UNIVERSITY OF HELSINKI

https://helda.helsinki.fi

Deep learning-assisted fluorescence spectroscopy for food quality and safety analysis

Yuan, Yuan; Ji, Zengtao; Fan, Yanwei; Xu, Qian; Shi, Ce ...

2025-02
Elsevier Ltd.
http://hdl.handle.net/10138/624458
Yuan, Y, Ji, Z, Fan, Y, Xu, Q, Shi, C, Lyu, J & Ertbjerg, P 2025, 'Deep learning-assisted fluorescence spectroscopy for food quality and safety analysis', Trends in Food Science & Technology, vol. 156, 104821. https://doi.org/10.1016/j.tifs.2024.104821

Downloaded from Helda, University of Helsinki institutional repository. https://helda.helsinki.fi
This is an electronic reprint of the original article.
This reprint may differ from the original in pagination and typographic detail.
Please cite the original version.

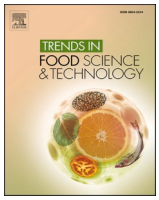
Trends in Food Science & Technology 156 (2025) 104821



Contents lists available at ScienceDirect

Trends in Food Science & Technology

journal homepage: www.elsevier.com/locate/tifs



Deep learning-assisted fluorescence spectroscopy for food quality and safety analysis

Yuan Yuan [a,e], Zengtao Ji [b,c,d], Yanwei Fan [b,c,d], Qian Xu [a,e,**], Ce Shi [b,c,d,*], Jian Lyu [f], Per Ertbjerg [f]

[a] College of Food Science and Engineering, Tarim University, Alar, 843301, China
[b] Information Technology Research Center, Beijing Academy of Agriculture and Forestry Sciences, Beijing, 100097, China
[c] Key Laboratory of Cold Chain Logistics Technology for Agro-product, Ministry of Agriculture and Rural Affairs, Beijing, 100097, China
[d] National Engineering Research Center for Information Technology in Agriculture, Beijing Academy of Agricultural and Forestry Sciences, Beijing, 100097, China
[e] Production & Construction Group Key Laboratory of Special Agricultural Products Further Processing in Southern Xinjiang, Alar, 843301, China
[f] Department of Food and Nutrition, University of Helsinki, 00014, Helsinki, Finland

ARTICLE INFO

Keywords:
Fluorescence spectroscopy
Limitations of machine learning
Classification and regression
Model optimization
Model performance evaluation
Application

ABSTRACT

Background: Fluorescence spectroscopy has been widely employed in the quality assessment of food and agricultural products due to its rapid and accurate measurement characteristics. The large amount of fluorescence data or images generated by fluorescence spectroscopy requires more efficient chemometric methods to process and analyze them. However, conventional machine learning models struggle to achieve high-precision predictions when analyzing high-dimensional fluorescence data samples. Deep learning algorithms exhibit powerful automatic learning capabilities in feature extraction and regression modeling of fluorescence spectra.

Scope and approach: The complex, abstract and high-dimensional features of fluorescence spectroscopy are firstly demonstrated through the characterization of fluorescent substances in food products. Secondly, this paper highlights various challenges confronting the fluorescence spectrum analysis process and summarizes several deep learning algorithms that can address these solutions, including the convolutional neural network (CNN), long and short-term memory network (LSTM), and auto encoder (AE). Additionally, the application of deep learning models based on fluorescent data in food detection is reviewed in this article according to different testing objectives, including food safety inspections, food quality assessment, adulteration identification, and variety identification. The review also focuses on the future development trend of this technique in food quality and safety detection.

Key findings and conclusions: Deep learning approaches combined with fluorescence spectroscopy exhibits immense potential in food quality detection and food discrimination classification. The selections of representative input parameters, suitable preprocessing methods and optimization methods can effectively tackle the problems of lack of samples and model over-fitting. Owing to the rapid advancement of artificial intelligence, the deep learning-based fluorescence spectroscopy technology is poised to evolve towards high precision, high throughput, automation and cost-effectiveness.

1. Introduction

At present, the issue of food quality and safety remains significant challenges for many developing countries. As a result of the globalization of the food trade, the transportation distance from producers to consumers has increased, and the risk with food safety has also increased. Factors such as environmental temperature and humidity, packaging materials, and intrinsic chemical properties contribute to spoilage during the storage period (Othman, Mavani, Hussain, Abd Rahman, & Ali, 2023). However, traditional food safety and quality detection methods such as chemical analysis and microbiological detection are both costly and destructive. In recent years, a variety of reliable and convenient spectroscopic techniques for food quality assessment have been developed, including Raman spectroscopy, visible

* Corresponding author. Information Technology Research Center, Beijing Academy of Agriculture and Forestry Sciences, Beijing, 100097, China.
** Corresponding author. College of Food Science and Engineering, Tarim University, Alar, 843301, China.
E-mail addresses: xuqiantaru@126.com (Q. Xu), shice001@163.com (C. Shi).

https://doi.org/10.1016/j.tifs.2024.104821
Received 8 September 2024; Received in revised form 30 November 2024; Accepted 2 December 2024
Available online 3 December 2024
0924-2244/© 2024 Elsevier Ltd. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

and near-infrared spectroscopy, and Fourier transform spectroscopy (Boukria, Boudalia, Bhat, Hassoun, & Aït-Kaddour, 2023). These techniques combined with chemicals have great application potential in food quality assessment, but fall slightly short in terms of complex component analysis and analytical accuracy.

As a fast and accurate analytical technique, fluorescence spectroscopy has been widely utilized in molecular structure and functional research within the fields of chemistry and biochemistry (Hassoun, Sahar, Lakhal, & Aït-Kaddour, 2019). Because fluorescent compounds are highly sensitive to their environment, fluorescence can be used to characterize conformational changes that occur during different manufacturing and storage conditions and provide novel methods for the detection of even trace substances in food products (Hassoun, 2021). Additionally, fluorescence spectroscopy techniques have extensive selectivity and multidimensional detection properties. The full-band fluorescence spectrum data in the range of ultraviolet and visible light can be collected for the test sample which provides convenience for the detection of food with complex ingredients.

One of the significant challenges in processing and analyzing fluorescence spectral data is the extraction of effective features from multivariate and non-selective high-dimensional spectral data. In addition, spectral interference resulting from the environment, instruments, complex components, and differences between food samples may lead to minor spectral differences that are difficult to distinguish (Saha & Manickavasagan, 2021). Therefore, effective algorithms are required for dimensional-reduction of spectral data. Popular machine learning algorithms, such as linear discriminant analysis (LDA) (Junges, Guerra, Canedo-Reis, Gomes, & Ferrao, 2023), support vector machine (SVM) (Ji et al., 2021), partial least squares regression (PLSR) (Boukria et al., 2023) and others can establish stable models by correlating several analytical variables with the nature of the analyzed objects and grouping samples with similar features. However, the process of analyzing fluorescence spectral data involves numerous variables and complex responses. These methods often involve a large number of calculations and make it difficult to achieve high-precision quantitative analysis. In contrast, deep learning offers advantages in terms of food safety and quality detection because of its higher precision, faster speed, and more flexible processing. Ahmed et al. (2020) utilized ResNet50 with fifty deep layers to extract image features from a pre-trained network to overcome the problem of insufficient training data. The algorithm achieved 87.3% accuracy in classifying watermelon seeds, which outperformed the traditional LDA and k-nearest neighbour algorithm (KNN). In another study, the long short-term memory (LSTM) was employed to predict protein and total volatile basic nitrogen (TVB-N) content in salmon fillets (Zou et al., 2024). In comparison to PLSR model, the LSTM model was highly accurate and showed better performance. Deep learning algorithms with more complex model structures can automatically learn features that provide higher classification accuracy and better generalization.

Deep learning is a powerful technique for data analysis and image processing. It is a subset of machine learning techniques that aims to build neural networks similar to those in the human brain to analyze and process huge amounts of data. Deep learning extracts image or data features automatically in a layered manner and then performs efficient classification, regression, and detection. Recent studies have indicated that deep learning algorithms can discover and learn patterns or regularities in raw data automatically. This technology optimizes models using a large amount of sample data, thus providing novel approaches and methodologies to address complex problems that cannot be addressed with traditional methods (Saha & Manickavasagan, 2021). Convolutional neural networks (CNNs), which are widely used in image processing, can automatically recognize the visual attributes of food products, including shape, texture, size, and location information (Itakura, Saito, Suzuki, Kondo, & Hosoi, 2018). LSTM models are capable of solving the problems of long-term dependence and gradient vanishing and have advantages in predicting time series data (Wu et al., 2021). In addition, SAE and transfer learning are commonly employed to create food quality monitoring models.

The use of Raman spectroscopy, visible and near-infrared spectroscopy, and Fourier transform spectroscopy with deep learning for food qualitative analysis and quantitative analysis (including fruits, grains, and crops) were reviewed in a general manner(Goyal, Singha, & Singh, 2024; Li et al., 2023; Qi et al., 2023). These reviews showed that deep learning has good performance and interpretability in spectral analysis. In other studies, the focus was placed on different types of deep learning models in food authenticity, shelf life prediction and food category recognition (Deng, Wang, Zheng, Zhang, & Yun, 2024; Zhang et al., 2023; Zhang, Yang, Lin, & Ying, 2021). However, despite the above reviews, no review is available on deep learning-assisted fluorescence spectroscopy for high-precision detection of food quality and safety. Therefore, we aim to provide a comprehensive review of research advances in the integration of deep learning methods with fluorescence spectroscopy for food quality and safety assessment. The search was conducted using the ISI Web of Science database for “deep learning”, “deep learning”, “fluorescence spectroscopy”, “food safety” and “food quality” in the “topic” field from 2014 to 2024. The high-dimensional nature of fluorescence data is highlighted through the analysis of food components and the challenges faced by fluorescence spectroscopy techniques in practical applications are identified. We then discuss the latest deep learning methods employed in food fluorescence analysis, describe their performance in handling fluorescence data, and detail the modelling process. We expect that this research will provide new insights into current food safety detection methods and provide trends for deep learning combined with fluorescence spectroscopy in the future, encouraging further research in the field.

2. Fluorescence spectroscopy

2.1. Principles of fluorescence spectroscopy

The concept of “fluorescence” was first introduced in 1852 by Storks, a British mathematician and physicist. In the presence of excitation light, certain fluorescent molecules or fluorophores in the samples absorb energy at specific wavelengths and subsequently emit energy in the form of light at higher wavelengths (Karoui & Blecker, 2011). This characteristic light produced in this process is called fluorescence, and the characteristic spectrum obtained is termed the fluorescence spectrum. The fluorescence properties of substances are reflected by fluorescence spectra. Based on the fluorescence energy and corresponding wavelengths of substances, fluorescence spectra are typically categorized into two basic types: excitation spectra and emission spectra. The excitation spectrum can be obtained by scanning the light source wavelengths while observing at a fixed wavelength by the emission device during the process of electronic transitions in the excited state (Dankowska, 2016). Usually, within 10^{-8} s after excitation, the electrons return to the stable ground state. The emission wavelength is generated based on the energy difference between electronic states, and these specific emissions form the emission spectrum, which is crucial in food analysis (Pandiselvam et al., 2022). The fluorescence properties of substances are reflected by fluorescence spectra. Different substances in food samples exhibit distinct fluorescence effects. Substances that produce fluorescence are usually characterized by a conjugated structure with aromatic properties and a rigid molecular backbone (Fig. 1), such as polycyclic aromatic hydrocarbons, heterocyclic compounds, and some highly unsaturated aliphatic compounds (Sikorska, Khmelinskii, & Sikorski, 2019).

2.2. Types of fluorescence spectroscopy

As a highly selective and sensitive analytical technique, fluorescence spectroscopy provides a powerful tool for the qualitative and quantitative analysis of food: it utilizes the fluorescence emission produced by a

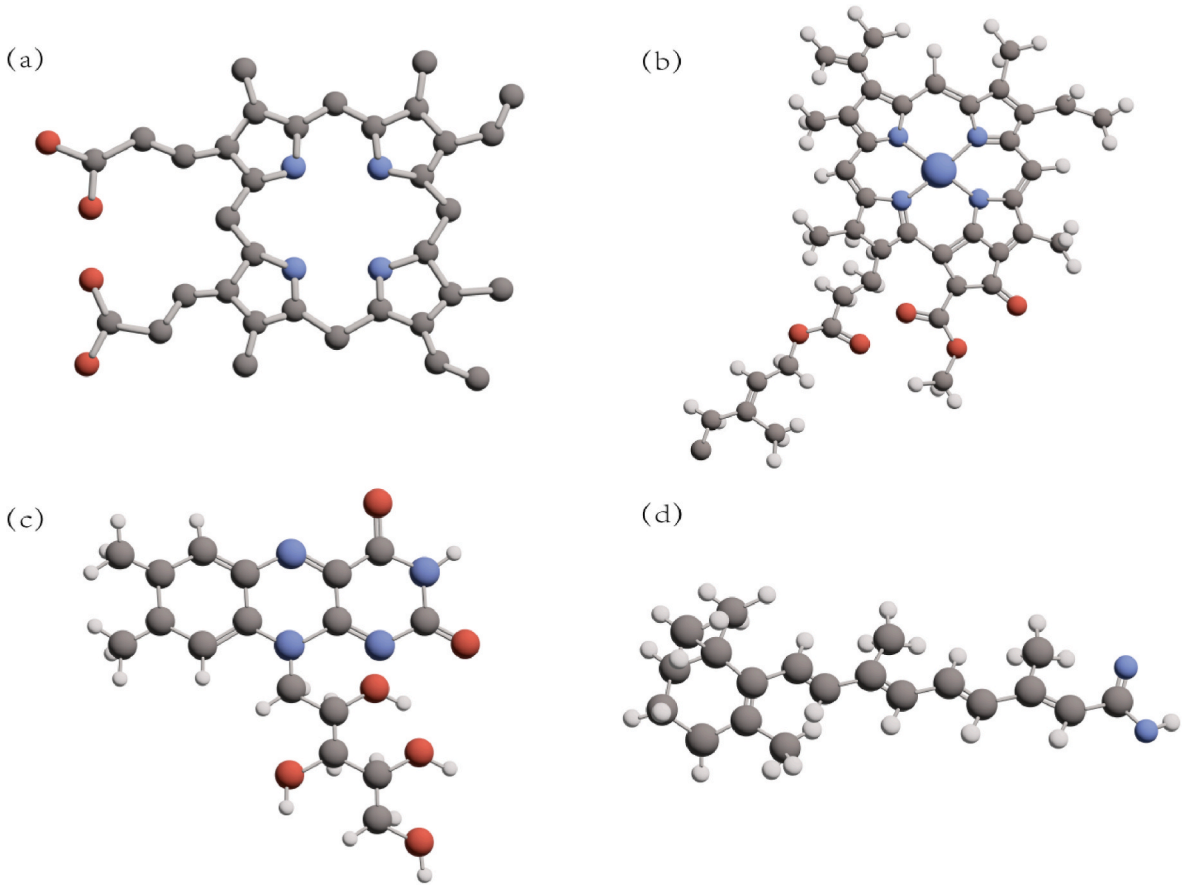


Fig. 1. Several fluorescent substances with conjugated structures and rigid molecular frameworks. (a) Porphyrin. (b) Chlorophyll *a*. (c) Vitamin B_2. (d) Vitamin A.

substance under the incidence of excitation light to obtain information about the characteristics of the sample. Conventional fluorescence spectroscopy techniques cannot be applied to the quantitative analysis of complex food products because simple excitation light sources and detectors are used. With the increasing number of studies on fluorescence, new fluorescence analysis techniques are constantly being introduced. Three-dimensional fluorescence spectroscopy (3DFS), front-face fluorescence spectroscopy (FFFS), synchronous fluorescence spectroscopy (SFS), multi-spectral fluorescence imaging (MFI), and fluorescence hyperspectral imaging (FHSI) are specifically introduced to address the complexity of analyzing real samples.

2.2.1. *Three-dimensional fluorescence spectroscopy*

3DFS is a relatively new fluorescence technique developed in recent decades, also known as the excitation-emission matrix (EEM). It represents the overall characteristics of samples within a selected wavelength range through three-dimensional projection or contour spectrum plots (Fig. 2 (a)). It depicts the relationship between fluorescence intensity and variations in excitation and emission wavelengths and provides a comprehensive description of fluorescent material features (Wang X. et al., 2023). The advantages of 3DFS lie in its ease of operation, rapid measurement and the absence of sample pretreatment requirements, thus preserving the integrity of food samples while achieving rapid analysis. In addition, the three-dimensional data generated by 3DFS contain rich information. Compared with two-dimensional fluorescence spectra, 3DFS is more applicable to the study of fluorescence changes in dynamic processes with the addition of a time dimension, such as enzyme activity and bio-molecular dynamics studies.

2.2.2. *Front-face fluorescence spectroscopy*

FFFS is a rapid, sensitive and nondestructive technique that illuminates samples at a special incident angle. As shown in Fig. 2 (b), the molecules on the surface of the samples emit fluorescence at a specific wavelength after the excitation light is irradiated, which is captured by the light collection system. The collected fluorescence signals are transmitted to a detector and finally analyzed and processed with computer software. This method primarily measures the fluorescence emitted from the surface of a sample and provides a spectral characteristic of the sample within seconds, thus reducing the impact of internal light filtering effects. In addition, this method enables the analysis of a wide range of foods without requiring chemicals or time-exhausting sample preparation processes (Liu, Zamora, Castillo, & Saldo, 2018). Numerous studies have shown that FFFS can distinguish various cereal products, and it has been used for the inter-facial characterization of oil-in-water emulsions to predict changes in the quality of milk. In addition, combining FFFS with chemometric tools enables monitoring of the oxidation status of various soft and hard cheeses throughout the maturation process (Karoui, Dufour, & De Baerdemaeker, 2007).

2.2.3. *Synchronous fluorescence spectroscopy*

Traditional fluorescence spectroscopy techniques often rely on the measurement of a single emission or excitation spectrum, which is insufficient for analyzing complex systems. In contrast, SFS allows for the simultaneous scanning of excitation and emission wavelengths while maintaining a constant wavelength difference between these two wavelengths. When the concentration of a substance remains constant, the intensity of the synchronous fluorescence signal is directly proportional to the product of the excitation and fluorescence emission spectrum signals. SFS is a powerful method for analyzing complex food matrices by narrowing the spectral band and obtaining information from multiple fluorophores rather than a single fluorophore (Wu et al., 2021). This technique has been extensively applied in the detection and

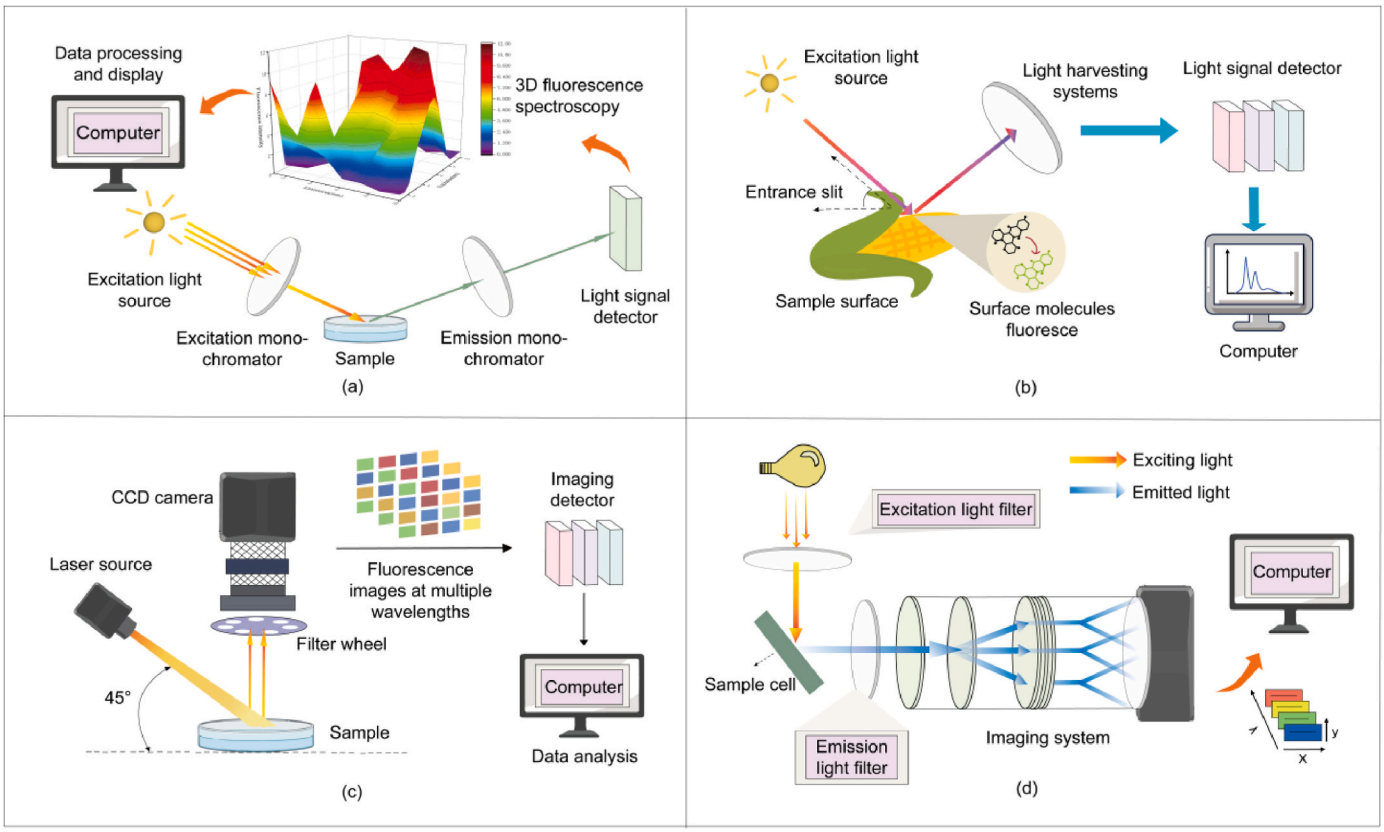


Fig. 2. Schematic diagram of fluorescence spectrum analysis technology. (a) Schematic diagram of three-dimensional fluorescence spectroscopy technology. (b) Schematic diagram of front surface fluorescence spectroscopy. (c) Schematic diagram of multi-spectral fluorescence imaging. (d) Fluorescence hyperspectral imaging schematic.

analysis of various foods, such as meat, edible vegetable oils, juices, and beers (Rodrigues et al., 2020).

2.2.4. *Multidimensional fluorescence spectroscopy*

Currently, a variety of automated imaging detection techniques and systems have been employed for food safety inspection, such as MFI and FHSI (He et al., 2022; Zhou, Sun, Tian, Yao, & Xu, 2022). As shown in Fig. 2 (c), a MFI system includes an excitation light source, an optical transmission assembly, a fluorescence signal collection system and a signal detection device. The purpose of MFI is to acquire spatial and spectral information at multiple key wavelengths. As an emerging technology, the MFI has been applied in different research fields, including bio-medicine, in recent years. Owing to the complex chemical composition of actual samples, identifying different components solely from monochrome images may not be accurate. However, the discriminatory ability may be increased if images at multiple wavelengths can be recorded. Seo et al. (2019) proposed a MFI system utilizing two band ratios for on-line implementation of poultry fecal residues. This study demonstrated the potential utility of MFI for food safety inspection. Fluorescence visualization also has important applications in food safety detection. A multi-probe-based MFI has been developed for odor identification and visualization studies (Yoshioka, Liu, & Hayashi, 2015).

2.2.5. *Fluorescence hyperspectral imaging*

Fluorescence combined with image analysis can be a very powerful tool. Frequently, the spectral reflectance characteristics of samples in relation to wavelength variations can be exceedingly intricate, and other minor features may not be resolved with coarser MFI methods. FHSI technique integrates hyperspectral imaging techniques with fluorescence microscopy (Fig. 2 (d)) to provide information about fluorescent components and their localization in food samples by exploiting fluorescence properties (Zhou, Zhao, Sun, Cheng, & Xu, 2024). With its broader spectral bands, FHSI enables the precise acquisition of more intricate fingerprint features through higher spectral resolution.

A hyper-spectral fluorescence image is a three-dimensional form of a spectrum that includes a two-dimensional spatial image and a three-dimensional fluorescence spectral image. This technique can simultaneously produce spatial and fluorescence spectral information from each pixel position within a sample. FHSI synthesizes the merits of hyperspectral imaging and fluorescence spectral techniques and addresses the problems of ordinary hyperspectral technology, such as inconspicuous peaks, noise interference and slow speed (Chun et al., 2024). Recent studies have investigated the efficacy of FHSI in assessing the quality and safety of food and agricultural products. Fu and Wang (2022) utilized FHSI for the detection of early abrasions in crown pears and concluded that it has certain feasibility in the detection of early damage in fruits. Lee, Kim, Lee, and Cho (2018) demonstrated a positive correlation exists between fluorescence intensity and the total volatile basic nitrogen (TVB-N) in pork, thus indicating the potential of FHSI in predicting TVB-N levels.

3. Limitations in the application of fluorescence spectroscopy for food detection and analysis

3.1. *Complex fluorescence spectral data*

Fluorescence spectroscopy can reflect the molecular structure and unique fingerprint information of compounds inherent present in samples. Under ideal analytical conditions, the fluorescence intensity of the emitted light is directly proportional to the excitation light and correlates directly with the substance's concentration (Fu et al., 2022). However, in practical sample analysis, the fluorescence characteristics

of substances are often influenced by various endogenous (molecular structure and properties) and exogenous factors (solvent, pH, temperature, and surfactant) (Table 1). As a result, the fluorescence spectroscopic data often exhibit complexity. In cases where the concentration of fluorescent molecules is high, the light intensity of analyzed objects can be mixed with fluorescence emitted by other fluorescent components or absorbed by other fluorescent or non-fluorescent components (internal filtering effect of spectra) (Wang, Zeng, & Li, 2017). This nonlinear relationship between the fluorescence intensity and fluorophore concentration hinders the application of the linear model. Fluorescence spectroscopy data is also typically high-dimensional, with each sample containing hundreds to thousands of features representing fluorescence intensity at different wavelengths. This high-dimensional feature space complicates data analysis and modelling. Additionally, spectral differences caused by noise and baseline drift pose additional challenges in the analysis and processing of fluorescence spectroscopy data.

3.2. Limitations of traditional machine learning models

The complexity of fluorescence spectra poses challenges in data analysis and modelling, which require the application of appropriate methods and techniques for processing and interpretation. Traditional machine learning models require manual design and manual selection of features to be provided to the model for training and have limitations in dealing with nonlinear, high dimensional and time series data (Zou et al., 2024). Linear regression and logistic regression are modeled linearly based on the linear relationship between the response signal of the target component and its concentration, which enables qualitative or quantitative analysis of the target component (Goyal et al., 2024). However, they depend on the distribution pattern of the data excessively and have limited ability to model non-linear data (Brandao, Neto, dos Anjos, & Bell, 2017). LDA and partial least squares-discriminant analysis (PLS-DA) can handle the data multicollinearity problem better, but may not work well for high-dimensionality and non-linearly differentiable datasets (Dramićanin, Lenhardt Acković, Zeković, & Dramićanin, 2018; Boukria et al., 2023). Fu et al. (2022) analyzed the interaction between excitation light and multiple components through mixture experiment, and indicated that fluorescence overlapping and the quenching due to mutual absorption have significant nonlinear effects on quantitative fluorescence analysis. In this case, the method of linear analysis is no longer valid. Nonlinear models such as soft independent modeling of class analogy (SIMCA), decision tree (DT), SVM and K-nearest neighbour (KNN) are sensitive to outliers and complex to calculate though they have the ability to solve nonlinear problems (Qiu et al., 2024; Suhandy & Yulia, 2018). SVM works on mapping raw data to a high dimensional feature space using a kernel function so that they can be correctly classified in the hyperplane (Ji et al., 2021). The KNN algorithm is a widely used pattern recognition method that calculates the distance between unknown samples and samples in a predefined training set (Qiu et al., 2018). These nonlinear models are effective when dealing with high-dimensional spaces, but their performance is limited when faced with too large a number of samples or too similar features, and it is particularly difficult to capture potential features in unstructured information such as images and text (Deng et al., 2024). Table 2 specifically describes the performance differences between machine learning and deep learning methods. These limitations result in the limited performance of traditional machine learning models in processing fluorescence spectroscopy data, making it difficult to achieve high prediction accuracy and generalizability.

However, the employment of deep learning methods offers solutions to these challenges. The advent of deep learning (especially convolutional neural networks) has allowed for sensitive and fast capture of image information and automatic extraction of features from the input without manual selection (Sun et al., 2022). The trained weights of CNN models can also be saved and reused on new datasets without the need to retrain the model (Gorji et al., 2022). In contrast to traditional machine learning algorithms, deep learning models can handle nonlinear relationships and complex structures in fluorescence data more flexibly through the augmentation of network depth (Ahmed et al., 2020). Powerful computer technology also supports efficient large-scale parallel computation for deep neural network models. These advantages give deep learning models stronger modelling ability and prediction performance in fluorescence spectral analysis, helping them to analyze and interpret complex features and information in fluorescence spectroscopy data more accurately.

Table 1
Factors affecting fluorescence characteristics (including endogenous and exogenous).

Influence factors	Sample	Instruments	Test objects	Reference
Molecular structure	Cantal-type cheese	FluoroMax-4 spectrofluorimeter	Protein and fat	Loudiyi et al. (2017)
	Milk	Horiba fluorolog standard fluorescence spectrophotometer	Riboflavin	Pandey and Joshi (2021)
	Rice	MW-GX-375 optical fiber coupler laser	Aflatoxin	Wang B. et al. (2023)
	Milk	F-4500 FL Spectrophotometer	Quantify penicillin G (PG), sulfadiazine (SF), tetracycline (TC)	Ntakatsane et al. (2020)
Internal filtration effect	Coffee, tea, energy drink	Jasco FP 6500 spectrofluorometer	Caffeine (CF), glibenclamide (GLB)	González, Corral, Zanini, Montejano, and Acebal (2020)
pH	Cantal-type cheese	FluoroMax-4 spectrofluorimeter	Protein and fat	Loudiyi et al. (2017)
	/	Fluoromax-4 commercial fluorescence spectrometer	Acridine analog, 9-acridinecarboxylic acid	Zhou, Zhao, Chen, and Zhang (2022)
Temperature	Soya bean	Fluorpen Z995-PAR	Chlorophyll	ul Huda, Mansha, Asim, and Shahzad (2022)
	Green pepper	Fluoro-spectrophotometer (Jasco Spectrofluorometer FP-8300)	Flavonoids substances	Fatchurrahman et al. (2020)
Solvent	DPEPO, DMAc-MPM, DMAc-PPM,	Fluorescence Spectrometer FLS-920	Chloroform (CF), chlorobenzene (CB)	Wang S. et al. (2023)
	Choline chloride/urea, choline chloride/glycerol and choline chloride/thiourea DESs	TEM (MC30 Philips), Vertex 70 FT-IR, Varian Cary 300 Bio, Cary eclipse and energy dispersive X-ray spectroscopy (EDS) (MIRA II TESCAN)	Carbon dots (CDs)	Tabaraki and Nazari (2023)
Surfactant	Hyaluronan	FluoroCube Horiba Scientific TCSPC spectrometer	Cetyltrimethylammonium bromide (CTAB), Septonex	Holinkova, Mravec, Venerova, Chang, and Pekar (2022)
	Galangin (Gal), baicalein (Bai), hemoglobin (HB)	F-7000 Spectrophotometer	Sodium taurodeoxycholate (NaTDC)	Kong et al. (2023)

Table 2
Performance differences between machine learning and deep learning methods.

	Algorithm	Theory	Benefits	Limitations	References
Machine learning	Linear regression (LR)	It aims to find a linear relationship between eigenvalues and target values.	A simple and fast algorithm that easy to explain and understand.	Sensitive to anomalies and fails to capture nonlinear relationships.	Brandao et al. (2017) Tang, Shen, Shao, Si, and Dong (2024)
	Logistic regression (LR)	The probability of an event through modeling of log odds functions is estimated.	Strong interpretability for linearly separable data.	Sensitive to noise and assumes a linear relationship.	Ropelewska et al. (2022)
	Linear discriminant analysis (LDA)	A linear classification method that aims to find one or more linear functions of the input variables, which are then used to categorize samples.	Computationally efficient and easy to interpret.	Highly dependent on the distribution pattern of the data and sensitivity to outliers.	Dramićanin et al. (2018)
	Partial least squares regression (PLSR)	It considers both independent and dependent variables to find latent variables (components) that can be used to model the relationship between the independent and dependent variables.	Handling multicollinearity for high-dimensional data.	Poor interpretability and need for adequate sample size.	Boukria et al. (2023) Brandao et al. (2017) Ji et al. (2021)
	Partial least squares-discriminant analysis (PLS-DA)	A supervised discriminant statistical method mainly used to deal with classification and discriminant problems.	Suitable for small samples and able to deal with multicollinearity.	Prone to overfitting and poor interpretation.	Boukria et al. (2023)
	Soft independent modeling of class analogy (SIMCA)	A supervised pattern recognition technique in which an individual PCA sub-model is created for each class and its boundary is calculated.	Dimensionality reduction, classification and anomaly detection of data.	Sensitive to outliers and complex to calculate.	Suhandy and Yulia (2018)
	Decision tree (DT)	It achieves the prediction and classification of data by building multiple decision trees and combining them into a “forest”.	Understandable and easy to visualize.	Prone to overfitting and sensitive to noise.	Qiu et al. (2024)
	K-nearest neighbour (KNN)	It calculates the distances between an unknown sample and the samples in the predefined training set.	A simple model that requires no assumptions and applies to multiple categories.	Sensitive to noise and high computational complexity.	Facci, Cezário, de Gois, Luna, and Pacheco (2021) Qiu et al. (2024)
	Support vector machine (SVM)	The model is classified by finding an optimal hyperplane that maximizes the distance from the support vectors to the hyperplane and improves the generalization of the model.	Suitable for high-dimensional data with powerful classification capabilities.	Sensitive to parameter settings and unsuitable for large data sets.	Facci et al. (2021) Ji et al. (2021) Qiu et al. (2024)
Deep learning	Convolutional neural network (CNN)	Extension of neural networks with hierarchical feature learning capability to handle complex nonlinear relationships.	Extract the deep features of images automatically.	Require large-scale data for learning to prevent overfitting.	Fan et al. (2024) Venturini et al. (2023) Wu et al. (2020) Yan et al. (2023)
	Long short-term memory (LSTM)	It is designed to solve the problem of vanishing or exploding gradients encountered by traditional RNNs when processing long sequences.	Long-term dependencies in data can be better captured.	Time-consuming calculations that require multiple iterations.	Fan et al. (2024) Wu et al. (2021) Zou et al. (2024)
	Auto encoder (AE)	It learns features from the input images and simplifies the data by reconstructing the image with encoders and decoders.	Ability to capture nonlinear relationships in the data and strong flexibility.	Requires large amounts of data for training and is highly influenced by hyperparameters.	Yan et al. (2024) Yu et al. (2021) Zhou X. et al. (2022)

4. Construction of the analytical process: deep learning-assisted fluorescence spectroscopy

Deep learning is pivotal in detecting and ensuring the quality and safety of food. Its powerful pattern recognition and feature learning capabilities enable it to efficiently process complex fluorescence spectral data, thus revealing potential issues in food quality. The following sections will be devoted to a detailed description of the various deep learning models and the modelling process (Fig. 3).

4.1. Preparation and preprocessing methods for fluorescence spectral data

Accurate and reliable detection of food quality and safety depends on high-quality sample data. The selection and preparation of samples, as well as the environment and conditions of the experiment, are crucial factors in capturing high-quality data. First, the sample chosen must be both representative and complete. It should encompass a diverse spectrum of variability concerning various quality attributes, levels of adulteration and potential contaminants, thus safeguarding the integrity of data in model development (Goyal et al., 2024). In addition, the size of the datasets significantly influences the development of the model. Before model training begins, the input data are usually divided into different subsets for model training, testing and validation (Kahloot & Ekler, 2021). These datasets should be as comprehensive as possible. The accuracy increases with the size of the datasets. However, the accuracy will no longer increase significantly after a certain point because of the information redundancy contained in training samples (Feng, Wu, Zhu, He, & Zhang, 2021). In practical applications, the hold-out method (Qiu et al., 2018) and cross-validation are recommended to increase the dependability and replicability of spectroscopic data. The error is reduced, and the model performance is improved through datasets augmentation.

Recently, several data preprocessing methods have been developed, including noise reduction, baseline correction, and outlier removal. Baseline drift is usually unrelated to the components of the food and needs to be removed first before training. Common baseline correction algorithms include the local median, polynomial fitting, asymmetric least squares and iterative polynomial fitting methods (Pan, Zhang, Daengngam, Peng, & Chongcheawchamnan, 2022). These algorithms can augment the visibility of spectral attributes and expedite accurate measurements of absorption or emission intensities. Common noise reduction methods include Gaussian smoothing, moving average, the Savitzky-Golay (SG) algorithm and wavelet transform. These methods can eliminate minor noise impacts, enhance the clarity of spectral features, and streamline identification and analysis processes (Zareef et al., 2020). In addition, to avoid interference from Rayleigh scattering,

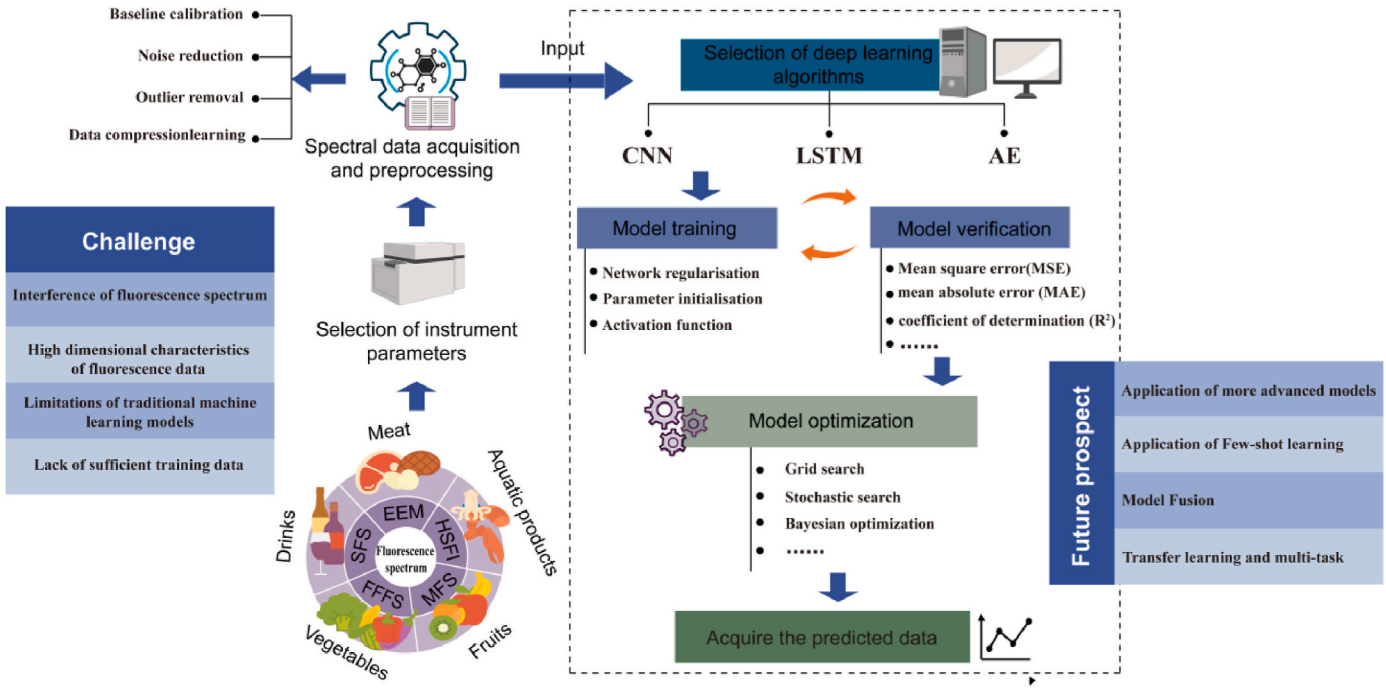


Fig. 3. Analytical process of deep learning-assisted fluorescence spectroscopy in food quality and safety detection.

methods such as blank subtraction and the insertion of missing values are also commonly used as preprocessing steps with fluorescence spectral data.

4.2. Feature selection and extraction

The original fluorescence data generate redundant information and noise, and the abundant information provided by high-resolution images in particular may lead to a decrease in classification accuracy (Zhao & Du, 2016). Therefore, feature selection and extraction are required before further analysis. Principal component analysis (PCA), independent component analysis (ICA), k-means clustering algorithms and parallel factor analysis (PARAFAC) are commonly employed for dimensionality reduction (Gu et al., 2020; Liu, Pu, & Sun, 2021). PCA retains only the principal components with high variance in the data during dimensionality reduction, which leads to loss of data information and poor capture of nonlinear relationships (Beattie & Esmonde-White, 2021). K-means clustering analysis makes the data points within each cluster as similar as possible by dividing the data into K clusters, while the data points between different clusters are more different (Shan et al., 2018). Xu et al. (2023) had employed the k-means clustering algorithm and the eigenvalue extraction method based on PCA to identify the protein samples. The k-mean clustering algorithm will pose a challenge to the differentiation of protein samples when the algorithm involves an unknown number of protein clusters. PARAFAC is a flexible and multi-dimensional fluorescence data processing technique that captures complex linear relationships in fluorescence spectra. Yan, Peng, and Ma (2019) proposed an improved method combining ICA and PARAFAC, which is effective in reducing noise in both spatial and spectral dimensions simultaneously. However, the difficulty of manual parameter tuning gradually increases as the data dimension increases. Deep learning can be utilized to identify different fluorescence components or features automatically during the analysis of fluorescence spectral images through stepwise learning at the levels of convolution, pooling, and activation functions (Banan, Nasiri, & Taheri-Garavand, 2020). Additionally, structures such as AE and generative adversarial networks (GAN) in deep learning can be utilized for unsupervised feature learning and data augmentation, which can help analyze and interpret complex spectral data more accurately (Kärkkäinen & Hänninen, 2023). Recently, a deep learning method based on wavelet transform and stacked denoising auto encoder (SDAE) was proposed (Zhou et al., 2023). The SDAE can learn the hidden features of fluorescent data by performing encoding and decoding operations on the input data. A generative adversarial network is a model that consists of two parts: a generator and a discriminator. The generator performs nonlinear mapping through multiple hidden layers to generate data, whereas the discriminator aims to determine the origin of the generated data from the real data (Zhang, Gong, Mao, Li, & Wu, 2018). This adversarial process allows the generator to learn the real probability distribution of the datasets and thus obtain high-quality data.

4.3. Deep learning methods for classification and regression

4.3.1. Convolutional neural network

In recent food studies, the CNN has emerged as a predominant tool because of its effectiveness and promise. CNN is considered the most popular architecture in deep learning, with powerful feature learning ability and good generalizability (Liu et al., 2021). The fundamental components of a CNN encompass the input layer, convolutional layers, pooling layers, fully connected layers and an output layer (Venturini et al., 2023). The input is usually a multichannel image or other form of gridded data. After a series of convolution and pooling operations, the CNN ultimately achieves effective classification or regression of the input data. The convolutional layer is the core composition, which contains multiple convolutional kernels, and generates lower-dimensional feature maps by calculating the dot product between the convolutional kernel entries and the input array (Fig. 4 (a)). In spectral data analysis, the pooling layer is able to reduce the dimensionality of the data while retaining essential peaks or spectral features in the spectrum. In contrast, the fully connected layer integrates the spectral characteristics derived from the convolutional and pooling layers and utilizes both linear and nonlinear transformations to produce the final output of the network. Activation functions are capable of performing nonlinear transformations in neural networks; thus, they are essential for the performance of the whole network. Commonly employed activation functions in CNNs include linear rectification

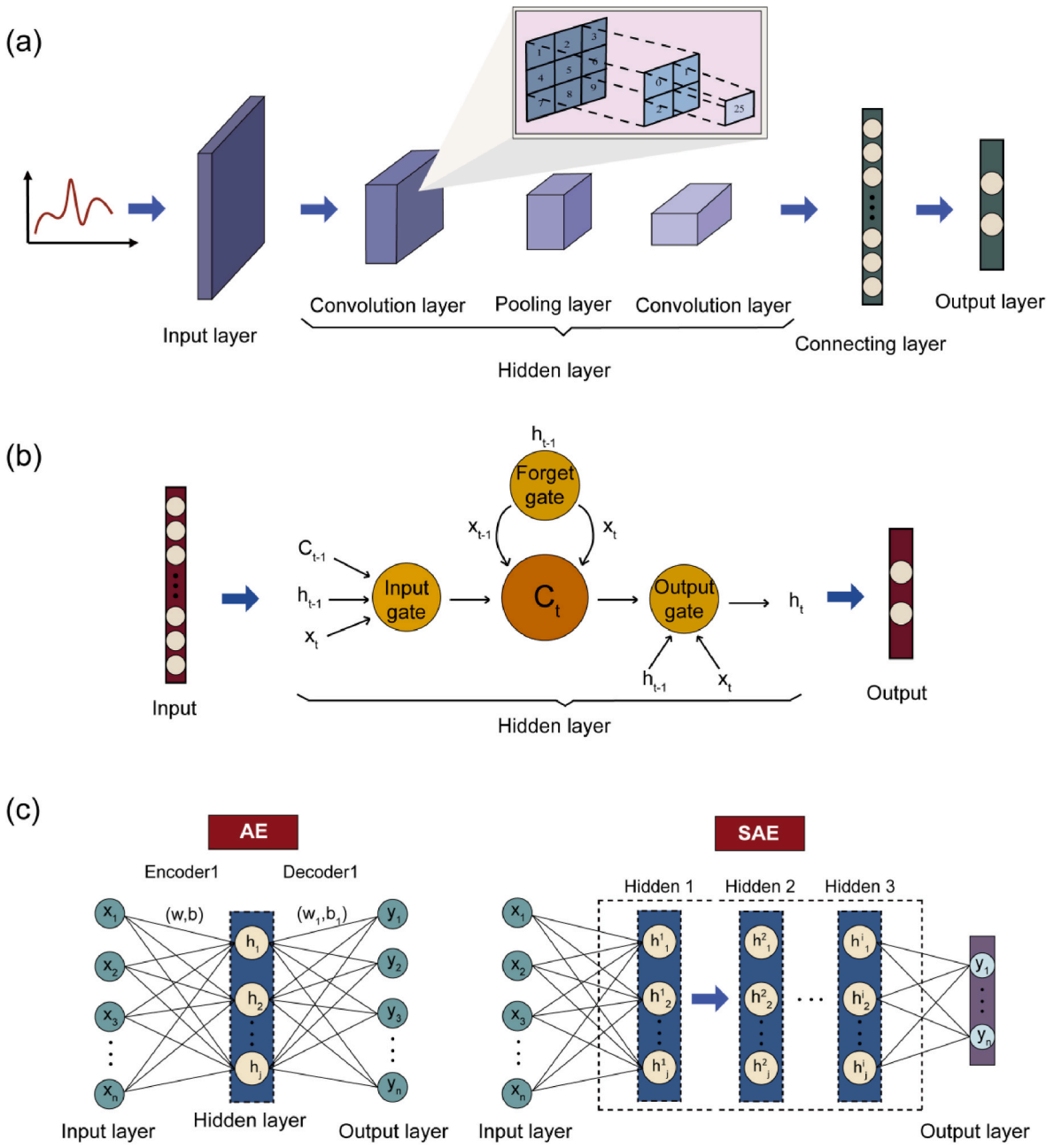


Fig. 4. Some structural examples of deep learning models. (a) The architecture of the CNN model. (b) The architecture of the LSTM. (c) The architectures of the AE and SAE.

function (ReLU), sigmoid, Tanh, and others (Wang, Ren, & Wang, 2022). Among these methods, the ReLU function stands out as one of the most extensively utilized activation functions:

$$f(x) = \max(0, x)$$

The sigmoid and tanh functions often cause the gradient to disappear because the values in backpropagation are too small. In contrast, ReLU functions can avoid the vanishing gradient problem and have a faster convergence rate (Szandała, 2021). However, when the input is on the negative half of the X-axis, some neurons are inactivated. To address this problem, researchers have introduced an improved function named leaky ReLU. The mathematical expression of this function is formulated as follows:

$$f(x) = \begin{cases} \alpha x, & x < 0 \\ x, & x > 0 \end{cases}$$

α is usually a small constant set by humans. According to the formula, ReLU can avoid the situation where the output of neurons is always zero.

The CNN can reduce the spatial dimension of the input data while retaining important features with good robustness in analyzing complex food components. However, it requires large datasets to be trained for a longer period of time. Some researchers believe that using migration learning in CNN models can speed up training and improve generalizability.

4.3.2. *Long short-term memory*

The LSTM model belongs essentially to the Recurrent Neural Network (RNN), which can effectively process and predict sequential data (Chen, Guo, Zeng, & Zhang, 2023). LSTM can be used to recognize different spectral signals in a spectral classification task. Structurally, the recurrent neural network has the capability to remember previous

information and use it to influence the output of subsequent nodes. In other words, the nodes within the hidden layers of the RNN are interconnected. The input to the hidden layer includes not only the output from the input layer but also the output from the previous time step of the hidden layer. However, the simple recurrent neural network may lose the ability to learn information that is far away when the text interval between the current predicted position and the relevant information is increasing. LSTM is a special network structure with three gates, including an input gate, a forgetting gate, and an output gate (Fig. 4 (b)). The input gate is capable of receiving input data at the current moment and determining the amount of information to store or pass by outputting a value between 0 and 1 via a sigmoid function. If the input is 1, it indicates that the new information should be completely retained; if the input yields 0, it denotes that the new information should be completely ignored. The forget gate controls the information in the memory cells from the previous moment and determines whether this information needs to be forgotten. Finally, the output ht is determined on the basis of the latest state c_t, the output h_{t-1} of the previous moment, and the current input x_t (Wu et al., 2021). In conclusion, LSTM addresses the issue of gradient vanishing in traditional RNNs through introducing three gates to control the flow and retention of information and is better able to address long sequences. Because of their good memory performance and sensitivity to time series, LSTM models have been applied to water quality prediction (Wu & Wang, 2022) and temperature prediction for grain silos (Ge & Chen, 2021).

4.3.3. Auto encoder

The AE is a powerful unsupervised learning model that performs data reduction and compression by reconstructing the input data (Kärkkäinen & Hänninen, 2023). The AE model aims to encode and decode data via a structure comprising an input layer, a hidden layer and an output layer (Fig. 4 (c)). Its core idea is to take the hidden layer output of the previous AE as the input of the next AE, thus extracting more abstract features layer by layer. The SAE is one of the more popular models used for fluorescence spectral analysis; it builds a deep neural network structure by connecting multiple AEs together (Zhou X. et al., 2022). This stacking approach greatly reduces the training time and improves the expressive power of the model. In the process of food testing, most samples are unlabeled. However, supervised learning methods typically rely on labeled samples for training, which limits their ability to exploit the feature and category information contained in unlabeled samples (Lai, Wang, Xiang, Quan, & Song, 2023). AEs can learn effective features from unlabeled spectral samples and have more extensive applicability compared with supervised learning methods. The conventional AE ignores the neighbourhood features of the image, and it performs a nonlinear transformation on the data with no specific constraints on the hidden variables generated by the encoding. By imposing additional constraints on the auto encoder, new deep learning methods can be obtained, such as the denoising auto encoder (DAE), variational auto encoder (VAE), and SAE (Chen et al., 2017). Currently, researchers have integrated CNNs with SAEs and designed a convolutional structure to preserve the neighbourhood features of fluorescence images, which is beneficial for analyzing low-concentration substances in complex backgrounds (Yu et al., 2021).

4.4. Model training

The purpose of model training is to minimize the discrepancy between actual and predicted values by varying the weights and biases iteratively. The training process requires multiple rounds of iterations. In each iteration, the performance of the model is evaluated by computing its loss function and accuracy so that it can be adjusted and optimized accordingly. The steps to establish a deep learning model based on fluorescence spectral data are shown in Fig. 3. Local calibration methods improve the robustness of the model by optimizing the distribution of the calibration subset with uniform samples (Luo et al., 2018). Global methods are available for the simultaneous exploration of multiple directions to search for optimal values. Furthermore, global optimization methods have the potential to locate global optima across robust error surfaces in a single run (Du et al., 2023). However, achieving this capability often necessitates significant effort and the determination of algorithmic parameters to increase performance. Various methods, such as network regularization, parameter initialization and activation function selection, are commonly employed during actual model training to accelerate network convergence and achieve more robust results. The training process of neural networks involves the automatic adjustment of parameters within the network. At the beginning of training, the parameters of the network need to be set from a certain state, which is known as neural network initialization (Scardapane, Comminiello, Hussain, & Uncini, 2017).

4.5. Optimization of hyper-parameters

The optimization of hyper-parameters is a key process in deep model training (Table S1). Common hyper-parameter optimization methods include grid search (Jiang & Xu, 2022) and stochastic search (Huber et al., 2021). Chegeni, Rashno, and Fadaei (2023) proposed a convolutional parameter optimization method for CNNs called CPOCNN. This was the first optimization model that assigned an upper bound on the adaptive convolutional parameters to reach the output layer based on the data dimensions of the current layer and the number of remaining layers, which improved the accuracy by more than 35%. However, CPOCNN can only optimize CNN with constant block structure and only optimizes the parameters in the convolutional layer. Bayesian optimization is increasingly popular because of its ability to handle complex objective functions such as multi-modal and non-convex functions (Shapiro, Zhou, & Lin, 2023). Bayesian optimization aims to fit the relationship between hyperparameters and model evaluation with various proxy functions and finally arrive at the best combination of hyper-parameters. This optimization method provides posterior probability distributions for parameters, thus helping explain why parameters are selected or excluded during the optimization process (Yang, Liu, & Wen, 2024). An enhanced Bayesian optimization method using the Gaussian process was proposed to estimate the distribution of Bayesian posterior probabilities accurately while reducing the computational cost (Zou, Cao, Zhou, & Gu, 2020).

4.6. Model performance evaluation

Model performance is evaluated and compared via various metrics, including the root mean square error (MSE), mean absolute error (MAE), coefficient of determination (R^2), accuracy, precision, and recall (Shi et al., 2022). The following are the precise formulations for these criteria:

$$MSE = \frac{1}{\mathrm{m}} \sum_{i=1}^{m} (X_E - X_P)^2 \tag{1}$$

$$MAE = \frac{1}{m} \sum_{i=1}^{m} |X_E - X_P| \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m} (X_E - X_P)^2}{\sum_{i=1}^{m} (X_E - \overline{X})^2} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN} \tag{4}$$

where m is the sample number, X_P represents the predicted value, and X_E signifies the actual value. Additionally, *TP*, *TN*, *FP* and *FN* represent true positive, true negative, false positive and false negative, respectively.

5. Application of deep learning-assisted fluorescence spectroscopy in food quality and safety analysis

Deep learning-assisted fluorescence spectroscopy analysis has been applied to the quality and safety testing of food and to the identification and classification of food products (Table 3). According to recent studies, food safety testing involves the identification of pesticide residues, heavy metals, contaminants and pathogenic bacteria. The main concerns in food quality testing are the internal structure, physiological information, and chemical quality indicators (acidity, peroxide, ethyl ester). Food adulteration recognition and food authentication are also important parts of the application.

5.1. Food safety detection

5.1.1. Pesticide residue detection

At present, pesticides are widely used in agricultural production to protect crops and increase yields (Wang Z. et al., 2022). Different kinds of highly toxic pesticides are used on crops, resulting in excessive drug residues in crops. Therefore, pesticide residue testing is critical to ensure food safety and to protect consumer health. Wang X. et al. (2023) detected and classified mixed pesticides with 3DFS and a modified CNN model structure based on the classical LeNet5, which is a classic CNN type for image processing with two convolutional layers, two pooling layers and three fully connected layers. The modified CNN model selected ReLU as the activation function and set the first convolutional layer with 6 convolutional kernels and the second convolutional layer with 12 convolutional kernels, which demonstrated the best performance and achieved 100% accuracy. Another study proposed a model consisting of a one-dimensional CNN backbone and a random forest (RF) classifier to recognize pesticide residues on black tea (Sun et al., 2022). The backbone of the 1D CNN extracted features from the input data, and then classified them with an RF classifier. Through comparing with other models (SVM, RF and 1D CNN), the performance of the proposed 1D CNN-RF model (90.05%) is superior with an accuracy of 90.5%. The above studies confirmed that CNN-assisted fluorescence spectroscopy technology has a broad application prospect in the field of pesticide residue detection.

5.1.2. Heavy metal detection

Heavy metals in food, such as Pb, Cs and As, generally originate from soil and water, and sometimes from food processing, storage and transportation. Excessive levels of heavy metals in food can cause serious risks to human health. The deep learning combined with fluorescence hyper-spectral technology has great potential for heavy metal detection in crops. A deep learning approach that based on wavelet transform (WT) and SDAE model was proposed to predict the lead content in oil seed rape leaves using FHSI (Zhou et al., 2023). The WT-SDAE proposed in this study utilized the WT algorithm to achieved the decomposition of fluorescence spectral data and SDAE was used to obtain the deep features under the optimal wavelet decomposition layer from the oil seed rape leaf images with three steps of contamination, encoding and decoding. The model was successfully used for the prediction of lead content in oil seed rape leaves. Zhou, Zhao, Chen, and Zhang (2022) utilized a modified Monte Carlo optimized wavelet transform stacked self-encoder (WT-MC-SAE) as a fluorescence spectral deep feature extractor to capture the features of 7 lead-contaminated fluorescence images of lettuce leaves and achieved good classification performance ($R^2 > 0.9$). The team also employed a deep migration learning model based on stacked convolution auto-encoder (SCAE) to predict lead content in oil seed rape leaves in silica-free and silica environments, which achieved excellent predictive results with R^2 of 0.9374, root mean square error (RMSEP) of 0.02071 and residual predictive deviation (RPD) of 3.268 (Zhou et al., 2024).

5.1.3. Contaminant and pathogen detection

Because of their fragile epidermis, some crops are susceptible to be infected by various contaminants and pathogens, which can cause economic losses. Deep learning has also been used for the detection of various contaminants and pathogens in foods. In a previous study on strawberry grey mould identification, FHSI was applied to establish a 1D-CNN model based on ResNet-50 to determine the infection stage of strawberry grey mould (Chun et al., 2024). ResNet-50 with deep structure utilized a convolutional layer to learn by exploiting the residuals between inputs (four sets of RGB images representing different levels of infestation) and outputs (probability distribution of categories), and used global average pooling and softmax functions as output layers to classify the stages of grey mould infection. The results showed that the classification accuracy of the ResNet-50 model in the stage of asymptomatic infection was 0.97, which demonstrated a good recognition performance. Gorji et al. (2022) have used an advanced CNN model (EfficientNet-B0) that can balance the scaling of the CNN in terms of depth, width, and input image resolution to identify meat surface images displaying fecal contamination. The EfficientNet-B0 model downscaled the input fluorescent images of meat surfaces through a 2D convolutional layer with 32 filters and 16 mobile inverted bottleneck convolutions (MBConvs) with different kernel sizes and employed binary cross-entropy as a loss function to calculated the prediction error and quantify the model's performance. The accuracy of the model in identifying clean and contaminated areas on the meat surface was 97.32%. The automated identification of fluorescence images by this team advanced real-time monitoring of food products.

5.2. Food quality detection

Recent studies have applied deep learning-assisted fluorescence spectroscopy to detect the quality of fruits, meats and oils. Color, texture, odor, pH and others are important quality assessment indicators of food products (Zhang et al., 2021). For example, the maturity of fruits is related to the Brix/acid ratio, which can be estimated by measuring the fluorescence intensity value of the fruit skin, thus estimating the ripeness of the fruit (Itakura et al., 2018). A prediction model based on CNN regression and EEM was developed for citrus maturity estimation (Itakura et al., 2018). The CNN proposed in this work took a 2D image of citrus peels as the output and calculated the estimation accuracy of each segmentation data through regression and Bayesian optimization. The optimized network structure including three layers reduced the time and cost of deep learning and estimated the absolute error of citrus Brix/acid ratio as 2.48, which was significantly better than the results obtained by another method (PCA). Zou et al. (2024) developed a five-layer NGO-LSTM model based on Northern Goshawk Optimization (NGO) to predict protein and TVB-N content in refrigerated and frozen-thawed salmon fillets. Changes in various fluorescent compounds in meat (tryptophan, tyrosine, porphyrin, and riboflavin) can alter the intensity of the fluorescent substance in the samples. In this study, the significant changes near the peak of the fluorescence spectral curve of samples collected on different days corresponded to the trend of protein content decreasing and TVB-N value increasing with the increase of days. FHSI can consider relevant factors comprehensively and detect changes in these quality parameters accurately, thus ensuring the reliability and accuracy of the analysis. The NGO algorithm found the optimal combination of the three key hyperparameters of the LSTM model (number of hidden layer units, initial learning rate, L2 regularization coefficients) through a search and optimization, and then transferred the hyperparameter optimization to the LSTM to obtain the prediction results. The R^2 value of the optimized protein prediction model achieved 0.910 and the R^2 value of the TVB-N prediction model achieved 0.987. Fan et al. (2024) constructed LSTM and CNN_LSTM based on EEM to predict the freshness indexes of rainbow trout, including K-value, total viable counts (TVC) and TVB-N. The results of the study concluded that CNN_LSTM model with 32 filters, 128 neurons of LSTM1 and 256

Table 3
Applications of deep learning-assisted fluorescence spectroscopy in food quality and safety detection.

Purpose	Objective	Fluorescence spectral type	Fluorescence photometer	Software	Sample size			Excitation wavelength (nm)	Emission wavelength (nm)	Spectral preprosessing	Types of deep learning	Model evaluation	References
					Total	Training set	Testing set						
Food safety inspection	Kasugamycin, spinosad, lambda-cyhalothrin	EEM	LS55 fluorescence spectrometer (PerkinElmer)	/	300	230	70	250–306	300–450	Delaunay interpolation method, normalizing	LeNet-5CNN	100% accuracy	Wang X. et al. (2023)
	Bifenthrin, diafenthiuron, tolfenpyrad, imidacloprid	FHSI	GaiaFluo (/Pro)-VN-HR	Python 3.8	125	94	31	390	495	MSC, SNV, UVE, SPA, CARS	1D CNN-RF	99.05% accuracy	Sun et al. (2022)
	Lettuce	FHSI	Fluorescence hyper-spectral imaging system	/	2800	2100	700	480–1000	/	SNV, 1 Der, 2 Der, 3 Der, 4 Der	WT-MC-SAE	$R_C^2 = 0.9802$, $R_P^2 = 0.9467$, RPD = 3.273	Zhou X. et al. (2022)
	lettuce leaves	FHSI	ImSpectorV10, Spectral Imaging Ltd, Oulu, Finland	Intel i7 12700H	1400	1050	350	480–1000	/	SNV, 1st Der, 2nd Der	WT-SDAE	$R^2 = 0.9388$	Zhou et al. (2023)
	Oil seed rape	FHSI	ImSpectorV10, Spectral Imaging Ltd, Oulu, Finland	/	2400	1800	600	/	670–750	SNV, 1st Der, 2nd Der	SCAE, T-SCAE	$R^2 = 0.9385$, RMSEP = 0.02017, RPD = 3.291	Zhou et al. (2024)
	Fecal contamination	FIS	CSI-D device	Tensorflow-GPU v2.6.0	108296	70%	10% (20% validation set)	270, 405	/	Compound scaling method	CNN (EfficientNet-B0)	97.66% precision, 97.06% recall, 97.59% specificity, 97.35% F-score, and 99.54% AUC	Gorji et al. (2022)
	Botrytis cinerea	FHSI	Hyper-spectral fluorescence imaging system	Keras 2.12.0	4200	70%	30%	405	463–800	Smoothing, normalization, SNV, MSC	1D-CNN	97% accuracy	Chun et al. (2024)
Food quality inspection	Citrus	FIS	Fluorescence imaging systems (FIS-1 and FIS-2)	MATLAB2014a	400	90%	10%	470	690	A sixth-order polynomial fit	MLP, AlexNet	95% accuracy	Neves, Wetterich, Sousa, and Marcassa (2023)
	Citrus	MFI	MV-CA005-20 GM, HIKVISION, China	Python	1489	60%	30%	380	440, 520, 690, 740	A standard diffuse reference plate	Mobile-Net V3	92.1% accuracy	He et al. (2022)
	Satsuma mandarins	EEM	Fluorometer (FP-8300, Jasco Co, Tokyo, Japan)	/	141	121	20	200–550	300–700	Bayesian Optimization	CNN	Absolute error for 2.48	Itakura et al. (2018)
	Olive oil	FS	Miniature spectrometer (STS-Vis, Ocean Optics, USA)	TensorFlow TM Python	97	64	16	340, 365, 395	650–750	Normalization	1D-CNN	/	Venturini et al. (2023)
	Frozen-thawed salmon fillets	FHSI	GaiaFluo (Pro)-VN-HR series FHSI system	ENVI 5.3	216	70%	30%	390, 495	400–1000	Northern Goshawk optimization algorithm (NGO)	LSTM	R^2 (protein) = 0.910 R^2 (TVB-N) = 0.987	Zou et al. (2024)
	Rainbow trout	EEM	Ultra-Dern FS5 fluorescence spectrophotometer	MATLAB 8.0	195	/	/	250–400	260–600	Linear interpolation	LSTM, CNN_LSTM, RBFNN	R^2 (RBFNN) > 0.96, RE<10%, R^2 (CNN_LSTM) > 0.9411,	Fan et al. (2024)

(*continued on next page*)

Table 3 (*continued*)

Purpose	Objective	Fluorescence spectral type	Fluorescence photometer	Software	Sample size			Excitation wavelength (nm)	Emission wavelength (nm)	Spectral preprosessing	Types of deep learning	Model evaluation	References
					Total	Training set	Testing set						
Adulteration recognition	Sesame oil	TSyF	FS920 fluorescence spec-trometer	Python 3.7	48	36	12	250–750	10–120	Linear interpolation, cropping, noise injection	RNN, LSTM, GRU, BLSTM, LSTMC	R^2 (LSTM) > 0.8987, 100% accuracy	Wu et al. (2021)
	Sesame oil	3DFS	FS920 fluorescence spectrometer	Matlab 2018b	360	252	108	250–550	260–750	Cropping and scaling of image	CNN	100% accuracy	Wu et al. (2020)
Adulteration recognition	Ningxia wolfberry	FF-EEM	F-7000 fluorescence spectrophotometer (HITACHI, Japan)	PyTorch 1.8.0, Torchmetrics (Version 0.9.3)	297	189	66	220–500	220–650	ATLD and normalization	CNN	98% accuracy	Yan et al. (2023)
	Zhenjiang aromatic vinegar (ZAV) case and the camellia oil (CAO)	EEM	/	MATLAB, Pytorch 1.80	150	70%	30%	200–500	250–600	Normalization and resize function	OC-CAE	97.8% accuracy, 100% specificity	Yan et al. (2024)

neurons of LSTM2 showed a better freshness prediction of rainbow trout than the LSTM ($R^2 > 0.9411$). The CNN_LSTM model showed good performance in the freshness prediction of rainbow trout under non-isothermal storage conditions with an R^2 above 0.9 and relative errors less than 10% for K-value, TVC and TVB-N.

In another study, a method based on fluorescence spectroscopy and 1D-CNN was provided to predict five chemical quality indicators of olive oil (acidity, peroxide value, K_{270}, K_{232} and ethyl esters) (Venturini et al., 2023). Olive oil contains many naturally occurring fluorescent compounds, such as chlorophyll, carotene, primary and secondary oxides, that change over time. The 1D-CNN in this work was able to extract the characteristic parameters of three qualities of virgin olive oil simultaneously, and considered sensor characteristics (resolution) and knowledge of the problem (expected number of features in the spectrum) to complete the classification accurately. In addition, they concluded that larger datasets can improve model performance, but also require more complex 1D-CNN architectures to support the processing of olive oil samples for analysis.

5.3. Food adulteration recognition and authentication

The persistent issue of food adulteration poses serious consequences for human health and economic losses. Since the adulterated samples are similar to the adulterants, it is difficult to distinguish the subtle differences. Therefore, food adulteration detection has become an important requirement for ensuring food quality and safety (El Sheikha, 2019). Deep learning has been applied to spectral data for adulteration identification in vegetable oils. Wu, Zhao, Tian, Shang, and Liu (2020) blended sesame oil with soybean oil, canola oil, and peanut oil respectively (the volume percentage of sesame oil flavor was 10–90% in 10% increments) and then developed a method that combines 3D fluorescence spectroscopy with a CNN (AlexNet) to detect counterfeit sesame oil. In this study, two data enhancement methods (image cropping and scaling) were investigated to obtain 360 images from 36 original fluorescence images. As the convolutional network was learning, the feature information extracted from the convolutional layer became abstract gradually and represented on the second fully connected layer eventually. The results revealed a good linear relationship ($R^2 > 0.99$) between the predicted and actual values of counterfeit samples. In another sesame oil identification study, the researchers designed five deep network architectures, all of which achieved good classification results with a smaller number of samples (42 samples) because of the data augmentation used in the model training (Wu et al., 2021). The above studies fully reflected the flexibility and power of deep neural networks in building discriminative models.

Food or agricultural products from different origins and different years lead to differences in fluorescence spectra and pose challenges for authentication of food products (Dufour, Letort, Laguet, Lebecque, & Serra, 2006). Deep learning algorithms based on fluorescence spectra currently provide powerful tools and methods for food authentication. Yan et al. (2023) combined front-face EEM (FF-EEM) fluorescence spectroscopy with a CNN model (two convolutional layers, two max-pooling layers, three fully connected layers and one softmax layer) to rapidly identify the storage year of Ningxia wolfberry. Convolutional layer and max-pooling layer were utilized to extract spectral feature information, fully connected layer was utilized to classify the extracted features, and the softmax layer was applied to determine the storage probability of the year in which the Ningxia wolfberry samples belonged. The accuracy of the training set and testing set reached 98.4% and 100%, respectively. A novel one-class convolutional auto-encoder (OC-CAE) was proposed for the authentication of Zhenjiang aromatic vinegar (ZAV) and camellia oil (CAO) (Yan et al., 2024). The OC-CAE algorithm with two convolutional layers, two maxpooling layers and two fully connected layers was designed to identify the authenticity of the samples utilizing the feature extraction function and the reconstruction error information from CAE together. The results showed that CAE method has better anomaly detection performance (classification accuracy exceeded 93%) and potential for application in food authentication compared to OC-SVM and PLS-DA methods. The above studies illustrated the potential of deep learning-assisted fluorescence spectroscopy in distinguishing between authentic and adulterated food products.

6. Conclusions and future prospects

6.1. Conclusions

In this paper, a review of several deep learning models for processing fluorescence spectroscopy data, including CNN, LSTM, AE and SAE and the application of deep learning-assisted fluorescence spectroscopy for food quality and safety (including food adulteration identification and authentication) is presented. The potential of deep learning-assisted fluorescence spectroscopy for food authentication is also emphasized. Deep learning methods based on fluorescence spectroscopy are powerful tools for nondestructive evaluation of the quality of agricultural products and can provide assurances for food safety and quality control. In practical applications, different types of deep learning algorithms are used for different types of food and different detection targets. Selecting representative input parameters, appropriate preprocessing methods and optimization methods can effectively improve the model performance. Deep learning shows better performance than traditional machine learning in complex and diverse fluorescence spectral analysis due to its powerful feature extraction capability and sample data base. Therefore, further research efforts are needed to overcome the challenges and develop more reliable and robust deep learning models that have new applications in the food industry. In addition, the focus should be on developing more efficient deep learning models that can meet the requirements of different types of food products with simple and portable design features.

6.2. Future prospects

Drawing upon this literature review, prospective research on deep learning-assisted fluorescence spectroscopy in the field of food detection is envisioned. The following outlines potential trends and directions:

1. The development of more advanced deep learning models. Current studies indicate the potential of deep learning approaches in the evaluation of food and agricultural product quality, but relevant studies remain scarce. Compared with conventional machine models, deep learning algorithms have the ability to autonomously discovering and learning patterns and regularities within the original data. These deep learning algorithms leverage substantial amounts of sample data to optimize models, thus achieving superior prediction accuracy. Future endeavors are expected to focus on the development of more model optimization algorithms and more advanced deep learning models that can be combined with fluorescence spectroscopy to enhance overall performance.
2. Wide application of few-shot learning. Deep learning has gained popularity because of its robust capacity for automatic feature learning. However, this method requires ample labeled data for effective training and exhibits strong data dependency. One of the future development directions is to explore few-shot learning methods, which can better adapt to scenarios of data scarcity in practical applications and reduce the cost of data labeling.
3. Model Fusion. Various deep learning algorithms (CNN, LSTM, and AE) each possess advantages in the analysis and processing of fluorescence data. The appropriate method should be chosen according to the actual situation of the samples when performing food analysis. Single models are prone to over-fitting, whereas the use of a fusion of multiple models can enhance the generalizability and predictive ability.

4. Multitask learning and transfer learning. Most data or tasks are interrelated. Transferring trained model parameters to new models aids in expediting training speed, thus avoiding the time-consuming process of starting from scratch. Acquiring extensive labeled data poses challenges, but in multitask learning, overall multitask learning can be improved by sharing information across multiple tasks and making full use of the acquired prior knowledge.

Declaration of competing interest

There are no conflicts to declare.

Acknowledgments

This research was financially supported by Beijing Academy of Agriculture and Forestry Sciences Outstanding young scientist training program, XPCC Science and Technology Innovation Talent Project (2024DB013), the Fund of Young Beijing Scholar, China, and Jiangsu Science and Technology Plan (Key Research and Development Plan Modern Agriculture) Project (BE2023315).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tifs.2024.104821.

Data availability

Data will be made available on request.

References

Ahmed, M. R., Yasmin, J., Park, E., Kim, G., Kim, M. S., Wakholi, C., et al. (2020). Classification of watermelon seeds using morphological patterns of X-ray imaging: A comparison of conventional machine learning and deep learning. *Sensors (Basel), 20*, 6753. https://doi.org/10.3390/s20236753

Banan, A., Nasiri, A., & Taheri-Garavand, A. (2020). Deep learning-based appearance features extraction for automated carp species identification. *Aquacultural Engineering, 89*, Article 102053. https://doi.org/10.1016/j.aquaeng.2020.102053

Beattie, J. R., & Esmonde-White, F. W. (2021). Exploration of principal component analysis: Deriving principal component analysis visually using spectra. *Applied Spectroscopy, 75*, 361–375. https://doi.org/10.1177/0003702820987847

Boukria, O., Boudalia, S., Bhat, Z. F., Hassoun, A., & Aït-Kaddour, A. (2023). Evaluation of the adulteration of camel milk by non-camel milk using multispectral image, fluorescence and infrared spectroscopy. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 300*, Article 122932. https://doi.org/10.1016/j.saa.2023.122932

Brandao, M. P., Neto, M. G., dos Anjos, V.d. C., & Bell, M. J. V. (2017). Detection of adulteration of goat milk powder with bovine milk powder by front-face and time resolved fluorescence. *Food Control, 81*, 168–172. https://doi.org/10.1016/j.foodcont.2017.06.008

Chegeni, M. K., Rashno, A., & Fadaei, S. (2023). Convolution-layer parameters optimization in convolutional neural networks. *Knowledge-Based Systems, 261*, Article 110210. https://doi.org/10.1016/j.knosys.2022.110210

Chen, G., Guo, Y., Zeng, Q., & Zhang, Y. (2023). A novel cellular network traffic prediction algorithm based on graph convolution neural networks and long short-term memory through extraction of spatial-temporal characteristics. *Processes, 11*, 2257. https://doi.org/10.3390/pr11082257

Chen, S., Liu, H., Zeng, X., Qian, S., Yu, J., & Guo, W. (2017). Image classification based on convolutional denoising sparse autoencoder. *Mathematical Problems in Engineering, 2017*, Article 5218247. https://doi.org/10.1155/2017/5218247

Chun, S.-W., Song, D.-J., Lee, K.-H., Kim, M.-J., Kim, M. S., Kim, K.-S., et al. (2024). Deep learning algorithm development for early detection of Botrytis cinerea infected strawberry fruit using hyperspectral fluorescence imaging. *Postharvest Biology and Technology, 214*, Article 112918. https://doi.org/10.1016/j.postharvbio.2024.112918

Dankowska, A. (2016). Advances in fluorescence emission spectroscopy for food authenticity testing. In *Advances in food authenticity testing* (pp. 117–145). Elsevier.

Deng, Z., Wang, T., Zheng, Y., Zhang, W., & Yun, Y.-H. (2024). Deep learning in food authenticity: Recent advances and future trends. *Trends in Food Science & Technology*. , Article 104344. https://doi.org/10.1016/j.tifs.2024.104344

Dramićanin, T., Lenhardt Acković, L., Zeković, I., & Dramićanin, M. D. (2018). Detection of adulterated honey by fluorescence excitation-emission matrices. *Journal of Spectroscopy, 2018*, Article 8395212. https://doi.org/10.1155/2018/8395212

Du, J., Zhang, M., Teng, X., Wang, Y., Law, C. L., Fang, D., et al. (2023). Evaluation of vegetable sauerkraut quality during storage based on convolution neural network. *Food Research International, 164*, Article 112420. https://doi.org/10.1016/j.foodres.2022.112420

Dufour, E., Letort, A., Laguet, A., Lebecque, A., & Serra, J. (2006). Investigation of variety, typicality and vintage of French and German wines using front-face fluorescence spectroscopy. *Analytica Chimica Acta, 563*, 292–299. https://doi.org/10.1016/j.aca.2005.11.005

El Sheikha, A. F. (2019). DNAFoil: Novel technology for the rapid detection of food adulteration. *Trends in Food Science & Technology, 86*, 544–552. https://doi.org/10.1016/j.tifs.2018.11.012

Facci, R. R., Cezário, P. S.d. O., de Gois, J. S., Luna, A. S., & Pacheco, W. F. (2021). Identification of counterfeit vodka by synchronous fluorescence spectroscopy and chemometric analysis. *Analytical Letters, 54*, 1522–1532. https://doi.org/10.1080/00032719.2020.1810694

Fan, Y., Dong, R., Luo, Y., Tan, Y., Hong, H., Ji, Z., et al. (2024). Deep learning models with optimized fluorescence spectroscopy to advance freshness of rainbow trout predicting under nonisothermal storage conditions. *Food Chemistry, 454*, Article 139774. https://doi.org/10.1016/j.foodchem.2024.139774

Fatchurrahman, D., Kuramoto, M., Al Riza, D. F., Ogawa, Y., Suzuki, T., & Kondo, N. (2020). Fluorescence time series monitoring of different parts of green pepper (*Capsicum annuum* L.) under different storage temperatures. *Computers and Electronics in Agriculture, 179*, 6. https://doi.org/10.1016/j.compag.2020.105850

Feng, L., Wu, B., Zhu, S., He, Y., & Zhang, C. (2021). Application of visible/infrared spectroscopy and hyperspectral imaging with machine learning techniques for identifying food varieties and geographical origins. *Frontiers in Nutrition, 8*, Article 680357. https://doi.org/10.3389/fnut.2021.680357

Fu, Y., Liu, T., Zhang, Z., Li, H., Li, W., & Huang, M. (2022). The crosstalk fluorescence spectroscopy analysis principle and an accurate fluorescence quantitative method for multi-composition fluorescence substances. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 280*, Article 121472. https://doi.org/10.1016/j.saa.2022.121472

Fu, X., & Wang, M. (2022). Detection of early bruises on pears using fluorescence hyperspectral imaging technique. *Food Analytical Methods*, 1–9. https://doi.org/10.1007/s12161-021-02092-3

Ge, L., & Chen, E. (2021). Research on grain storage temperature prediction model based on improved long short-term memory. *Journal of Computational Methods in Science and Engineering, 21*, 1145–1154. https://doi.org/10.3233/jcm-204751

González, N., Corral, S. P. L., Zanini, G., Montejano, H., & Acebal, C. C. (2020). An inner filter effect based sensing system for the determination of caffeine in beverage samples. *Analyst, 145*, 2279–2285. https://doi.org/10.1039/c9an02483b

Gorji, H. T., Shahabi, S. M., Sharma, A., Tande, L. Q., Husarik, K., Qin, J., et al. (2022). Combining deep learning and fluorescence imaging to automatically identify fecal contamination on meat carcasses. *Scientific Reports, 12*, 2392. https://doi.org/10.1038/s41598-022-06379-1

Goyal, R., Singha, P., & Singh, S. K. (2024). Spectroscopic food adulteration detection using machine learning: Current challenges and future prospects. *Trends in Food Science & Technology*. , Article 104377. https://doi.org/10.1016/j.tifs.2024.104377

Gu, H., Liu, K., Huang, X., Chen, Q., Sun, Y., & Tan, C. P. (2020). Feasibility study for the analysis of coconut water using fluorescence spectroscopy coupled with PARAFAC and SVM methods. *British Food Journal, 122*, 3203–3212. https://doi.org/10.1108/bfj-12-2019-0941

Hassoun, A. (2021). Exploring the potential of fluorescence spectroscopy for the discrimination between fresh and frozen-thawed muscle foods. *Photochem, 1*, 247–263. https://doi.org/10.3390/photochem1020015

Hassoun, A., Sahar, A., Lakhal, L., & Aït-Kaddour, A. (2019). Fluorescence spectroscopy as a rapid and non-destructive method for monitoring quality and authenticity of fish and meat products: Impact of different preservation conditions. *LWT, 103*, 279–292. https://doi.org/10.1016/j.lwt.2019.01.021

He, C., Li, X., Liu, Y., Yang, B., Wu, Z., Tan, S., et al. (2022). Combining multicolor fluorescence imaging with multispectral reflectance imaging for rapid citrus Huanglongbing detection based on lightweight convolutional neural network using a handheld device. *Computers and Electronics in Agriculture, 194*, Article 106808. https://doi.org/10.1016/j.compag.2022.106808

Holinkova, P., Mravec, F., Venerova, T., Chang, C. H., & Pekar, M. (2022). Hyaluronan interactions with cationic surfactants-Insights from fluorescence resonance energy transfer and anisotropy techniques. *International Journal of Biological Macromolecules, 211*, 107–115. https://doi.org/10.1016/j.ijbiomac.2022.05.067

Huber, N. R., Missert, A. D., Gong, H., Hsieh, S. S., Leng, S., Yu, L., et al. (2021). Random search as a neural network optimization strategy for Convolutional-Neural-Network (CNN)-based noise reduction in CT. *Medical Imaging 2021: Image Processing, 11596*, 509–515. SPIE.

Itakura, K., Saito, Y., Suzuki, T., Kondo, N., & Hosoi, F. (2018). Estimation of citrus maturity with fluorescence spectroscopy using deep learning. *Horticulturae, 5*, 2. https://doi.org/10.3390/horticulturae5010002

Ji, R., Han, Y., Wang, X., Bian, H., Xu, J., Jiang, Z., et al. (2021). Analysis of pesticide residues by a support vector machine combined with fluorescence spectroscopy. *Applied Optics, 60*, 10383–10389. https://doi.org/10.1364/AO.439844

Jiang, X., & Xu, C. (2022). Deep learning and machine learning with grid search to predict later occurrence of breast Cancer metastasis using clinical data. *Journal of Clinical Medicine, 11*, 5772. https://doi.org/10.3390/jcm11195772

Junges, C. H., Guerra, C. C., Canedo-Reis, N. A. P., Gomes, A. A., & Ferrao, M. F. (2023). Discrimination of whole grape juice using fluorescence spectroscopy data with linear discriminant analysis coupled to genetic and ant colony optimisation algorithms. *Analytical Methods, 15*, 187–195. https://doi.org/10.1039/d2ay01636b

Kahloot, K. M., & Ekler, P. (2021). Algorithmic splitting: A method for dataset preparation. *IEEE Access, 9*, 125229–125237. https://doi.org/10.1109/access.2021.3110745

Kärkkäinen, T., & Hänninen, J. (2023). Additive autoencoder for dimension estimation. *Neurocomputing, 551*, Article 126520. https://doi.org/10.1016/j.neucom.2023.126520

Karoui, R., & Blecker, C. (2011). Fluorescence spectroscopy measurement for quality assessment of food systems—a review. *Food and Bioprocess Technology, 4*, 364–386. https://doi.org/10.1007/s11947-010-0370-0

Karoui, R., Dufour, É., & De Baerdemaeker, J. (2007). Front face fluorescence spectroscopy coupled with chemometric tools for monitoring the oxidation of semi-hard cheeses throughout ripening. *Food Chemistry, 101*, 1305–1314. https://doi.org/10.1016/j.foodchem.2006.01.028

Kong, J., Li, M. Y., Li, Y. T., Liu, M., Zhang, Q., Liu, J., et al. (2023). Effect of the bile salt surfactant sodium taurodeoxycholate on the physicochemical properties of a mixed system of Galangin-Hemoglobin and Baicalein-Hemoglobin. *Journal of Molecular Liquids, 391*, 10. https://doi.org/10.1016/j.molliq.2023.123302

Lai, J., Wang, X., Xiang, Q., Quan, W., & Song, Y. (2023). A semi-supervised stacked autoencoder using the pseudo label for classification tasks. *Entropy, 25*, 1274. https://doi.org/10.3390/e25091274

Lee, H., Kim, M. S., Lee, W.-H., & Cho, B.-K. (2018). Determination of the total volatile basic nitrogen (TVB-N) content in pork meat using hyperspectral fluorescence imaging. *Sensors and Actuators B: Chemical, 259*, 532–539. https://doi.org/10.1016/j.snb.2017.12.102

Li, T., Wei, W., Xing, S., Min, W., Zhang, C., & Jiang, S. (2023). Deep learning-based near-infrared hyperspectral imaging for food nutrition estimation. *Foods, 12*, 3145. https://doi.org/10.3390/foods12173145

Liu, Y., Pu, H., & Sun, D.-W. (2021). Efficient extraction of deep image features using convolutional neural network (CNN) for applications in detecting and analysing complex food matrices. *Trends in Food Science & Technology, 113*, 193–204. https://doi.org/10.1016/j.tifs.2021.04.042

Liu, J. F., Zamora, A., Castillo, M., & Saldo, J. (2018). Modeling of the changes in bovine milk caused by ultra-high pressure homogenization using front-face fluorescence spectroscopy. *Journal of Food Engineering, 233*, 88–97. https://doi.org/10.1016/j.jfoodeng.2018.04.010

Loudiyi, M., Karoui, R., Rutledge, D. N., Lavigne, R., Montel, M. C., & Aït-Kaddour, A. (2017). Contribution of fluorescence spectroscopy and independent components analysis to the evaluation of NaCl and KCl effects on molecular-structure and fat melting temperatures of Cantal-type cheese. *International Dairy Journal, 73*, 116–127. https://doi.org/10.1016/j.idairyj.2017.05.004

Luo, X., Ye, Z., Xu, H., Zhang, D., Bai, S., & Ying, Y. (2018). Robustness improvement of NIR-based determination of soluble solids in apple fruit by local calibration. *Postharvest Biology and Technology, 139*, 82–90. https://doi.org/10.1016/j.postharvbio.2018.01.019

Neves, R. F., Wetterich, C. B., Sousa, E. P., & Marcassa, L. G. (2023). Multiclass classifier based on deep learning for detection of citrus disease using fluorescence imaging spectroscopy. *Laser Physics, 33*, Article 055602. https://doi.org/10.1088/1555-6611/acc6bd

Ntakatsane, M., Chen, P., Liu, J. S., Mosebi, P., Xu, L. L., Matebesi, P., et al. (2020). Multi-dimensional fluorescence spectroscopy coupled with chemometrics in rapid antibiotic detection and discrimination. *Journal of Food Measurement and Characterization, 14*, 1892–1900. https://doi.org/10.1007/s11694-020-00436-x

Othman, S., Mavani, N. R., Hussain, M., Abd Rahman, N., & Ali, J. M. (2023). Artificial intelligence-based techniques for adulteration and defect detections in food and agricultural industry: A review. *Journal of Agriculture and Food Research, 12*, Article 100590. https://doi.org/10.1016/j.jafr.2023.100590

Pan, L., Zhang, P., Daengngam, C., Peng, S., & Chongcheawchamnan, M. (2022). A review of artificial intelligence methods combined with Raman spectroscopy to identify the composition of substances. *Journal of Raman Spectroscopy, 53*, 6–19. https://doi.org/10.1002/jrs.6225

Pandey, G., & Joshi, A. (2021). Riboflavin as an internal marker for spoilage and adulteration detection in milk. *Food Chemistry, 357*, 7. https://doi.org/10.1016/j.foodchem.2021.129742

Pandiselvam, R., Kaavya, R., Martinez Monteagudo, S. I., Divya, V., Jain, S., Khanashyam, A. C., et al. (2022). Contemporary developments and emerging trends in the application of spectroscopy techniques: A particular reference to coconut (cocos nucifera L.). *Molecules, 27*, 22. https://doi.org/10.3390/molecules27103250

Qi, Y., Hu, D., Jiang, Y., Wu, Z., Zheng, M., Chen, E. X., et al. (2023). Recent progresses in machine learning assisted Raman spectroscopy. *Advanced Optical Materials, 11*, Article 2203104. https://doi.org/10.1002/adom.202203104

Qiu, Z. J., Chen, J., Zhao, Y. Y., Zhu, S. S., He, Y., & Zhang, C. (2018). Variety identification of single rice seed using hyperspectral imaging combined with convolutional neural network. *Applied Sciences-Basel, 8*, 212. https://doi.org/10.3390/app8020212

Qiu, Y., Tan, Y., Zhou, Y., Li, Z., Miao, Z., Li, C., et al. (2024). Study on rice origin and quality identification based on fluorescence spectral features. *Agriculture, 14*, 1763. https://doi.org/10.3390/agriculture14101763

Rodrigues, A.d. P., de Gois, J. S., Costa, M. A., da Silva, C. S., Xavier, V. L., & Luna, A. S. (2020). Exploring multivariate linear regression methods for the prediction of total phenolic content in standard American lager beers using synchronous fluorescence spectroscopy fused data. *Chemometrics and Intelligent Laboratory Systems, 206*, Article 104168. https://doi.org/10.1016/j.chemolab.2020.104168

Ropelewska, E., Slavova, V., Sabanci, K., Aslan, M. F., Masheva, V., & Petkova, M. (2022). Differentiation of yeast-inoculated and uninoculated tomatoes using fluorescence spectroscopy combined with machine learning. *Agriculture, 12*, 1887. https://doi.org/10.3390/agriculture12111887

Saha, D., & Manickavasagan, A. (2021). Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review. *Current Research in Food Science, 4*, 28–44.

Scardapane, S., Comminiello, D., Hussain, A., & Uncini, A. (2017). Group sparse regularization for deep neural networks. *Neurocomputing, 241*, 81–89. https://doi.org/10.1016/j.neucom.2017.02.029

Seo, Y., Lee, H., Mo, C., Kim, M. S., Baek, I., Lee, J., et al. (2019). Multispectral fluorescence imaging technique for on-line inspection of fecal residues on poultry carcasses. *Sensors (Basel), 19*, 3483. https://doi.org/10.3390/s19163483

Shan, J., Wang, X., Zhou, H., Han, S., Al Riza, D. F., & Kondo, N. (2018). Variable selection based on clustering analysis for improvement of polyphenols prediction in green tea using synchronous fluorescence spectra. *Methods and Applications in Fluorescence, 6*, Article 025006.

Shapiro, A., Zhou, E., & Lin, Y. (2023). Bayesian distributionally robust optimization. *SIAM Journal on Optimization, 33*, 1279–1304. https://doi.org/10.1137/21m1465548

Shi, X., Zhang, J., Shi, C., Tan, Y., Hong, H., & Luo, Y. (2022). Nondestructive prediction of freshness for bighead carp (Hypophthalmichthys nobilis) head by Excitation-Emission Matrix (EEM) analysis based on fish eye fluid: Comparison of BPNNs and RBFNNs. *Food Chemistry, 382*, Article 132341. https://doi.org/10.1016/j.foodchem.2022.132341

Sikorska, E., Khmelinskii, I., & Sikorski, M. (2019). Fluorescence spectroscopy and imaging instruments for food quality evaluation. In *Evaluation technologies for food quality* (pp. 491–533). Elsevier.

Suhandy, D., & Yulia, M. (2018). Discrimination of several Indonesian specialty coffees using Fluorescence Spectroscopy combined with SIMCA method. *IOP Conference Series: Materials Science and Engineering, 334*, Article 012059. IOP Publishing.

Sun, J., Hu, Y., Zou, Y., Geng, J., Wu, Y., Fan, R., et al. (2022). Identification of pesticide residues on black tea by fluorescence hyperspectral technology combined with machine learning. *Food Science and Technology, 42*. https://doi.org/10.1590/fst.55822

Szandała, T. (2021). Review and comparison of commonly used activation functions for deep neural networks. *Bio-Inspired Neurocomputing*, 203–224.

Tabaraki, R., & Nazari, F. (2023). Microwave synthesis of carbon dots in ten choline chloride-based deep eutectic solvents: Effect of solvent molecular structure on carbon dots fluorescence and sensing properties. *Journal of Photochemistry and Photobiology A: Chemistry, 444*, Article 114891. https://doi.org/10.1016/j.jphotochem.2023.114891

Tang, C., Shen, Q., Shao, S., Si, J., & Dong, S. (2024). Quality authentication of camellia (Camellia oleifera Abel.) oil based on fluorescence spectroscopy. *Journal of Food Composition and Analysis, 136*, Article 106690. https://doi.org/10.1016/j.jfca.2024.106690

ul Huda, Z., Mansha, A., Asim, S., & Shahzad, A. (2022). Effect of pH on fluorescence spectra of coumarin derivatives. *Journal of Fluorescence, 32*, 57–66. https://doi.org/10.1007/s10895-021-02829-7

Venturini, F., Sperti, M., Michelucci, U., Gucciardi, A., Martos, V. M., & Deriu, M. A. (2023). Extraction of physicochemical properties from the fluorescence spectrum with 1D convolutional neural networks: Application to olive oil. *Journal of Food Engineering, 336*, Article 111198. https://doi.org/10.1016/j.jfoodeng.2022.111198

Wang, X., Chen, X., Ji, R., Wang, T., He, Y., Bian, H., et al. (2023). Mixed pesticide recognition based on three-dimensional fluorescence spectroscopy and a convolutional neural network. *Applied Optics, 62*, 9018–9027. https://doi.org/10.1364/ao.501646

Wang, Z., Li, S., Hu, P., Dai, R., Wu, B., Yang, L., et al. (2022). Recent developments in the spectrometry of fluorescence, ultraviolet visible and surface-enhanced Raman scattering for pesticide residue detection. *Bulletin of Materials Science, 45*, 202. https://doi.org/10.1007/s12034-022-02774-6

Wang, X., Ren, H., & Wang, A. (2022). Smish: A novel activation function for deep learning methods. *Electronics, 11*, 540. https://doi.org/10.3390/electronics11040540

Wang, B., Shen, F., He, X. M., Fang, Y., Hu, Q. H., & Liu, X. Q. (2023). Simultaneous detection of *Aspergillus* moulds and aflatoxin B1 contamination in rice by laser induced fluorescence spectroscopy. *Food Control, 145*, 8. https://doi.org/10.1016/j.foodcont.2022.109485

Wang, S., Sun, Y. Y., Wu, Z. Y., Zhao, L., Liu, Y. L., Li, S. H., et al. (2023). Effect of solvent polarity on the performance of thermally activated delayed fluorescence OLEDs. *Dyes and Pigments, 220*, 8. https://doi.org/10.1016/j.dyepig.2023.111578

Wang, T., Zeng, L.-H., & Li, D.-L. (2017). A review on the methods for correcting the fluorescence inner-filter effect of fluorescence spectrum. *Applied Spectroscopy Reviews, 52*, 883–908. https://doi.org/10.1080/05704928.2017.1345758

Wu, J., & Wang, Z. (2022). A hybrid model for water quality prediction based on an artificial neural network, wavelet transform, and long short-term memory. *Water, 14*, 610. https://doi.org/10.3390/w14040610

Wu, X., Zhao, Z., Tian, R., Niu, Y., Gao, S., & Liu, H. (2021). Total synchronous fluorescence spectroscopy coupled with deep learning to rapidly identify the authenticity of sesame oil. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 244*, Article 118841. https://doi.org/10.1016/j.saa.2020.118841

Wu, X., Zhao, Z., Tian, R., Shang, Z., & Liu, H. (2020). Identification and quantification of counterfeit sesame oil by 3D fluorescence spectroscopy and convolutional neural network. *Food Chemistry, 311*, Article 125882. https://doi.org/10.1016/j.foodchem.2019.125882

Xu, J., Xu, J., Tong, Z., Du, B., Liu, B., Mu, X., et al. (2023). Performance of feature extraction method for classification and identification of proteins based on three-dimensional fluorescence spectrometry. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 285*, Article 121841. https://doi.org/10.1016/j.saa.2022.121841

Yan, X., Jia, B., Long, W., Huang, K., Wang, T., Wu, H., et al. (2024). A novel one-class convolutional autoencoder combined with excitation–emission matrix fluorescence

spectroscopy for authenticity identification of food. *Journal of Chemometrics, e3592*. https://doi.org/10.1002/cem.3592

Yan, R., Peng, J., & Ma, D. (2019). Dimensionality reduction based on parallel factor analysis model and independent component analysis method. *Journal of Applied Remote Sensing, 13*, 014532-014532.

Yan, X.-Q., Wu, H.-L., Wang, B., Wang, T., Chen, Y., Chen, A.-Q., et al. (2023). Front-face excitation-emission matrix fluorescence spectroscopy combined with interpretable deep learning for the rapid identification of the storage year of Ningxia wolfberry. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 295*, Article 122617. https://doi.org/10.1016/j.saa.2023.122617

Yang, K., Liu, L., & Wen, Y. (2024). The impact of Bayesian optimization on feature selection. *Scientific Reports, 14*, 3948. https://doi.org/10.1038/s41598-024-54515-w

Yoshioka, H.-T., Liu, C., & Hayashi, K. (2015). Multispectral fluorescence imaging for odorant discrimination and visualization. *Sensors and Actuators B: Chemical, 220*, 1297–1304. https://doi.org/10.1016/j.snb.2015.07.073

Yu, J., Cao, Y., Shi, F., Shi, J., Hou, D., Huang, P., et al. (2021). Detection and identification of organic pollutants in drinking water from fluorescence spectra based on deep learning using convolutional autoencoder. *Water, 13*, 2633. https://doi.org/10.3390/w13192633

Zareef, M., Chen, Q., Hassan, M. M., Arslan, M., Hashim, M. M., Ahmad, W., et al. (2020). An overview on the applications of typical non-linear algorithms coupled with NIR spectroscopy in food analysis. *Food Engineering Reviews, 12*, 173–190. https://doi.org/10.1007/s12393-020-09210-7

Zhang, Y., Deng, L., Zhu, H., Wang, W., Ren, Z., Zhou, Q., et al. (2023). Deep learning in food category recognition. *Information Fusion, 98*, Article 101859. https://doi.org/10.1016/j.inffus.2023.101859

Zhang, M., Gong, M., Mao, Y., Li, J., & Wu, Y. (2018). Unsupervised feature extraction in hyperspectral images based on Wasserstein generative adversarial network. *IEEE Transactions on Geoscience and Remote Sensing, 57*, 2669–2688. https://doi.org/10.1109/tgrs.2018.2876123

Zhang, X., Yang, J., Lin, T., & Ying, Y. (2021). Food and agro-product quality evaluation based on spectroscopy and deep learning: A review. *Trends in Food Science & Technology, 112*, 431–441. https://doi.org/10.1016/j.tifs.2021.04.008

Zhao, W., & Du, S. (2016). Spectral–spatial feature extraction for hyperspectral image classification: A dimension reduction and deep learning approach. *IEEE Transactions on Geoscience and Remote Sensing, 54*, 4544–4554. https://doi.org/10.1109/tgrs.2016.2543748

Zhou, X., Sun, J., Tian, Y., Yao, K., & Xu, M. (2022). Detection of heavy metal lead in lettuce leaves based on fluorescence hyperspectral technology combined with deep learning algorithm. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 266*, Article 120460. https://doi.org/10.1016/j.saa.2021.120460

Zhou, H. M., Zhao, Y., Chen, X. H., & Zhang, S. J. (2022). Ultrafast spectroscopic studies of the pH responsive 9-acridinecarboxylic acid as a ratiometric and fluorescence lifetime pH indicator. *Microchemical Journal, 176*, 8. https://doi.org/10.1016/j.microc.2022.107240

Zhou, X., Zhao, C., Sun, J., Cao, Y., Yao, K., & Xu, M. (2023). A deep learning method for predicting lead content in oilseed rape leaves using fluorescence hyperspectral imaging. *Food Chemistry, 409*, Article 135251. https://doi.org/10.1016/j.foodchem.2022.135251

Zhou, X., Zhao, C., Sun, J., Cheng, J., & Xu, M. (2024). Determination of lead content in oilseed rape leaves in silicon-free and silicon environments based on deep transfer learning and fluorescence hyperspectral imaging. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*. , Article 123991. https://doi.org/10.1016/j.saa.2024.123991

Zou, D., Cao, Y., Zhou, D., & Gu, Q. (2020). Gradient descent optimizes over-parameterized deep ReLU networks. *Machine Learning, 109*, 467–492. https://doi.org/10.1007/s10994-019-05839-6

Zou, Z., Li, M., Wang, Q., Wu, Q., Zhen, J., Yuan, D., et al. (2024). A non-destructive detection method of protein and TVB-N content changes in refrigerated and frozen-thawed salmon fillets using fluorescence hyperspectral technology. *Journal of Food Composition and Analysis, 133*, Article 106435. https://doi.org/10.1016/j.jfca.2024.106435