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Machine Learning and Application in Terahertz Technology: A Review on Achievements and Future Challenges

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ABSTRACT Terahertz (THz) radiation (0.1∼10 THz) shows great potential in agricultural products detection, biomedical, and security inspection in recent years. Machine learning methods are widely used to support the user demand of higher efficiency and high prediction accuracy. The technological and key challenges of machine learning methods are for THz spectroscopy and image data preprocessing, reconstruction algorithms, and qualitative and quantitative analysis. In this paper, an exhaustive review of recent related works of THz detection and imaging techniques and machine learning methods are presented. The application of machine learning methods combined with THz technology in quality inspection of agricultural products, biomedical, security inspection, and materials science are highlighted. Challenges of machine learning methods for these applications are addressed. The development trend and future perspectives of THz technology are also discussed.

INDEX TERMS Terahertz spectrum, terahertz imaging, machine learning, agricultural products, detection application.

I. INTRODUCTION

Terahertz (THz) radiation [1], also known as submillimeter radiation or THz waves, refers to the electromagnetic waves that cover a frequency range of 0.1∼10 THz, corresponding to a wavelength range of 0.03∼3 mm with a typical center frequency of 1 THz [2]. In early stages of terahertz technology development, the low efficiency of terahertz energy sources and detectors was a major hindrance to progress. With the emergence of ultrafast lasers, terahertz spectroscopic techniques have progressively been growing, being successfully adapted in some interdisciplinary fields [3] that are as follows. Figure 1 shows the position of the terahertz band in the electromagnetic spectrum and its application areas.

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(1) Quality inspection of agricultural products and food [4], [5]. Terahertz waves are able to penetrate various non-polar media, allowing one to gather information about the vibration properties of biomolecules.

(2) Security inspection [6], [7], e.g., explosives and dangerous items.

(3) Biomedicine [8], [9] where terahertz waves can be used for in-depth probing of various substances to gain insight into the biological processes, chemical composition, spectral characteristics and radiation as well as performing THz labeling in medical diagnosis and drug analysis [10], [11].

(4) Characterization of room-temperature and high-temperature superconductors [12]. Similar to radio waves, terahertz waves can penetrate various objects such as plastics, textiles, ceramics, semiconductors, lipids, and powders [13]. Like X-rays, terahertz waves can also be applied for imaging.

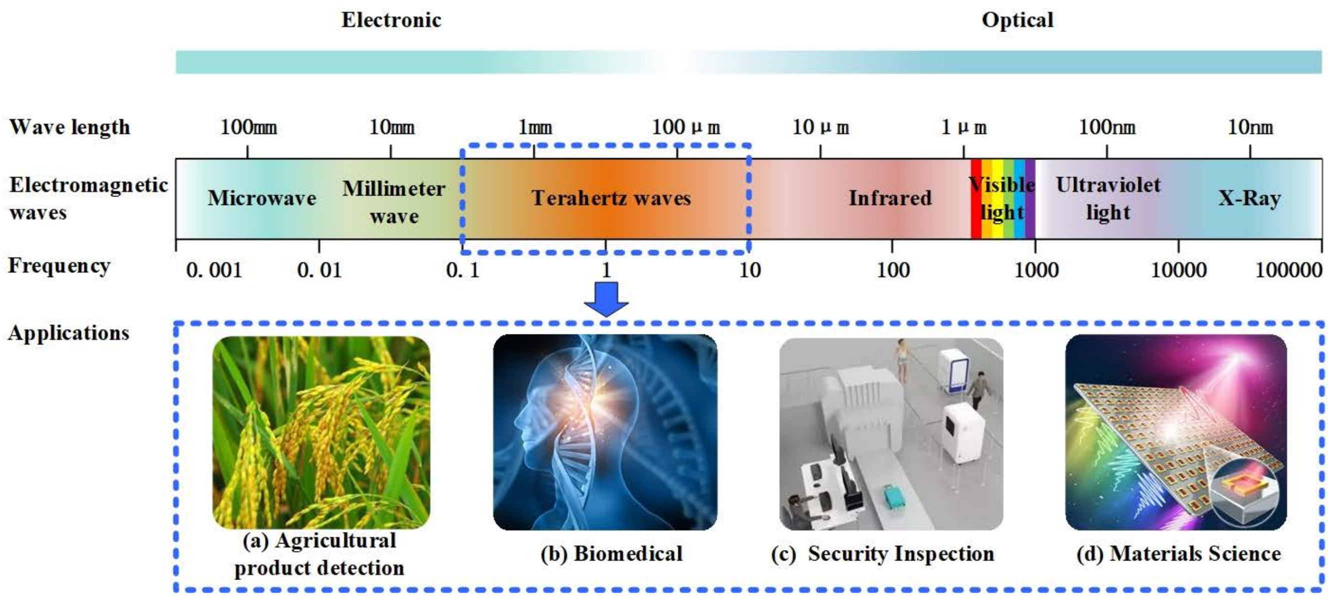

FIGURE 1. The position of the terahertz band in the electromagnetic spectrum and the application areas of terahertz technology. (a) Agricultural product testing field [15] (b) Biomedical field [16] (c) Security Inspection [17] (d) Materials Science Field [18].

Meanwhile, the photon energy of terahertz radiation is within a range of 1-10 MeV, which is only a few millionths of that of X-rays. At such a low energy level, terahertz waves will cause neither photoionization nor biomolecular damage. This property is highly desirable in the field of non-destructive testing [14], which explains why terahertz waves are favored by many researchers.

In recent years, machine learning [19] has been widely used to enhance terahertz technology, reducing the number of variables, and providing support for data processing. The common machine learning algorithms related to terahertz technology include the following elements.

Denoising and reconstruction algorithms intended for spectrum and image preprocessing, which allow one to greatly reduce the number of variables and remove the irrelevant information from the optical and image parameters, thereby improving the efficiency of data analysis [20].

Algorithms for multivariate qualitative and quantitative data analyses [21], [22] are used for the high-precision recognition of samples.

This article reviews the recent advances in the machine learning applications for THz spectrum and image detection, focusing on food safety [23], agricultural product testing [24], biomedicine, and security inspection [25], [26]. In addition, the advantages and shortcomings of fusing machine learning and THz detection methods are summarized as well.

II. EQUIPMENT AND METHODS

A. TERAHERTZ DETECTION TECHNIQUE

Depending on the physical and chemical properties of the material to be tested, THz spectroscopy techniques can be divided into three types [27], [28]: terahertz time-domain spectroscopy (THz-TDS), terahertz time-resolved spectroscopy (TRTS), and terahertz emission spectroscopy (TES).

THz-TDS consists in determining the complex permittivity of the sample, providing static characteristics of the sample. This technique is mainly employed for quality inspection and control in various fields of chemistry, medicine, and biology. Figure 2 shows the schematic diagram of a transmission-type THz-TDS detection system that is composed of a femtosecond laser, a THz radiation generator, a THz radiation detection device, and a time-delay control system [29]. The system operates as follows. A titanium-sapphire femtosecond mode-locked laser generates a laser beam. The beam is split into a pump beam and a probe beam by a beam splitter. The pump beam makes the terahertz transmitter to excite and generate terahertz pulses that are afterwards focused on the sample by a parabolic mirror. The probe beam is used to measure the instantaneous electric field amplitude of the THz pulse. While the time-domain waveform of the THz electric field strength can be obtained by scanning the relative time delay between the probe beam and the THz pulse, the frequency- domain spectrum of the specimen is the result of the Fourier transform on the time-domain waveform.

TRTS, also known as transient THz spectroscopy, is a useful tool for studying the onset and evolution of ultrafast phenomena at low energies on time scales ranging from femtoseconds to nanoseconds [30]. The TRTS setup is similar to THz-TDS, with the addition of a third pump beam to the THz generation and detection beams.

Kinetic properties are measured by introducing an optical pump beam with variable time delay between the optical pump and the terahertz probe. TRTS allows you to measure the dynamic and formational characteristics of materials.

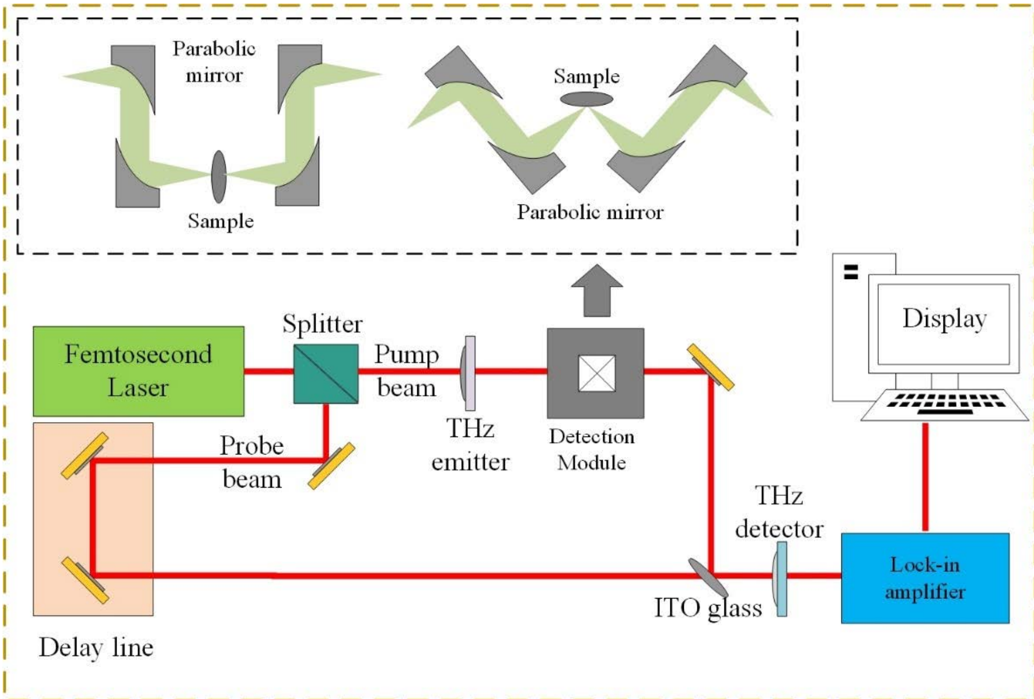

FIGURE 2. Schematic diagram of a THz-TDS setup.

Semiconductor research is one of its most important application fields.

Finally, the TES method ensures information about the characteristics of specimens (such as semiconductors, superconductors, etc.) via analysis of the shape and amplitude of THz waves [31]. TES has many of the basic features of THz-TDS, where pulsed light is irradiated to produce THz radiation from a sample. Conversely, TES analyzes the amplitude and shape of the transient electric field emitted by the sample, whereas THz-TDS uses only radiation from a well-characterized source to detect a single sample. To avoid artifacts, TES is usually done with a detector in the near field of an amplified laser and emitter, and it should always be done without focusing the optical elements [32].

B. TERAHERTZ IMAGING TECHNIQUES

Terahertz imaging techniques have been developed on the basis of terahertz time-domain spectroscopy. Since the THz wave can penetrate into non-polar materials such as cloths, woods, and ceramics without causing damages and can be used to form images of the interior of an object, it has attracted more and more attention in the imaging field. Based on the concept of the THz-TDS system, THz imaging has been developed with an additional imaging unit [24] Similar to the imaging installations working in other frequency bands, the terahertz imaging tests consist in irradiating the sample with THz rays and acquiring the transmitted and reflected rays, thus forming the two dimensional image [33].

The time-domain system allows one to directly measure the electric field, providing phase and amplitude information at the same time. Therefore such parameters as refractive index, absorption coefficient, and other material properties related to frequency can be assessed within the THz frequency range. The image obtained from the sample has the characteristic of ‘‘map-spectrum integration,’’ that is, both the spatial and spectral data can be collected contemporaneously [34].

Over the past years, the rapid development of terahertz technology has led to a breakthrough in the terahertz radiation methods. Depending on the type of a terahertz source, terahertz spectral imaging can be divided into THz pulse wave imaging and THz continuous wave imaging [34]. The THz imaging instrumentation are classified by the four types: THz-TDS installations; THz focal-plane array systems supporting real-time imaging; near-field imaging tools achieving sub-wavelength resolution, and compressed sensing imaging appliances allowing sub-sampling rate imaging [35]–[38].

Equipped with a raster scanning device, a THz-TDS imaging system enables one to obtain the value of each pixel by point-by-point scanning, thus resulting in the entire image. One drawback of such a configuration is a lengthy detection process. To solve this problem, the THz focal-plane array imaging technique has been developed. The use of a focal plane array detector allows the image of the sample to be formed in one step, achieving the higher detection speed.

For the first time, Wu et al [39] presented an innovative method for detecting terahertz bands using focal plane arrays. The method focuses the THz wave passing through the sample onto a large area electro-optical crystal and extends the detection beam to fill the entire nonlinear crystal using

TABLE 1. Common terahertz spectral imaging techniques and their characteristics.

Imaging technique	Imaging mode	Advantages	Disadvantages
THz-TDS imaging**[45]**	Point-by-point scanning	Acquisition of relatively complete THz information (including information about signal amplitude and phase)	Low spectral resolution; lengthy two-dimensional raster scanning, insufficient imaging speed
THz focal-plane array imaging**[46]**	Real-time imaging	Real-time imaging; high frequency; compact structure; adjustable frequency point	Size-limited one-time imaging area; costliness; high power required
Near-field imaging**[47]**	Subwavelength resolution imaging	No limits in image resolution in terms of wavelength	Limits in the signal strength by the aperture size; excessive noise from semiconductors
Compressed sensing imaging**[48]**	Sub-sampling rate imaging	Ability to acquire sparse and compressible signals; lower number of sampling points than required by Shannon's sampling law	High computational complexity; poor stability of reconstruction algorithms; low efficiency of sparse decomposition algorithms

a lens device. The THz beam causes transient birefringence in the crystal, similar to free-space electro-optical sampling, affecting the polarization state of the probe beam (typically a femtosecond pulse). The method focuses the THz wave passing through the sample onto a large electro-optical crystal using a lens device, then extends the probe beam to fill the entire nonlinear crystal.

The near field is defined in diffractive optics as the light field that falls outside the Rayleigh length of the focal spot when the incident light wave is a plane wave [40]. Near-field imaging techniques include both aperture-based near-field imaging and apertureless near-field imaging. Aperture-based near-field imaging in the near-field is the simplest way to implement near-field imaging, and the resolution varies depending on the aperture size. In general, sensitivity decreases rapidly in a super-linear manner as aperture size decreases. The resolution of the obtained image is not limited by the wavelength, but depends rather on the size of the local aperture or needle tip. Giordano et al [41], for example, integrated a nanowire-based metal aperture probe into an 18 μm aperture detector to achieve subwavelength spatial resolution interferometric terahertz near-field imaging.

Aperture-free near-field imaging [42] confines focused terahertz radiation to a small area by mechanically modulating a metal tip at a fixed frequency. For remote detection, the metal tip interacts with and scatters the abrupt terahertz field in the near-field region of the sample surface. The terahertz field at the probe's oscillation frequency is then measured using a lock-in amplifier and a terahertz detector. The area of interaction is determined by the size of the tip which hence determines the spatial resolution.

The basic idea of compressed sensing imaging is as follows. Given that the signals are sparse in the natural environment, it makes it feasible to restore the original signal using far less sampling points than required by Shannon sampling law, thereby reducing the workloads of sampling and data storage [43]. Chan et al [44] were the first to propose a compressive sensing-based terahertz imaging system, which eliminates the need for raster scanning of the object or terahertz beam while maintaining the high sensitivity of a single-element detector. It achieves high-speed image acquisition using a single-pixel detector and a series of random masks, and the acquired signal is used for image reconstruction. The number of measurements required for compression sensing image reconstruction is greatly reduced, allowing for a significant increase in acquisition speed.

Each of these imaging techniques possesses its own advantages and shortcomings, and their competent combination allows a joint promotion of effective THz imaging tools. More details about each terahertz spectral imaging method can be found in Table 1.

C. MACHINE LEARNING METHODS

The development of machine learning(ML)methods bring new opportunities and challenges to various industries. It aims to enable machines to learn to autonomously analyze and process data, thus freeing up more human resources to complete tasks and make decisions with precision and speed. ML methods are widely used in the field of THz technology, mostly as tools for terahertz spectroscopy and image preprocessing [49] and techniques for qualitative and quantitative multivariate data analysis. ML has also been extended to applications in THz imaging such as image super-resolution, signal reconstruction, compressive sensing, and medical imaging. All of these applications have demonstrated high performance and results to specific problems beyond the state-of-the-art methods currently available. Table 2 shows some of the machine learning methods applied to terahertz technology.

Data preprocessing approaches mainly include smoothing using Savitzky-Golay function [50] and asymmetric least squares (AsLS), as well as Savitzky-Golay first- and second-derivative procedures [51]. Preprocessing aims to improve signal-to-noise ratio and reduce the dimensionality of data, ensuring the better accuracy of the analysis. Multivariate techniques are classified as qualitative and quantitative regression methods, which include principal component analysis (PCA), partial least squares (PLS) regression, and

TABLE 2. **Machine learning methods applied to terahertz technology.**

		Algorithm	Method of use	References
Data pre-processing	Noise reduction	Savitzky-Golay smoothing	Terahertz spectral data denoising	Luo et al.[57]
		Wavelet transform	Terahertz time-domain spectral denoising	Cui et al.[58]
		wavelet transform, baseline elimination	Terahertz frequency-domain spectral denoising	Peng et al.[56]
		WaveNet	Improving the signal-to-noise ratio of terahertz signals	Choi et al.[59]
	Dimensionality reduction	PCA	Spectral Data Dimensionality Reduction	Liu et al.[54]
		SNE	The original data to a low dimensional vector.	Wei et al.[60]
		t-SNE	Spectral Data Dimensionality Reduction.	Yi et al.[61]
		Isomap	Reduce the dimensionality of the measured dataset	Liu et al.[62]
Multivariate analysis	Qualitative and quantitative analysis	DNN	Classification of the spectrum of glucose and lactose	Li et al.[63]
		PLS	Conduct quantitative analysis of amino acids mixtures	Lu et al.[64]
		RF	Classification and identification of herbal species	Zhang et al.[65]
		BPNNs	Early detection of germinated wheat grains	Jiang et al.[53]
		LDA	Non-destructive testing of rhubarb samples	Wang et al.[66]
		SVM	Identifying GMO and non-GMO soybeans	Chen et al.[67]
		DA	Identification of genetically modified rice and non-genetically modified rice	Xu et al.[68]
		KNN	Rapid recognition of pharmaceutical bi-heterocyclic compounds	Nowak et al.[69]
Terahertz imaging	Image enhancement and denoising	NL-means	Removal of noise from terahertz images	Shen et al.[70]
		CLS deconvolution.	Improved terahertz imaging resolution	Ning et al.[71]
		CNN	Super-resolution reconstruction of terahertz images	Wang et al.[72]
		Generative Adversarial Network	Super-resolution reconstruction of terahertz images	Wan et al.[73]
	Target identification and classification	CNN	Rapid and effective detection of impurities contained in wheat	Shen et al.[74]
		Faster R-CNN	Real-time detection of hazardous materials	Zhang et al.[75]
		Fuzzy C-Means	Fast detection of targets from terahertz images	Xie et al.[76]
		Transfer learning	Classification of breast cancer tissue	Liu et al.[77]

support vector machine (SVM) algorithms [52]. PCA consists in extracting features and reducing the dimensions of THz spectra to establish prediction models for data analysis. PLS, a widely used linear regression tool, accomplishes linearization by using the latent variables from a set of THz spectra. Besides these, one can mention PLS discriminant analysis (PLS-DA), back-propagation neural networks (BPNNs) [53], random forests (RFs) [54], simple linear regression (SLR) algorithms [55], stepwise multiple linear regression (SMLR) routes and algorithms being applied to qualitative and quantitative multivariate data analysis of mixed components [56]. It also includes image reconstruction algorithms for image enhancement and denoising. Machine learning applied to the field of terahertz imaging, based on compressed sensing, and super-resolution reconstruction algorithms.

TABLE 3. Latest developments in combining machine learning methods with terahertz spectroscopy for agricultural products/food testing.

Detection object	Spectral range	Research method	Result	References
Nutritional ingredients in dietary supplements	0.5-0.9 THz	PLSR, LLSR	The classification accuracy levels of L-histidine and α-lactose are 94.8% and 98.9%, respectively.	Wang et al.[79], (2020)
Alum content in starch	0.2-1.4 THz	PLS, SVM	The prediction accuracy is as high as 98.2%.	Guan et al.[80], (2019)
Additives in flour	1.0-3.0 THz	PLS, LS-SVM, BPNN	Rp = 0.9945, RMSEP = 0.66%.	Hu et al.[81], (2019)
Water content in fruit	0.75-1.1 THz	SVM, D-Tree, KNN	The classification accuracy is close to 100%.	Ren et al.[82], (2019)
Additives in agricultural products	0.2-1.6 THz	iPLS, PSO-SVC	The accuracy of the calibration set and verification set are as high as 99.01% and 98.01%, respectively	Jiang et al.[83], (2020)
Rice varieties	0~357.97 cm^{-1} spectrum	SVM	The prediction accuracy based on absorption coefficient and refractive index spectra are 98.5% an 89%,respectively..	Li et al.[84], (2022)
Peanut varieties	0.3-3.6 THz	BPNN, SVM	The overall recognition accuracy is as high as 93.3%.	Liu et al. [85, 86], (2018)

III. APPLICATION OF MACHINE LEARNING METHODS IN THZ TECHNOLOGY

A. QUALITY INSPECTION OF AGRICULTURAL PRODUCTS/FOOD

Agricultural product/food safety is a public health issue, and the quality inspection is essential to ensure the manufacturing process and meet the standards in the area of industry. In that regard, implementing suitable scientific inspection methods is a relevant task [78]. The unique characteristics of THz radiation endow THz technology with a significant research value and great potential of application. In recent years, various scholars have used THz-based feature extraction methods and qualitative/quantitative modeling tools to assess the quality of agricultural products/food and have achieved certain results (for details, see Table 3).

For example, Lu et al [64] carried out the THz-TDS experiments of a binary mixture of L-glutamic acid and L-glutamine in the yellow rice flour sample. The absorption spectra were preprocessed using partial least squares and interval partial least squares regression methods to construct a quantitative analysis model. The model achieved high classification accuracy, and could also be applied for analysis of amino acids in other grains.

Kou et al [87] developed a new method for qualitative and quantitative analysis of F11 in American ginseng that allows for accurate, rapid, and cost-effective identification and quantitative analysis of 24(R)-pseudoginsenoside F_{11} in American ginseng to distinguish it from other herbs or materials. Western ginseng was distinguished from many similar substances by PCA using quantitative data from terahertz spectrometry and HPLC triple quadrupole mass spectrometry. A new idea was provided for the identification of western ginseng.

Liu et al [88] obtained the ADPSO-SVM recognition model for identification of genetically modified cotton by combining SVM and adaptive dynamic particle swarm optimization (ADPSO). The developed model was compared with a PSO-SVM recognition method and was shown to achieve the higher recognition accuracy, thus providing a fast, accurate, non-destructive method for the testing of genetically modified cottons.

THz-TDS was used by Wang et al [66] to detect official and unofficial rhubarb samples. After collecting the THz spectra samples, analytical models of PCA-LDA and SVM, based on absorption coefficients were established. The study's findings showed that this method can classify rhubarb samples non-destructively and accurately, and that it can also be used to classify and quality control other herbal medicines.

Xu et al [68] looked at transgenic and non-transgenic rice separately. The obtained time-domain spectra were converted into frequency-domain spectra. The accuracy of the discriminant analysis model to discriminate the of transgenic rice from non-transgenic rice was 89.4 percent and 85.0 percent, respectively, and the results suggest that terahertz spectroscopy and machine learning provide a new and viable pathway for the differentiation of transgenic rice.

Chen et al [67] collected THz time-domain spectra of transgenic and non-transgenic soybean seeds in the 0.2-1.2 THz band. He then combined the CS-SVM method with a combination of the cuckoo search algorithm and support vector machine method to build a model to classify transgenic and non-transgenic soybean seeds, proving that the model has high classification accuracy. The study's findings showed that THz spectroscopy combined with the SC-SVM method provides a reliable and fast method for identifying GMOs and non-GMOs.

TABLE 4. Latest advances in the application of machine learning methods in terahertz spectroscopy for disease diagnosis.

Detection object	THz range	Research method	Result	References
Liver cancer tissue	0.2-1.2 THz	PCA, SVM, PNN, Isomap	The prediction accuracy is 99%.	Zhang et al.[98], (2018)
Prostate cancer tissue	0.3-1.0 THz	SVM	The classification accuracy of the prediction model is 100%.	Anastasia et al.[94], (2020)
Heterocyclic compound	10~70cm^{-1} spectrum	SVM, KSVM	Classification of tested chemical compounds in milliseconds with 100% accuracy.	NOWAK M R et al.[96], (2019)
Herbal varieties	0.2-1.2 THz	PCA, SVM, DT, RF	The PCA-RF method achieves a prediction accuracy of 99%.	Zhang et al.[65], (2017)
Harmful additives in herbal medicine	0.2-1.6 THz	VIP-SPLS, PLS, SPLS	R_p= 0.9464, RMSEP = 0.3237.	Zhang et al.[103], (2018)
Protein molecular conformation	0 -2.0 THz	RF, SVM, t-SNE, XGBoost	R_P= 0.9710, RMSEP = 0.2673.	Cao et al.[104], (2020)
Glucose and lactose	0.1-1.5 THz	SVN, DNN	The accuracy levels of classification and testing are 99% and 89.6%, respectively.	Li et al.[63], (2020)
Biheterocyclic compound		KNN, SVM	The recognition accuracy is as high as 99%.	Nowak et al.[69], (2019)

Liu et al [89] propose a SVM identification model based on affinity propagation clustering algorithm for genetically GMOs. in the establishment of identification model, fewer errors introduced by human annotation are introduced, which improves the accuracy of identification. The results of the experiments show that the algorithm has a low false positive rate and a high recognition rate, allowing it to effectively identify the types of samples to be tested. It also provides a new method for detecting and identifying GMOs using terahertz spectroscopy.

Machine learning methods enable the accuracy of terahertz technology in the inspection process of agricultural products. Quite informative data have been collected during the agricultural product/food quality inspection based on fusion of THz technology and machine learning methods, and the obtained prediction models have reached high levels of stability and accuracy. However, most studies were carried out under laboratory conditions, which is somewhat different from practical applications [90]–[92]. In addition, information inadequacy and redundancy in the THz spectral data is still a challenge. Therefore a complementary research is required to simplify data and improve the performance of the models, which will allow a breakthrough in data modeling and related areas such as selection of model kernel functions, classifier over-fitting, and model robustness.

B. BIOMEDICAL FIELD

At present, terahertz technology for biomedical applications includes: biological tissue examination [93], [94], biomolecular detection [95], [96], disease diagnosis [97], [98], and so on (as shown in Table 4). THz has a low ionization energy and can identify most biomolecules based on their spectral fingerprints, making it an excellent tool for cancer detection [99]. Though feasibility of terahertz technology in oncology diagnostics has been proved, the distinction of cancerous issues from normal tissues based on differences in water absorption and refraction still makes it impossible to identify the type of cancer accurately [100], [101]. Since water exerts a strong absorption effect on the THz wave, the use of terahertz technology in the field of biomedicine is mostly limited to disease diagnostics in epidermic and isolated tissues. In this respect, application of terahertz technology to living tissues is among the main future research directions.

Using gastric tubular adenocarcinoma tissues on the gastric mucosa as the detection object, Zhang Yi et al [102] introduced tissue chip technology to acquire the histopathology and terahertz detection results. The terahertz absorption coefficients and refractive index spectra were exposed to PCA, and SVM along with logistic regression (LR) techniques were applied for data classification, ensuring high-accuracy distinction of cancerous gastric tubular gland cells from normal cells.

In other work, Hou et al [93] performed the THz-TDS study on dehydrated gastric cancer tissues and normal tissues to detect the central areas of sliced tissues by combining PCA with T tests to extract valuable spectral information. The k-means and SVM were used to build a classification model, enabling one to successfully distinguish cancerous tissues from normal gastric tissues.

Huang et al [95] employed a terahertz attenuated total reflection technique to examine glycoprotein solutions with a concentration gradient of 0.2-50 mg/ml. He then implemented the composite multi-scale entropy (CMSE) analysis to obtain features and clustered them using the k-means algorithm. For comparison, the data were also exposed

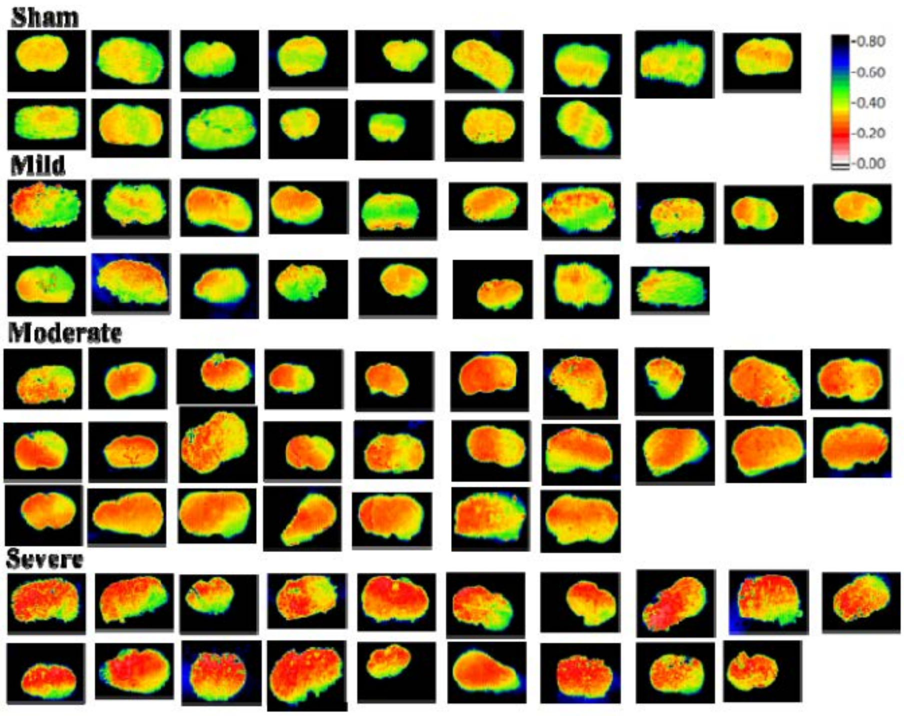

FIGURE 3. THz images of TBI samples.

to PCA treatment. According to the results, the CMSE method allows one to not only extract features with better specificity and sensitivity, but also is more suitable for qualitative identification, thus being promising for cancer identification.

Based on the spatial distribution characteristics of the transmittance and the statistical distribution parameters of the normalized gray histogram, KNN, SVM and RF algorithms were applied in study [97] to identify and evaluate traumatic brain injury (TBI), achieving an accuracy level up to 85% (as shown in Figure 3. The THz images are displayed in 5-colors, different colors indicating the transmittance of THz wave). The method was shown to be suitable for detection of other diseases and be a powerful tool in automatic biomedical diagnosis.

C. SECURITY INSPECTION

The combination of machine learning methods and THz technology has a wide range of applications in security inspection. The identification of dangerous items and suspicious objects is also a research direction of THz technology in the field of security inspection [105]. Compared with other imaging technologies such as X-ray imaging, THz technology has the outstanding advantages that are as below [106], [107]: 1) a zero risk of radiation hazard; 2) the ability to detect non-metal and non-polar materials; 3) the aptness to identify explosives and illegal drugs. Existing terahertz security screening cameras only report the approximate locations of suspicious objects, and the resulting images are noisy, thus leading to low recognition efficiency. Various scholars have attempted to use machine learning methods to improve the quality of THz imaging and reduce image noise, and build accurate target recognition models. Figure 4 and table 5 shows the application of THz technology and machine learning in the field of security detection.

Mohamed et al [108] proposed a clustering algorithm developed on the basis of k-means approach, and so-called the ranked k-means clustering. This algorithm was found to be more effective than other clustering techniques suitable for segmenting THz images with large-scale data sets.

Shi et al [109] have developed a terahertz image enhancement method based on the dual-threshold canny equalization algorithm, which allows one to improve the imaging quality of a terahertz imaging system and obtain images with higher resolution and clearer edges. Furthermore, its ability to capture clear image contours and edges along with enhanced ability to identify hidden objects makes terahertz imaging attractive in security applications.

As another example, a technique combining ant colony algorithm (ACA) and compressed sensing was proposed by Li et al [110] to improve the quality of terahertz imaging. In this method, the image reconstruction is attained via the use of ACA for edge detection along with a partial Fourier reconstruction algorithm for noise reduction of the non-edge part of the image. With the ability to drastically reduce the image noise while retaining the edge information, the approach has great potential in security inspection.

Xi et al [111] introduced a spatiotemporal information of THz security images into the Faster-R-CNN framework through sparse low-rank decomposition (SLD), achieving high accuracy and efficiency in the recognition of suspicious targets.

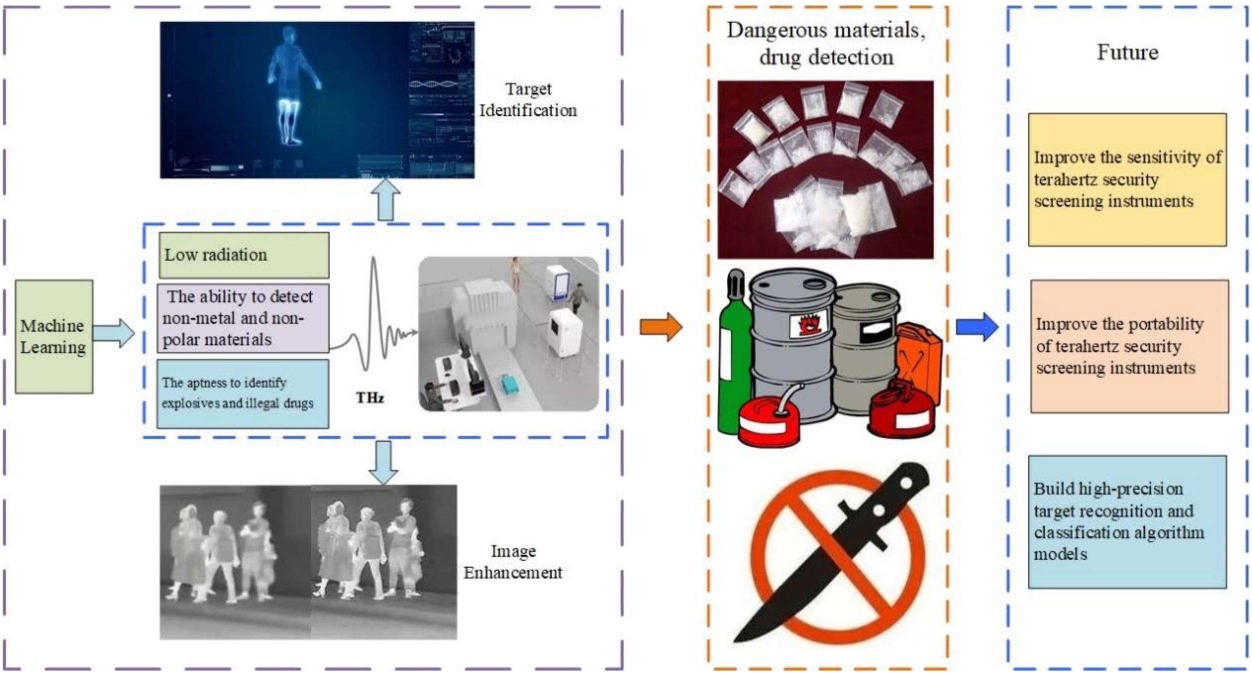

FIGURE 4. THz technology and machine learning in the field of security detection.

Dong et al [112] proposed a method for isolating hidden weapons in samples with poor imaging quality in the THz band range by generating a conditional generation confrontation network (CGAN) called Mask-CGAN. This enabled one to isolate target objects from samples with low-quality, noisy images after a small training dataset. The method was shown to be superior to CGANs and Mask-RCNN models in terms of processing speed, recall, and precision.

Xiao et al [113] performed mean filtering to reduce the noise of the THz image, and employed the RCNN algorithm to detect and identify the dangerous items in the denoised image, achieving a recognition accuracy of 89.6%.

Murate et al [114] combined machine learning with is-TPG spectroscopic measurements to identify reagents hidden by various shielding materials. Three machine learning algorithms were tested, SVM demonstrated the best discrimination performance after training the algorithms on a large amount of spectroscopic data. The results show that machine learning improves the accuracy of terahertz wave methods for detecting illicit drugs and other substances hidden in packaging.

Yi et al [115] elaborated the technique for identifying various explosives and related substances in a mixture using a micro-genetic algorithm for terahertz spectrum uncertainty analysis, thus obtaining the better results compared to the traditional methods allowing identification of compositions of mixtures. Tan et al [116] used the reflection THz-TDS system to measure nineteen different liquids and applied PCA algorithm to mark the safety threshold. Their study revealed that the contribution of the first principal component to the total deviations is up to 96.52%, which means that flammable and explosive liquids can be identified easily.

The above-mentioned works have laid a theoretical foundation for the application of terahertz technology in the field of security inspection. At present, terahertz technology has been practiced in the detection of explosives, drugs, guns, and other contrabands. Various terahertz security inspection instruments have been put into use all over the world, and the application of machine learning methods has improved the detection accuracy of these tools. In the future, they need to develop towards high sensitivity and portability.

D. MATERIALS SCIENCE

Since terahertz radiation can penetrate into non-polar and dielectric composites such as ceramics, carbon plates, cloth, plastics, etc. THz waves allow one to test the matter in a non-contact, damage-free, and non-ionizing manner. The detection accuracy is high and there is no need for coupling [117]. For this reason, terahertz technology is widely used in the field of non-destructive testing of materials [118]. Table 6 shows the application of THz technology and machine learning for non-destructive testing of materials.

Tu et al [119] combined neural network technology and wavelet analysis to carry out non-destructive terahertz testing of marine protective coatings, and performed multiple regression analysis in combination with a BP neural network prediction method to make predictions on coatings.

Ye et al [120] used a transmission type THz-TDS with a zero incident angle to obtain the spectral data from a variety of thermal barrier coatings, which were afterwards PCA-

TABLE 5. Latest advances in the application of machine learning methods in terahertz spectroscopy for security inspection.

Detection object	Research method	Result	References
Segmenting THz images	K-means, Ranked-K-means	k-means clustering based on ranked set sampling is more efficient than other clustering techniques .	Mohamed et al. [108]
Terahertz image enhancement	Canny Equalization Algorithm	The algorithm has a good noise reduction effect on terahertz images, can retain image details, enhance and improve image contrast and image quality.	Shi et al. [109]
Improve the quality of terahertz imaging	Colony algorithm, Compressive sensing	The method can largely reduce noises and preserve the edge information.	Li et al. [110]
Target Recognition	CNN, R-CNN	The method performs well in a short period of time for both simple and complex cases, with improved accuracy and increased efficiency.	Xi et al.[111]
Target Recognition	CGANS, Mask-RCNN, Mask-CGANS	Mask-CGANs with an optimal model structure and a proper loss function, has abilities in segmenting concealed objects in such low quality and noisy Terahertz samples within a small training dataset.	Dong et al. [112]
Image denoising and target recognition	Mean filter, Faster RCNN	The proposed algorithm can effectively identify the dangerous articles of controlled knives in terahertz images, and the recognition rate can reach 89.6%.	Xiao et al.[113]
Recognition of reagents hidden by shielding materials	SVM, KNN, RF	Through the low-attenuation untrained shield, all learning methods achieved 100% accuracy; Through the high-attenuation untrained shield, the SVM, KNN and RF algorithms achieved 88.9%, 77.8%, and 80.0% accuracy, respectively.	Murate et al.[114]
Explosives Recognition	GA, Micro-GA	The multi-objective micro-GA method has been utilised to determine the explosive mixture components via THz spectroscopic statistical analysis supported.	Yi et al.[115]
Flammable and explosive liquid recognition	PCA	The first principle component contribution a rate of 96.5% to all deviation. This works show that the flammable and explosive liquids can be identified feasibly by THz-TDS with PCA algorithm.	Tan et al.[116]

processed to reduce their dimensions in a range of 0.6 to 1.4 THz. The complementary methods such as MLR, BP, and SVM, were applied for regression analysis as well. According to the results, the prediction accuracy of the PCA-SVM model enriches a level of 95%. This new approach combining terahertz time-domain spectroscopy and machine learning is promising for microstructural characterization of thermal barrier coatings and high-accuracy prediction on the coating.

Yin et al [121] offered a tool based on THz-TDS and CS-SVM (cuckoo search algorithm-support vector machine) for rubber detection. In this method, PCA is adopted to reduce the spectral data dimensions and improve the accuracy of the SVM model by optimizing its penalty factor and function parameters via cuckoo search algorithm. This enabled one to increase the recognition accuracy of the test up to 100%.

Liu et al [122] applied PCA to the THz spectra of three dyes, simultaneously using the SG smoothing algorithm to improve the recognition accuracy along with FCM and k-means approaches to evaluate the recognition results. Their study revealed the high efficiency of combined SG smoothing algorithm and PCM in THz data processing of dyes. To elucidate the physical properties of coal/rock in the THz band range, Wang et al [123] established a recognition model of THz absorption coefficient spectra and refractive indices based on PCA and SVM, achieving a recognition accuracy of 100%.

Data such as phase and amplitude signals can be obtained directly when terahertz is used to detect materials. Material parameters are difficult to obtain because they necessitate multiple analysis steps, each of which can introduce errors into the calculations. To replace the conventional fitting function, Nicholas *et al.* [124] proposed an efficient neural network for extracting material parameters and estimating the refractive index of the material. The experimental results show that the method can be used to replace the traditional fitting function with high accuracy, speed, and ease of implementation.

The advantageous background of terahertz technology has resulted in the emergence of terahertz metamaterials, which have created the conditions for the development of terahertz devices. For conventional devices, the magnetic permeability and dielectric constant of the material affect

TABLE 6. Latest advances in the application of machine learning methods in terahertz spectroscopy for materials science.

Detection object	Research method	Result	References
Marine protective coating	BPNN, Multiple-regression analysis	The hybrid signal processing approach could be recommended for terahertz non-destructive testing applications of marine protective coating	Tu et al.[119]
Thermal barrier coatings	PCA, SVM, MLR, BP	The correlation coefficient comparisons showed that the characterization accuracy of PCA-SVM reached by over 95% and outperformed the other models.	Ye et al.[120]
Rubber	Cuckoo search algorithm(CS), PCA, SVM	The identification rate of testing sets for CS-SVM is 100%	Yin et al.[121]
Dyestuffs	FCM, SG, PCA, K-means	SG smoothing coupled with PCA achieved the highest accuracy of 94.44%.	Liu et al. [122]
Coals and Rocks	PCA, SVM	The recognition rate of coals/rocks reaches to 100 % and the recognition rate of different bituminous coals reaches to 97.5 %.	Wang et al. [123]

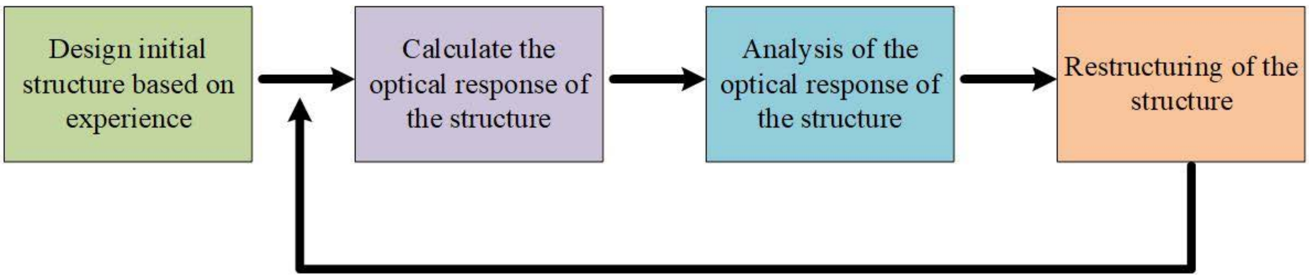

FIGURE 5. The conventional design process for metamaterials.

the final optical response of the device, which becomes a limitation for the light source wavelength. However, the emergence of metamaterial devices breaks this limitation because metamaterial devices can be designed with structural parameters to tune the response band of the metamaterial. The conventional design process for metamaterials, shown in Figure 5, involves solving a system of Maxwell's equations, and the highly nonlinear nature of Maxwell's equations and complex boundary conditions make this computational process very difficult and almost impossible for complex structures [125]. Based on the superiority of machine learning, by allowing the neural network to learn a data set containing the structure of the metamaterial and its corresponding optical response, neural networks can obtain the ability to predict the structure of the metamaterial from its optical response. This avoids the problems of high nonlinearity and complex boundary conditions encountered in traditional methods of solving Maxwell's equations. Moreover, the network can also predict the optical response of metamaterials based on their structures, a process that is much faster and more accurate than traditional numerical computation methods. Therefore, it is a convenient, efficient, and important approach to apply machine learning to the design of metamaterial structures.

IV. PROBLEMS TO BE SOLVED

As an emerging sensor technique, THz technology finds application in various industries, including agriculture. While the combination of machine learning methods and terahertz technology brings great benefit to society, especially in terms of public health and safety, there are still some shortcomings that still limit their large-scale use, which are as follows.

A. HIGH COST OF TERAHERTZ EQUIPMENT

The costiveness of terahertz sources and detectors is a key factor hindering the commercialization of terahertz technology. Because of the high price of hardware, terahertz technology is used rather in academic research than for commercial goals. If terahertz technology could be applied to more fields, the increasing demands for terahertz systems would cause the cost drop. On the other hand, further R&D needs to be carried out to design terahertz imaging systems with low-cost and high-efficiency source and detector, and to enlarge the applicability of terahertz instruments and techniques.

B. INFLUENCE OF SCATTERING EFFECT ON INSPECTION RESULT

Scattering effect always takes place when exposing the sample to terahertz waves. This is caused by particle nonuniformities such as irregular shape and different sizes, which affect the refractive index of the matter and, consequently, the test results [126]. Grinding the specimen and compressing it into fine, smooth particles enables one to reduce the scattering effect.

C. NEED TO IMPROVE GENERALIZATION ABILITY AND ROBUSTNESS OF MACHINE LEARNING MODELS

The effectiveness of machine learning is limited by the quantity and quality of data used to train the model [127]. Model training may suffer from the "over-fitting," which will exert a certain impact on the accuracy and robustness of the prediction model. On the other hand, the training accuracy of the ML model depends on the selection and optimization of parameters. Existing modeling methods [128], [129] require a certain amount of training samples to accomplish tasks such as parameter selection, learning and training, which affects the accuracy and calculation speed of model analysis. At present, the common machine learning modeling tools only touch on a shallow structure. Since the in-depth analysis of THz spectra and image features is a challenge, large-scale application of these approaches has been limited up to date.

V. OUTLOOK

At present, it is imperative to keep developing novel techniques by combining machine learning methods with terahertz technology so as to overcome the bottlenecks encountered in practical applications, which would allow one to meet actual market demands[126, 130]. In spite of some limitations, the constantly increasing availability of terahertz systems and rapid development of terahertz technology in various fields will gradually expand its application from laboratories to workshops and households. In the future, the advances of terahertz technology will be evident from the following aspects.

A. IMPROVING PERFORMANCE OF TERAHERTZ SYSTEMS

Terahertz technology has developed into a means of fast nondestructive testing. The performance of a terahertz system is jointly determined by the imaging speed, spectral resolution, spatial resolution, and the amount of information the system can provide. However, due to hardware restrictions, the sensitivity and imaging resolution of terahertz systems have to be improved. In this respect, a cost-effective, high-performance terahertz system has great application value.

B. COMBINING TERAHERTZ TECHNOLOGY AND DEEP LEARNING

The commonly used modeling tools are mostly based on machine learning algorithms that touch on the shallow structures. The fact that gathering the in-depth feature information from spectral images is a challenge affects the accuracy and robustness of the prediction model, thus limiting the application of these algorithms in many fields. Therefore, it is recommendable that deep learning methods are applied in terahertz technology. Currently, deep learning algorithms can be divided into three types: convolutional neural networks for image data analysis and processing, recurrent neural networks for text analysis and natural language processing, and generative confrontation networks for unsupervised learning. In the future, introducing them into terahertz technology to improve the accuracy and robustness of prediction models will be within the scope of many research and practical projects.

C. ESTABLISHING TERAHERTZ DATABASE

Establishing standard databases of terahertz bands in various research fields and developing effective methods for their use is essential for a breakthrough of THz techniques.

Such databases can provide reference data to support qualitative and quantitative analysis of substances, thereby simplifying the prediction and detection processes.

D. OPTIMIZING THz SOFTWARE SYSTEMS

When it comes to analyzing and processing terahertz spectrum and image data, it is necessary to test different machine learning methods in order to find an optimal model. Since this process is very time-consuming, the future terahertz software systems should incorporate multiple machine learning modeling methods to realize the automatic data analysis, and be furnished with a standard terahertz database, thus forming a human-machine interaction platform with a set of functions including user management, database, data reading, data preprocessing, and data analysis.

E. APPLYING MACHINE LEARNING IN THE FIELD OF TERAHERTZ COMMUNICATION

Terahertz (THz) band communication is considered a key technology for next-generation wireless systems, and is expected to support a wide range of delay-sensitive applications with various data requirements. Terahertz communication would play an important role in the next-generation 6G systems due to the ability to provide extremely high data rates and huge bandwidths[]. When terahertz technology is applied in wireless communication, the system can transmit data at a much higher speed than conventional wireless communication appliances. However, the management of networks and services, such as huge network traffic, excessive resource management pressure and energy inefficiency, will face great challenges that can be overcome via new technologies and efficient strategies.

Machine learning is an emerging field in the research of AI-assisted networks. Being one of the best solutions for managing large amounts of data, machine learning enables one to achieve the higher level of sophistication in network application monitoring and management, improve operational efficiency, and make terahertz communication system smarter. With the help of machine learning, it is feasible to extract valuable information from a large amount of raw data and support smarter control and optimization of wireless communication networks.

VI. CONCLUSION

Terahertz technology can be used in the fields of agricultural products\food quality inspection, biomedicine, security inspection, and materials science, also having great potential for many other applications. Higher performance of terahertz technology can be achieved when combined with machine learning approaches. Since the development of terahertz techniques is hindered by some shortcomings such as high water absorption, low accuracy, limited spatial resolution, and high cost, machine learning methods enable one to improve the generality and robustness of models for analyzing terahertz spectra and image data. In order to reduce the costs of terahertz technology, a complementary study aiming to improve detection accuracy, increase signal-to-noise ratio of the instruments, establish terahertz database, and amplify the performance of terahertz hardware and software systems has to be conducted. Terahertz communication technology is promising in short-distance ultra-high-speed wireless communication due to its extremely high data rate and huge bandwidth, offering a solution for some problems faced by current wireless communication appliances. In the near future, terahertz technology is expected to be extensively practiced in more fields.

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