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Machine learning-based non-destructive terahertz detection of seed quality in peanut

Weibin Jiang [a,c], Jun Wang [a,*], Ruiquan Lin [a,*], Riqing Chen [b], Wencheng Chen [a], Xin Xie [a], Kan-Lin Hsiung [c], Hsin-Yu Chen [c]

[a] College of Electrical Engineering and Automation, Fuzhou University, Fuzhou 350108, China
[b] College of Computer and Information Sciences, Fujian Agriculture and Forestry University, Fuzhou 350000, China
[c] Department of Electrical Engineering, Yuan Ze University, Taoyuan 35002, Taiwan

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ABSTRACT

Rapid identification of peanut seed quality is crucial for public health. In this study, we present a terahertz wave imaging system using a convolutional neural network (CNN) machine learning approach. Terahertz waves are capable of penetrating the seed shell to identify the quality of peanuts without causing any damage to the seeds. The specificity of seed quality on terahertz wave images is investigated, and the image characteristics of five different qualities are summarized. Terahertz wave images are digitized and used for training and testing of convolutional neural networks, resulting in a high model accuracy of 98.7% in quality identification. The trained THz-CNNs system can accurately identify standard, mildewed, defective, dried and germinated seeds, with an average detection time of 2.2 s. This process does not require any sample preparation steps such as concentration or culture. Our method swiftly and accurately assesses shelled seed quality non-destructively.

1. Introduction

Peanut seeds are a primary source of food and bio-oil, with high commercial value. About 45% of the world's peanut products are used for global human food consumption, and about 41% of the remaining production is used to extract bio-oil (Davis & Dean, 2016; Fletcher & Shi, 2016; Kumar, Rai, et al., 2021; Yang et al., 2020). At the same time, peanut seeds are also used in the manufacture of automobile fuel and the reserve of agricultural cultivation (Sorita et al., 2020). Poor-quality peanut seeds can be mildewy, defective, dried or germinated (Luparelli et al., 2022; Michelotto et al., 2022; Salgado & Ng, 2019; Singleton & Pattee, 1991; Sobolev et al., 2019). These can cause serious harm when consumed or processed. For example, mildewy seeds may contain aflatoxin, one of the most toxic known mycotoxin (Bediako et al., 2019). AFT contamination can occur at all stages of cultivation, collection, storage, transportation and processing (Ezekiel et al., 2012; Ghiasian et al., 2011). AFT-contaminated foods could increase the probability of human cancer and neonatal malformations (Ding et al., 2012). Therefore, the AFT-contaminated seeds cause at least 1.2 billion food waste (Ajmal et al., 2022; Kumar, Pathak, et al., 2021), at least thousands of direct or indirect deaths, and tens of billions of dollars in economic losses worldwide each year (Ajmal et al., 2022; Iqbal et al., 2012; Kumar et al., 2017; Schmidt et al., 2021). The international Agency for Research on Cancer (IARC) of the World Health Organization (WHO) classified AFT B1 as a Class I carcinogen in 1993 (Majeed et al., 2013).

In addition to the significant harm caused by AFT, defective, dried and germinated seeds also adversely affect grain quality and processing efficiency. Defective seeds, resulting from shell and kernel damage due to external factors and insect infection during collection and transportation (Luparelli et al., 2022), not only fail to germinate and grow properly but also increase the risk of the AFT contamination, thus compromising seed processing and planting potential. Dried seeds, caused by moisture loss in the kernel due to temperature factors, contain less than the 10% water required for germination, rendering them inactive. While suitable for food processing, if these seeds undergo further dehydration during processing, carbonization may occur, potentially producing carcinogenic substances harmful to human health (Sobolev et al., 2019). Seeds may germinate during transportation and storage. However, as most seeds maintain an intact shell, internal

* Corresponding authors at: College of Electrical Engineering and Automation, Fuzhou University, No.2 Xueyuan Road, Fuzhou, Fujian Province 350000, China.
E-mail addresses: 210110008@fzu.edu.cn (W. Jiang), wangjun_online@hotmail.com (J. Wang), rqlin@fzu.edu.cn (R. Lin), riqing.chen@fafu.edu.cn (R. Chen), convex@saturn.yzu.edu.tw (K.-L. Hsiung), s1048505@mail.yzu.edu.tw (H.-Y. Chen).

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germination is often not directly observable. Using such seeds for food or fuel processing can lead to food contamination and fuel quality degradation (Singleton & Pattee, 1991). Therefor, quality detection of peanut seeds can effectively mitigate the impact of inferior seeds on grain and related processing industries.

Several methods have been developed to detect the AFT and assess seed quality, including Thin Layer Chromatography (TLC), High-Performance Liquid Chromatography (HPLC), immunoassay, and biosensor techniques. Each method has its advantages and limitations. The TLC, the earliest and most widely used technique, offers simple and low-cost detection suitable for monitoring numerous samples. However, it requires complex sample preparation, which affects detection sensitivity and safety (Var et al., 2007). The HPLC provides accurate quantification and high reliability but shares TLC's drawbacks of complex sample pretreatment, a long detection cycle, and the need for professional reagent configuration (Khayoon et al., 2010). The immunochemical methods, particularly the widely used colloidal gold detection, offer high specificity, sensitivity and simplicity. While they don't require special instruments, they still involve lengthy sample pretreatment (Masinde et al., 2013; Raysyan et al., 2020). The biosensor methods, combining biotechnology and electronics, provide high selectivity and fast response but are hindered by high detection costs (Liu et al., 2020). Traditional observation methods can identify seeds with obvious defects but fail to detect internal issues in seeds with intact shells. Moisture content measurement techniques, such as the drying method or near-infrared spectroscopy, either destroy the seed structure or require shell removal (Li et al., 2019; Xu et al., 2019). Generally, these methods face challenges of complex processes, long detection times and high costs, highlighting the need for a more efficient and non-destructive detection technique.

Traditional detection methods often render seeds unsuitable for further consumption or processing (Groot et al., 2022), leading to significant losses and incomplete detection. This undersores the urgent need for continuous, non-destructive detection technology at each stage of seed processing to eliminate inferior seeds and ensure food and fuel quality.

Recent advances in non-destructive detection technologies, including X-rays, visible light, and terahertz waves, have gained significant attention in seed detection research. Terahertz wave detection technology, in particular, offers unique advantages over X-rays and visible light methods. It utilizes low-energy photons and non-ionizing radiation, making it non-destructive and safe for biological samples (Han & Gao, 2019; Wang et al., 2018). Terahertz waves are highly sensitive to moisture content due to their strong interaction with hydrogen bonds in water molecules. This property enables the detection of moisture distribution within seeds, providing valuable information about seed quality (Jiusheng, 2010). The technology has shown promise in various fields, including material science and biomedical applications (Afsah-Hejri et al., 2019).

Recent studies have demonstrated the potential of combining advanced imaging techniques with machine learning for plant stress detection and seed variety identification. For instance, hyperspectral imaging (HSI) and chlorophyll fluorescence imaging (CHl-FI), coupled with Convolutional Neural Networks (CNNs), have achieved high accuracy in detecting herbicide and heavy metal stress in rice plants (Zhang et al., 2022). similar approaches have been successful in early detection of rice bacterial leaf blight (Cao et al., 2022) and identification of rice seed varieties (Jin et al., 2022; Qiu et al., 2018). These advancements in imaging technology and machine learning algorithms provide a foundation for developing more efficient and accurate seed quality assessment methods.

Fig. 1 illustrates the working principle of the terahertz wave imaging system employed in this study. The system utilizes a pulse signal scanning mechanism to scan the target point-by-point on a two-dimensional plane. As the target moves perpendicular to the terahertz wave transmission, the system records transmission or reflection information at different positions, generating time-domain waveforms for each pixel. Fourier transform techniques extract phase and amplitude information, enabling spectral analysis for image construction. This approach offers high signal-to-noise ratios and submillimeter resolution, providing rich, multidimensional data beyond mere intensity information.

This work study explores the application of terahertz wave imaging technology for seed quality differentiation. Through comprehensive analysis, this work identified distinct characteristics associated with varying seed qualities and established a correlation between seed quality and internal moisture distribution. This approach enables non-destructive and rapid evaluation of seeds by analyzing moisture distribution patterns.

This paper presents a novel, highly automated method that combines terahertz imaging technology with machine learning algorithms (Gao et al., 2023) to accurately assess peanut seed quality. This method eliminates the need for traditional sample preparation steps such as concentration, culture or incubation. It simultaneously detects five distinct quality types of peanut seeds (standard, AFT contamination, defects, germination status, and dehydration) throughout the supply chain, from cultivation to processing. This work methodology demonstrates robustness in delivering real-time, efficient, and universally applicable detection results with high accuracy.

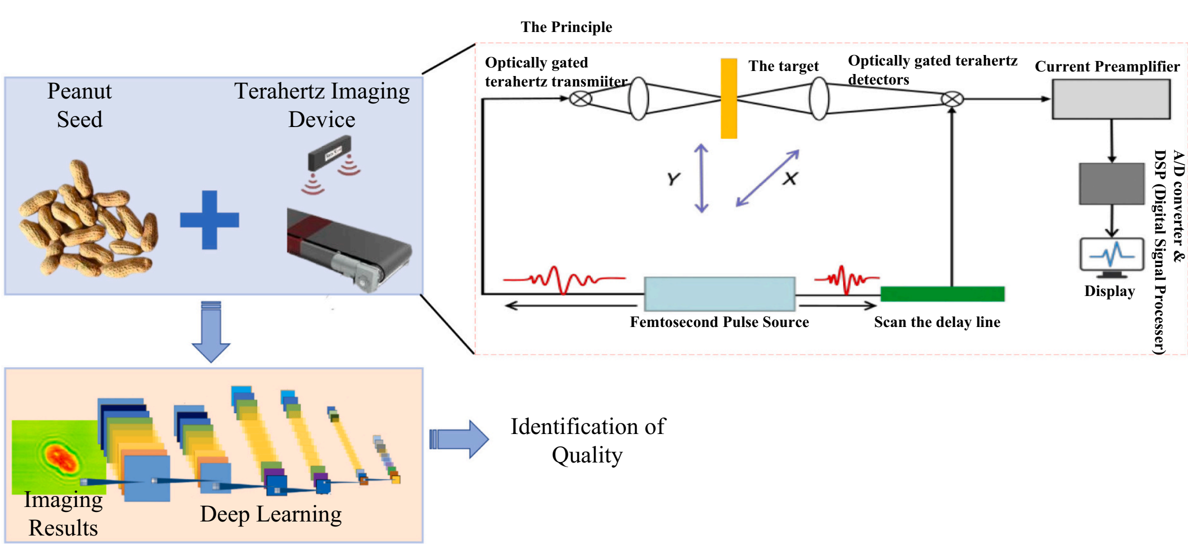


Fig. 1. Terahertz wave imaging system and its application in peanut seed quality assessment.

2. Materials and methods

2.1. Materials and reagents

Peanut seed samples were from Henan Yuhua 9326, registration number GPD peanut (2018) 410069; As shown in Fig. 2, terahertz signal generators, terahertz signal receivers and conveyor belts were purchased from TeraSense; The colloidal gold (aflatoxin B1) detection cards (Catelog No. G702302) were purchased from Finde; The analytical reagent was composed of 70% methanol and 30% deionized water. The oscillator was purchased from Scientific Industries; The centrifuge was purchased from Eppendorf; The near-infrared spectroscopy moisture meter was purchased from Born.

2.2. Sample manufacturing

It is important to note that all analyses in this study were conducted on whole, unshelled peanuts. This approach was chosen to maintain the integrity of samples and to simulate real-world conditions where peanut quality assessment often needs to be performed without removing the shell. The terahertz waves used in the proposed imaging system are capable of penetrating the peanut shell, allowing for analysis of the internal kernel quality without the need for deshelling.

In this study, the samples were first subjected to terahertz imaging equipment to screen out the seeds in the non-standard state of the imaging results, and the defective seeds were screened out by observation method. The terahertz wave images of the defective seeds were saved and marked. The screened samples were divided into four groups and numbered, and the seeds in the group were numbered. Four groups of samples were cultured as follows.

The first group of samples was placed in a semi-open container with an ambient temperature of 30 °C and air humidity of 30% after culturing for 20 days. A total of 10 cultivated samples were selected by sampling, and a colloidal gold detection card was used to detect aflatoxin B1. If the results of the samples were positive, it was considered that mildewed peanut seeds had been cultivated.

Before the colloidal gold test card detected the sample, the sample was taken out and crushed. The crushed sample was passed through a 20-mesh sieve, and 2 g was taken out and transferred to a 15 mL covered centrifuge tube. The tube was added with 4.0 mL of methanol and deionized water and sealed, and the centrifuge tube was placed in the oscillator for 5 min. After shaking, the centrifuge tube was placed in a centrifuge and centrifuged at 4000 rpm for 1 min. After the liquid was stratified, 2.0 mL of the upper clear liquid was taken to a 50 mL glass beaker with a scale tube, and the upper clear liquid was heated at a low temperature to blow dry. The beaker was cooled to room temperature, and 1.5 mL of diluent was added to redissolve to obtain the test solution. Removed the pollution-free colloidal gold detection card with a pipette to absorb the test solution, and then slowly added 3–5 drops of the test solution to the test card holes, next waited for 5 min after the interpretation of the results.

Fig. 2. The Terahertz test platform of seed quality.

The second group of samples were placed in a semi-open container with an ambient temperature of 20 °C, air humidity of 50% and soil humidity of 55% after culturing for 10 days. The samples with surface mildew were screened and eliminated by observation. A total of 10 samples after culturing were selected, and aflatoxin B1 was detected by a colloidal gold detection card. If the results of the samples were negative, it was considered that the germinated peanut seeds without mildew were cultured.

The third group of samples were placed in an open container and sent to the drying oven, and the ambient temperature was set to a constant 65 °C for 5 min, 10 min, and 15 min of drying, respectively. Ten samples were selected and sent to the near-infrared spectroscopy moisture meter to detect the moisture of the seeds. If the mean value of the test results was less than 10%, the peanut seeds with water shortage were considered to be obtained. The fourth group of samples served as standard peanut seeds.

For each quality category (standard, mildewed, defective, dried, and germinated), a total of 8000 samples were prepared. The whole peanuts, with their shells intact, were placed individually on the scanning platform of the terahertz imaging system for analysis. Terahertz imaging equipment scanned mildewed, germinated, dried, and standard peanut seeds, respectively, to obtain terahertz wave images of each sample and marked them.

2.3. Image dataset preprocessing

The complexity and repeatability of quality analysis made human visual recognition methods extremely difficult, and convolutional neural networks provided a highly automated, highly reproducible, and accurate detection solution. The image needs to be preprocessed before it was fed into the convolutional neural network and batch produced as datasets for CNN training and testing. In this study, Matlab was used to process the captured raw images to form a dataset of peanut seed quality. The imread() function of MATLAB extracted the collected terahertz wave imaging results. The imcrop () function of MATLAB was used to capture the image, so the seed was located in the center of the image. The imrotate () function of MATLAB was used to rotate the image to generate multiple sets of image data with different angles. The imresize () function of MATLAB was used to scale the image to the standard 32×32 size. As shown in Fig. 4, the data of images were finally formed, and the normalisation processing was completed. The image data was transformed from a 0–255 integer interval to 0–1 floating point interval data. Finally, each image was labeled, and the label included the quality type and serial number. Among them, the standard seed was type 0, the mildewed seed was type 1, the defective seed was type 2, the germinated seed was type 3, and the dried seed was type 4.

2.4. Machine learning and recognition

The collected data sets of different qualities of peanut seeds are divided into training data and test data in a ratio of 70% and 30% to train and verify the accuracy of the convolutional neural network. The advantage of the convolutional neural network architecture is that the accuracy of recognition is greatly improved with the increased training data set and repeatability. The accuracy of the test in the study is expressed by the accuracy curve, which is the standard representation of the neural network results. The test accuracy is an accurate indicator of the applicability of the model. Pytorch (Facebook, Menlo Park, CA) was used to perform convolutional neural network training on Spyder Python 3.7 (MIT, Cambridge, MA). On the eight-layer neural network (an input node, an output node, two fully connected layers, two convolutional layers, and two pooling layers), 16,000 steps (iterations) were used to optimise the neural network and test the maximum accuracy. The image was the input layers of the network model, and the size of each channel's data was 32×32; the convolution layer of each channel adopted a 3×3 convolution kernel to realize the convolution operation of the input layer image. After the convolution layer, the data was activated by the ReLU function; the maximum pooling principle was adopted in the pooling layer; the Softmax function classified the fully connected layer, and the final output result was obtained. The size of the output layer was 5, which corresponds to 5 qualities of peanut seeds. The training parameters of this paper also included a convolution step length of 2 learning rate of 0.02, and AdamOptimizer optimised the network to minimised the cross entropy.

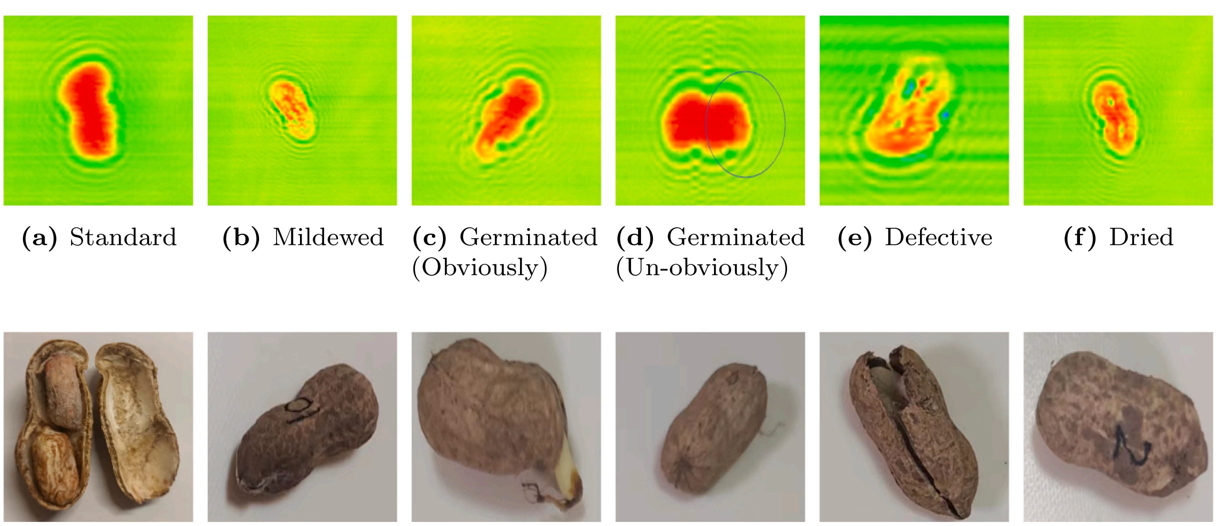
3. Results

3.1. Quality verification under terahertz wave imaging technology

The results of terahertz wave detection of standard peanut seeds are shown in Fig. 3a. The image depicts a thermographic representation of a peanut seed, where the background, represented in green, signifies an empty space devoid of physical entities, yet exhibits wave-like patterns. The delineation of the peanut seed's shell is characterized by a yellow contour, enveloping the seed's core. The central region, highlighted in red, corresponds to the endosperm of the seed. The shell's depiction is one of continuity and smoothness, devoid of discernible irregularities. The background's wave-like patterns exhibit gradational attenuation with increasing distance from the seed, suggesting a diffusion effect. The endosperm region manifests a consistent and homogenous distribution, with a notable exception at the interface with the shell where an irregular diminution is observed, potentially indicative of structural or compositional variances. Fig. 3b is the terahertz wave imaging results of mildewed seeds. The shell is discontinuous, and the spiculation is serious; the ripples in the background space appear to be obvious faults and unevenness; severe mottled distribution appeared in the fruit area, while voids and unevenness appeared in the central area.

Fig. 3g and Fig. 3h are the interior and exterior of the mildewed seeds. There is noticeable mildew inside the seeds, and mildew characteristics appear in some exterior areas. This stduy aimed to verify the effectiveness of terahertz imaging in identifying mildewed seeds and conducted a comparative analysis using colloidal gold detection cards. Four batches of 100 seeds each were tested, fifty mildewed seeds and fifty standard seeds were uniformly mixed, with each batch containing a mix of mildewed and standard seeds identified by terahertz imaging. The seeds with similar terahertz wave imaging results and mildew characteristics were selected as samples for artificial identification. The colloidal gold test results showed high consistency with the terahertz imaging identification, with accuracy rates of 95%, 100%, 97.5% and 97.5% for the four batches, respectively. This high level of agreement demonstrates the reliability of terahertz imaging in detecting mildewed seeds, with an average accuracy of 97.5% across all tested samples. The presence of AFT in the sample was verified to prove the mildew in the seed. The results show that terahertz wave imaging technology can effectively show the characteristics of mildewed seeds, and the accuracy of identifying mildewed seeds based on terahertz wave scanning results is high.

Fig. 3c and Fig. 3d are the imaging results of THz detection of germinated peanut seeds. The un-obviously germinated seeds have no obvious change in the shell. The circle indicates the germination point, showing a distinct moisture distribution. However, the ripples in the background space are discontinuous and faulted, and the ripples in the germination point area are open; the color distribution in the fruit area is uneven, and shallow color holes appear near the germination point. Fig. 3e is the imaging result of terahertz wave detection of defective seeds. The background space ripples at the current defect vacancy and large-scale fracture; the shell has prominent vacancies, but it can still present the overall contour; the fruit area is obviously missing at the defect site, and cavities and blue spots appear, showing a mottled distribution as a whole.



(a) Standard **(b)** Mildewed **(c)** Germinated (Obviously) **(d)** Germinated (Un-obviously) **(e)** Defective **(f)** Dried

(g) Internal view of a mildewed peanut seed **(h)** Appearance of a mildewed peanut seed **(i)** Appearance of a obviously germinated peanut seed **(j)** Appearance of a un-obviously germinated peanut seeds **(k)** Appearance of a Defective Peanut Seedtive **(l)** Appearance of a dried peanut seeds

Fig. 3. Terahertz imaging results (a-f) and actual appearances (g-l) of peanut seeds with different qualities. (a,g) Standard, (b,h) Mildewed, (c,i) Germinated (Obviously), (d,j) Germinated (Un-obviously), (e,k) Defective, (f,l) Dried.

Fig. 3f shows the imaging results of THz detection of dried seeds. The ripple of the background space is intact and continuous; the distribution of the fruit area shows a slightly mottled distribution but is significantly different from the imaging results of the defective seeds. According to statistical analysis, the number of cavities in the center of the fruit corresponds to the number of internal fruits, which is 1–3, and the shape of the cavity is related to the shape of the fruit.

3.2. Machine learning pattern recognition using convolutional neural networks

The variety and morphology of peanut seeds are different, and the number of actual detection scenarios is huge. The pattern library method based on the artificial visualization principle is time-consuming and difficult to achieve. As shown in Fig. 4, we developed and trained a convolutional deep neural network to extract the characteristics of peanut seeds with different qualities and realize the quality identification and classification of peanut seeds.

The classification accuracy of the convolutional neural network for five kinds of peanut quality is shown in Fig. 5a. The results show that the accuracy of the recognition method reached 98.7% in the test dataset. The convolutional neural network is fundamentally different from the analysis method of artificial identification. It does not depend on predetermined standard features. The size and position of the image output from the terahertz device are changed by image preprocessing operations. Set appropriate model parameters and iterative learning training times to minimize the cross entropy and loss function values. The loss curve in Fig. 5a tends to a stable value as the number of iterations increases, indicating that the network is convergent. The accuracy of the proposed method for quality classification is further verified. 1200 samples of peanut seeds for each quality are selected as dataset of the CNN, the training dataset and test dataset are 70% and 30% respectively. Fig. 5b shows the results of the classification test for five different peanut qualities. The average results of quality identification are 98.75%, 99.08%, 97.92%, 97.75% and 98.58%.

Taking the detection of mildewed seeds as an example, the average detection time (including sample pretreatment time) of the proposed method and the colloidal gold detection method is 0.04 min and 15 min, respectively, and the detection time is shortened by about 375 times. This method can detect multiple peanut seeds simultaneously in one treatment cycle and identify different seed qualities.

4. Discussion

This study proves a new non-destructive testing method for peanut seed quality that is universal, efficient and automated, which can meet the real-time detection of actual detection scenarios. This method can be extended to the quality inspection of most shelled crops. This can prevent the occurrence of food poisoning and infection caused by untimely detection and long cycle during the planting, picking, transportation and processing of similar crops. Traditional quality detection methods rely on rich experience in manual identification, expensive detection instruments and cumbersome detection processes. Before detection, the structure of the seeds needs to be destroyed, and the seeds that have been detected cannot continue to be used. As a sampling method, traditional methods cannot screen all seeds, so there is a risk of contamination. The detection method proposed in this paper can effectively identify the quality of seeds, such as standard, mildewed, defective, dried and germinated. This method does not require sample pretreatment before detection, suitable for a rapid and comprehensive on-site environment to achieve low-cost real-time non-destructive testing.

The absorbance of the terahertz wave scanner is proportional to the content of the measured object's polar substance, which is water. The polar substance can increase the attenuation value of the terahertz waves (Jiusheng, 2010). Jiusheng (2010) pointed out that the moisture distribution of seeds was related to the diseased tissue, and standard seeds' carbohydrate and protein mass accounted for about 40% of the total nutrients. During the growth of fungal organisms, the hyphae secrete specific enzymes that will decompose the nutrients in the seeds. This reaction process requires a lot of water to participate, so the moisture of mildewed seeds is small. This explains the discontinuous phenomena of the terahertz wave imaging results of mildewed, mottled, and corrugated seeds.

Based on the theory of Jiusheng (2010), we conducted several experiments and found that the moisture distribution of seeds can be used as a basis for identifying germinated defective and dried seeds. The moisture distribution in seeds is related to the integrity of seeds, which is mainly reflected in the trend of ripples in the background space. The ripples of standard seeds are continuous and have regular dense distribution. On the contrary, the defective seeds show discontinuous, sparse and broken ripples. To determine the presence of fungi, an invasive method of detection was used (Masinde et al., 2013). The detection and recognition model proposed in this paper can detect the quality of peanut seeds in real time and accurately without destroying the seed structure and causing radiation damage after training. This model relies on a weakly supervised training method, so it requires the scanning results of the terahertz wave to be preprocessed to generate an new image. The R channel, the G channel and edge detection data of the image are extracted as the model's input data to realize the identification of seed quality.

Fig. 5a shows that as the number of training iterations increases, the algorithm's accuracy is improved. As the size of the training iterations increases, the trained neural network will provide higher accuracy and

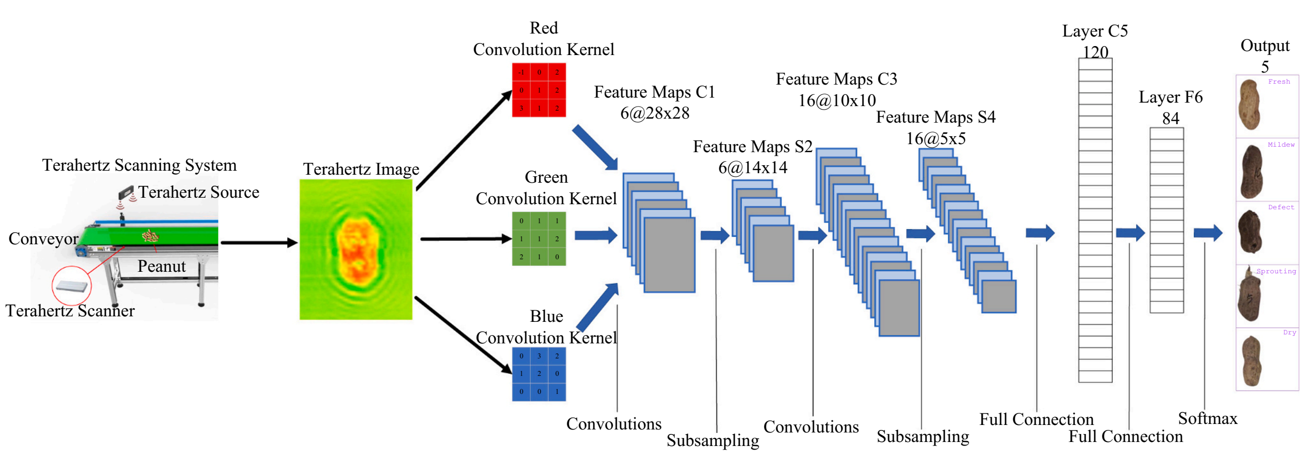
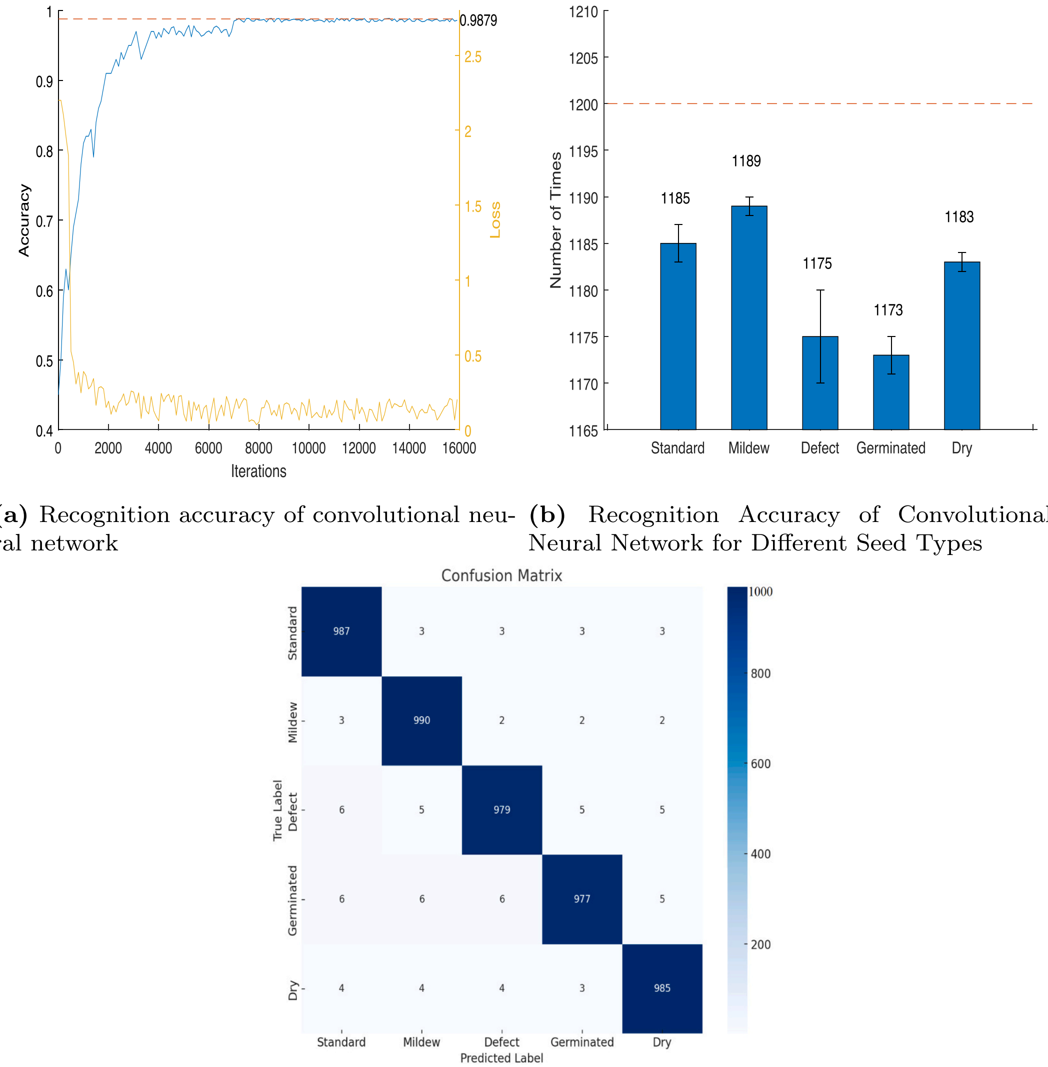


Fig. 4. Terahertz Imaging System and Convolutional Neural Networks.



(a) Recognition accuracy of convolutional neural network

(b) Recognition Accuracy of Convolutional Neural Network for Different Seed Types

(c) Confusion Matrix of the Seed Classification Model within CNN.

Fig. 5. Performance Analysis of Convolutional Neural Network for Peanut Seed Classification.

less loss of overall change. However, it is necessary to avoid over-training neural networks, which may amplify potential features, cause over-fitting, and reduce the recognition accuracy. Here, the results are observed after 16,000 iterations of training, and there is no significant decrease in training accuracy.

Fig. 5c illustrates the classification efficacy of the seed categorization algorithm, encapsulated within a 5 × 5 confusion matrix. Diagonal values represent accurate predictions, with a majority class-wise precision ranging from 97.75% to 99.08%. Notably, misclassifications are uniformly scattered across other classes, indicating an absence of systemic bias. Despite the high accuracy observed, the "Defect" and "Germinated" classes evidenced marginal decrements in predictive performance, suggesting potential avenues for model refinement. Overall, the algorithm demonstrates robust classification capabilities with balanced error distribution, thus reinforcing its applicability in automated seed quality assessment.

In conclusion, the terahertz imaging technology and convolutional neural network detection method proposed in this paper can be used as fast, non-destructive and universal detection equipment to identify the quality of peanut seeds. Compared with the traditional detection methods, the neural network model using cross entropy and loss function can automatically process a large amount of data, reduce data acquisition work (reduce training repetition) and calculation work, and have a standard unified judgment standard. As the size of the training data set increases, the recognition accuracy can be improved to meet the actual production quality inspection and consumer terminal detection scenarios.

5. Conclusion

This study demonstrates the efficacy of combining terahertz imaging technology with convolutional neural networks for rapid and non-destructive detection of peanut quality. The proposed methods achieved a high accuracy of 98.7% in distinguishing five different seed qualities: standard, mildewed, defective, dried and germinated. The terahertz wave images revealed distinct characteristics for each quality type, enabling precise identification without damaging the seed structure. The developed system significantly reduced detection time to an average of 2.2 s per seed, approximately 375 times faster than traditional methods. This substantial improvement in speed, coupled with the elimination of sample preparation steps, makes this study approach highly suitable for real-time, continuous quality assessment in industrial settings. This paper's findings represent a significant advancement in seed quality detection technology, offering potential benefits for food safety and quality control in the peanut industry. The high accuracy, speed and non-destructive nature of the proposed method make it particularly valuable for large-scale quality assessment throughout the peanut supply chain. Future research could explore the application of the proposed method to other crop types and its integration into existing production lines to enhance quality control processes in the food industry.

CRediT authorship contribution statement

Weibin Jiang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jun Wang:** Writing – review & editing, Writing – original draft, Funding acquisition, Data curation, Conceptualization. **Ruiquan Lin:** Software, Project administration, Methodology. **Riqing Chen:** Writing – review & editing, Supervision, Project administration. **Wencheng Chen:** Resources, Project administration, Methodology, Formal analysis. **Xin Xie:** Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Kan-Lin Hsiung:** Validation, Supervision. **Hsin-Yu Chen:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data used in this study and models developed are available upon request from the first author, Weibin Jiang, email: 210110008@fzu.edu.cn

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