of strong manual dependence, long data processing cycle and complex spectrum analysis in terahertz filter testing, a test data acquisition and performance evaluation system based on Internet of Things architecture and deep learning model is proposed. The system links the terahertz time-domain spectrum test platform, edge computing nodes and cloud analysis module to realize the process processing of data acquisition, transmission, modeling and visual output, which makes the test work change from the previous offline analysis mode to the real-time, automatic and traceable operation mode. The model structure constructs convolutional neural network and introduces attention mechanism. The model can identify the structural difference features from the spectrum curve more accurately and maintain high robustness under noise interference conditions. The experimental results show that the model achieves high accuracy in classification and performance prediction tasks, and the performance attenuation under noise disturbance is obviously lower than that of the traditional model, which shows that it has strong engineering adaptability.

The system integration test shows that the edge computing module can still maintain low reasoning delay and the overall response speed is within the acceptable range of real-time monitoring under the condition of multi-node concurrency, which verifies the scalability and deployment feasibility of the system. The above results show that the proposed system can improve the efficiency and accuracy of terahertz filter testing process, and also provide support for batch testing, on-site monitoring and structural tuning, and has clear engineering promotion potential. There are still some limitations in this study, the data set is still collected under experimental conditions, and more production-level samples need to be introduced to enhance the generalization ability of the model. The model structure still has room for improvement in dealing with long-range global feature correlation, and the spectral feature modeling method based on Transformer can be explored in the future. We can consider linking the model prediction results with the adjustable filter device to construct a closed-loop optimization system to realize the automation from detection to parameter adjustment.

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