UDC 664.3.032.9
https://doi.org/10.31548/humanhealth.1.2026.154

HYPERSPECTRAL IDENTIFICATION OF COMPOSITE CHINESE SAUSAGES

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Abstract. With the increasing diversity of compound sausage types, the development of a rapid, accurate, and non-destructive identification model has become essential. The aim is to develop a robust model that operates without damaging the sausage surface or structure, meeting real-time, lossless, and high-throughput recognition requirements in practical applications. "Lossless recognition" refers to non-destructive analysis of surface spectra using hyperspectral imaging technology – without chemical treatment, grinding, or slicing into the interior of the sausage. Hyperspectral imaging technology was employed to collect spectral data over 400 – 1000 nm for eight types of compound sausages. For each image, 50 sampling regions were randomly selected, and the average reflectance values were extracted. First, three preprocessing algorithms – Multiplicative Scatter Correction (MSC), Savitzky-Golay smoothing (SG), and Neighborhood Averaging (NA) – were applied to the raw hyperspectral data. To enhance modeling efficiency, Principal Component Analysis (PCA) was used to reduce the dimensionality of the original 328 spectral bands, retaining the first 10 principal components, which explained over 95% of the total variance, as the new feature set. The classification results demonstrate that hyperspectral imaging combined with machine learning algorithms can effectively distinguish between the eight compound sausage types. Among all methods, the SVM model exhibited the highest classification accuracy, highlighting its excellent discriminative ability and robustness in high-dimensional hyperspectral data analysis. Classification models that combined MSC preprocessing with any of the three algorithms achieved prediction accuracies of over 99%.
Keywords: spectroscopic analysis; complex product structure; modeling; principal component analysis; classification; cross-validation.

УДК 664.3.032.9
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ГІПЕРСПЕКТРАЛЬНА ІДЕНТИФІКАЦІЯ КОМПОЗИТНИХ КИТАЙСЬКИХ КОВБАС

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Анотація: Зі зростанням різноманітності структури ковбас, розробка швидкої, точної та неруйнівної моделі ідентифікації стала надзвичайно важливою. Метою дослідження є створення надійної моделі, яка працює без пошкодження поверхні чи структури ковбаси, щоб відповідати вимогам розпізнавання в режимі реального часу без втрат та

високопродуктивного розпізнавання у практичних умовах. Таке «розпізнавання без втрат» означає неруйнівний аналіз поверхневих спектрів за допомогою технології гіперспектральної візуалізації, тобто без хімічної обробки, подрібнення або нарізання внутрішньої частини ковбаси. Технологію гіперспектральної візуалізації було використано для збирання спектральних даних у діапазоні 400 – 1000 нм для восьми різних типів композитних ковбас. Для кожного зображення випадковим чином вибирали 50 областей вибірки, із яких визначали середні значення коефіцієнта відбиття. Спочатку до необроблених гіперспектральних даних застосовували три алгоритми попередньої обробки, а саме, мультиплікативну корекцію розсіювання (MSC), згладжування Савіцького-Голея (SG) та межове усереднення (NA). Для підвищення ефективності моделювання було використано аналіз головних компонент (PCA), щоб зменшити розмірність вихідних 328 спектральних смуг, зберігаючи перші 10 головних компонент, які пояснюють понад 95% загальної дисперсії, як основний набір ознак. Результати класифікації демонструють, що гіперспектральна візуалізація в поєднанні з алгоритмами комп'ютерного аналізу може ефективно розрізняти вісім типів композитних ковбас. Серед усіх методів модель SVM продемонструвала найвищу точність класифікації, що підкреслює її високу дискримінаційну здатність та стійкість у високовимірному гіперспектральному аналізі даних. Моделі класифікації, які поєднували попередню обробку MSC з будь-яким із трьох алгоритмів, досягли точності прогнозування понад 99%.
Ключові слова: спектроскопічний аналіз; складна структура продукції; моделювання; аналіз головних компонент; класифікація; перехресна валідація.

INTRODUCTION. In China, sausage culture has a long-standing tradition, renowned for its distinct color, aroma, taste, and shape. With improving living standards, there is an increasing demand for nutritious sausages suitable for all age groups. Composite sausages, characterized by their high protein, low fat, high fiber, and multi-vitamin content, can be made by combining various types of meat, fresh vegetables, coarse grains, edible fungi, and spices. This enhances their flavor, taste, and quality, while also boosting their nutritional value and supporting both specific and non-specific immune functions of the human body (Feng et al., 2020). Consequently, as people place greater emphasis on balanced nutrition, composite sausages have become a promising green health food with significant market potential (Liu et al., 2021). However, the complexity and variety of composite sausages present challenges. Although various sausage identification methods exist, there is practical value in developing a comprehensive, systematic, online, lossless sausage recognition model better to support production, processing, distribution, and storage, and to meet consumer demand for different sausage types. The developed method for identifying the quality state of sausages using mathematical modeling based on factor areas and spaces proved quite effective in terms of simplicity and assessment accuracy. The latter characteristics are defined by the product's quality parameters, which are specified in geometric models using polar coordinates (Palamarchuk et al., 2025; Mushtruk et al., 2023).

In recent years, the widespread use of hyperspectral imaging technology, absorption spectroscopy, and spectral analysis techniques combined with machine learning in food testing has offered new approaches for the classification and prediction of sausage varieties (Palamarchuk et al., 2024; et al., Su et al., 2018; Liu et al., 2017).

Hyperspectral technology is an emerging non-destructive testing technique that combines the strengths of traditional imaging and spectroscopy. This dual capability allows hyperspectral imaging to simultaneously capture both the image texture and spectral features of the object being analyzed, providing high spatial resolution (Huang et al., 2023; Zhao et al., 2022; Wang et al., 2020).

This approach aims to provide valuable insights for the rapid classification and quality detection of real-world sausage products. Initially, the operational workflow and processing outcomes of three hyperspectral preprocessing algorithms, PCA dimensionality reduction analysis, and three classification models were examined using MATLAB and OriginPro. The confusion matrix and prediction accuracy results obtained were used as the basis for evaluating the subsequent classification models.

LITERATURE REVIEW. Among these, the integration of hyperspectral analysis with machine learning algorithms for food origin identification and quality detection has gained increasing prominence in recent years. This approach allows the simultaneous acquisition of spatial and spectral information, enabling detailed characterization of the chemical composition, structural properties, and visual attributes of food products without destroying the sample. The combination of hyperspectral imaging with advanced computational techniques has significantly expanded the possibilities for automated quality control in the meat processing industry.

Kalinichenko et al. employed basic odor discrimination and an electronic nose to capture feature data, which were then analyzed using a probabilistic neural network (PNN) to assess the quality of soy protein sausages (Kalinichenko et al., 2020). The electronic nose system collected volatile compound profiles from the samples, forming a multidimensional dataset that reflects aroma characteristics associated with product freshness and composition. Two analytical approaches were evaluated: conventional pattern recognition and machine learning–based classification. After evaluating both methods, the second approach, a probabilistic neural network, achieved 100% classification accuracy, demonstrating the effectiveness of combining sensor-based detection with artificial intelligence for rapid, objective assessment of sausage quality.

Recent advancements in spectroscopic imaging and artificial intelligence have enabled high-precision non-destructive assessment of meat products. Hyperspectral imaging integrates spectroscopy and digital imaging, enabling each image pixel to contain a complete spectral signature. This enables the detection of subtle chemical and physical variations that are difficult to observe with traditional analytical techniques. A study by Zhang et al. investigated the classification of Chinese Cantonese sausages using hyperspectral imaging (HSI) combined with machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF) (Liu, Y., Zhang et al., 2017; Wang et al., 2019). Their results demonstrated that both whole and sliced sausages could be accurately classified into different quality grades, with classification accuracies exceeding 90%. The study also highlighted that the use of advanced feature extraction techniques improved model robustness and reduced computational complexity.

Guo Peiyuan applied hyperspectral technology to develop an iterative decision tree machine learning model for sausage colony identification (Dong, X., Guo, P. et al., 2017). In this research, spectral information collected from sausage surfaces was used to detect microbial colonies and predict contamination levels. The developed model demonstrated root mean square errors of 0.001 and 0.003, with determination coefficients (R^2) of 0.998 and 0.996, respectively, indicating extremely high predictive accuracy and strong correlation between predicted and measured values. Such results confirm the potential of hyperspectral analysis combined with machine learning for rapid microbiological monitoring in meat products.

Huang et al. applied hyperspectral imaging, combined with multivariate analysis and image processing, to detect and visualize color differences in cooked sausages stuffed into various modified casings (Huang et al., 2023). Color is an important indicator of processing conditions, ingredient composition, and consumer acceptability. The study utilized Partial Least Squares Regression (PLSR) and k-means clustering to analyze the spectral data, enabling effective differentiation of sausage samples based on visual and compositional features. In addition, the hyperspectral images enabled researchers to visualize the spatial color distribution across the sausage surface, providing deeper insight into the interactions between casing materials and meat matrices.

Overall, the reviewed studies demonstrate that hyperspectral imaging combined with machine learning algorithms represents a powerful tool for rapid, accurate, and non-destructive evaluation of sausage quality. These technologies enable automated classification, detection of microbial contamination, monitoring of color and compositional changes, and verification of product authenticity. Consequently, their integration into industrial food quality control systems can significantly enhance process monitoring, ensure product safety, and improve consumer confidence in meat products (Liu, Y., Zhang et al., 2017; Wang et al., 2019; Huang et al., 2023; Kalinichenko et al., 2020; Dong, X., Guo, P. et al., 2017).

MATERIALS AND METHODS. Eight types of common complex sausage products were used in the study. For hyperspectral analysis, corresponding hyperspectral images of the test samples were obtained. Each sausage sample was partially cut to ensure the product's internal structure was representative during scanning. The obtained hyperspectral images of the samples are shown in Figure 1.

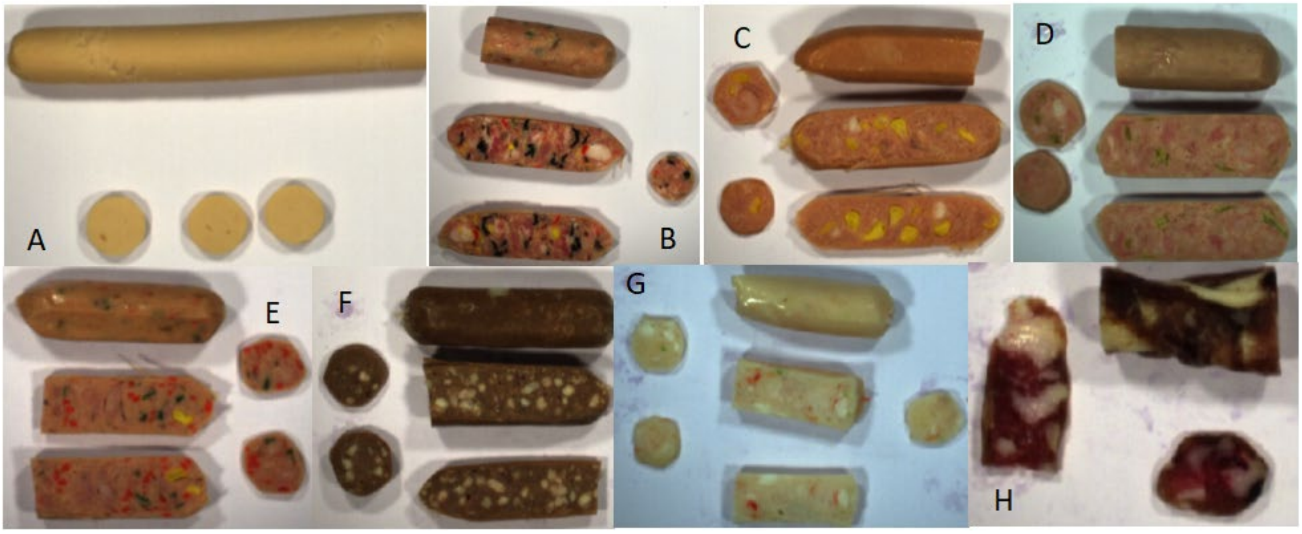

Figure 1. Hyperspectral image of 8 sausage samples: A – chicken sausage; B – meat sausage; C – corn dietary sausage; D – green pepper sausage; E – vegetable dietary sausage; F – beef-flavored sausage; G – shrimp smooth sausage; H – Chinese Cured Pork Sausage.

The indoor hyperspectral imaging system used in this study includes a darkroom system (GaiaSorter-Dual, Dualix, China), a visible and near-infrared hyperspectral imager (GaiaField-V10, Dualix, China), a near-infrared hyperspectral imager (GaiaField-N7E-HR, Dualix, China), and data acquisition and preprocessing software (SpecView, Dualix, China). The GaiaSorter-Dual system features a maximum sample space of 300 mm (length) × 300 mm (width) × 100 mm (height), with lighting space uniformity maintained at 95%. Its power input operates at 220 V AC ±10 %, while the adjustable working distance ranges from 180 mm to 600 mm. The sample stage provides an 800 mm scanning travel distance and includes a standard calibration whiteboard measuring 300 mm × 25 mm × 10 mm–a polytetrafluoroethylene-pressed, 99% standard diffuse reflection board.

To reduce the influence of external stray light and ensure the stability and accuracy of spectral measurements, hyperspectral data were acquired using the GaiaField-V10 visible–near-infrared hyperspectral imager installed inside the GaiaSorter-Dual darkroom system. Using a closed, darkroom environment minimizes interference from ambient illumination and enables consistent spectral acquisition under controlled lighting conditions.

The imaging system operates based on a push-broom scanning technique, in which the sensor sequentially captures spectral information line by line as the sample moves relative to the detector. This approach enables simultaneous recording of spatial and spectral information, forming a three-dimensional hyperspectral data cube with two spatial dimensions and one spectral dimension. The hyperspectral camera operates over 400–1000 nm, covering the visible and near-infrared regions, which are highly informative for analyzing food composition and surface characteristics. The spectral sampling rate was 0.7 nm per minute, yielding 328 spectral bands with a sampling resolution of 3.5 nm, providing sufficient spectral detail for subsequent data analysis and classification.

During the experiment, slices of eight different sausage products were arranged in batches on the sample stage of the imaging system. The samples were illuminated by a dome-shaped, uniform light source integrated into the darkroom, ensuring homogeneous illumination of the sample surface and reducing shadows and reflection artifacts. The illumination system provides a full-spectrum range from 350 to 2500 nm, enabling stable spectral acquisition across the hyperspectral sensor's operating range. Such an experimental setup allows the collection of high-quality hyperspectral images suitable for subsequent machine learning analysis and product classification.

The configuration and main components of the indoor hyperspectral imaging system used in this study are illustrated in Figure 2.

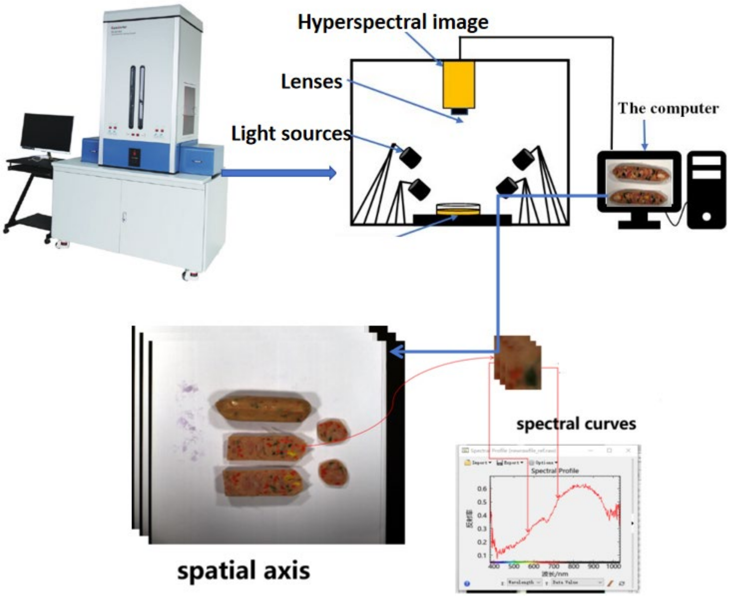

Figure 2. Hyperspectral experimental setup and experimental process.

For the visible near-infrared hyperspectral imager (instrument selected in this study), the GaiaField-V10 model covers 400–1000 nm and achieves a spectral resolution (FWHM) of 3.5 nm. It offers a minimum spectral sampling point of 0.7 nm and employs a high-performance CCD detector. This imager provides 1392 spatial channels and 520 spectral channels, outputs 14-bit camera data, and is equipped with a C-mount lens featuring a 25 mm focal length.

RESULTS AND DISCUSSION. Matlab was used to perform Multiplicative Scatter Correction (MSC) preprocessing of spectral data from eight types of composite sausages. MSC preprocessing is commonly applied in hyperspectral data analysis to minimize the effects of light scattering, baseline shifts, and other spectral distortions arising from variations in sample surface structure, particle size, or uneven illumination conditions.

The application of MSC normalizes spectral signals by correcting multiplicative and additive effects relative to a reference spectrum. As a result, the spectral curves become more comparable and better reflect the actual chemical composition of the samples rather than external measurement artifacts. This preprocessing step is particularly important when analyzing food products such as sausages, where heterogeneous structures and differences in fat, protein, and moisture distribution can significantly influence spectral responses.

After MSC preprocessing, the corrected spectral data showed improved consistency and reduced spectral noise, thereby enhancing the reliability of subsequent data analysis and classification procedures. The processed spectra provided a clearer representation of the characteristic absorption features in the visible–near-infrared region, which are associated with the chemical components of meat products. Consequently, the MSC-preprocessed dataset served as the basis for further modeling and machine learning analysis to distinguish among the different types of composite sausages.

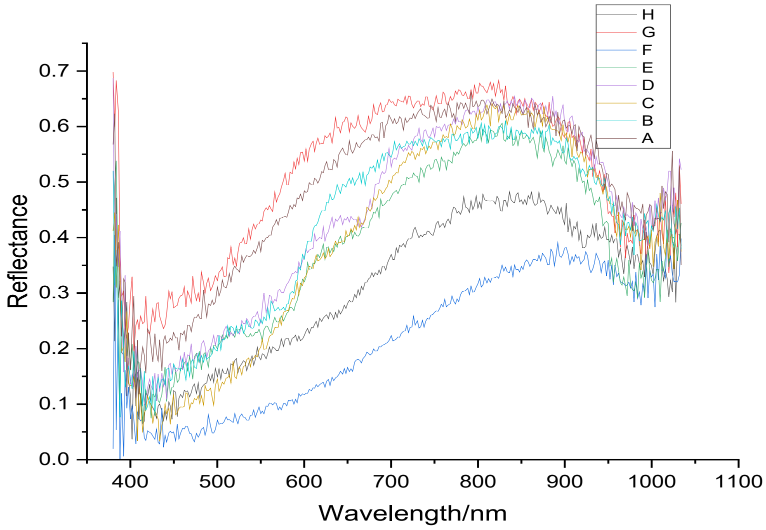

Figure 3. Representative graph of original spectral data curves of 8 kinds of sausages
Source: developed by the authors

Figures 3 and 4 display the representative spectral curves for the sausages, including both the original and MSC-processed curves. It is clear that the MSC treatment significantly reduces noise and centers the data in comparison to the original spectral curves. Consequently, the MSC-processed hyperspectral curves provide improved discrimination of spectral features.

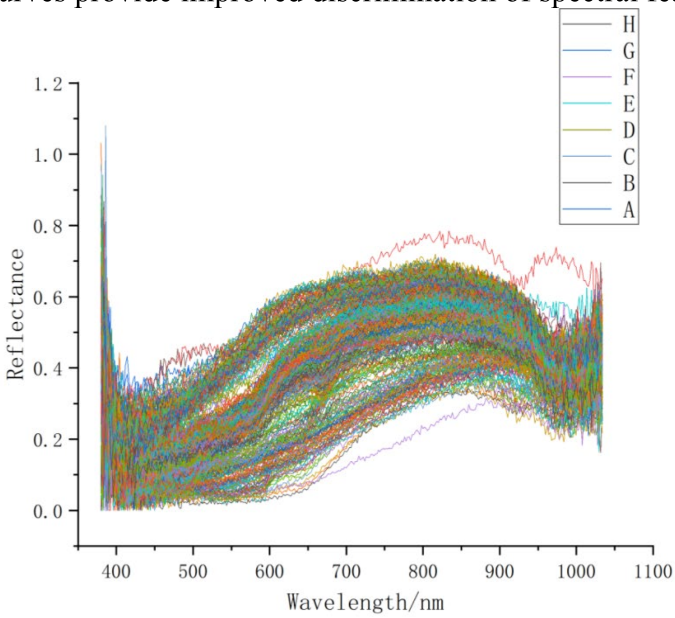

Figure 4. Complete raw spectral patterns of 8 sausage species
Source: developed by the authors

For this classification, the SG smoothing technique is applied to the data using Origin's smoothing function. For the «Algorithm Preprocessing» step, the Origin program was used to preprocess the hyperspectral data using the neighborhood-average method (Figure 5).

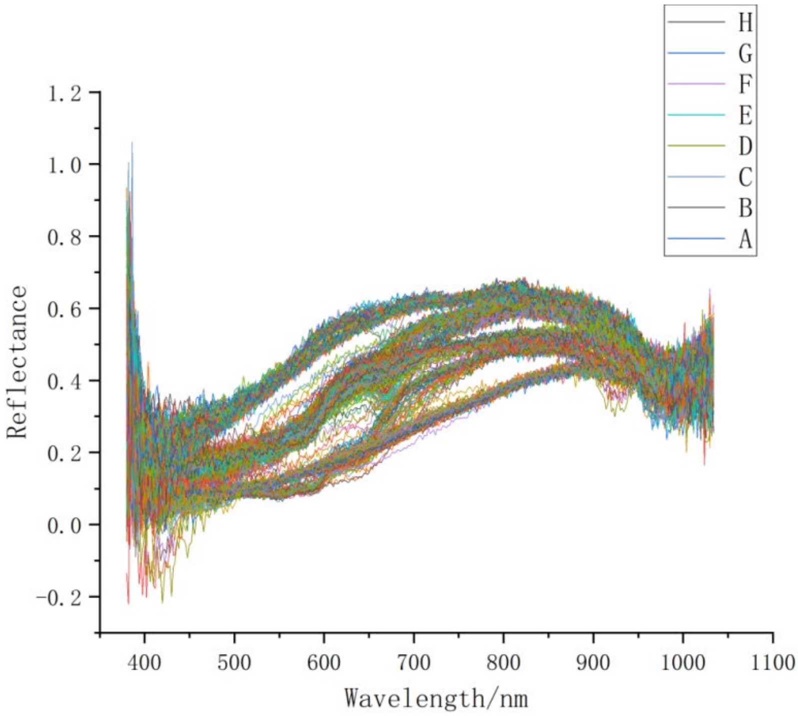

Figure 5. Complete spectral curves after MSC treatment.
Source: developed by the authors

The process followed the same steps as the SG smoothing. On the smoothing page, the neighborhood-average method was selected for data processing. The final spectral data image is presented in Figure 6.

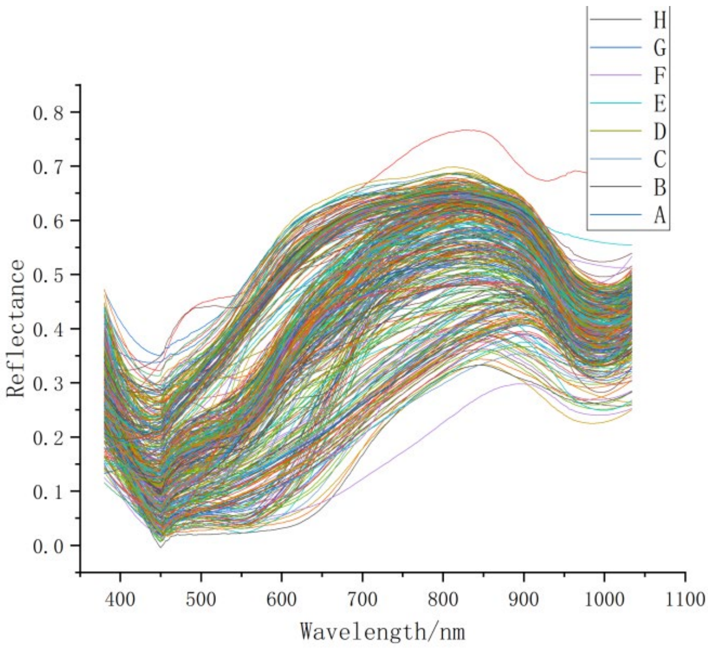

Figure 6. Complete hyperspectral curve after SG smoothing.
Source: developed by the authors

Upon examining the hyperspectral curves of the sausages processed by the three methods, it is clear that the spectral differences between the eight sausage types are not distinct. Additionally, the 328 bands in the 400–1000 nm range result in high feature dimensions, introducing redundancy.

This redundancy can lead to inefficiency in machine learning for classification and limit the generalization capability of the trained model (*Son et al., 2024; Yang et al., 2019; Xia et al., 2021*).

Therefore, we conducted a comparative analysis between PCA-processed and non-PCA-processed data. After SG processing, principal component analysis yielded the cumulative contribution rates for PC1-PC10 as follows: 86.92417, 95.10919, 97.19433, 98.48592, 99.22994, 99.64845, 99.80852, 99.87624, 99.92173, and 99.95849.

For data processed using the adjacent averaging method, the cumulative contribution rates for PC1-PC10 after principal component analysis were 85.13105, 93.18345, 95.72803, 97.51157, 98.31266, 98.89775, 99.29545, 99.47274, 99.61852, and 99.71805, respectively.

After preprocessing the original hyperspectral data with MSC, PCA yielded cumulative contribution rates for PC1-PC10 of 80.4519, 86.21714, 88.7409, 90.34385, 91.67426, 92.78757, 93.69049, 94.44586, 95.14513, and 95.6151.

The results demonstrate that after applying principal component analysis (PCA) to spectral data preprocessed by these three methods, the original 328-dimensional data was reduced to as few as 10 dimensions while retaining more than 95% of the original information. This indicates that the filtered data has a minimal effect on the overall dataset, with the first ten principal components containing the majority of the relevant information. These results show that PCA significantly reduces the input data for the sausage classification model, minimizes training time, and achieves data-preprocessing goals while preserving the key hyperspectral information of the sausages.

Hyperspectral imaging (HSI) has emerged as a powerful non-destructive analytical technology for evaluating the quality and safety of meat products. The technology integrates spectroscopic analysis with imaging techniques, enabling simultaneous acquisition of spatial and spectral information from food samples. This combination allows researchers to assess multiple quality attributes such as chemical composition, freshness, fat content, and microbial contamination without damaging the product. Recent studies have demonstrated that hyperspectral imaging can effectively characterize the physicochemical and sensory properties of meat, including protein and water distribution, oxidation levels, and microbial spoilage indicators.

The results of the present study show that the hyperspectral curves of the eight composite sausage types exhibited relatively small spectral differences when analyzed directly. Such behavior is typical for complex meat matrices, where overlapping spectral features of proteins, lipids, and water often produce highly correlated spectral signals. Consequently, hyperspectral datasets typically contain hundreds of spectral bands, each of which is highly redundant. According to Xu et al. (2024), hyperspectral datasets often require advanced preprocessing and dimensionality reduction techniques to improve data interpretability and classification performance. The findings of the present work confirm this statement, since the initial 328-dimensional dataset required transformation before it could be effectively used for machine-learning-based classification.

The application of principal component analysis (PCA) in this study proved to be an efficient strategy for dimensionality reduction. After PCA transformation, the hyperspectral data were reduced from 328 spectral variables to 10 principal components, while retaining more than 95% of the total variance for most preprocessing methods. This result indicates that the majority of the spectral information describing the sausage samples can be represented in a significantly smaller feature space. Similar conclusions were reported by Rogers (2023), who analyzed wavelength selection strategies in hyperspectral imaging and emphasized that reducing the number of spectral variables is essential to improving computational efficiency and classification accuracy in food analysis models.

In addition to improving computational efficiency, dimensionality reduction methods help machine-learning algorithms focus on the most informative spectral features. Das et al. (2025) noted that hyperspectral imaging generates large volumes of highly correlated data, which can negatively affect the performance of classification algorithms. Their review demonstrated that integrating machine learning with feature extraction techniques, such as PCA or wavelength selection, significantly enhances model robustness and prediction accuracy. The results of the present research support this conclusion, as PCA preserved the essential spectral information while reducing data redundancy.

Another important observation in this study is the influence of different preprocessing methods on PCA's effectiveness. Among the examined preprocessing approaches, Savitzky–Golay filtering and adjacent averaging yielded higher cumulative variance values for the first principal components than MSC preprocessing. This suggests that smoothing and noise-reduction techniques can better preserve the spectral structure of hyperspectral data before dimensionality reduction. Similar observations were reported in hyperspectral studies of meat freshness. For instance, Kim et al. (2024) demonstrated that applying spectral preprocessing combined with multivariate modeling improved the detection of quality indicators, such as lipid oxidation and volatile nitrogen compounds, in beef samples. Their work highlights the importance of preprocessing in extracting meaningful spectral information from complex meat products.

Beyond preprocessing and dimensionality reduction, recent research has increasingly focused on integrating hyperspectral imaging with artificial intelligence and deep learning methods. Nikzadfar et al. (2024) emphasized that artificial intelligence techniques can efficiently handle the complexity of hyperspectral datasets by automatically extracting relevant spectral features and constructing predictive models for food quality evaluation. The authors highlighted that machine-learning algorithms are particularly effective when the input data have been appropriately preprocessed and reduced to the most informative features. This concept is consistent with the methodological framework of the present study, in which PCA served as a key step in preparing hyperspectral data for subsequent classification modeling.

Another important aspect highlighted in recent literature is the growing use of hyperspectral imaging for simultaneously monitoring multiple quality attributes. Yi et al. (2025) reported that hyperspectral imaging can simultaneously evaluate various meat quality parameters, including freshness, intramuscular fat content, microbial contamination, and nutritional composition, in a single analytical process. This multifunctional capability distinguishes hyperspectral technology from traditional analytical methods, which often require separate laboratory tests for each quality parameter. The present study contributes to this research area by demonstrating that hyperspectral spectral patterns can be used to differentiate between several types of composite sausage products after appropriate data preprocessing and dimensionality reduction.

Furthermore, integrating hyperspectral imaging with modern machine-learning frameworks is considered one of the most promising directions in food quality control. Recent research indicates that combining hyperspectral data with advanced modeling techniques, such as neural networks, support vector machines, or ensemble learning algorithms, significantly improves prediction accuracy and enables real-time quality monitoring in food production systems. In this context, dimensionality reduction methods like PCA play an essential role by reducing computational complexity and facilitating faster model training. The results of the current study confirm that PCA effectively compresses hyperspectral information without substantial loss of data quality, thereby enabling more efficient implementation of machine-learning models.

Overall, the findings of this research align with the general trends reported in contemporary hyperspectral food analysis studies. Most researchers emphasize that hyperspectral datasets require appropriate preprocessing and feature extraction to achieve reliable classification results. The comparison with previous studies shows that the approach used in this work – combining spectral preprocessing with PCA – aligns with widely accepted practices in hyperspectral data analysis. At the same time, the present study extends existing knowledge by demonstrating the effectiveness of this approach specifically for composite sausage products, which represent complex multicomponent food systems.

In conclusion, the obtained results confirm that hyperspectral imaging combined with PCA-based dimensionality reduction is a promising approach for analyzing and classifying sausage products. By reducing spectral dimensionality from hundreds of bands to a limited number of informative principal components, it is possible to maintain the essential spectral characteristics while significantly improving computational efficiency. These findings support the growing application of hyperspectral imaging and machine learning technologies for rapid, non-destructive quality assessment in the meat industry.

Conclusions. This study demonstrated the feasibility of combining hyperspectral imaging with machine learning algorithms for rapid, non-destructive classification of composite sausage products. Hyperspectral data were collected from eight commercially available sausage varieties in the visible–near-infrared spectral range. To improve the quality of the raw spectral signals, three preprocessing methods – Multiplicative Scatter Correction (MSC), Savitzky–Golay (SG) smoothing, and neighborhood averaging (NA) – were applied to reduce noise and enhance spectral stability. Considering the high dimensionality of hyperspectral datasets, Principal Component Analysis (PCA) was used to reduce data complexity. The first ten principal components retained more than 95% of the total spectral variance, indicating that the essential information of the original spectra was effectively preserved while significantly reducing the number of input variables.

The reduced feature set was subsequently used to train three classification models: k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF). Model performance was evaluated using five-fold cross-validation, confusion matrices, and prediction accuracy. All models achieved strong classification results, with average accuracies exceeding 90%. The SVM model showed the highest overall performance with an accuracy of 95.79%. Notably, when MSC preprocessing was applied, the prediction accuracy of all classification models exceeded 99%, demonstrating the importance of appropriate spectral preprocessing in improving model performance.

Overall, the results confirm that hyperspectral imaging combined with dimensionality reduction and machine learning techniques represents an effective approach for automated identification and quality evaluation of sausage products. The proposed methodology has strong potential for application in intelligent food quality control systems within the meat processing industry.

Acknowledgements. None.

Conflict of interest. None.

References

Das, M., Sharma, P., & Kumar, S. (2025). Machine learning in hyperspectral imaging for food safety and quality monitoring: A comprehensive review. *Artificial Intelligence in Agriculture, 11*, 35–52. https://doi.org/10.1016/j.aiia.2025.02.003

Dong, X., Guo, P., & Xu, P. (2017). Prediction of total viable count in sausages using hyperspectral imaging combined with an iterative decision tree. *Modern Food Science and Technology, 33*(7), 308–314. https://doi.org/10.13982/j.mfst.1673-9078.2017.7.043

Feng, T., Wang, X., Wang, H., Song, S., & Sun, J. (2020). Enhancement of nutritional value and functional properties of compound sausages through incorporation of edible mushrooms and coarse cereals. *Journal of Food Science and Technology, 57*(8), 3023–3034.

Huang, L., Zhao, J., Chen, Q., & Zhang, Y. (2023). Rapid detection of adulteration in minced mutton using hyperspectral imaging combined with chemometric methods. *Chemosensors, 11*(2), 136. https://doi.org/10.3390/chemosensors11020136

Jo, K., Lee, S., Jeong, S.-K., & Lee, D.-H. (2024). Hyperspectral imaging-based assessment of fresh meat quality: Progress and applications. *Microchemical Journal, 197*, 109785. https://doi.org/10.1016/j.microc.2023.109785

Kalinichenko, A., & Arseniyeva, L. (2020). An electronic nose combined with chemometric approaches to assess the authenticity and adulteration of sausages by soy protein. *Sensors and Actuators B: Chemical, 303*, 127250. https://doi.org/10.1016/j.snb.2020.127250

Kim, M., Park, J., & Lee, S. (2024). Early detection of beef quality indicators using hyperspectral imaging and spectral modeling. *Food Control, 158*, 110137. https://doi.org/10.1016/j.foodcont.2023.110137

Liu, Y., Pu, H., & Sun, D.-W. (2017). Hyperspectral imaging technique for evaluating food quality and safety: A review. *Chemosensors, 5*(4), 28. https://doi.org/10.3390/chemosensors5040028

Liu, Y., Zhang, M., & Wang, D. (2021). Consumer perception and market potential of novel healthy meat products: A case study of compound sausages in China. *Food Control, 130*, 108356. https://doi.org/10.1016/j.foodcont.2021.108356

Mushtruk, M., Palamarchuk, I., Palamarchuk, V., Petrychenko, I., & Pylypchuk, O. (2023). Mathematical modelling of quality assessment of cooked sausages with the addition of vegetable additives. *Potravinarstvo Slovak Journal of Food Sciences, 17*, 242–255.

Nikzadfar, M., Rahman, A., & Lee, J. (2024). Hyperspectral imaging aiding artificial intelligence for food quality and safety control: A review. *Applied Sciences, 14*(21), 9821. https://doi.org/10.3390/app14219821

Palamarchuk, I., Fu, Y., Zhuravel, D., Petrychenko, I., Blishch, R., Holovatyuk, A., Domin, O., & Kostiuk, T. (2024). Spectroscopic assessment and quantitative analysis of the trace element composition of vegetable additives to meat products. *Potravinarstvo Slovak Journal of Food Sciences, 18*, 480–496. https://doi.org/10.5219/1965

Palamarchuk, I., Zavialov, V., Fu, Y., Palamarchuk, V., & Popova, N. (2025). Mathematical modeling by the factorial area method in evaluating the quality characteristics of the studied samples. In *Advances in design, simulation and manufacturing processes VIII* (pp. 147–156). https://doi.org/10.1007/978-3-031-95218-0_13

Rogers, M. (2023). Wavelength and texture feature selection for hyperspectral food analysis: A review. *Journal of Food Measurement and Characterization, 17*, 5120–5136. https://doi.org/10.1007/s11694-023-02044-x

Son, W.-Y., Kang, M.-H., Hwang, J., Kim, J.-H., Dixit, Y., & Kim, H.-W. (2024). Hyperspectral imaging combined with machine learning can be used for rapid and non-destructive monitoring of residual nitrite in emulsified pork sausages. *Foods, 13*, 3173. https://doi.org/10.3390/foods13193173

Su, W.-H., & Sun, D.-W. (2018). Fourier transform infrared, Raman, and hyperspectral imaging techniques for quality determinations of powdery foods: A review. *Comprehensive Reviews in Food Science and Food Safety, 17*(4), 104–120.

Wang, Q., & He, Y. (2019). Rapid and nondestructive classification of Cantonese sausage degree using hyperspectral images. *Applied Sciences, 9*(5), 822. https://doi.org/10.3390/app9050822

Wang, Y., Yang, Z., & Cheng, J. (2020). Application progress of multispectral imaging for food nutritional quality detection. *Science and Technology of Food Industry, 41*(4), 339–347. https://doi.org/10.13386/j.issn1002-0306.2020.04.058

Xia, S. J., Yang, C. Y., Zhou, C. G., et al. (2021). Review of the application of common machine learning methods in the field of traditional Chinese medicine diagnosis. *Journal of Guangzhou University of Traditional Chinese Medicine, 38*(4), 826–831. https://doi.org/10.13359/j.cnki.gzxbtcm.2021.04.026

Xu, Z., Li, Y., Wang, H., & Chen, Y. (2024). Research progress on the quality detection of livestock and poultry meat using machine vision and hyperspectral technology. *Foods, 13*(3), 469. https://doi.org/10.3390/foods13030469

Yang, C., Zhao, Y., & Liu, H. (2025). Deep learning hyperspectral imaging: A rapid and reliable alternative for food quality and safety evaluation. *Journal of Agricultural and Food Chemistry, 73*, 14562–14575. https://doi.org/10.1021/acs.jafc.4c11492

Yang, J. F., Qiao, P. R., Li, Y. M., et al. (2019). A review of machine learning classification problems and algorithms. *Statistics and Decision, 35*(6), 36–40. https://doi.org/10.13546/j.cnki.tjyjc.2019.06.009

Yi, X., Zhang, Y., & Chen, L. (2025). Advances in hyperspectral imaging for multi-attribute analysis of meat quality. *Food Chemistry, 435*, 137558. https://doi.org/10.1016/j.foodchem.2024.137558

Zhao, J., Dong, Q., Chen, P., et al. (2022). Application progress of hyperspectral imaging technology in the rapid detection of microbial contamination in animal-derived food. *Science and Technology of Food Industry, 43*(7), 467–473. https://doi.org/10.13386/j.issn1002-0306.2021050236

Отримано 30.12.2025 р., прийнято до друку 01.03.2026 р.