

Detection of physical hazards from fruit processed products using hyperspectral imaging and prediction based on PLS-DA and logistic regression machine learning models

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ABSTRACT

The current study aims to investigate a prediction model from reflection values and the spectral angle mapper (SAM) obtained from hyperspectral imaging (HSI) technology for the detection of three types of foreign materials – a branch, a knife, and rubber – that are associated with the various fruit-processed products. The study found that the maximum and minimum reflection values in the 900 to 1700 nm range for juices (apple, grape, tomato) and jams (strawberry, peach, tomato) differed depending on the presence or absence of physical hazards. The presence of physical hazards was also confirmed by the color difference in the SAM image. The partial least squares discriminant analysis model (PLS-DA) and logistic regression implemented on the Jupyter Notebook platform through the Anaconda prompt provided accuracy, F1 score, specificity, and sensitivity based on the confusion matrix. The maximum value was 100.0 %, while the minimum value was 97.6 % of the result of the PLS-DA modeling in the testing set. Logistic regression modeling also had a similar result: the maximum value was 100.0 %, while the minimum value was 97.8 % in the testing set. The sensitivity value in the testing set, which is a meaningful result for detecting physical hazards, was a maximum of 100.0 % for both PLS-DA and logistic regression. Results from the current study suggest that the reflection value and SAM data obtained through hyperspectral imaging could build a big data platform for early determination of physical hazards during agricultural product processing.

1. Introduction

The presence of foreign materials (FMs) in food is a major problem in the food industry, as the Ministry of Food and Drug Safety confirmed that FMs are very diverse and depend on processed products (Park et al., 2017). In general, FMs refer to substances that are undesirable and unwanted pieces of solid matter present in a product. They include plastic, stone, and metals, and these substances can end up in the final product (Graves et al., 1998). Among them, physical hazards that reduce freshness and quality are becoming a problem in the current industry since they can cause not only health problems for consumers but also contamination problems for manufacturers (Tunny et al., 2022). It is

therefore essential to ensure the removal of all types of physical hazards from foods (Haff & Toyofuku, 2008). Several studies have been performed to identify physical hazards in different types of foods by using a metal detector, X-ray, near-infrared spectroscopy, thermal imaging, ultrasound, and terahertz methods (Jha et al., 2011). Metal detectors are commonly used in various food processing industries, but they can only detect metal (Pallav et al., 2009). The detection of plastics, plant fragments (including chips, sticks, and broken pallets), cartons, or insects remains unresolved (Díaz et al., 2011). Various imaging technologies have recently been developed in the food industry to improve food quality (Du et al., 2020). Due to the advantage of being able to distinguish subtle spectral differences, hyperspectral imaging (HSI) is widely

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applied in numerous fields (Li et al., 2018). With advancements in imaging technology, HSI has been applied in agriculture and food production for a wide range of purposes, particularly for developing platforms for food safety inspection and quality control (Gowen et al., 2007; Lu et al., 2020; Tunny et al., 2023). Various types of FMs that could deteriorate freshness have been detected using HSI (Saeidan et al., 2021; Tunny et al., 2022). Remarkable progress has been made in recent years through machine learning technology, going beyond identifying external substances using spectral imaging such as HSI (Park et al., 2017). In 2019, the Food and Drug Administration (FDA) announced a declaration on “steps to usher the US into a new era of smarter food safety,” in which machine learning applications and artificial intelligence in food safety were proposed (Deng et al., 2021). Machine learning is a technology that generates output of results by learning the input of data on a computer, enabling computers to identify physical hazards, which is a new method for faster and more accurate food safety monitoring and prediction (Wang et al., 2022). HSI is being used in conjunction with deep learning technology for testing of food quality and safety (Saha & Manickavasagan, 2021). Detecting and predicting food quality through machine modeling based on HSI data (Ivorra et al., 2013). Hence, the aim of this study was to collect imaging data to identify physical hazards and to apply the physical hazard discrimination technique using hyperspectral images (HSI) from fruit processed products more accurately and more rapidly than before. The current study investigated the identification of physical hazards, including a branch, a knife, and rubber, during fruit processing steps using hyperspectral imaging. This study then developed a partial least squares-discriminant analysis model (PLS-DA) and a logistic regression prediction model by using the Jupyter Notebook platform through the Anaconda prompt.

2. Materials and methods

2.1. Sample preparation

This study utilized various fruit processed products, including 15 samples of juices (apple juice, grape juice, tomato juice) and jams (strawberry jam, peach jam, tomato jam). The apple juice was made of Fuji apples in Goesan (Chungcheong-do, South Korea), the grape juice from Campbell Early grapes in Gapyeong (Gangwon-do, South Korea), and tomato juice from Hoyong tomatoes in Asan (Chungcheong-do, South Korea). The strawberry jam was made of Seolhyang strawberries in Cheongju (Chungcheong-do, South Korea), peach jam from white peaches in Goesan (Chungcheong-do, South Korea), and tomato jam from Hoyong tomatoes in Hoengseong (Gangwon-do, South Korea). To obtain a large amount of reflection value data from each of the 15 samples, data was collected on a pixel basis. Three types of physical hazards that can occur during processing of fruit processed products – a branch, a knife, and rubber – were used in this study. Detection of physical hazards were performed both before and after the processing. To simulate the processing process, the juices were placed in glass bottles, and the jams were spread out on plates. Samples containing physical hazards were prepared by placing them inside the sample.

2.2. Acquisition and normalization of hyperspectral image (HSI)

A hyperspectral camera (Specim FX17, Geostory, Finland), with a wavelength range of 900 to 1700 nm, was used to take images, and then each image was divided into 112 bands. Spectral imaging software (Lumo scanner, Middleton Spectral Vision, USA) was used to capture the image, and after shooting, normalization was carried out to subtract the black and white values. The black value was the reflection value taken in a dark state, while the white value was the reflection value of the white bar, which served as the standard for positioning the sample during image capture. Two values were removed through normalization because they can affect the reflection values. Through this process, the

HSI of each sample was obtained.

2.3. Reflection value data and spectral angle mapper (SAM) images

Reflection value data, graphs, and *spectral angle mapper* (SAM) images obtained from normalized HSI of the samples were analyzed using a software program ENVI (NV5, USA). Reflection value data was saved in pixel units and plotted as a graphs against wavelength. The SAM images were obtained using the ENVI program's own classification system. The images designated several areas of a captured image by assigning specific colors to those regions and displayed areas with similar reflection values in the same color. Areas of the same color in the SAM images meant they that had similar reflection values and comparable components, and the expression of individual colors indicated different reflection values.

2.4. Prediction models implementation

Partial least squares-discriminant analysis (PLS-DA) and logistic regression as prediction models, both commonly used for binary classification, were applied to the current study. These models classified data through training, validating, and testing processes and were run on Jupyter Notebook based on Anaconda. After the training and testing process, PLS-DA and logistic regression models output the F1 score, accuracy, and confusion matrix using the number of correctly predicted and classified samples from the total number of samples. The F1 score represents the harmonic mean of precision and recall, while the accuracy refers to the proportion of samples that were correctly classified out of all predictions. The confusion matrix showed the relationship between actual data and predicted result data. Additionally, specificity and sensitivity were calculated based on the confusion matrix. The confusion matrix is expressed in four numbers:

Actual positives that are correctly predicted positives: true positives (TP);

Actual positives that are wrongly predicted negatives: false negatives (FN);

Actual negatives that are correctly predicted negatives: true negatives (TN);

Actual negatives that are wrongly predicted positives: false positives (FP).

And the model performance assessing indicators are commonly as follows:

$$F1\ score(\%) = 2 \times \frac{Precision \times recall}{Precision + recall} \times 100$$

$$Accuracy\ (\%) = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

$$Specificity\ (\%) = \frac{TN}{TN + FP} \times 100$$

$$Sensitivity\ (\%) = \frac{TP}{TP + FN} \times 100$$

2.5. Modeling of prediction for classification

PLS-DA is an application of partial least squares (PLS) regression to binary classification problems and a regression technique that models linear relationships between independent and dependent variables. It is particularly useful in addressing multicollinearity issues between variables. PLS-DA works by finding a new axis (principal component) that captures the characteristics of the dataset and then projecting the data onto this axis to separate classes. It allows for the construction of a multidimensional model for the prediction of the features, implemented in dependent variable Y, utilizing independent variables X. The basis of PLS-DA is to reduce the size of original data X and replaced it with the

matrix of scores and loadings, maximizing the covariance between X and Y. The level of reduction is determined by the number of significant latent variables (LV). A simplified partial least squares model with f latent variables can be presented as

$$X_{[m,n]} = T_{[m,f]}P_{[f,n]} + E_{[m,n]}$$

$$Y_{[m,k]} = U_{[m,f]}H_{[f,k]} + G_{[m,k]}$$

Selection of the appropriate number of LV is essential to balance the model's ability to predict features (Y) for samples used to create the model (the MODEL set). This is often achieved through the cross-validation procedure, where the variation of the root mean squared errors of the cross-validation parameter (RMSECV) is observed.

$$RMSECV = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where n represents the number of validation groups in cross-validation, y_i denotes the real feature value for the object (sample), and $\hat{y}_i$ signifies the feature value for the object (sample) estimated using a model constructed from a training set that excludes the object.

Logistic regression was performed in the current study, as it is one of the primary machine learning techniques widely employed in data analysis, enabling the comprehension and prediction of data patterns while providing probabilistic outcomes. It has also been widely utilized in addressing binary classification problems due to its ease of interpretation and high computational efficiency. The fundamental equation of logistic regression is as follows: $P(Y = 1|x_1, x_2, \dots, x_n)$, where $P(Y = 1|x_1, x_2, \dots, x_n)$ represents the probability of the dependent variable Y being 1 given the input variables $x_1, x_2, \dots, x_n$, and $\beta_0, \beta_1, \dots, \beta_n$ are the coefficients.

$$P(Y = 1|x_1, x_2, \dots, x_n) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n)}}$$

The process of logistic regression analysis began with collecting data, where outliers and missing values were removed, and each data sample

was labeled. Subsequently, the collected data was divided into training and testing sets at a 6:4 ratio. During the training phase, the model estimated coefficients $\beta_0, \beta_1, \dots, \beta_n$ by minimizing the binary cross-entropy described in equation. N represents the number of data points used for training, while y_i and $\hat{y}_i$ represent the actual class and the model's predicted probability, respectively.

$$BCELoss = -\frac{1}{N} \sum_{i=1}^N (y_i \times \log \hat{y}_i + (1 - y_i) \times \log(1 - \hat{y}_i))$$

3. Results and discussion

3.1. Visualization of the detected physical hazards using HSI and SAM images

Fig. 1 shows the reflection value graphs obtained from 900 to 1700 nm and spectral angle mapper (SAM) images for each of the 15 of the apple juices without physical hazards (Fig. 1A, B) and apple juices with physical hazards, including a branch (Fig. 1C, D), a knife (Fig. 1E, F), and rubber (Fig. 1G, H). The SAM images show areas with same color as similar reflection values of that the specified area. The areas for apple juice, sample plate, camera tray, and physical hazards including a branch, a knife, and rubber are shown as a green, yellow, blue, and red, respectively. Apple juice samples without physical hazards showed the maximum reflection value of 2173.836 at 1069.07 nm and the minimum reflection value of 0.532 at 1469.15 nm (Fig. 1A). SAM images confirmed that there were no physical hazards present other than the juice (Fig. 1B). Fig. 1C exhibits the maximum reflection value of apple juice with a branch is 9221.374 at 1076.03 nm, and the minimum reflection value is 7.399 at 1496.15 nm. The shape for reflection value graph of an apple juice with a branch was clearly different from that of apple juice only. The SAM image for apple juices with a branch shows a red color, indicating the presence of an branch in the juices (Fig. 1D). In case of apple juice samples with a knife added, the maximum reflection value was 2941.673 at 1069.07 nm, and the minimum reflection value

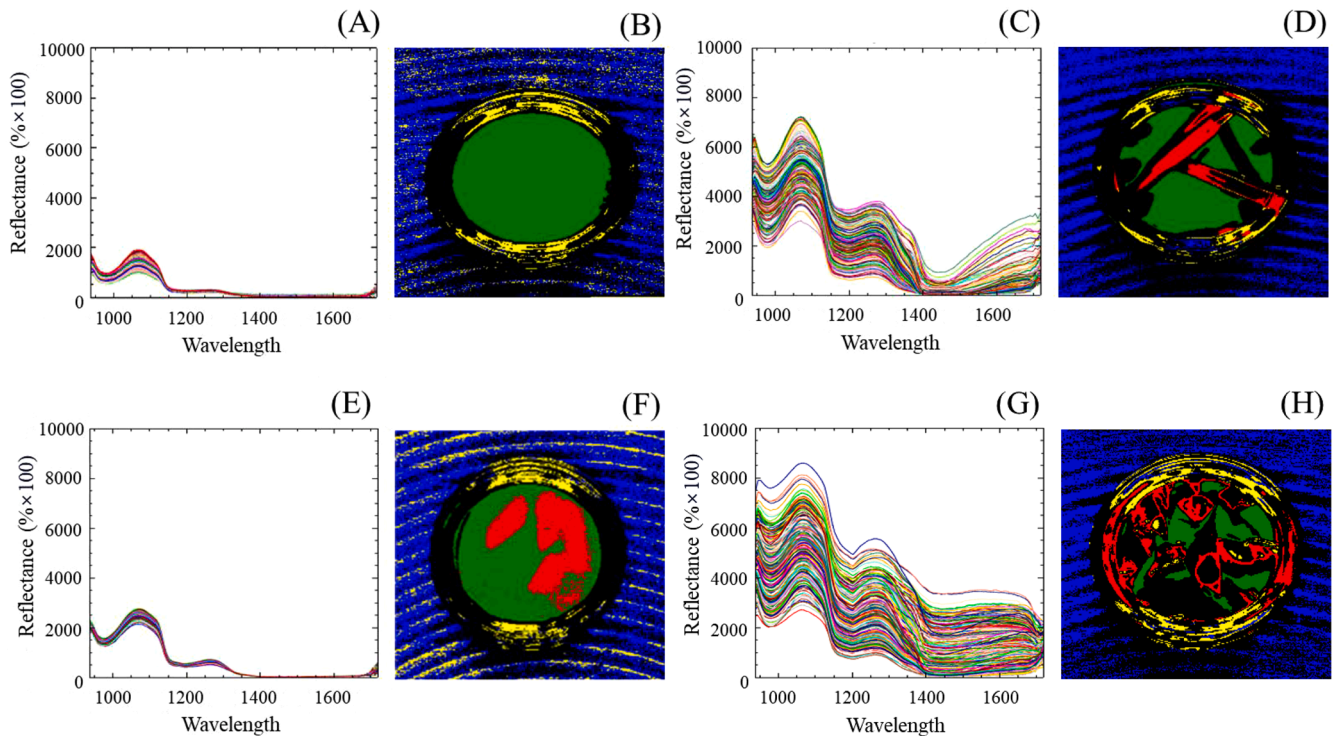


Fig. 1. Reflectance graphs and SAM images of apple juice without foreign materials (A, B) and apple juice with foreign materials including branch (C, D) knife (E, F) and rubber (G, H) obtained by a hyperspectral camera.

was 0.979 at 1469.23 nm (Fig. 1E). The reflection value graph was similar to apple juice with a branch, but its maximum reflection value was higher than that with a branch (Fig. 1E). In the SAM image shown in Fig. 1F, the red area indicates the presence of physical hazards, such as a knife. For the apple juice containing rubber, the reflection value graph was different from apple juice alone at 1400–1500 nm, showing a maximum value of 9912.302 at 1055.16 nm and a minimum reflection value of 9.284 at 1406.71 nm (Fig. 1G). The SAM image confirmed the presence of physical hazards in the apple juice, as indicated by the visible red area (Fig. 1H). Results from the current study confirmed that the presence of physical hazards was assessed using both the reflection value graph and the SAM images.

Fig. 2 shows the reflection value graphs ranged from 900 to 1700 nm and SAM image for each of the 15 grape juices, including those without physical hazards (Figs. 2A, B) and those with a branch (Figs. 2C, D), knife (Figs. 2E, F), and rubber (Figs. 2G, H). In the SAM images, as with the apple juices, foreign substances were colored in red, the juice is green, the plate is yellow, and the camera tray is blue. The reflection value graph for grape juices without physical hazards (Fig. 2A) exhibited a maximum reflection value of 1500.944 at 1055.16 nm and a minimum reflection value of 4.13 at 1504.59 nm. The reflection value graph looks similar for grape juice with a branch (Fig. 2C) and with rubber (Fig. 2G), but the maximum reflection value of grape juice with a branch was 9423.673 at 1089.94 nm, the minimum reflection value was 12.201 at 1476.23 nm (Fig. 2C), the maximum reflection value of grape juice containing rubber was 8511.727 at 1062.12 nm, and the minimum reflection value was 463.716 at 1454.99 nm (Fig. 2H). The maximum reflection value of grape juice with a knife was 2969.203 at 1076.03 nm, and the minimum reflection value was 0 at 1689.81 nm (Fig. 2E). The shape of the reflection value graph for rubber (Fig. 2G) was similar to that of a branch (Fig. 2C), but the reflection values were different. When compared to grape juices with a knife, the reflection value graphs showed differences at 1200 nm and 1400–1500 nm, with a larger range observed for grape juices with a knife. The physical hazards were properly distinguished as only green appears in the grape juices without

any physical hazards. Comparing all SAM images, the red areas showing physical hazards only appeared in samples containing actual physical hazards. In the SAM image with a branch (Fig. 2D), a knife (Fig. 2F), and rubber (Fig. 2H), the red areas represent a different shape for each type of physical hazard, enabling the classification of the physical hazards using the SAM images.

Fig. 3 shows the reflection value graphs from 900 to 1700 nm and SAM images for 15 of tomato juices without foreign substances (Figs. 3A, B) and those with physical hazards, including a branch (Figs. 3C, D), a knife (Figs. 3E, F), and rubber (Fig. 3G, H). As with the apple juices and grape juices, physical hazards were colored in red, the juice was colored in green, the plate was colored in yellow, and the camera tray was colored in blue. For the reflection value graph, the maximum reflection value of tomato juice without foreign substances was 2433.633 at 1069.07 nm, and the minimum reflection value was 0 at 1504.59 nm (Fig. 3A). The reflection value graph of tomato juice with a branch (Fig. 3C) had a clearly different shape compared to the reflection value graph of tomato juice without physical hazards (Fig. 3A). The maximum reflection value of tomato juice with a branch was 6864.657 at 1069.07 nm, and the minimum reflection value was 0 at 1462.07 nm (Fig. 3C). The reflection value graph of tomato juice with a knife (Fig. 3E) showed a similar pattern to the reflection value graph of tomato juice without physical hazards (Fig. 3A), but its maximum reflection value was 3813.492 at 1076.03 nm, and the minimum reflection value was 1.405 at 1462.07 nm. It was confirmed that there was a difference in the reflection value for tomato juice without physical hazards. The reflection value graph of tomato juice with rubber (Fig. 3G) was similar to that of tomato juice with a branch (Fig. 3C), but the shape of the graph was different at 1400–1600 nm, and the maximum reflection value of tomato juice with rubber was 7440.692 at 1069.07 nm, while the minimum reflection value was 14.545 at 1454.99 nm, indicating that the numerical value was different. In the SAM image of each sample (Figs. 3B, D, F, H), the red areas (physical hazards) were clearly visible, indicating that the reflection values of the physical hazards differed from those of the tomato juice. It could be inferred that the presence or

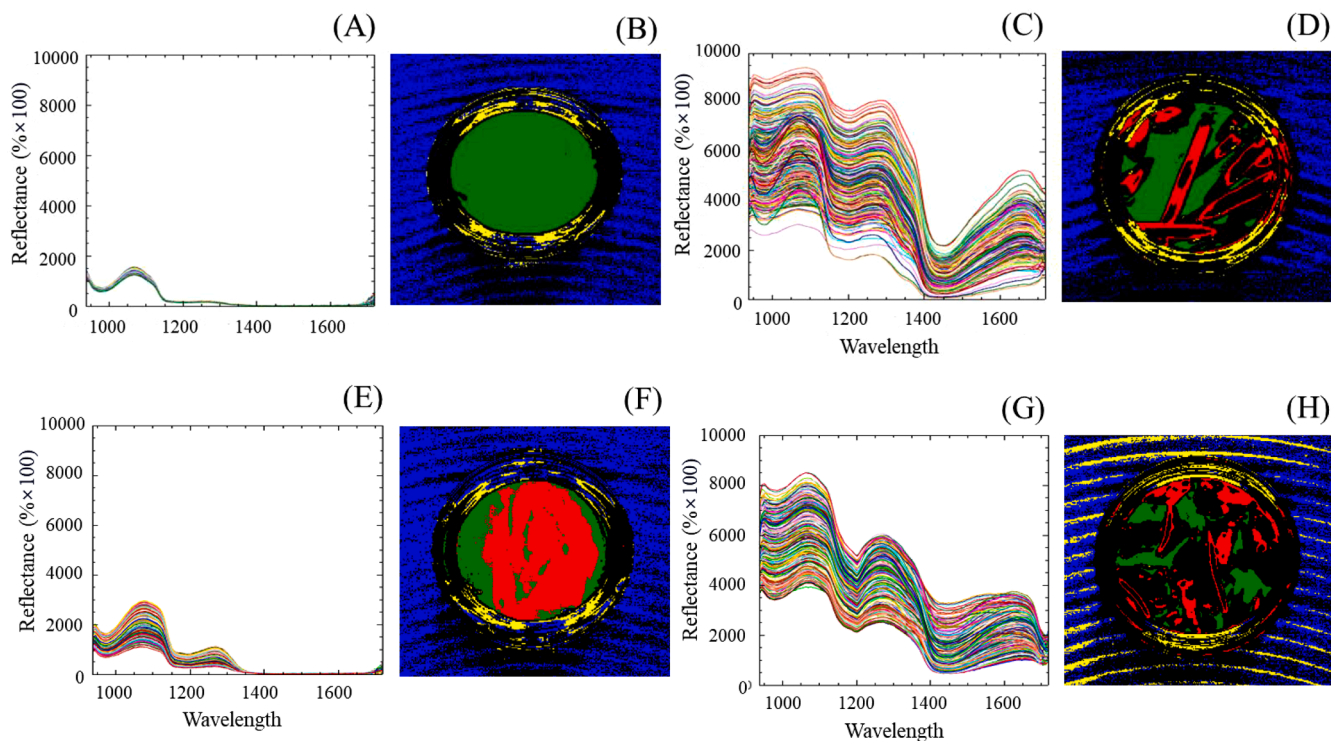


Fig. 2. Reflectance graphs and SAM images of grape juice without foreign materials (A, B) and grape juice with foreign materials including branch (C, D) knife (E, F) and rubber (G, H) obtained by a hyperspectral camera.

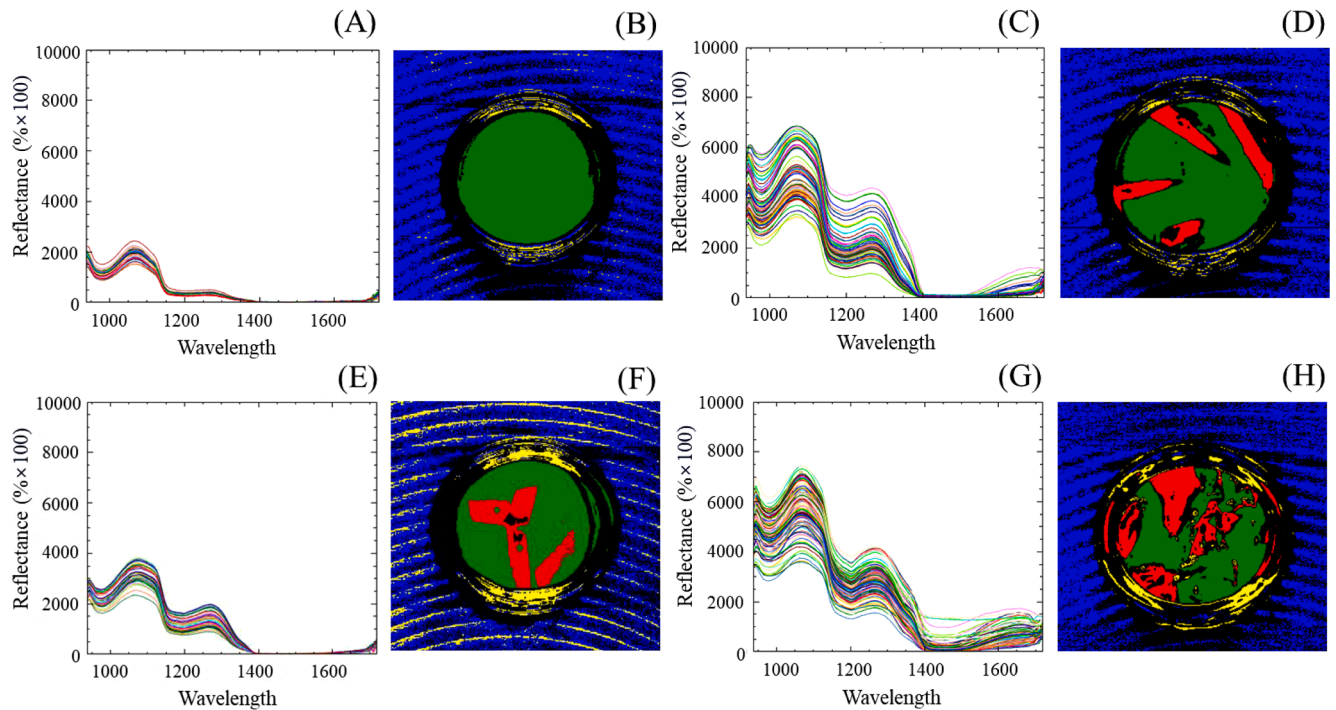


Fig. 3. Reflectance graphs and SAM images of tomato juice without foreign materials (A, B) and tomato juice with foreign materials including branch (C, D) knife (E, F) and rubber (G, H) obtained by a hyperspectral camera.

absence of physical hazards can be determined using the reflection value data of the samples.

Fig. 4 shows the reflection value graphs and SAM images in the 900 to 1700 nm range obtained hyperspectral imaging. SAM images are shown for strawberry jam without physical hazards (Fig. 4A, 4B), strawberry jam with physical hazards including a branch (Fig. 4C, 4D), a

knife (Fig. 4E, 4F), and rubber (Fig. 4G, 4H). Like other samples, physical hazards, jam, plate, and camera tray were marked in red, green, yellow, and blue, respectively. The reflection value graph of strawberry jam without physical hazards (Fig. 4A) showed the highest reflection value of 5108.938 at 951.16 nm and the lowest reflection value of 8.301 at 1454.99 nm. The red color indicates that the physical hazards were

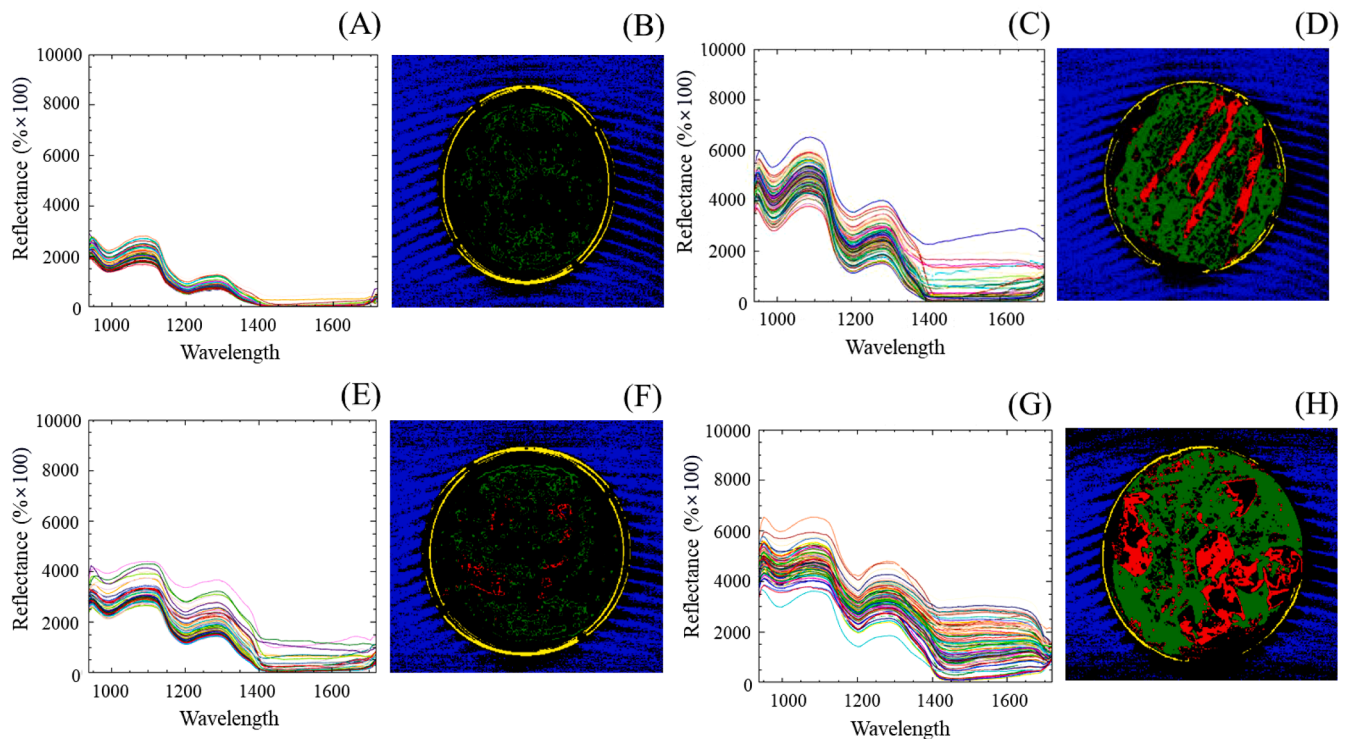


Fig. 4. Reflectance graphs and SAM images of strawberry jam without foreign materials (A, B) and strawberry jam with foreign materials including branch (C, D) knife (E, F) and rubber (G, H) obtained by a hyperspectral camera.

not found in the SAM image (Fig. 4B). In the reflection value graph of strawberry jam with a branch (Fig. 4C), the maximum reflection value was 9215.613 at 951.16 nm, and the minimum reflection value was 39.537 at 1462.07 nm. In the SAM image (Fig. 4D), the branch is displayed in red. Strawberry jam with a knife (Fig. 4E) showed a maximum reflection value of 9617.286 at 1299.80 nm and a minimum reflection value of 18.090 at 1454.99 nm. The knife was also displayed in red in the SAM image (Fig. 4F). The reflection value graph of strawberry jam containing rubber (Fig. 4G) was a maximum of 8422.809 at 944.25 nm and a minimum of 33.314 at 1469.15 nm, and the rubber was clearly visible in the SAM image in red (Fig. 4H). The reflection value graph of strawberry jam (Fig. 4A, C, E, G) looked similar in all aspects, but there were differences in maximum and minimum values. The SAM image confirmed the presence or absence of physical hazards.

Fig. 5 shows the reflection value graph and SAM image in the 900 to 1700 nm range for peach jam without physical hazards (Fig. 5A) and peach jam with a branch (Fig. 5C), a knife (Fig. 5E), and rubber (Fig. 5G). In the case of the SAM image (Figs. 5B, D, F, H), the physical hazards were displayed in red as before. In the reflection value graph of peach jam without a physical hazard (Fig. 5A), the maximum reflection value was 3884.052 at 951.16 nm, and the minimum reflection value was 8.504 at 1483.32 nm. The SAM image (Fig. 5B) shows that there was no red area, indicating no physical hazards. The reflection value graph of peach jam with branch (Fig. 5C) showed a maximum reflection value of 9016.832 at 1082.98 nm and a minimum reflection value of 13.206 at 1447.91 nm, and the SAM image (Fig. 5D) showed that the branch was displayed in red. The reflection value graph with a knife (Fig. 5E) showed a maximum reflection value of 8989.945 at 1124.78 nm and a minimum reflection value of 10.861 at 1054.59 nm, and in the SAM image (Fig. 5F), the knife was confirmed to appear in red color. The reflection value graph of peach jam containing rubber (Fig. 5G) showed a maximum reflection value of 8454.731 at 951.16 nm and a minimum reflection value of 18.116 at 1483.32 nm, and the rubber was confirmed to appear red in the SAM image (Fig. 5H). Although there was a significant deviation in the graphs of peach jam with a branch and a knife

(Fig. 5C, E) compared to peach jam without physical hazards (Fig. 5A), the presence or absence of physical hazards could be judged through the difference in maximum and minimum reflection values and the SAM images.

Fig. 6 shows the reflection value graph and SAM image obtained by hyperspectral imaging of tomato jam without physical hazards (Fig. 6A) and tomato jam with a branch (Fig. 6C), a knife (Fig. 6E), and rubber (Fig. 6G). The SAM images (Figs. 6B, D, F, H) were the same as before with enhanced material. In the reflection value graph of tomato jam without a physical hazard (Fig. 6A), the maximum reflection value was 3448.144 at 1082.98 nm, and the minimum reflection value was 4.195 at 1464.15 nm, confirming that no physical hazards appeared in the SAM image (Fig. 6B). In the reflection value graph of tomato jam with a branch (Fig. 6C), the reflection value was a maximum of 9417.790 at 1082.98 nm and a minimum of 6.620 at 1483.32 nm, and in the SAM image (Fig. 6D), the branch is expressed in red. The reflection value graph of tomato jam with a knife (Fig. 6E) showed a maximum reflection value of 523.452 at 1096.91 nm and a minimum reflection value of 5.314 at 1490.41 nm, and in the SAM image (Fig. 6F), the knife clearly appeared in red. In the reflection value graph with rubber (Fig. 6G), the reflection value showed a maximum of 7703.317 at 1082.98 nm and a minimum of 10.202 at 1497.50 nm, confirming that the rubber was clearly visible in red in the SAM image (Fig. 6H). The case of tomato jam, the highest peaks were especially frequent at 1082.98 nm, and the lowest peaks were mainly found in the late 1400 nm. Tomato jam also showed a similar reflection value graph, but it was possible to determine the presence or absence of physical hazards by comparing the maximum and minimum reflection values and analyzing the SAM image.

3.2. Development of prediction model using PLS-DA and Logistic regression based on machine learning

When evaluating a model's performance, a higher F1 score indicates higher results in both precision and recall. Accuracy refers to the percentage of samples that the model correctly determines as free of

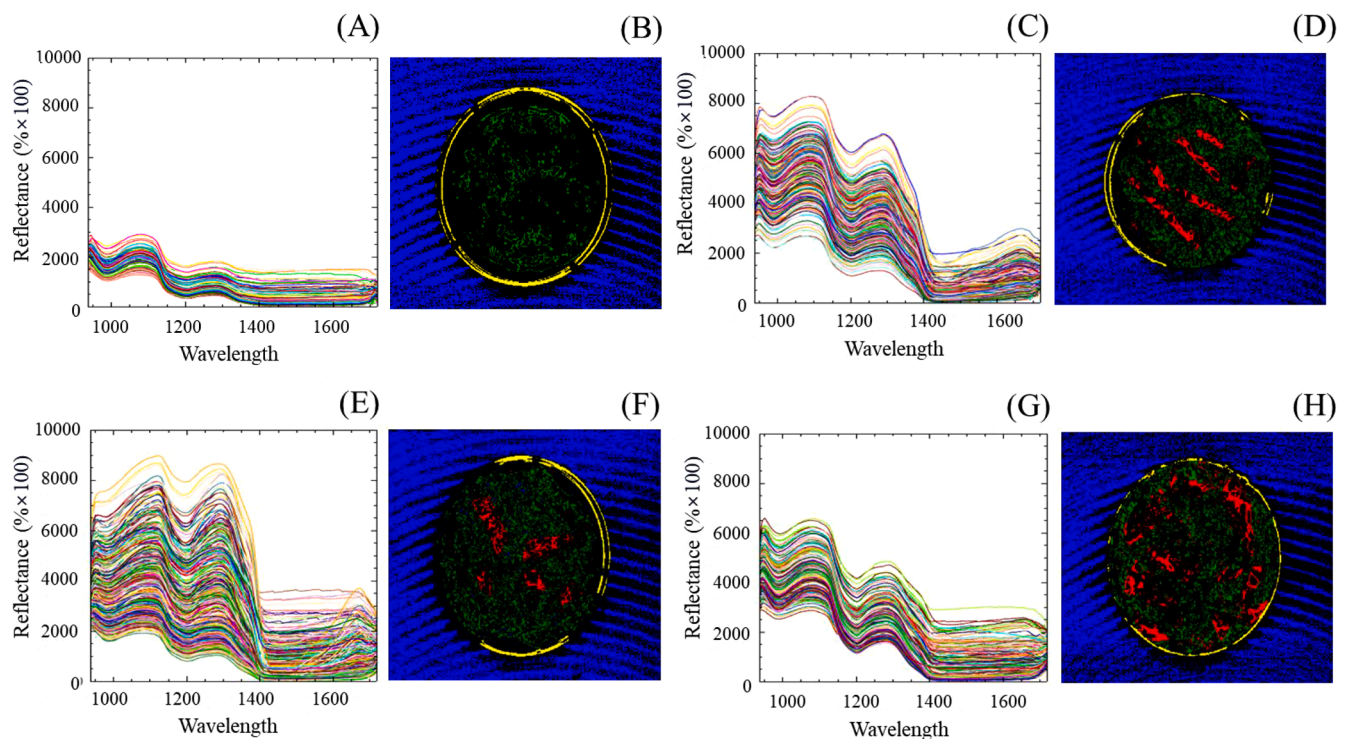


Fig. 5. Reflectance graphs and SAM images of peach jam without foreign materials (A, B) and peach jam with foreign materials including branch (C, D) knife (E, F) and rubber (G, H) obtained by a hyperspectral camera.

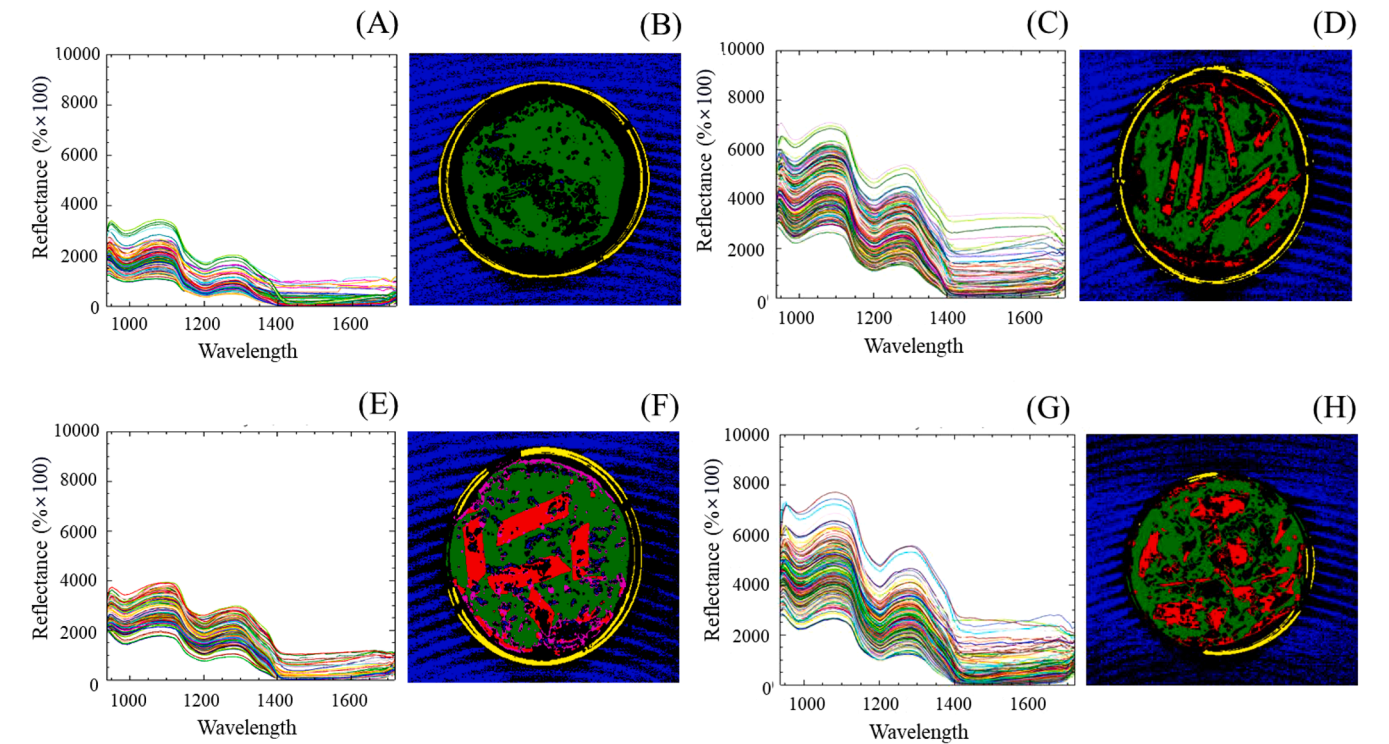


Fig. 6. Reflectance graphs and SAM images of tomato jam without foreign materials (A, B) and tomato jam with foreign materials including branch (C, D) knife (E, F) and rubber (G, H) obtained by a hyperspectral camera.

physical hazards. In the confusion matrix, TN is the number of samples that the model correctly classified as containing no physical hazards, and FP is the number of samples that the model incorrectly classified as containing physical hazards. FN is the number of samples with physical hazards that the model incorrectly judged to be without physical hazards, and TP is the number of samples that correctly classified as having a physical hazard. Specificity, obtained with these four numbers, refers to the rate at which the model correctly predicts that there are no foreign materials when there are no foreign materials, and sensitivity refers to the rate at which the model correctly predicts that there is a foreign material when there is a foreign material.

Table 1 shows the learning performance of the PLS-DA and logistic

regression models on the collected reflection data in the training set. The learning performance of the models was expressed in terms of %f1 score, %accuracy, %specificity, and %sensitivity, and the values were to 100.0 %, meaning that the models had trained the data well. In the juice results, when learning the reflection value data in the training set of apple juice containing branches, the accuracy of the PLS-DA was 99.6 %, 99.5 %, 98.8 %, 100.0 %, while logistic regression was 100.0 %. The apple juice containing a knife was well classified with 100.0 % in the PLS-DA model. In the logistic regression model, it achieved and F1 score and accuracy of 99.1 %, specificity of 100.0 %, and a sensitivity of 98.3 %. When learning the reflection value data of apple juice with rubber, the PLS-DA model had an F1 score of 99.8 %, an accuracy 99.8 %, a

Table 1
F1 score, accuracy, specificity, and specificity of train set with the PLS-DA and logistic regression model of HSI image reflection value data.

Train									
Sample	FMs	%F1 score		% Accuracy		% Specificity		% Sensitivity	
		PLS-DA	Logistic Regression	PLS-DA	Logistic Regression	PLS-DA	Logistic Regression	PLS-DA	Logistic Regression
Apple juice	Branch	99.6	100.0	99.5	100.0	98.8	100.0	100.0	100.0
	Knife	100.0	99.1	100.0	99.1	100.0	100.0	100.0	98.3
	Rubber	99.8	99.9	99.8	99.9	99.6	100.0	100.0	99.8
Grape juice	Branch	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Knife	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Rubber	99.9	99.3	99.9	99.1	99.9	100.0	100.0	98.7
Tomato juice	Branch	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Knife	100.0	99.9	100.0	99.9	100.0	99.9	100.0	99.9
	Rubber	99.0	100.0	98.9	100.0	97.6	100.0	100.0	100.0
Strawberry jam	Branch	99.9	99.3	99.9	99.3	100.0	99.5	99.8	99.1
	Knife	100.0	98.5	100.0	98.6	100.0	99.1	100.0	98.0
	Rubber	100.0	99.3	100.0	99.0	100.0	99.2	100.0	98.9
Peach jam	Branch	99.1	99.6	99.2	99.6	98.3	100.0	100.0	99.3
	Knife	99.9	99.5	99.9	99.5	99.9	99.9	100.0	99.1
	Rubber	99.9	99.9	99.9	99.9	99.8	100.0	100.0	99.8
Tomato jam	Branch	100.0	99.6	100.0	99.6	100.0	99.6	100.0	99.6
	Knife	99.9	99.6	99.9	99.6	99.8	99.5	100.0	99.6
	Rubber	99.8	99.3	99.8	99.2	99.9	99.0	99.7	99.3

specificity 99.6 %, and a sensitivity 100.0 %. In the logistic regression model, the F1 score, specificity, and sensitivity were 99.8 %, 100.0 %, and 99.8 %, respectively. In the case of grape juice, when a branch and knife were added, all values were 100.0 % in both models. When rubber was added, the values in the PLS-DA model were 99.9 % and 100 %, while the logistic regression model showed values of 99.3 %, 99.1 %, 100 %, and 98.7 %. In tomato juice, when a branch was included, it was all 100.0 % in both models, and when a knife was included, it was 100.0 % in the PLS-DA model and 99.9 % in the logistic regression model. When rubber was added, the specificity learning of the PLS-DA model was relatively low at 97.6 %, but it showed good performance in the learning data. Looking at the overall learning performance of the juices, it appears that the learning performance of both models was very good, from 97.6 % to 100.0 %. In the results for strawberry jam, when a branch was included, the PLS-DA model showed 99.9 %, 99.9 %, 100.0 %, and 99.8 % accuracies, while the logistic regression model showed accuracies of 99.3 %, 99.3 %, 99.5 %, and 99.1 %. Even when a knife and rubber were included, both showed 100.0 % accuracy in the PLS-DA model and accuracies ranging from 98.9 % to 99.3 % in the logistic regression model. The learning performance of peach jam also showed good learning performance at 99.0 % for all values, except for the specificity of 98.3 % in the PLS-DA model when a branch was added. In the case of tomato jam, the values of both models ranged from 99.0 % to 100.0 %, regardless of the presence of foreign materials. This confirmed that the performance of learning from the training set data of jams was very good.

Table 2 shows the performance of the model in predicting new data that was not included in the reflection value data during training. Table 1 confirms the learning performance, while Table 2 provides an assessment of the actual model's performance. In the case of apple juice, when a branch was included, the F1 score, accuracy, specificity, and sensitivity were 99.5 %, 99.7 %, 99.4 %, and 100.0 %, respectively, in the PLS-DA model, and 99.8 %, 99.8 %, 100.0 %, and 99.6 %, respectively, in logistic regression model. When a knife was included, the PLS-DA model was 100.0 % in all measures, while the logistic regression model was 99.2 %, 99.3 %, 100.0 %, and 98.6 %. When rubber was included, the logistic regression model achieved at 99.0 % and 100.0 %. In the case of grape juice, when rubber was included, the F1 score and sensitivity of the logistic regression model were 100.0 %, except for 99.6 % and 99.2 %. In tomato juice, when a branch was included, the F1 score, accuracy, and specificity of PLS-DA model were 100.0 %, except for 98.1 %, 98.2 %, and 98.5 %. In the juice category, the performance of

the two models was better than the learning performance, so it could be said that they had good prediction performance. Looking at the model performance on jam data, in the case of strawberry jam, both models showed values from 99.0 % to 100.0 %. When a knife was included, the sensitivity in the logistic regression model was 97.8 %, which is lower than other indicators, but it was still close to 100.0 %, indicating good overall model performance. In the same case, the PLS-DA model achieved 100.0 % in all metrics. In peach jam, the overall figure was in the 99.0 % range, and the specificity of the logistic regression model and sensitivity of the PLS-DA model were both confirmed to be 100.0 %. The case of tomato jam, all indicators were confirmed to be 99.0 %, indicating that both models had good performance.

4. Conclusions

Identification of physical hazards and their removal is extremely important to prevent accidents and ensure the high quality of final food products. The current study found that the presence or absence of physical hazards can be determined by using the reflectance value data obtained through hyperspectral imaging in various ways, and it was expected that the early detection of physical hazards during processing of agricultural products would be possible.

The test results of PLS-DA and logistic regression modeling show that the specificity was at least 97.6 %, and the all indicators were at most 100 % in the PLS-DA model. The sensitivity was at least 97.8 %, and all indicators were at most 100 % for all items in the logistic regression model. These results indicate that the indicators for determining the presence or absence of physical hazards using the PLS-DA and logistic regression models demonstrate satisfactory performance. Both the learning and prediction performances of the two models were found to be good, with the prediction performance being relatively higher than the learning performance. The results of this study show that HSI is suitable for use in detecting FMs in food, and that it is even possible to predict FMs through machine learning modeling. The prompt and accurate early detection of physical hazards through hyperspectral imaging is expected to have a positive impact on profitability, marketability, and overall quality of products, and the resulting economic effects appear to be clear. Based on the results of this study, further research is required to analyze more types and colors of FMs using HSI and to validate the modeling results.

Table 2

F1 score, accuracy, specificity, and specificity of test set with the PLS-DA and logistic regression model of HSI image reflection value data.

Test Sample	FMs	%F1 score		% Accuracy		% Specificity		% Sensitivity	
		PLS-DA	Logistic Regression	PLS-DA	Logistic Regression	PLS-DA	Logistic Regression	PLS-DA	Logistic Regression
Apple juice	Branch	99.5	99.8	99.7	99.8	99.4	100.0	100.0	99.6
	Knife	100.0	99.2	100.0	99.3	100.0	100.0	100.0	98.6
	Rubber	99.7	100.0	99.7	100.0	99.5	100.0	100.0	100.0
Grape juice	Branch	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Knife	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Rubber	100.0	99.6	100.0	100.0	100.0	100.0	100.0	99.2
Tomato juice	Branch	98.1	100.0	98.2	100.0	98.5	100.0	100.0	100.0
	Knife	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Rubber	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Strawberry jam	Branch	99.7	99.4	99.7	99.4	100.0	99.5	99.3	99.2
	Knife	100.0	98.4	100.0	98.5	100.0	99.2	100.0	97.8
	Rubber	99.7	99.1	99.7	98.8	100.0	99.6	99.3	98.5
Peach jam	Branch	99.0	99.8	98.9	99.8	97.6	100.0	100.0	99.7
	Knife	99.8	99.8	99.8	99.8	99.6	100.0	100.0	99.7
	Rubber	100.0	99.7	100.0	99.7	100.0	100.0	100.0	99.4
Tomato jam	Branch	99.8	99.4	99.8	99.4	100.0	99.2	99.7	99.6
	Knife	99.8	99.1	99.8	99.1	100.0	98.9	99.7	99.3
	Rubber	99.7	99.4	99.7	99.3	99.7	99.0	99.7	99.7

Ethical statement-studies in humans and animals

Statement of human and animal rights*

This study did not involve any experiments with human participants or animals. Therefore, ethical approval was not required.

* Ethical considerations in the conduct and reporting of research: Protection of human subjects and animals in research

When reporting experiments on human subjects, authors should indicate whether the procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2008. If doubt exists whether the research was conducted in accordance with the Helsinki Declaration, the authors must explain the rationale for their approach and demonstrate that the institutional review body explicitly approved the doubtful aspects of the study. When reporting experiments on animals, authors should indicate whether the institutional and national guidelines for the care and use of laboratory animals were followed.

CRediT authorship contribution statement

Na-Yeon Lee: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Investigation. **In-Su Na:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Investigation. **Kang-Woo Lee:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Investigation. **Dong-Ho Lee:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Investigation. **Jin-Woo Kim:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Investigation. **Moo-Chang Kook:** Validation, Project administration, Investigation. **Suk-Ju Hong:** Methodology, Funding acquisition, Project administration, Software. **Jae-Yong Son:** Project administration, Funding acquisition, Resources. **A-Young Lee:** Methodology, Funding acquisition, Project administration, Resources. **Ae-Son Om:** Validation, Project administration, Investigation. **Young-Min Kim:** Writing – review & editing, Methodology, Formal analysis, Software, Validation, Visualization. **Soon-Mi Shim:** Writing – review & editing, Validation, Methodology, Formal analysis, Data curation, Conceptualization, Investigation, Project administration.

Declaration of competing interest

The authors have nothing to declare.

Data availability

Data will be made available on request.

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