

Article

Recognition of Heat-Damaged Corn Seeds Based on Fusion of Laser Ultrasonic Signal and Infrared Image Features

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Abstract: Corn is widely cultivated on a global scale. However, high temperatures during storage and transportation can lead to thermal damage to the kernels, negatively impacting their quality. Traditional methods for identifying heat-damaged grains primarily rely on manual inspection, which is characterized by low efficiency and accuracy. This study proposes a novel identification method that integrates laser ultrasonic signals with infrared image texture features. A pulsed laser stimulates the seeds to generate laser ultrasonic signals, while an infrared camera captures infrared images of the seeds. We extract time-domain, frequency-domain, and Hilbert-domain features from the laser ultrasonic signals, in addition to texture features from the infrared images. These features are combined using Canonical Correlation Analysis (CCA). Subsequently, the fused features are classified using a Backpropagation (BP) neural network, Support Vector Machine (SVM), and Particle Swarm Optimization–Support Vector Machine (PSO–SVM). The results indicate that the recognition rate achieved with the fused ‘signal-image’ features reaches 99.17%, providing a novel approach for detecting heat-damaged corn seeds.

Keywords: heat-damaged kernels; laser ultrasonic; signal features; image features; feature fusion; infrared images



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1. Introduction

Corn is widely cultivated across various regions due to its unique flavor and rich nutritional content. However, heat damage to seeds during production significantly limits the benefits associated with its cultivation and processing [1]. Heat-damaged corn grains primarily result from exposure to high temperatures during storage and transportation, leading to the loss of essential components. This damage severely impacts the germination rate and growth potential of the seeds [2]. Timely and accurate identification and removal of heat-damaged grains are crucial for enhancing the quality and production efficiency of corn seeds. Traditional methods for detecting heat-damaged grains predominantly rely on manual visual inspection [3], which is inefficient, subjective, and prone to errors. Therefore, the establishment of a rapid, accurate, and non-destructive method for identifying heat-damaged corn grains holds significant practical importance [4].

In recent years, spectroscopic technology has been extensively studied and applied for the non-destructive testing of seed quality. Common spectroscopic detection techniques include near-infrared spectroscopy and hyperspectral imaging. Wang Dong et al. [5] utilized near-infrared multispectral technology to develop an identification model for heat-damaged maize grains, achieving correctness rates ranging from 96% to 100% for multispectral data and 92% to 100% for cross-validated data. Yating Hu et al. [6] extracted spectral and spectral image features of maize seeds using hyperspectral imaging technology and applied an improved inverse sparrow search algorithm alongside a random forest algorithm to the

validation set, achieving a classification accuracy of 96% in distinguishing sound maize grains from those that are moldy or insect-damaged. Building on this foundation, many scholars have employed various methods to extract and fuse texture and spectral features to further enhance classification accuracy. For instance, Ye Wenchao et al. [7] proposed a hybrid classification method for rice seeds by integrating image and spectral information, which improved classification correctness. Ding Ziyu et al. [8] enhanced classification accuracy from 92.5% to 93.1% using an SVM model by selecting false-color images synthesized from three feature bands in the near-infrared range, extracting texture features, and fusing them with spectral features. Chengkun Wang et al. [9] introduced a multi-feature wood classification algorithm based on wood image and spectral information, demonstrating that spectral and texture features can complement each other to improve classification accuracy. However, the acquisition of spectral data necessitates broadband wavelength scanning [10], which is typically high-dimensional; consequently, data acquisition, processing, and feature extraction can be inefficient, and the cost of imaging spectrometers is high [11].

Compared to pure spectroscopic detection, laser ultrasound offers a greater detection depth [12]. Extracting laser ultrasonic signal characteristics directly from corn kernels eliminates the need for expensive spectrometers that require broadband wavelength scanning [13], thereby enhancing detection efficiency. When a short-pulse laser with a wavelength of 532 nm irradiates the surface of corn seeds, the seed material absorbs the laser energy, leading to transient thermoelastic expansion caused by localized temperature elevation [14]. This rapid thermal expansion generates ultrasonic waves within the seed. For healthy seeds, these ultrasonic waves propagate at specific speeds and patterns [15]. However, heat damage alters the seed's internal structure and physical properties—such as decreased density, reduced modulus of elasticity, and disrupted tissue structure—resulting in slower ultrasound propagation [16], increased signal attenuation, and waveform distortion. By analyzing changes in time delay, signal amplitude, and spectral characteristics of laser ultrasonic signals, it is possible to identify the degree of thermal damage in seeds. Unlike methods that rely solely on surface temperature information from infrared images, laser ultrasound technology is highly sensitive to alterations in the internal structure of seeds, enabling a more comprehensive assessment of thermal damage. The integration of laser ultrasonic signal features with infrared image features can enhance the recognition accuracy of heat-damaged seeds [17], providing reliable technical support for seed quality control and agricultural production.

Infrared imaging technology has advanced sufficiently to capture changes in the spatial structural features of corn kernel surfaces associated with thermal damage [18]. Consequently, this study integrated the laser ultrasonic signal features of corn samples with the texture features of infrared images. We collected laser ultrasonic signals and infrared images from both control and heat-damaged groups of maize, utilizing the fused 'signal-image' features to distinguish between the two groups. The feasibility of this method was validated, highlighting its potential for rapid and non-destructive identification of heat-damaged maize grains. This approach provides a novel perspective for the swift non-destructive testing of heat-damaged maize grains.

2. Materials and Methods

2.1. Experimental Samples

The experimental samples consisted of 2000 corn seeds (Wuhan Chuanhe Agricultural Technology Co., Ltd., Wuhan, Hubei, China), with a total of 960 seeds divided into a control group and three heat-damaged groups, each containing 240 seeds. The heat-damaged samples were treated under different temperature and time conditions: heat-damaged group 1 was dried in an electric blast drying oven at 80 °C for 8 h, heat-damaged group 2 at 70 °C for 6 h, and heat-damaged group 3 at 60 °C for 6 h.

2.2. Instruments and Equipment

The data acquisition platform primarily consists of a laser ultrasonic acquisition system and an image acquisition device, as illustrated in Figures 1 and 2. The laser ultrasonic acquisition system comprises six main components: a laser (3635 Peterson Way, Santa Clara, CA, USA), a water-immersed ultrasonic probe (model:I3-0508-S-SU) (panametrics olympus, Tokyo, Japan), a ultrasonic preamp (model:5676PREAMP) (panametrics Olympus, Tokyo, Japan), a stepper motor controller(Sanying Precision Instruments Co., Ltd., Tianjin, China), an MSO7104A oscilloscope (Agilent Technologies, Santa Clara, CA, USA), and a focusing lens(THORLABS, Newtown, NJ, USA). At the outset of the experiment, the seeds were positioned beneath a membrane at the bottom of a water tank using the stepper motor controller, maintaining a distance of approximately 8 mm between the seeds and the ultrasonic probe. The membrane served to separate the seeds from the water, ensuring that they were not directly immersed. The stepper motor enabled precise positioning of the seeds, optimizing the laser and ultrasonic signals to achieve maximum response and facilitate accurate data collection. The laser was subsequently adjusted to share a common focal point with the ultrasonic probe. Upon irradiation by the pulsed laser, the corn kernels were excited, resulting in the production of laser ultrasonic signals. For infrared imaging, an infrared camera was utilized to capture images of the corn kernels. During image acquisition, the seeds were placed at a designated position on the platform, and the camera was manually focused to ensure the clarity of the images.

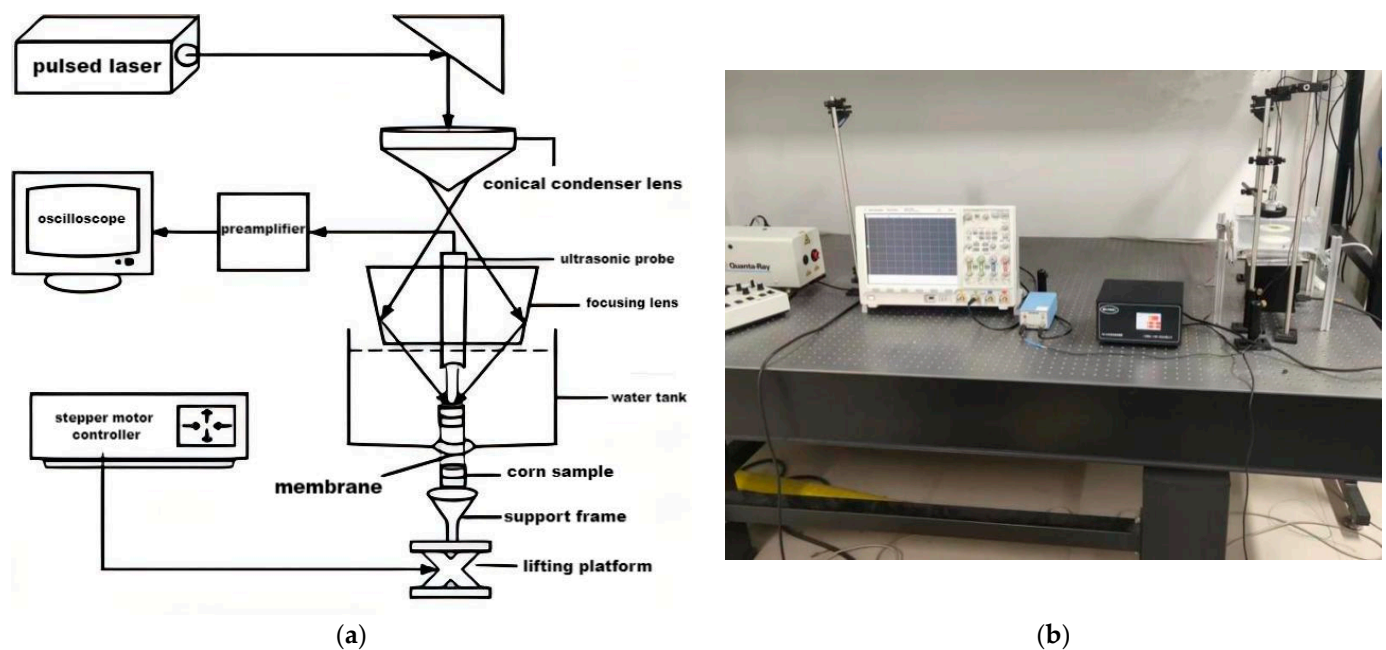


Figure 1. Laser ultrasonic acquisition system: (a) Structural diagram; (b) Actual photo.

The laser utilized in this experiment is the INDI-40-20-HG Nd model, operating at a frequency of 20 Hz, with an energy output of 160 mJ and a wavelength of 532 nm. Within the thermoelastic regime, the energy density of the laser remains below the damage threshold of the object under investigation, thereby ensuring the safety of the seeds. Typically, the thermal damage threshold for agricultural seeds ranges from approximately 1 to 10 J/cm². Given that the laser energy density employed in the experiment is substantially lower than this threshold, the risk of seed damage is minimal.



Figure 2. Image acquisition device.

2.3. Feature Extraction Methods

2.3.1. Preprocessing and Feature Extraction of Laser Ultrasonic Signals

Data analysis was performed using MATLAB R2023b (MathWorks, Natick, MA, USA). To account for slight variations in the time-domain laser ultrasonic signals—caused by laser irradiation at different positions on the seed surface—each seed was measured ten times. The average of these ten measurements was taken as the representative laser ultrasonic signal for that seed. During the experiments, the laser ultrasonic signals were susceptible to factors such as equipment stability and environmental fluctuations, which led to considerable high- and low-frequency noise in the acquired signals. To mitigate this noise, Ensemble Empirical Mode Decomposition (EEMD) was employed for signal denoising. In this study, EEMD was applied to the raw laser ultrasonic signal data to effectively reduce noise, which is often introduced due to equipment stability and environmental variations during signal collection. Without the application of EEMD, the raw data contained significant high- and low-frequency noise, negatively impacting the reliability of the extracted features. Analyses performed without EEMD utilized unprocessed signals, which were found to be less effective in distinguishing between control and heat-damaged corn kernels. EEMD was conducted to decompose the signals into several Intrinsic Mode Functions (IMFs), and in our analysis, different signals yielded between 4 to 6 IMFs depending on their characteristics. This approach allowed for improved feature extraction, particularly in the Hilbert-domain, thereby enhancing classification accuracy.

Subsequently, the original feature parameters of the laser ultrasonic signals were analyzed individually in the time-domain, frequency-domain, and Hilbert-domain. Principal Component Analysis (PCA) was then employed to extract distinguishable features from these original parameters. The extracted features enabled the classification and identification of corn seeds in both the control group and the heat-damaged group.

2.3.2. Infrared Image Texture Feature Extraction

The texture features of infrared images of maize seeds reflect surface changes associated with thermal damage, including wrinkle distribution, surface smoothness, and color variations. To extract these texture features, we employed the Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrix (GLCM), and Tamura algorithms. Given the high dimensionality of the extracted texture feature data, which can introduce redundant information and negatively impact the detection efficiency and accuracy of the classification model, we applied Principal Component Analysis (PCA) for dimensionality reduction. Features were retained based on a cumulative variance contribution rate of 97%. During

the texture feature extraction process, the dimensions of the seed images were resized to specific pixel dimensions.

To help readers understand how LBP, the GLCM, and the Tamura algorithm extract texture features from infrared images, this overview presents their principles and effects concisely. LBP compares each pixel's gray value with its neighbors to encode local texture information. For each pixel, a neighborhood (typically a 3×3 window) is defined. Neighbors with gray values greater than or equal to the center pixel are marked as '1', while others are marked as '0'. These binary results form a code representing the local texture pattern. LBP is robust against illumination changes but sensitive to noise, making preprocessing steps such as noise reduction essential when applied to infrared images. The GLCM captures texture by analyzing the frequency of pairs of pixel gray levels occurring together at a specific distance and direction. The image's gray levels are quantized to simplify computation. The GLCM is constructed by counting occurrences of pixel value pairs, which are then normalized to represent probabilities. Texture features such as contrast, entropy, and homogeneity are extracted from this matrix. While the GLCM effectively captures global texture features useful for classification, the choice of parameters, such as gray-level quantization and spatial relationships, can significantly affect the results.

The Tamura algorithm extracts texture features based on human visual perception, emphasizing coarseness, contrast, and directionality. Coarseness quantifies texture granularity by identifying the scale at which the average gray-level differences are maximized. Contrast reflects the distribution and variation of gray levels, calculated using statistical measures. Directionality evaluates the distribution of edge orientations through the application of gradient operators. While the Tamura algorithm is effective for analyzing complex textures, it is sensitive to noise and variations in illumination, which necessitates preprocessing for infrared images. In summary, LBP, GLCM, and the Tamura algorithm provide distinct approaches to texture feature extraction: LBP concentrates on local texture patterns, GLCM examines spatial gray-level relationships, and the Tamura algorithm focuses on perceptual texture properties. Effective texture feature extraction for further analysis of infrared images requires careful preprocessing and parameter selection when employing these methods.

2.3.3. Feature Fusion

In feature fusion, Canonical Correlation Analysis (CCA) combines features from two sets by identifying linear combinations that maximize their correlation, thereby enhancing the characterization of relationships within the data. According to Sun's definition, there are two fusion strategies for CCA: the 'concat' and 'sum' strategies, which are utilized to classify and identify samples using the fused feature vectors. This paper employs both the 'concat' and 'sum' fusion strategies for sample classification and recognition.

In the concatenation (or concat) strategy, feature vectors from various data sources or modalities are combined by appending them side by side to create a single, extended feature vector. This method treats each feature set independently, preserving their unique structures without any additional transformation or modification. While the concat strategy retains all original feature dimensions, it may lead to high-dimensional vectors, which can sometimes introduce redundancy or superfluous information. In practical applications, dimensionality reduction techniques, such as Principal Component Analysis (PCA), are often employed to manage the resulting dimensionality and enhance computational efficiency.

The sum strategy, in contrast, first employs Canonical Correlation Analysis (CCA) to optimize the feature sets and identify their most correlated components within a shared dimensional space. Once aligned, this strategy combines the features through element-wise addition of corresponding values from the two feature sets. By emphasizing the relationships among the correlated components of each feature set, the sum strategy effectively creates a single fused feature vector that contains more meaningful and correlated information while also managing dimensionality. By ensuring balanced contributions from each feature set, the sum strategy often achieves a greater integration of information

compared to simple concatenation, which can enhance performance in classification or recognition tasks.

In the ‘concat’ fusion strategy, laser ultrasonic signal features and infrared image texture features—extracted using GLCM, LBP, and Tamura methods—are treated as distinct data modalities. These features are concatenated to create a single feature vector for subsequent analysis. Conversely, the ‘sum’ strategy employs Canonical Correlation Analysis (CCA) to identify the optimal linear combinations of the laser ultrasonic signal features and the infrared image texture features, thereby ensuring strong correlations between the two sets of features across the same dimensions. The features from both modalities are then summed element-wise to produce a fused feature vector.

2.4. Machine Learning-Based Classification Methods

To compare optimal models for recognizing heat-damaged maize grains, we employed Backpropagation (BP) neural networks, Support Vector Machines (SVM), and Particle Swarm Optimization–Support Vector Machines (PSO–SVM) algorithms. Model evaluation was conducted using confusion matrices, and we analyzed the advantages and disadvantages of each model based on their recognition accuracy.

(1) BP Neural Network Parameter Setting and Optimization Process.

In optimizing the BP neural network model, we experimentally determined that a configuration of 12 hidden layer nodes yields optimal performance. This choice strikes a balance between the network’s learning capacity and complexity, allowing the model to effectively capture the nonlinear characteristics of the data while mitigating the risk of overfitting associated with an excessive number of nodes. The momentum factor was set to 0.95, which accelerates the gradient descent process, reduces training time, and helps prevent the model from becoming trapped in local minima. This setting achieves a reasonable balance between convergence speed and network stability. Additionally, the maximum number of iterations was set to 1000, ensuring that the model undergoes sufficient training rounds to avoid underfitting due to an inadequate number of iterations.

(2) PSO–SVM Parameter Setting and Optimization Process

In optimizing the PSO–SVM model, Particle Swarm Optimization (PSO) was employed to adjust the hyperparameters C and γ of the Support Vector Machine (SVM). Both the local search parameter $c1$ and the global search parameter $c2$ were set to 2. This configuration ensures that the particle swarm maintains strong global search capabilities in each iteration while effectively conducting fine-grained searches within local regions, thereby promoting convergence to the optimal solution. The inertia weight was set to 1, which ensures a moderate particle velocity in the parameter space, preventing the swarm from skipping potential optimal solutions due to excessive inertia or limiting the exploration range due to insufficient inertia. The number of particles in the swarm was established at 20, which provides adequate exploration capacity to cover a large parameter space while controlling computational costs.

For the two key hyperparameters, C and γ , of the Support Vector Machine (SVM), the search range was established between 0.1 and 100. This range encompasses both weak and strong regularization scenarios, thereby accommodating data distributions with varying complexities of kernel functions. Through these optimization strategies, the final Particle Swarm Optimization–SVM (PSO–SVM) model demonstrated superior performance compared to the Backpropagation (BP) neural network in the classification task, thereby validating the efficacy of the particle swarm optimization algorithm in fine-tuning SVM hyperparameters.

3. Results and Discussion

3.1. Data Preprocessing

Laser ultrasonic signals were collected from 960 seed samples, evenly divided between the control group and the heat-damaged group. After preprocessing, the extracted laser ultrasonic signals and the reconstructed signals using EEMD are shown in Figure 3. In this figure, the waveforms of the laser ultrasonic signals from the heat-damaged group exhibit higher oscillation frequencies and significant differences in peak amplitudes compared to those of the control group. These disparities can be attributed to changes in the surface or internal structure of the maize seeds resulting from heat damage, which affects the propagation of laser-induced ultrasonic waves within the kernels. The signal-to-noise ratio of the signals was enhanced through EEMD preprocessing, improving the quality of the data for subsequent analysis.

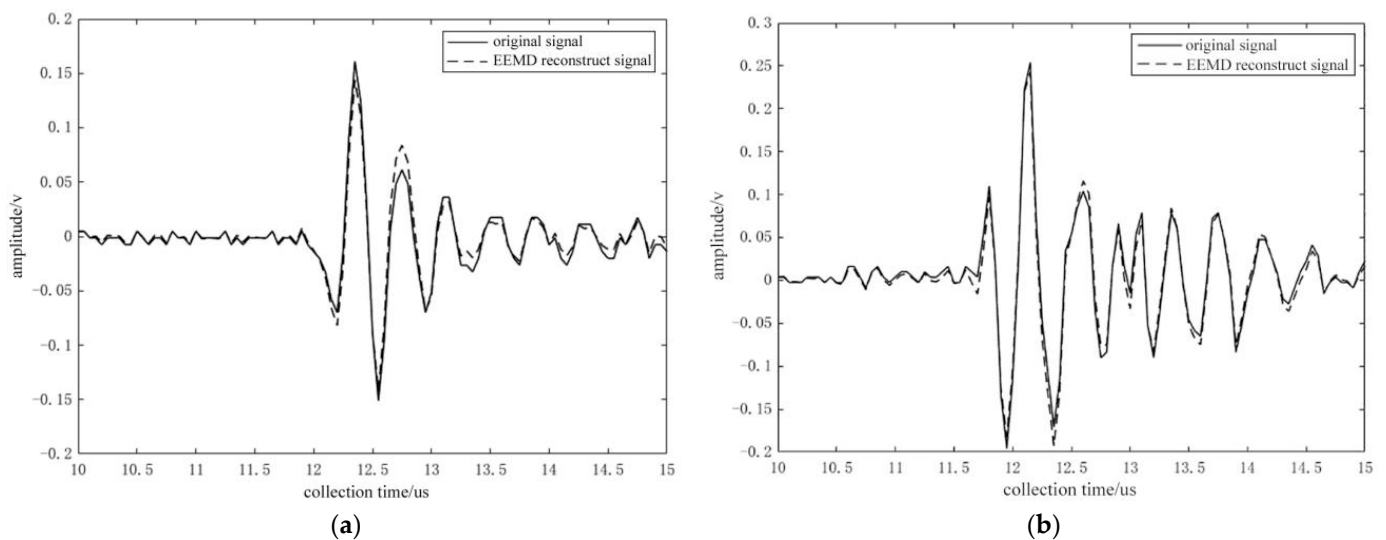


Figure 3. Laser ultrasonic signal and EEMD reconstruction signal: (a) The control group; (b) The heat-damaged group.

Using freshly harvested corn as the material, heat-damaged grain samples were obtained through artificial heating and aging methods. The original and grayscale images of the control and damaged grains are shown in Figure 4.

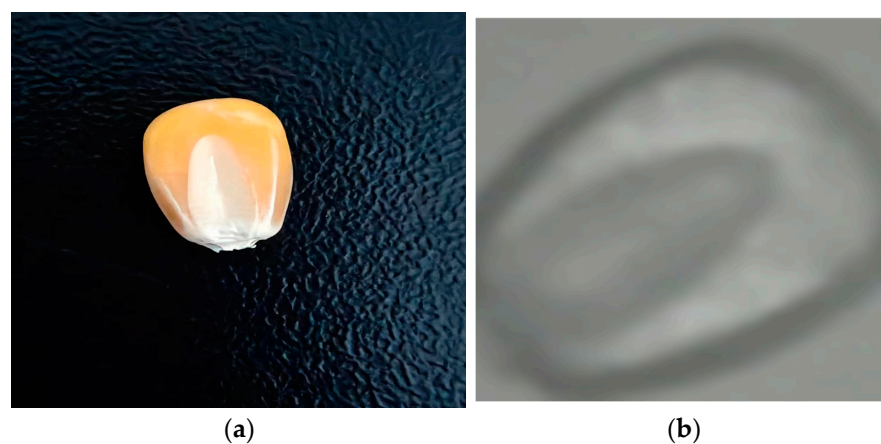


Figure 4. Cont.

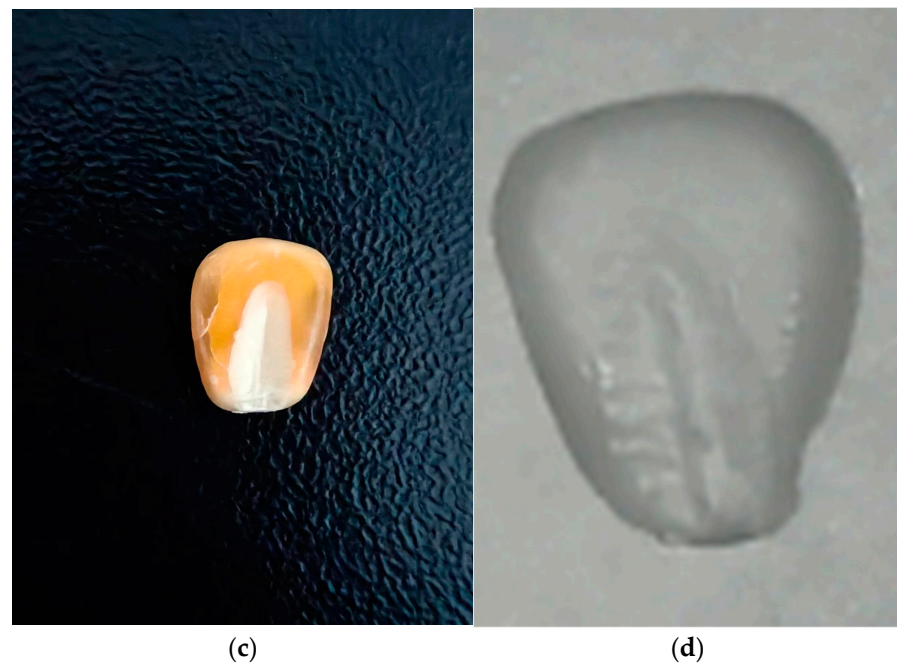


Figure 4. Corn grain samples: (a) Control group original image; (b) control group grayscale image; (c) damaged grains original image; (d) damaged grains grayscale image.

3.2. Identification of Heat-Damaged Kernels Using Individual Features

After applying noise reduction preprocessing, we analyzed the laser ultrasonic signals to extract time-frequency characteristic parameters. Using only the laser ultrasonic data, we classified and identified the control and heat-damaged groups. Four time-domain feature parameters were extracted from the laser ultrasonic signals: peak-to-peak value, standard deviation, crest factor, and impulse factor. Among these, the crest factor and impulse factor demonstrated better effectiveness in identifying the heat-damaged grains. The distribution of the extracted time-domain features is shown in Figure 5.

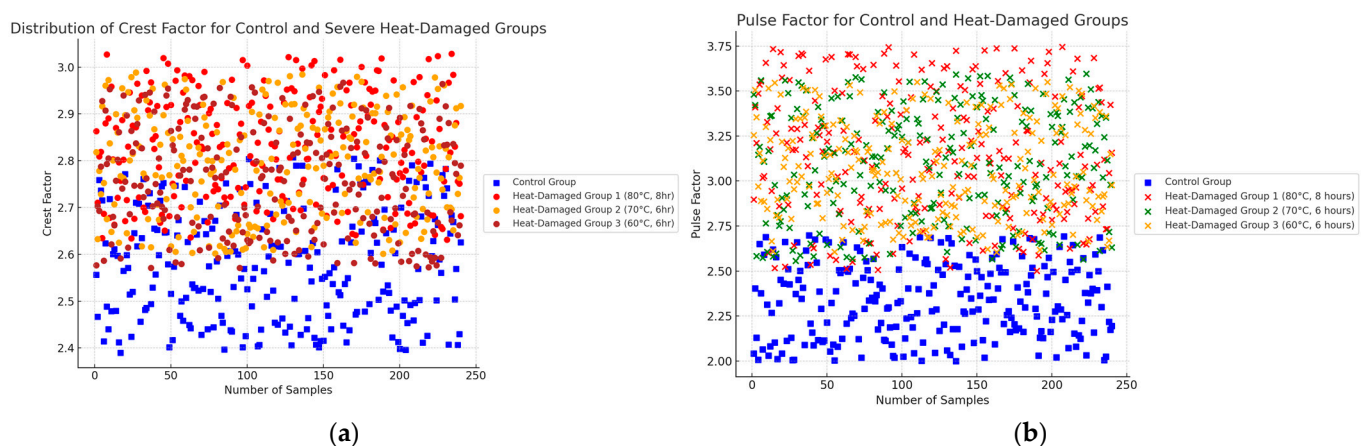


Figure 5. Time-domain feature distribution map: (a) Crest factor; (b) Pulse factor.

As shown in Figure 5, the crest factor and impulse factor exhibit noticeable differences between the control group and the three different heat-damaged groups. The results observed from the responses of the three heat-damaged groups demonstrate the distinctions between the characteristic parameters. While the classification accuracy for heat-damaged group 2 and group 3 might be lower compared to the strongest treatment (i.e., heat-damaged group 1), this illustrates the potential of the method for detecting heat treatment in general. This suggests that despite varying treatment intensities, the characteristic parameters of

laser ultrasonic signals are still effective in distinguishing the differences among the groups, demonstrating the adaptability and reliability of this method under different heat treatment conditions.

The time-domain features extracted for peak-to-peak value and standard deviation are shown in Figure 6.

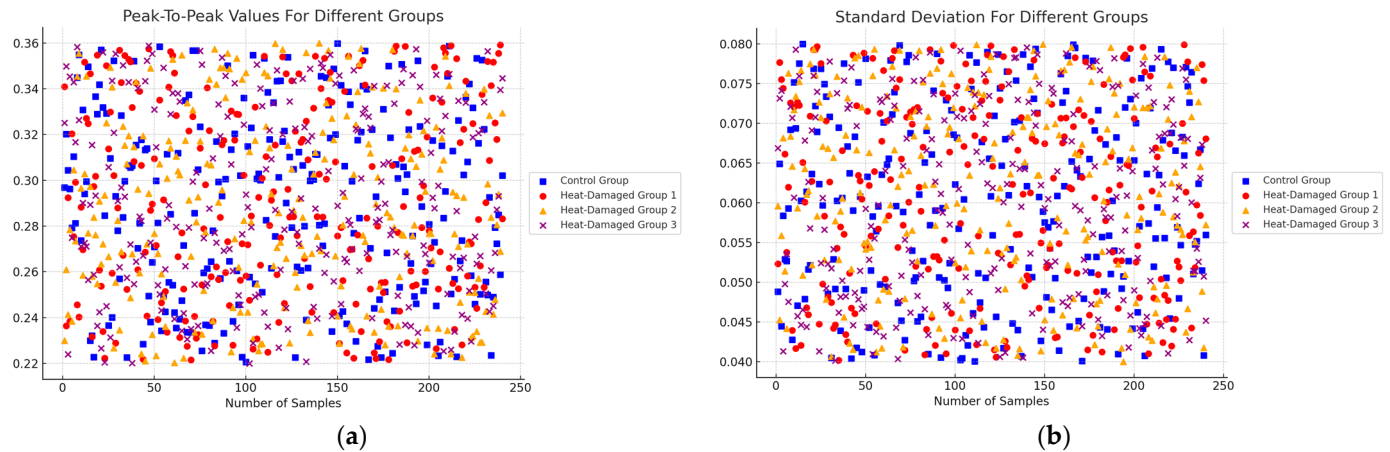


Figure 6. Time-domain feature distribution map (a) peak-to-peak value; (b) Standard deviation.

As shown in Figure 6, there is limited distinction in the crest factor and pulse factor between the control group and the three heat-damaged groups. This may be due to subtle variations in the signal waveform that are not significantly amplified in these specific parameters. In cases of heat damage, structural changes in the kernels may affect certain aspects of the signal, such as amplitude and waveform sharpness, but these changes may not be strongly captured by the crest factor and pulse factor alone. Consequently, these two parameters may lack sensitivity in detecting minor differences caused by heat damage, making them less effective in distinguishing between the control group and the damaged groups. Therefore, it is not recommended to use the crest factor and pulse factor as characteristic parameters for distinguishing the control group from the damaged groups.

The time-domain laser ultrasonic signals were transformed into frequency-domain signals using the Fast Fourier Transform (FFT). Four characteristic parameters were extracted in the frequency-domain: center-of-gravity frequency, mean-square frequency, frequency inverse, and standard deviation. Additionally, the IMFs obtained from EEMD were analyzed in the Hilbert-domain, from which three characteristic parameters were extracted: high-frequency energy, low-frequency energy, and envelope mean. The frequency range from 1 to 5 MHz was divided into two parts: 3 to 5 MHz for the high-frequency range and 1 to 3 MHz for the low-frequency range.

Center-of-Gravity Frequency: This parameter is calculated by determining the weighted average of the frequency components of the signal, where each frequency is weighted by its corresponding amplitude. Mathematically, it can be represented as:

$$f_{cg} = \frac{\sum f_i A_i}{\sum A_i} \quad (1)$$

where f_i is the frequency, and A_i is the corresponding amplitude of the signal at that frequency. It effectively represents the “balance point” of the frequency spectrum, highlighting the dominant frequency range.

Mean-Square Frequency: This parameter is obtained by squaring the frequency components and calculating their average. It indicates the power distribution across frequencies and helps identify the spread of energy in the frequency-domain:

$$f_{ms} = \frac{\sum f_i^2 A_i}{\sum A_i} \quad (2)$$

It emphasizes the contribution of higher frequencies more than lower frequencies, thus providing insight into the energy spread of the signal.

Frequency Inverse: This is calculated by taking the inverse of the frequencies and determining their average weighted by amplitude. It is useful for capturing information about the lower frequency components:

$$f_{inv} = \frac{\sum A_i / f_i}{\sum A_i} \quad (3)$$

This parameter can provide insight into the distribution of energy among lower frequencies, helping detect anomalies or changes in propagation characteristics.

Barycentric Frequency: This term is often used interchangeably with the center-of-gravity frequency. It indicates the average frequency where the majority of the signal energy is concentrated, calculated in a similar way to the center-of-gravity frequency. It essentially serves the same purpose of determining the focal point of the frequency distribution.

The distributions of these seven feature parameters in the frequency and Hilbert-domains were analyzed. The results indicated that the center-of-gravity frequency in the frequency-domain and the high-frequency energy in the Hilbert-domain showed clear separability between the control group and the three heat-damaged groups. This finding also confirms the differences between data under different treatment conditions. Therefore, these parameters can be used as characteristic features for classification and identification. The distributions of the frequency-domain and Hilbert-domain features are illustrated in Figure 7.

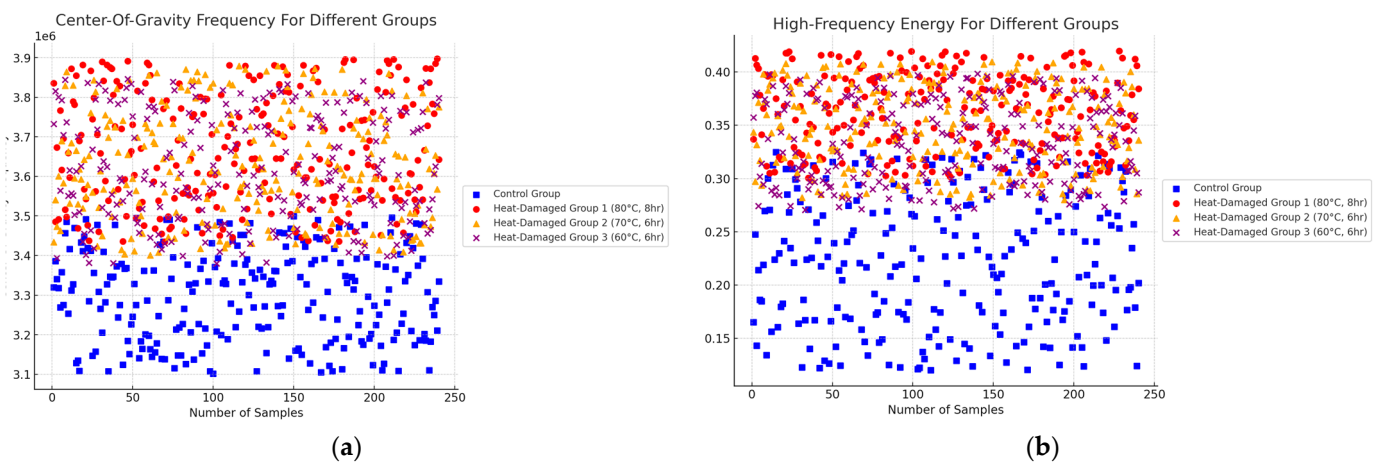


Figure 7. Feature distribution map: (a) Center-of-gravity frequency; (b) High-frequency energy.

In summary, the crest factor, impulse factor, center-of-gravity frequency, and high-frequency energy were selected as key feature parameters for distinguishing between the control and heat-damaged groups. In the classification process, the dataset of 960 corn samples was divided into a training set and a test set at a ratio of 3:1, with the samples grouped into three heat-damaged categories. Specifically, for each independent experiment, 720 corn samples were randomly selected as the training set, while the remaining 240 samples were used as the test set. The four selected feature parameters served as the input data for constructing the BP neural network, SVM, and PSO-SVM models. The classi-

fication prediction accuracies based on the laser ultrasonic signal features are presented in Table 1.

Table 1. Laser ultrasonic feature prediction classification accuracy.

Model	BP	SVM	PSO-SVM
Group 1 Training Accuracy (%)	90.41	93.05	95.28
Group 1 Test Accuracy (%)	91.94	92.78	94.44
Group 2 Training Accuracy (%)	90.33	92.46	93.55
Group 2 Test Accuracy (%)	90.46	92.31	93.39
Group 3 Training Accuracy (%)	89.98	91.36	92.32
Group 3 Test Accuracy (%)	90.14	90.55	91.57

Table 1 shows that the test accuracies of all three models exceed 90%, indicating that the laser ultrasonic signal characteristics effectively capture the differences between the heat-damaged group and the control group. Among these classification models, the PSO-SVM model demonstrates the best performance, with a classification accuracy of 94.44%. This higher accuracy compared to the standard SVM model suggests that optimizing the SVM parameters using the particle swarm optimization algorithm enhances the classification effectiveness of the SVM. Additionally, the accuracy of Group 1 is higher than that of the other two groups, and as the heat treatment temperature increases and duration lengthens, model accuracy improves. This result demonstrates the potential of this method to detect heat treatment effects under typical conditions.

In the subsequent experiments, only Heat-Damaged Group 1 was used for analysis. This is because the treatment conditions of temperature and duration for Heat-Damaged Group 1 are more extreme, leading to more distinct features. This helps to validate the effectiveness of the classification model in identifying significant heat damage. Therefore, selecting only Heat-Damaged Group 1 better demonstrates the method's capability in detecting the pronounced effects of heat treatment.

When using texture features alone to identify the control and heat-damaged groups of maize, the images were converted to grayscale to eliminate the influence of color variations on the texture features. Three methods—GLCM, LBP, and Tamura—were employed to extract texture features from the samples. The extracted texture features were then subjected to dimensionality reduction using PCA. The relationship between the cumulative variance contribution rate and the number of feature dimensions after PCA is shown in Figure 7.

As illustrated in Figure 8, the classification and recognition accuracy improves with an increase in the number of feature dimensions. Specifically, the three texture feature extraction methods—GLCM, LBP, and Tamura—achieved recognition accuracies exceeding 97% for maize samples when the feature dimensions were reduced to 8, 10, and 10, respectively. After applying PCA for dimensionality reduction, these texture features were used for classification and recognition. The classification results are summarized in Table 2.

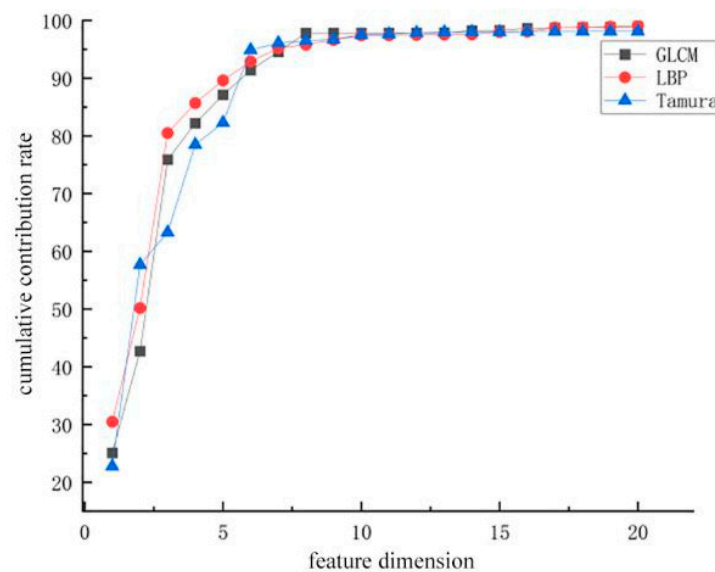


Figure 8. The relationship between cumulative contribution rate and characteristic dimension.

Table 2. Classification accuracy of texture feature test set.

Approach	BP Neural Network (%)	SVM (%)	PSO-SVM (%)
GLCM	85.67	90.24	91.21
LBP	89.33	90.57	91.43
Tamura	90.33	87.27	88.81

From Table 2, it is evident that among the three texture feature extraction methods, the Local Binary Pattern (LBP) method consistently achieves high classification accuracy across all three models. Notably, the Particle Swarm Optimization–Support Vector Machine (PSO–SVM) model attains the highest classification accuracy of 91.43% when utilizing LBP features. Furthermore, the classification accuracies presented in Tables 1 and 2 indicate that models employing laser ultrasonic features outperform those that rely on texture features. This superiority is attributed to the ability of laser ultrasound to detect internal information within the maize seeds, thereby effectively identifying internal heterogeneity and structural features. In contrast, image texture features are limited to capturing the external characteristics of the seed and are less effective in detecting internal information.

3.3. Identification of Heat-Damaged Kernels Using Fused Features

The feature vectors extracted from the laser ultrasonic signals (GGCS) were fused with the feature vectors obtained from the texture characterization methods—GLCM, LBP, and Tamura—using both the “concat” and “sum” fusion strategies of CCA. Specifically, we combined the GGCS features with each of the texture feature sets (GLCM, LBP, and Tamura) separately, employing both fusion strategies to enhance the classification performance.

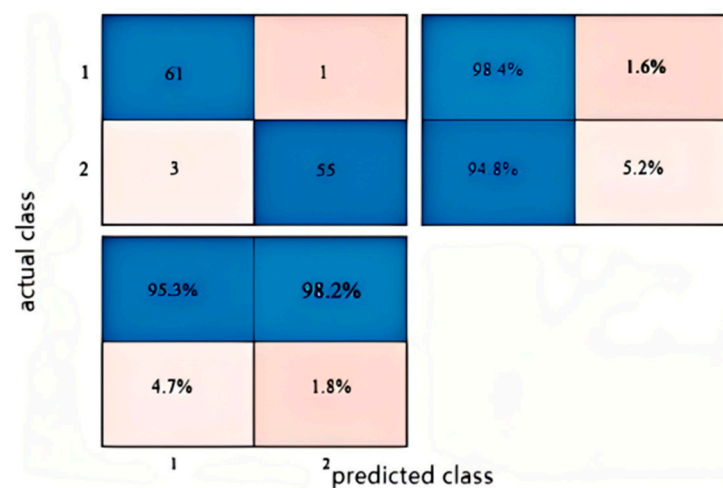
Table 3 illustrates the differences in the highest classification accuracies achieved using the “concat” and “sum” fusion strategies. In the “concat” fusion strategy, combining GGCS feature vectors with LBP texture feature vectors in the PSO–SVM model yields the best classification performance, achieving an accuracy of 99.17%. In contrast, the “sum” fusion strategy attains its highest classification accuracy of 98.33% by fusing GGCS feature vectors with GLCM texture features.

Table 3. Recognition accuracy under two fusion strategies.

Integration Methods	Concat			Sum		
	BP Neural Network (%)	SVM (%)	PSO–SVM (%)	BP Neural Network (%)	SVM (%)	PSO–SVM (%)
GGCS–GLCM	94.72	96.72	98.06	96.39	95.28	98.33
GGCS–LBP	94.44	97.44	99.17	96.33	95.83	97.51
GGCS–Tamura	93.33	95.28	95.83	95.66	96.24	96.39

Compared to using laser ultrasonic features or texture features alone, as shown in Tables 1 and 2, the fused features significantly improve the recognition accuracy for classifying the heat-damaged maize group. To present the classification results more intuitively, a confusion matrix was employed to display the specific classifications, and the number of instances in each category was recorded. The confusion matrix corresponding to the highest classification accuracy of 99.17% is shown in Figure 6, where “Real Class 1” represents the heat-damaged group and “Real Class 2” represents the control group.

As shown in Figure 9, the PSO–SVM model correctly classified 61 grains from the heat-damaged group, misclassifying only 1 grain as belonging to the control group. This results in a classification accuracy of 98.40% and a misclassification rate of 1.60% for the heat-damaged group. For the control group, 55 grains were correctly classified, while 3 grains were misclassified as part of the heat-damaged group, yielding a classification accuracy of 94.80% and a misclassification rate of 5.20%. These results indicate that the misclassification rate can be substantially reduced when using the PSO–SVM model to classify fused features.

**Figure 9.** Confusion matrix. The blue area represents the correct group data, while the flesh-colored area represents the misclassified group data.

4. Conclusions

Laser ultrasonic information and near-infrared image data of both the control group and the heat-damaged group of maize were collected using a laser and an infrared camera. After extracting the laser ultrasonic features and texture features from the maize samples, the two sets of features were fused using CCA. The heat-damaged samples were then classified and identified using BP neural networks, SVM, and PSO–SVM. The following conclusions were drawn:

- (1) Classification Using Laser Ultrasonic Features Alone: When using only laser ultrasonic features to classify and identify the control and heat-damaged groups, all three classification algorithms achieved accuracies higher than 90%. Among them, the PSO-SVM model exhibited the best classification performance.
- (2) Classification Using Texture Features Alone: Using texture features extracted by the LBP method combined with the PSO-SVM model yielded higher classification effectiveness, with an accuracy reaching 91.43%.
- (3) Classification Using Fused Features: When using fused features for recognition, the classification accuracies of all three algorithms improved, with the highest accuracy reaching 99.17%.

The results demonstrated differences between different heat-damage treatments. For lower-intensity treatments, the classification accuracy was lower compared to the strongest treatment, but this also demonstrated the potential of the method to detect heat treatment effects under general conditions. This study demonstrates the feasibility of classifying and recognizing heat-damaged maize grains based on the fusion of laser ultrasonic signals and infrared image features. This approach avoids the need for broadband light source wavelength scanning and the use of high-cost spectrometers inherent in hyperspectral “spectral image” fusion detection methods, offering a novel perspective for grain heat damage detection. Future research should consider using low-cost, low-power semiconductor lasers as the excitation source for laser ultrasonic signals and thin-film piezoelectric sensors for signal collection. By combining these with infrared imaging systems, it is possible to reduce system costs and improve the efficiency of signal and image acquisition for practical application scenarios.

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