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Hyperspectral Imaging Aiding Artificial Intelligence: A Reliable Approach for Food Qualification and Safety

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Abstract: Hyperspectral imaging (HSI) is one of the non-destructive quality assessment methods providing both spatial and spectral information. HSI in food quality and safety can detect the presence of contaminants, adulterants, and quality attributes, such as moisture, ripeness, and microbial spoilage, in a non-destructive manner by analyzing spectral signatures of food components in a wide range of wavelengths with speed and accuracy. However, analyzing HSI data can be quite complicated and time consuming, in addition to needing some special expertise. Artificial intelligence (AI) has shown immense promise in HSI for the assessment of food quality because it is so powerful at coping with irrelevant information, extracting key features, and building calibration models. This review has shown various machine learning (ML) approaches applied to HSI for quality and safety control of foods. It covers the basic concepts of HSI, advanced preprocessing methods, and strategies for wavelength selection and machine learning methods. The application of HSI to AI increases the speed with which food safety and quality can be inspected. This happens through automation in contaminant detection, classification, and prediction of food quality attributes. So, it can enable decisions in real-time by reducing human error at food inspection. This paper outlines their benefits, challenges, and potential improvements while again assessing the validity and practical usability of HSI technologies in developing reliable calibration models for food quality and safety monitoring. The review concludes that HSI integrated with state-of-the-art AI techniques has good potential to significantly improve the assessment of food quality and safety, and that various ML algorithms have their strengths, and contexts in which they are best applied.

Keywords: non-destructive methods; machine learning; food processing; digitalization

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1. Introduction

Food quality plays a vital role in the elucidation and development of preferences of consumers and processors, among other end-users. Food quality is basically perceived by the consumer according to its appearance, texture, and taste. Recently, food quality monitoring also required rapid analytical procedures [1]. Food quality ensures these products meet standards related to nutrition, freshness, and taste, while consistency appeals to consumers. Also, food safety is defined as avoiding the contamination of biological, chemical, and physical hazards to prevent adverse public health consequences, including foodborne illness. Moreover, large lots of low-quality food can be produced before processing difficulties are observed [2,3]. These again result in food losses. As a result of this fact, some intrinsic and extrinsic critical parameter checking methodologies have been developed; these are much faster, more reliable, and non-destructive [4–6].

Hyperspectral imaging is a non-destructive approach that finds an important application in food safety for authentication [7–9] as well as microbial [10,11], chemical, and physical contaminant identifications within the food industry [12–15]. The hyperspectral imaging system of the qualification of foods captures the spectral reflectance of food items across a wide range of wavelengths, which may be used to identify chemical and physical properties related to moisture, freshness, and contamination. It captures comprehensive spectral information at each pixel, creating spatially resolved maps that differentiate between distinct food components or parameters of quality and permit non-destructive analysis in real time [6,11]. The main challenges of hyperspectral imaging rely on extracting interesting information from high-dimensional data often containing redundant information [15]. Other relevant challenges are sensor noise, changing illumination conditions, and environmental conditions, sample heterogeneity, and anisotropy [16,17]. The development of an efficient algorithm and chemometric techniques is essential to reduce the dimensionality in the hyperspectral data for improving the practical applications in real-time food monitoring using HSI. These algorithms can reduce computational time, improve model performance, and increase robustness by removing irrelevant variables and redundancies [18].

Machine learning can help in food safety, contaminant detection, spoilage prediction, and quality assessment through the analysis of large datasets received from sensors. This is enabled by training algorithms with historical data on the identification of patterns, risk classification, or making real-time predictions based on new input data [19–24]. With ML came the offspring of AI, which encompasses a wide range of algorithms drawing meaningful information from data and using the knowledge to teach themselves for better classification [25–27] and prediction [28–30] within the food safety and quality sections. Also, deep learning relies on an artificial neural network composed of several layers, which automatically learn hierarchical features from raw data, with gradual changes to abstract and nuanced representations. DL in some cases is stronger than traditional ML and can process large volumes of big data in unstructured information represented through images and videos without manual feature extraction, hence improving accuracy and scalability [16,29,31–34]. The literature indicates that AI catalyzes new revolution hyperspectral image and data analysis. Moreover, the effective preprocessing and deliberate choice of wavelengths in hyperspectral imaging are recommended to reduce extraneous factors that can affect the quality of measured spectra, such as the morphological variations and light-scattering characteristics of different food items [33,35,36]. So, the integration of hyperspectral imaging with AI, including optimized preprocessing and wavelength selection in view of food quality monitoring, remains so far poorly addressed, and relevant studies have been identified only in [1,10,15,18,37,38].

This review focuses on the potential of ML algorithms in analyzing HSI data, which has the capacity to extract patterns, classify materials, and carry out predictive modeling on high-dimensional and complex data produced with a view to food quality and safety. HSI is being practiced on a wide variety of foodstuffs, including fruits, vegetables, grains, meats, and seafood. Also, we discussed how HSI allows for a very accurate assessment of freshness, nutrient content, and contamination. The techniques, as complemented by ML, greatly enhance classification performance and predictive modeling, driving the optimization of decision-making. In addition, the limitations are that the models require high equipment costs, computation demands, and large well-annotated datasets to be effectively trained. Furthermore, this review discusses various applied preprocessing methods in HSI, something important in ensuring that the data being fed to ML algorithms are accurate and reliable upon application.

2. HSI Procedure

As mentioned before, compared to the normal images, hyperspectral images are very different in both spectral and spatial features. While regular images record light in three broad bands, namely red, green, and blue (RGB), hyperspectral images record hundreds of narrow contiguous spectral bands ranging from 380 to 2500 nm. This provides the HSI with detailed spectral information on the identification of materials and their properties, which is very important in many applications like agriculture and environmental monitoring [16]. Taking different types of images to RGB requires different types of devices, accessories and processes. Moreover, the preprocessing and feature extraction techniques of hyperspectral images may different from regular images.

2.1. HSI System

Hyperspectral imaging represents one of the advanced technologies which can capture the spatial as well as spectral data of any sample in great detail pixel by pixel. The objective lens, imaging spectrograph consisting of collimator lens, diffraction grating, an input slit, a detector like a CCD or CMOS sensor, and a focus lens constitute the HSI system. This configuration enables high-precision spectral and chemometric analysis, making HSI superior to traditional digital cameras in detecting and recognizing features across a wide spectral range [16].

The technique of HSI produces a three-dimensional data structure, popularly called the hypercube. It consists of two spatial dimensions and one spectral wavelength dimension. Many scanning techniques are utilized, such as pixel-by-pixel scanning, line scanning, and full-field scanning. While this provides very accurate results, it is slow and hence less useful for fast applications. On the other hand, linear scanning enables the simultaneous acquisition of spatial and spectral data, making them more suitable for fast and online detection. Full-field scanning involves no motion of either the sample or the detector to acquire images from a fixed scene, thereby increasing the efficiency of the process.

The system can also operate in reflectance, transmittance, or interactance mode, depending on whether external, internal, or both kinds of parameters are analyzed (Figure 1) [2,39]. HSI can be carried out on any sample size and shape in several regions of the electromagnetic spectrum, including ultraviolet, visible and near-infrared (Vis-NIR), and short-wave infrared, for each of which there are specific applications [9]. Combining spectroscopy with imaging results in continuous images taken over all the wavelengths of the investigated range, a fact that constitutes an important advantage of the technique for sample characterization in general.

2.2. Preprocessing

Raw hyperspectral images are often unsuitable for direct use in models due to inherent noise that can distort both spectral and spatial features. Noise pollution, originating from factors such as image acquisition errors, camera sensitivity, and atmospheric interference, can significantly impact the accuracy of hyperspectral data analysis [35,40]. Preprocessing techniques typically involve mathematical operations, applied on the spectral data of HSI images, that are essential to mitigate these issues, enhancing feature extraction and classification accuracy. Effective preprocessing copes with high-dimensional data and inter-class correlations, hence improving the model's performance [35].

2.2.1. Multiplicative Scatter Correction (MSC)

It was stated that MSC could correct for multiplicative effects such as baseline shifts, light scattering, and instrumental variations in order to make the true spectral characteristics of samples clearer [39,41]. MSC is typically carried out by regressing the measured spectrum against a reference spectrum and applying corrections according to the regression model. An appropriate benchmark spectrum is used for effective MSC. Predefined weight vectors have been used in several studies to arrive at an optimum correction performance. MSC removes an estimate of the scattering component of the spectral data and can therefore increase the intensity of absorption bands, which is related to the composition of the sample [9,41]. When combined with other preprocessing techniques, such as moving average (MA), Savitzky–Golay (SG) smoothing, and regression coefficients, MSC has been shown to improve model calibration, including partial least squares regression (PLSR) [39]. This has proven effective for monitoring moisture content in food samples.

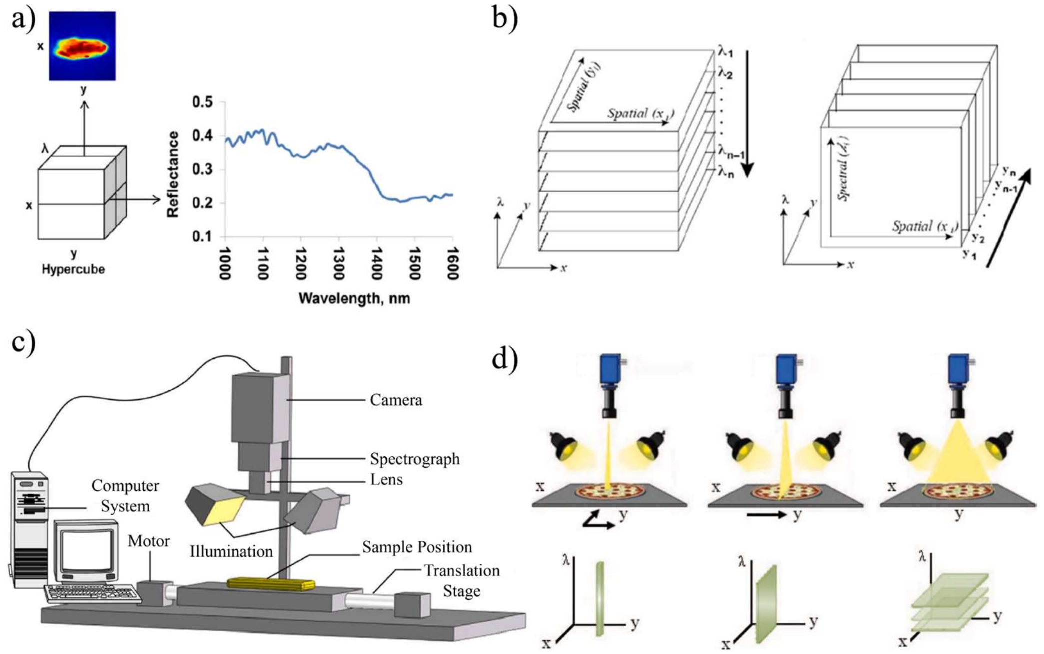

Figure 1. The whole HSI system including (**a**) the hypercube diagram, (**b**) the relationship between spatial and spectral dimensions, and (**c**) the main components of the HSI system. Furthermore, (**d**) there are three approaches for generate hyperspectral images, as follows: when the image is acquired point by point, whiskbroom imaging (point scanning) emerges (left); push-broom imaging (line scanning) is carried out where the image is captured line-by-line along one axis (middle); and finally, area imaging (wavelength scanning) is the case where the entire object or area is imaged at a single wavelength at a time (right) [2].

Particularly, MSC has been proven to play a significant role in enhancing predictive models, especially the performance of models on complex tasks. For instance, the inclusion of MSC in the SVM + PCA + MSC + SPA model developed high accuracy for the detection and location of ADFM in soybean protein meat semiproducts [42]. This preprocessing step therefore improved the accuracy of the detection of the contaminants to enhance the quality of the production and the food safety. Similarly, MSC was applied in the MSC-CARS-CNN model in the classification of beef origin to select 29 critical feature wavelengths while achieving a high classification accuracy [43]. As a result, further studies can be focused on the quality assessment of different meat types using MSC preprocessing. Also, detecting the origin of meat products, especially those that grow in different areas, is a field in which it is possible that MSC can assist in achieving a high-accuracy model.

2.2.2. Standard Normal Variate (SNV)

Standard Normal Variate normalization is a preprocessing technique that attempts to take those variations into account due to the effects of light scattering as well as particle size. Light scattering can cause shifts in the levels of absorbance that produce curvature and baseline shifts of the spectra [44]. In contrast with MSC, based on a reference spectrum, SNV normalizes each individual spectrum by the subtraction of the mean and division by the residual spectrum. Indeed, this method is effective in countering scattering effects without the need for least squares fitting, and is useful for variables with different units or measurement ranges [39]. For instance, a study analyzing wolfberry fruit quality using hyperspectral imaging mentions the enhancement of model accuracy when dealing with variables measured across diverse scales [45]. Furthermore, SNV was effective when it was applied to improve classification tasks for hyperspectral data in quality control systems for fruits and vegetables [15]. It helps to adjust the data by centering and scaling, which improves the accuracy of multivariate analysis techniques, ensuring consistency across variables despite their different units.

SNV has been widely applied to improve the performance of predictive models on various assessments related to food quality. The technique is important, improving the HSI performance in conducting a task such as assessing the quality and safety of foods. SNV applied to predict beef color when combined with PLSR was reported to perform very well. It was also combined with SNV and algorithms like SPA and GS-SVM to produce very high accuracy in classifying the bruises on apples [46]. The effectiveness of SNV in classifying egg freshness was agreed upon, in particular, when combined with wavelet threshold denoising (WTD) and an improved Support Vector Machine (SVM) model [47]. Li et al. (2023) also applied SNV to authenticate levels of adulteration in minced Atlantic salmon with high prediction accuracy after the application of a CNN model [48]. According to these findings, the potential of SNV preprocessing to assess the quality of other kinds of food, such as seeds and leafy vegetables, can be studied further in order to guarantee the effectiveness of this method in various food products.

2.2.3. Savitzky–Golay (SG)

The Savitzky–Golay filter is a powerful noise-reducing and signal-smoothing tool in HSI. This digital filter applies local polynomial regression to smooth data while preserving important features [49]. SG is a finite impulse response (FIR) filter, and since it is a zero-phase filter, it can also keep the fundamental information of the signals unaltered [50]. By adjusting the polynomial order and filter length, SG can compute up to the fifth derivative, ensuring optimality conditions are met for accurate results [51]. SG is also known for its ability to smooth signals while preserving important high-frequency components, unlike standard FIR averaging filters, which tend to eliminate both noise and high-frequency content. SG filters achieve this by fitting a polynomial to the data points and minimizing the least-squares error within the window, which leads to better preservation of signal details compared to traditional FIR filters that might blur or remove critical frequency [52]. By enhancing the metrics of SNR and MSE, the spectral data clarity is increased by SG, which helps in the finer analysis of raw data. In fact, the effectiveness of this approach depends upon the optimization of parameters such as polynomial order and window length. Some studies reported that certain combinations of these parameters result in optimal performance in classification. There are, however, certain limitations of SG, and hence some alternative methods, including those coming under the category of FFT, are also explored for spectrum processing [53–55].

Smoothing is widely used in conjunction with other preprocessing methods to refine spectral data by removing noise at a small scale and enhancing clarity [9]. It is very effective in high-noise conditions, as it emphasizes the shape rather than the height of the spectrum. However, careful attention should be given to the choice of window size, because if the window size is too small, noise can increase, while if it is too large, significant features may be masked [56]. When combined with SG, it can improve the clarity of spectral features, and enable easier identification and analysis [41].

SG is generally used in spectroscopic applications where the attenuation of high-frequency noises is intrinsic. The application of SG is quite common as a preliminary step toward improving spectral resolution and eliminating baseline variations in commonly applied spectral derivation methods [9].

When a fractional-order SG filter was used along with enhancing water content prediction in corn leaves, results were optimal when combined with SG and wavelength selection methods [57]. SG convolution smoothing was also applied to HSI for the accurate evaluation of chicken flesh composition [58]. Additionally, the importance of SG when performing predictions on egg freshness was demonstrated, especially when integrated with advanced techniques for wavelength selection [47]. Since SG was impactful in predicting solid food quality parameters, it is recommended to investigate its potential on the measurement of liquid quality parameters.

2.2.4. Orthogonal Signal Correction (OSC)

OSC is one of the powerful preprocessing methods, removing irrelevant variations from spectral data, which improves the predictive accuracy of machine learning models [59]. By filtering out the unrelated spectral components for a target variable, the relationship between the spectral data and the variable of interest is enhanced [60]. It works particularly well in combination with other preprocessing techniques, since its integration with CARS showed large enhancements in the coefficients of determination and a decrease in RMSE with the combined SNV-OSC-CARS-SVR model [61]. For instance, in the case of Kim et al. (2024), OSC was used with SNV and CARS on the HSI data in predicting protein content in dried laver. Similarly, Xiao et al. (2024) demonstrated the application of the OSC-CARS-Support Vector Machine model for the SSC prediction of Agaricus bisporus slices during ultrasound-assisted osmotic dehydration. By improving model accuracy, OSC has become a useful tool in non-destructive food analysis [60], with applications across a wide range of agricultural products. In this case, studying the usefulness of OSC in products like fruits and vegetables can be considered for evaluation.

Although OSC's advantages are obvious, it can lead to misconceptions regarding the separation of predictive and non-predictive information, potentially confusing model interpretation [62].

2.2.5. Auto Scaling (AS)

Auto Scaling is a normalization method that standardizes spectral data by normalizing each variable against its standard deviation to achieve a mean of zero and a standard deviation of one. This extends mean centering by considering data variations and transforming the data into user-specific ranges, such as between −1 and 1 or 0 and 1. AS works well when splitting spectral data into training and validation datasets, maintaining better consistency during model development. One major disadvantage of AS is that it inflates small spectral values and is highly sensitive to outliers. Applications of AS in food quality assessment are rare [16,63].

Although applications of AS in food quality assessment are still limited, Kim et al. (2024) showed the potential of AS to predict protein content in dried laver. In their study, a variant of AS in combination with SNV and OSC as preprocessing steps enhanced prediction accuracy, as reflected in the high coefficients of determination and low root mean square errors obtained from their SVR models [61]. In the case of limit studies, the feasibility demonstrates AS's promise for non-destructive food quality assessment though further studies will be required to generalize its applicability across different food products, such as different types of algae, in predicting different quality parameters.

2.2.6. Mean Centering (MC)

MC is one of the preprocessing methods that reposition the origin at zero by subtracting a variable mean from the variables, which does not change the variance of such a variable. Such a transformation would be helpful for interpreting deviations from the mean, and most importantly for mitigating problems in statistical models that present multicollinearity, for instance, moderated regression and structural equation models. Because MC only mitigates micro-collinearity and does not comprehensively solve the correlations between the variables, its efficiency in managing the collinearity in complex models can be debated [16,64].

MC can also enhance the performance of calibration models when combined with other preprocessing methods applied to HSI. An example was provided by Marín-Méndez et al., who, during the development of a rapid non-destructive analytical method for predicting nutritional content in food products, de-applied MC in a combined manner with SNV and Savitzky–Golay first and second derivatives. Their analysis results indicated that Ridge regression, after MC preprocessing, provided high accuracy in the prediction of protein and moisture content; however, for carbohydrate and ash content, the model was slightly less effective in terms of accuracy [64]. Further improvement can be obtained simply by increasing the sample size or by combination with MSC to reduce the effect of external noise, and this would increase the model's accuracy for better prediction in hyperspectral food analysis data [39]. In addition, since MC showed effectiveness in data extraction to evaluate food composition, suggesting the effect of this preprocessor in detecting the compositions of useful products such as dairy and eggs.

2.2.7. Moving Average (MA)

MA-based techniques play a very important role in HSI, especially in estimating global statistics from partial data. They provide a very efficient way of computing mean and covariance values, which can then be utilized by other applications such as anomaly detection and classification. On remotely sensed hyperspectral or multispectral imagery, MA sometimes has an application to denoising by smoothing the pixel values to achieve the purpose of noise suppression with retention of the significant features [65].

In the food industry, MA has been widely applied to enhance the accuracy and robustness of the analytical models. For example, in the case of spinach juice droplets located on the surface of stainless steel, MA filters were used for noise smoothing and enhancing the clarity of spectral features, thus giving rise to a very high classification accuracy with SVM models [66]. Similarly, when MA was applied with other preprocessing methods to improve the quality of spectral data in the prediction of protein content in potato flour noodles, the performance of both PLSR and PCR models significantly improved. For instance, the MA-CARS-PCR technique gave highly accurate predictions [59].

Nevertheless, in some cases, other more powerful techniques, such as OSC or OSC combined with CARS, showed improved performances compared to MA-based methods; the latter's performances relied so greatly on the type of machines used during pre-processing [59]. These sometimes identified that MA preprocessing could reduce accuracy when labeled by certain ML models [66]. Therefore, great attention should be paid when selecting the appropriate ML model with MA as the preprocessor.

2.2.8. Minimal Noise Fraction (MNF)

Minimal Noise Fraction is the linear transformation method that tends to improve the SNR of spectral data. It assumes no correlation between signal and noise, involving the simultaneous filtering of both low- and high-frequency signals with a view to estimating a covariance matrix. This was originally very good at extracting useful spectral information, although it has some limitations with regard to the automatic separation of signal and noise in real-time processing [39].

While MNF has sometimes been considered a method of preprocessing, others have referred to it as a method of feature extraction because of its part played in the transformation of spectral data [16,67]. Luka et al. (2024) have clearly defined what MNF does to spectral data, hence the reason it is placed firmly here within preprocessing tool categories [39]. Also, the noise-reduction feature, transforming noisy data into components ordered by signal-to-noise ratio, was mentioned in other studies [68,69].

So far, in practical applications, MNF has been employed to detect milk powder adulteration using near-infrared HSI. Variability and noise were introduced into the data by the brand diversities; hence, MNF was used in the pretreatment of the data to separate noise from the data carrying information for the detection of adulterants like vanillin and melamine in milk powder. Also, treatments such as MNF yielded robust PLSDA and PLSR models that were able to identify the presence of adulterants at very low concentrations [70].

In comparison with PCA, MNF mostly overcame the sensitivity to the noise of PCA by filtering noise from the informative signal separately through successive applications of PCA [71,72]. Unlike standard PCA, this makes sure that the first few components are guaranteed to contain significant variations while containing minimal noise [70]. However, it was once demonstrated in a study that even with the noise-reduction capability of MNF, applying PCA resulted in a better capturing of strong signals of absorption in spectral data. Zhang et al. (2024) identified that models based on PCA were superior to MNF in prediction capability related to moisture content and in ginseng. It has been stated that MNF is useful in datasets with significant noise, but PCA remains a formidable alternative when the data contain critical chemical absorption signals [73]. In this situation, further research is required to understand the performance of MNF and PCA in different aspects of food quality. The effectiveness of MNF as a preprocessing tool in HSI, especially in food engineering, requires its comparison with other methods in order for the performances to be optimized over a wide area of applications.

It is noteworthy that due to the characteristics of different food products, the performance of MNF varies. More research on the efficiency of applying MNF in different products, from fruits and vegetables to ready-to-eat foods, can better determine the benefit rate of this preprocessing method.

2.2.9. Log (1/R)

The log(1/R) transformation is one of the spectral data processing methods used to linearize the relationship between wavelength and the response variable. This technique is helpful if the data in the spectra have a nonlinear relationship; it enhances absorption spectra and sharpens important features. The reflectance can be logarithmically transformed, whereby the sum of a small constant avoids undefined logarithmic values stemming from zero or negative reflectance values; therefore, it does not change the stability and maintains the relative differences [39].

Logarithmic transformation, Log(1/R), has been one of the most widely used transformations in HSI for monitoring moisture content along with other quality attributes of food items during processing, such as binary mixtures of food powders [74], fat content [75], and classification [76]. Arefi et al. 2021 used this transformation in tandem with visible and near-infrared (Vis-NIR) hyperspectral imaging to monitor the moisture decay of apple slices during hot-air drying. Logarithm transformation significantly cleaned the spectral noise, and hence it was helpful for selecting wavelengths that carry information on moisture content [77].

Similarly, Achata et al. (2021) applied a logarithmic transformation log(1/R) to assess drying processes on beef jerky. Along with NIR HSI and chemometric models, the method increased the precision of predicting moisture content in the drying process [78]. Due to the improved spectral features, it was possible to develop superior process control and a more complete prediction of moisture content, therefore proving the efficiency of transformation to improve model performance in meat quality monitoring. In such a case, it is suggested to ensure its efficacy by applying it to assess different quality aspects in different meat products.

Consequently, the preprocessing algorithms have significantly enhanced the feature extraction and generated more accurate predictive models while retaining much of the increased clarity and interpretability in hyperspectral data. The proper application of preprocessing techniques not only optimizes model performances but also provides more reliable outcomes in the assessment of food quality and safety. Some pre-processing techniques of the spectrum are summarized below in Table 1. Since hyperspectral imaging is an advancement in a continuous manner, embedding the steps of preprocessing will remain important in realizing how to exploit this premium technology in a wide range of applications related to food industries.

Table 1. A summary of the application of spectral pre-processing techniques used in hyperspectral imaging system in the food industry.

Preprocessing Method	Objective	Advantage	Limitation and Challenges	Reference
MSC	Detect foreign matter in meat products	Achieves 95% accuracy with SVM + PCA + MSC + SPA model	Requires complex modeling; performance may vary by contaminant	[42]
MSC	Origin classification	Improved model accuracy (91.01%) with spectra reconstruction from RGB images	High device costs, long imaging times, and low image resolution hinder broader use	[43]
SNV	Detection of adulteration	High accuracy with SVM models, enhanced by feature wavelength selection	Parameter optimization (GA, grid search) adds complexity; requires pretreatment and variable selection	[48]
SNV + SG	Freshness classification	Achieved high classification accuracy using SVM models, with feature wavelength selection techniques improving model performance	Parameter optimization using GA and grid search adds computational complexity; requires data pretreatment and variable selection	[47]
SG	Estimation of water content	High accuracy with FOSGD and PLS models; reduced RMSE	Complex preprocessing with multiple wavelength selection methods; computationally intensive	[57]
SG	Rapid determination of chemical compositions (moisture, protein, ash)	High prediction accuracy and visual chemical distribution maps	Requires multiple preprocessing steps and feature selection for optimal performance	[58]
OSC	Predict soluble solid content (SSC) during ultrasound-assisted osmotic dehydration	High accuracy with OSC-CARS-SVM model, capable of visualizing SSC distribution	Involves complex wavelength selection (CARS) and computationally intensive full-spectrum modeling	[60]
OSC	Non-destructive assessment of protein content	High prediction accuracy, aiding precise quality control of dried laver	Involves multiple preprocessing steps and advanced regression, increasing computational complexity	[61]
AS (Standard Scaler)	Non-destructive assessment of protein content	Enhanced model accuracy combined with CARS and other preprocessing techniques	Involves multiple preprocessing steps and complex wavelength selection, increasing computational demands and may complicate implementation	[61]
MC	Prediction of energy and macronutrient content	Accurate predictions of protein and nutritional values with Ridge regression	Lower accuracy for carbohydrates and ash predictions; model selection and evaluation can be complex	[64]
MA	Prediction of protein content	Enhances accuracy of regression models like PLSR for food composition	May lead to loss of fine spectral details and may require additional techniques for feature extraction	[59]
MA	Droplets detection	Improves classification accuracy of hyperspectral images for detecting diluted spinach juice with SVM models	Requires optimization to reduce wavelengths and computation time; may underperform with highly diluted samples	[66]
MNF	Detection of adulteration	Effectively reduces noise and brand interference, enhancing the clarity of adulterant signals in hyperspectral data	Requires complementary algorithms for improved classification accuracy and quantification of adulterants	[73]

Table 1. *Cont.*

Preprocessing Method	Objective	Advantage	Limitation and Challenges	Reference
log (1/R)	Predicting various quality parameters during hot-air drying	Achieves high accuracy in predicting vitamin C, SSC, moisture content, and shrinkage with lower computational demands for multispectral systems	GPR models may struggle with predicting parameters like rehydration ratio and total phenolic content	[77]
log (1/R)	Predicting moisture content during drying	Delivers high prediction performance for moisture content, achieving RPD values > 4, which is effective for process control	Requires careful spectral preprocessing and band selection, adding complexity and computational demands	[78]

2.3. Hyperspectral Wavelength Selection

It can capture a wide range of wavelengths, which helps in the detailed analysis of materials. However, not all wavelengths contribute equally to model accuracy, and some may introduce noise or redundancy, hence leading to reduced efficiency in predictive models. Due to this fact, wavelength selection has been considered one of the most important steps in model enhancement, reducing computation time, and thus increasing interpretability. These include various methods of wavelength selection developed independently, such as filter, wrapper, and embedded approaches, each with their ideas of how best to enhance the predictive capability of HSI data [16,39].

Images captured and stored by the device will follow the steps in the processing (Figure 2). Image preprocessing will be carried out in three layers, namely low-level, intermediate-level, and high-level image processing. Three different multi-variate algorithms are applied for each distinct level of analysis [16].

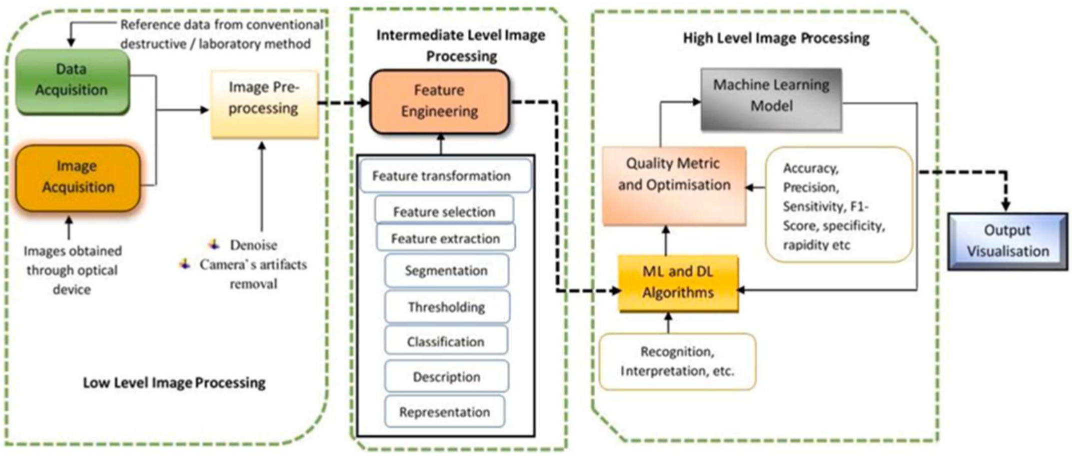

Figure 2. Stages of image processing for deep learning operations [16].

2.3.1. Competitive Adaptive Reweighted Sampling (CARS)

CARS, inspired by Darwin's evolutionary theory of survival of the fittest, is a very effective method of variable selection, reducing data dimensionality and collinearity. The method employs Monte Carlo sampling to create spectral subsets, followed by an exponential decay function that removes less-informative wavelengths. The steps continue with ranking the rest of the wavelengths through Adaptive Reweighted Sampling, based on their regression coefficients in descending order of their predictive relevance. This cross-validation, which is usually carried out with the RMSE, helps in selecting the optimal wavelengths. Thus, CARS has a number of advantages in balancing between minimum collinearity and high robustness of models [39,78].

In the work of Bonah et al. (2020), CARS was combined with PSO to carry out the classification of bacterial pathogens on agar plates. The reduced number of wavelengths resulted in a correct classification rate of 99.47% in the training set and 98.44% in the prediction set, which served as evidence of the capability of the technique in reducing spectral data without compromising accuracy [79]. Then, using the CARS-PLS-DA model for a fish freshness assessment distinguished fresh, refrigerated, and frozen–thawed samples with high accuracy. Furthermore, a good predictive ability was found for the storage time estimation both under room temperature and refrigerated storage, with correlation coefficients of 0.948 and 0.9319, respectively [80]. Durojaiye et al. 2024 further showed the potential of CARS when presenting that the method was applied for chicken flesh chemical composition prediction, and after processing, a high accuracy regarding protein content prediction was achieved, hence showing the non-destructive potential of the method in food analysis [16].

2.3.2. Principal Component Analysis (PCA)

PCA is a traditional technique that has shown satisfactory performance in reducing the dimensions of HSI. This algorithm orthogonally transforms the dataset by capturing most of the data variance into fewer dimensions, enabling it to perform data visualization and analysis efficiently. In terms of exploratory data analysis, it has already occupied a leading position, as it normally learns the data structure with no optimization toward any specific prediction tasks [81]. PCA often finds applications in HSI, mainly because it reduces the processing load and simplifies data interpretation by selecting a very small subset of the best features. For example, in PCA, due to minimum loss of information, computational cost and time can be reduced; at the same time, it reveals the natural latent structure present in the data. However, it is unsupervised and hence cannot give specific classes. Thus, PCA might not be suitable for detailed classification problems [9].

PCA has high potential for use in conjunction with machine learning models that improve classification efficiency in agricultural products. In one novel study, PCA was performed for modeling degradation kinetics and estimating the shelf life of chia seeds. Using scores of the first PC1 that monitored compositional degradation, the shelf life under different storage conditions was predicted. [82]. Likewise, during the assessment of beef moisture and tenderness upon heating with PCA, the result yielded an R^2 value of 0.912 in the prediction of moisture and a value of 0.771 in tenderness. PCA also provided an important understanding in developing a visual of the condiment distribution on cooked meat and its overall quality analysis [83]. Another application of PCA is in identifying the variety of sorghum; based on this, Zhao et al. (2024) made use of PCA to reduce the dimensionality of the HSI data. These MVC-reduced data were then fed into a SICNN, which yielded the result of >98% in classification accuracy [84].

2.3.3. Successive Projections Algorithm (SPA)

The SPA is a robust method for variable selection with the aim of reducing multicollinearity in hyperspectral data. In this algorithm, the variables are iteratively projected to maximize the variance, thereby enabling SPA to choose the most informative wavelengths by reducing redundancy as much as possible. In this respect, SPA is particularly useful to simplify such a complex dataset and enhance the interpretability of models [85]. There has been a wide variety of applications using SPA in HSI-based food quality and safety assessments. We have shown the efficiency of SPA in the SSC and FI of Malus micromalus Makino. A combination of SPA with ELM and GWO-SVM can ensure a fast, non-destructive prediction of the features of fruit quality [86]. Simultaneously, the reduction in data complexity did not affect the accuracy; therefore, SPA is suitable for large-scale applications of quality control.

In seafood analysis, the freshness of largemouth bass filet under different thawing conditions was assessed using SPA. According to the values of electrical conductivity in the SPA-PLSR model, seven key wavelengths were selected for the prediction of freshness, which showed high accuracy and thus enabled the mapping of spatial distribution [87]. Spatial distribution maps were used to visually display freshness in filets as a rapid, non-invasive analytical technique to quality control in seafood. Furthermore, Jiang et al. (2021) applied the SPA to authenticate fresh and cooked mutton rolls with pork and duck adulteration. Herein, the SPAPLS-DA model was able to classify samples into their categories with 100% accuracy with minimum computational complexity, hence proving to be useful for investigation in food fraud detection problems [88]. This kind of application is of paramount importance in view of ensuring authenticity and safety in food items.

2.3.4. Uninformative Variable Elimination (UVE)

UVE is an effective technique for the selection of variables. It offers enhancements to improve the predictive modeling in the analysis of hyperspectral data by removing either redundant or otherwise irrelevant variables. PLS refines the regression models by evaluating the stability of the regression coefficients and eliminates unstable variables that will have low predictive power. This approach is very useful when one has to deal with a high volume of spectral information, as usually happens with HSI [89]. UVE has been widely followed to enhance the performance and increase the accuracy of the HSI models. In one of these, chestnut quality detection was made using UVE. The critical wavelengths were found near 1000, 1400, and 1600 nm. The choice of those critical target wavelengths gave a fabulous result in developing a deep learning model, FD-UVE-CNN, with a high accuracy of 97.33% that reduced recognition time massively and enhanced the performance of the model [90]. This demonstrates the capability of UVE to simplify spectral data for rapid, yet accurate qualitative analysis, especially in areas where speed is of the essence.

Similarly, Zhang et al. (2020) combined UVE with the Successive Projections Algorithm (SPA) into analyzing fat and moisture content in salmon filets. The incorporation of UVE optimized the LS-SVM model through spectral refinement and improved the accuracy of the predictions at higher magnitude [91]. This case is an example of the synergism of UVE with other preprocessing methods, especially in the area of optimization and fine-tuning for models related to complex food matrices. Another case where UVE is used is in the starch content detection in maize kernels, in combination with MSC and texture features. Given the robustness for rapid detection with complications arising due to water interference, UVE definitely plays an important role in enhancing robustness when the sample conditions are adverse [92]. This makes UVE an important tool for enhanced reliability and precision in predictive models, across diverse food quality assessments.

2.3.5. Variable Importance in Projection (VIP)

The VIP method answers which variables are important for the predictive capability of the model and ranks them in order of importance. This method, included in PLS regression, calculates scores for each variable. The higher the score, the more important the variable. The VIP method identifies the critical variables with a minimum loss of information that reduces the dimensionality of the data while enhancing the robustness of the model. Normally, a threshold is fixed by the user in order to filter out less important variables and focus the analysis on those that contribute most to model accuracy [93]. This is evident in the application of VIP in machine learning models for reducing data dimensionality during the prediction of beef rancidity while it is cooling. Machine learning models optimized by VIP learned to effectively forecast beef rancidity. The results showed how useful and efficient this method was for a non-destructive quality assessment of foods [94]. The rationale behind the trend in the recent application of variable importance in projection and improving the accuracy of postharvest handling operations comes from how the method manages to reduce dimensionality in spectral data, producing faster results with less computational cost but retaining high accuracy.

Ryu et al. (2024) applied VIP to predict freshness indicators such as pH, TVB-N, and K values of chub mackerel during seafood quality evaluation. With partial least squares regression and Support Vector Regression methods trained by the VIP-PLSR model, high accuracy in its prediction was reached. Such facility of variable selection on the part of VIP enhanced the general efficiency in freshness evaluations and demonstrated wide applicability to various food matrices [95]. In addition, during nutritional analysis, where VIP has proved useful, the model, upon improvement using VIP, showed high accuracy in flavonoid content prediction and could predict total flavonoid content in fruits of Cerasus Humilis during storage [96].

In general, it is believed that the choice of optimal wavelength maximizes the performance of hyperspectral imaging systems. Well-chosen wavelengths enhance the models' accuracy, reduce computational burdens, and bring better interpretability. CARS, PCA, SPA, UVE, and VIP are some of the various methods used for the refinement in analyzing the spectral data. Each of the techniques identified has strengths and applications in different areas of material analysis and quality control for which it is superior. Table 2 provides an overview of many of the currently available techniques for wavelength selection and applications.

Table 2. The potential of hyperspectral wavelength selection in HIS system.

Wavelength Selection	Application	Drawbacks	Proposed Corrections	Reference
CARS	Classification, freshness assessment, predictive modeling	High computational cost, potential overfitting	Combined with other optimization techniques like PSO for improved accuracy	[79,80]
PCA	Dimensionality reduction, data visualization, exploratory data analysis	Does not distinguish between specific classes, unsupervised	Integration with machine learning models for improved classification	[81–84]
SPA	Quality control, freshness assessment, authenticity detection	May require large sample sizes for optimal performance	Use in combination with other algorithms like ELM and SVM for enhanced accuracy	[85–88]
UVE	Quality detection, compositional analysis, rapid detection	May require careful calibration of threshold values	Combine with other techniques like MSC for improved robustness	[89–92]
VIP	Nutritional analysis, freshness prediction, quality monitoring	Best used as a complementary technique, requires careful threshold setting	Integration with other methods for optimal performance and accuracy	[93–96]

3. Artificial Intelligence Approach

Artificial intelligence (AI) integrated with HSI has turned the traditional form of predictive modeling in quality and safety assessments upside down. The AI techniques can be named advanced food quality assessments, since they open up a whole new scale for high-dimensional and complex datasets from high-spectral imaging, which bear the potential for much more accurate, efficient, and automated data analysis. Among several supervised and unsupervised ML-based regression techniques, classification methods, and deep learning algorithms, those that will be discussed in this section, are for enhancing food product evaluation and detection systems. The supervised methodologies comprising linear regression analysis, decision trees, and partial least squares are widely used in predictive tasks where the output is known. Unsupervised methods find hidden patterns in data and, in general, will be very useful in cases where labels are unavailable. This is mainly because deep learning, able to model nonlinear relationships and learn hierarchical feature representations, holds even further potential for advanced food quality assessments.

3.1. Supervised ML

Supervised learning is one of the most popular paradigms in machine learning, where models are trained on labeled inputs and their corresponding outputs. It is especially suitable for the problem scenarios where the expected model output is known, and model learns from patterns in the data to generalize later to unseen datasets [97]. With this in mind, several supervised learning methods have been developed to enhance the performance and efficiency of AI models in HSI.

3.1.1. Linear and Logistic Regression

Linear regression is a straightforward method that calculates the dependence of a dependent variable on one or more independent variables. Where there is the presence of more than one independent variable, the concept of MLR extends to multiple predictors, which predict the variance in a dependent variable [98,99]. However, MLR has generally been applied in a number of HSI uses to analyze sensory features of food products. However, due to its simplicity, MLR may not execute as well compared to nonlinear methods when dealing with complex datasets where the relationships among variables might not follow a strictly linear pattern [46]. For example, Paz et al. (2024) suggested that a new combination of digital imaging and multivariate calibration techniques such as SPA-MLR be applied for color determination in sugar. This very promising technique provided high accuracy cost-effectively and non-destructively, apart from some possible traditional chemical analyses [100]. In this respect, the use of SPA-MLR witnesses the increasing application of sophisticated regression models in food-quality control applications. Combining MLR with other techniques can be investigated in further research.

Similarly, Song et al. (2024) applied MLR for the prediction of oil content within corn kernels by using HSI and highlighting some of the innumerable uses within agricultural monitoring. This technique will provide a fast and non-destructive way; hence, MLR became very useful in field applications [101]. Further investigation in similar cases such as wheat, soybeans, and canola oils are required to evaluate the efficiency of MLR in oil content prediction.

Partial least squares regression is a linear regression method that is applicable when the dataset possesses high dimensions and the predictors are collinear, or when the samples are outnumbered. It extracts latent variables with key predictive information, thus effective in complicated data analysis [102]. Food quality could be assessed by PLSR in combination with near-infrared hyperspectral imaging (NIR-HSI) to determine oil and fatty acid content in Brassica seeds [103] and textural properties in mozzarella cheese [104]. The results from these works showed the robustness of PLSR in handling complex datasets, which is useful in observing the quality of the food.

While both MLR and PLSR add large value to hyperspectral data analysis, each has its strong points. MLR works best in simple, low-order linear data, while PLSR generally tends to perform better with high-dimensional, complex datasets. In choosing between the two methods in HSI applications, an understanding of the intricacies of each method will be important in the process.

Logistic regression, by construction, is mainly used for binary classification. It estimates the conditional probability of an outcome given a set of input features; hence, it yields a direct solution to classification problems [105]. In a study, a fruit contaminant classifier using logistic regression is presented that exhibited very high sensitivity and accuracy [106]. Based on spectral data, this model achieved high predictions in physical hazards like branches or foreign objects, indicating the feasibility of this model in food safety applications in real time. For classifying pesticide residue levels in grapes by NIR spectra, logistic regression achieved accuracy above 97%. Its performance is pretty strong in these applications regarding the detection of agricultural hazards and will be valuable for hyperspectral data analysis in the context of food safety [107]. These studies represent that logistic regression has been very successful in food safety for the detection of foreign materials in foodstuffs and can also be studied in the case of detecting toxins on the surface of citrus and other fruits.

3.1.2. Linear Discriminant Analysis (LDA)

LDA is a machine learning methodology in a supervised manner to classify data or perform dimensionality reduction. It has provided the idea of projecting data in lower-dimensional space by finding a linear combination of features, which maximizes the separation between different classes. This approach implicitly assumes that data belong to a normal distribution, with classes sharing a common covariance matrix, and under those conditions, it works very effectively [108,109].

The studies have applied this technique to classify tea varieties from different geographical origins using NIR spectra, which resulted in a 100% discrimination of five varieties, namely Argentinean and Brazilian green teas and Sri Lankan black tea [110]. The application of LDA in the detection and classification of adulterants in minced beef and pork has also been explored by HSI. The method successfully discriminated the pure from the adulterated, whilst identifying the adulterants themselves [111]. Another work, that of Kang et al. 2021, uses LDA in conjunction with the Hyperspectral Microscopic Imaging (HMI) technique for the classification of foodborne pathogens, resulting in a classification accuracy of 92.9% [112]. The potential of LDA in terms of classification will lead to the study of the classification of different foods by this method in future studies.

Despite its advantages, LDA also faces some drawbacks in terms of requiring certain distributional assumptions and being constrained with regard to linear transformations; hence, nonlinear or advanced models may perform better in many cases [112]. In this case, it is necessary to completely understand the characteristics of the products and the reason behind using LDA.

3.1.3. Partial Least Square (PLS)

PLS represents a multivariate statistical approach intended for both dimensionality reduction and regression analysis. It is specially fitted for the analysis of spectral data, in which datasets are usually big and collinear. So far, PLS has been the most frequent application in the food industry, with the aim of predicting chemical composition among other attributes in high-dimensional datasets. Moreover, the combination of PLS-DA and a PLSR model for fish freshness classification was able to predict successfully storage time under different temperature treatments, indicating the versatility of this technique in the food industry [81]. In another similar study, the detection of fungal contamination in maize kernels using HIS was carried out by PLS-DA, showing how PLS can be adapted for food safety [113].

The flexibility of the PLS model is also shown through various key components in several food products: the prediction of protein content in black fly soldier larvae [114], the quantification of oil and fatty acid content in Brassica seeds [102], or assessing adulteration in Atractylodes rhizoma powders [115]. Although it may lag behind in nonlinear relationships for which other methods like the Support Vector Machine Regression or deep learning can provide superior performances [116], it is a powerful approach in food quality and safety assessments because of its complexity in dealing with collinear data, in addition to reducing dimensionality.

3.1.4. Decision Trees (DTs)

Decision Trees (DTs) are widely used in food science for their simplicity and interpretability. DTs split data into subsets based on feature values, creating a tree-like structure where nodes represent decision rules, and branches represent outcomes [117]. Food quality assessment is the field in which DTs can be applied in HSI to evaluate different quality parameters, with high accuracy.

Research using DTs coupled with NIR-HSI for the classification of black tea quality reached an accuracy of 93.13% using the fine tree model, which evidently proved the capability of DTs to manage complex, multi-factorial datasets on their own [118]. In addition to that, DTs proved to be very resilient in agricultural applications, as evidenced by their capability to estimate firmness and soluble solids in apples using hyperspectral images with R^2 values of 0.881 and 0.679, respectively [119]. While decision trees bring in these advantages, more sophisticated models, such as random forests or gradient boosted trees, would easily outperform in a noisy dataset or with higher demands on accuracy.

3.1.5. Random Forest (RF)

RF is an ensemble machine learning algorithm that trains many decision trees and combines the predictions of individual trees for improving classification or regression predictive performance. It has good robustness and is capable of handling high-dimensionality data [31]. The potential of RF in rapidly and confidently food monitoring and assessing the durability and variety of food products has been demonstrated, making this method an applicable model in these areas. Also, the combination of RF with CARS to select the wavelength has shown promising results in the classification tasks. In this context, RF has classified Coix seed samples regarding storage years based on HSI data. Although the developed RF classifier had a good performance, other deep learning models, including ResNet and SVM, achieved better accuracy [31]. As a result, this model is useful for non-destructive food analysis.

In another application, RF was applied to classify 27 different varieties of sorghum using VNIR-HSI. The model returned a calibration precision of 94.58% and a prediction precision of 64.44%. With dimensional reduction using the CARS algorithm, the proposed CARS-RF model improved the prediction accuracy to 84.07%, reflecting the capability of RF to deal with high-dimensional spectral data from imaging techniques [120]. It was further shared how RF can predict wheat characteristics and compared similar models such as the SVM and XGBoost gradient boosting trees. While RF was outperformed by more advanced ensemble models, RF performed well, thus indicating its reliability for spectral data in food quality prediction [121].

3.1.6. Support Vector Machine (SVM)

The Support Vector Machine is a powerful supervised learning algorithm with broad applications in the evaluation of food quality, mainly in combination with HSI. It is particularly capable of dealing with high-dimensional data, which comprehensively makes SVM suited for a wide variety of food attribute classification and contaminant detection cases. SVM has extensive potential for the capture of very subtle spectral variations reflecting changes in food composition, freshness, or contamination. Its strength lies in handling complex datasets where similar visual features mask significant spectral differences [16].

With the ability to capture complicated nonlinear relationships between spectral data and chemical compositions, a widely conducted model in food analysis includes the Support Vector Machine-based model, namely Support Vector Machine Regression—SVMR. For example, it has been used to predict protein content in chickpeas [122] and to detect Robusta adulteration in Arabica coffee [123]. In addition, deep learning-integrated SVM models further improved their performance, such as in convolutional neural networks. The studies that combined CNNs with SVMR showed success regarding adulterants in processed meat. Thus, this hybrid approach represents a reliable and non-destructive method of food safety monitoring. Although SVMR has some shortcomings, for example, its careful parameter tuning and high computational burden, this technique possesses great generalization abilities; therefore, it is very useful in food science [124].

3.1.7. K-Nearest Neighbor (KNN)

K-nearest neighbor is a straightforward yet effective algorithm for classification and regression analysis. It simply classifies unknown food items by matching their spectral signature with the known ones. K-nearest neighbors assume that similar food items are located around one another in a feature space. It is not surprising then that the technique has been found quite useful in a variety of HSI-based food quality assessments [125]. KNN has been successful in finding applications in foodborne pathogen detection, classifying moldy tea leaves, and identifying adulteration in meats with the help of hyperspectral data due to its high accuracy in non-invasively identifying bacterial strains [126]. Xin et al. (2019) classified mold contamination levels in dried tea leaves using KNN with optimal wavelengths and roughness penalty smoothing methods [127]. KNN has also been applied to meat authenticity through the determination of adulteration in cooked mutton kebabs, which helped in distinguishing the mutton from the skim alternatives like chicken or pork [128]. While a method such as KNN may not give superior results to more complicated models, its simplicity and performance are good enough to make it a practical option when a rapid food quality assessment is needed.

3.1.8. Naïve Bayes

The Naïve Bayes is a basic probability classification algorithm based on features in conditional independence. It is simple yet effective in many applications, since the full joint distribution needs not to be estimated. Despite this, Naïve Bayes can be useful in preliminary food quality screening because it has computational efficiency [129]. In a study, Naïve Bayes was the main ML model classifying oat samples according to the mycotoxin content; it could detect DON contamination with moderate success. While less accurate than more complex models like random forest, Naïve Bayes nevertheless provided meaningful insights on those classification tasks [130]. Simplicity makes it a suitable tool for early-stage screening, but the feature independence assumption tends to bind its accuracy in applicative cases where variable interactions are present.

3.1.9. Soft Independent Modeling of Class Analogy (SIMCA)

SIMCA is a classification technique using the principal component analysis method. When one class is modeled separately and new samples are classified according to their degree of fit in these models, it can be subjected to some strong advantages: soft classification approach, whereby some samples could be members of more classes or perhaps none. In conducting one-class classification, SIMCA is suitable for modeling in the detection of unknown adulterants of the food products [9]. When this technique was applied to HSI for adulterant detection in almond powder, a high level of sensitivity and specificity was achieved [131]. A similar situation occurred when SIMCA was used along with NIR-HSI to classify adulterated cumin at an accuracy of 95%, showing great efficiency in food authentication [132]. Then, De Araújo et al. (2021) applied SIMCA for the authentication of gourmet coffee varieties using both NIR spectroscopy and digital images to classify the coffee samples into high-value and commercial categories [133]. The versatility reported by this technique is one of the most popular powerful tools in food authentication, especially in systems where it is necessary to quickly test and analyze large numbers of samples or data points, such as quality control sections.

3.2. Unsupervised ML

Unsupervised learning refers to a class of machine learning methods based on knowledge discovery from data. There are no explicit regularities in the form of pre-defined labels or structured semantic relationships between such labels. By contrast, supervised learning involves algorithms that are usually trained by examples of pre-defined input–output pairs; correspondingly, unsupervised learning operates directly on raw, unstructured data without explicitly predefined labels with the intent of discovering hidden structures or patterns [134].

3.2.1. Cluster Analysis

A cluster analysis is a statistical method of grouping objects into classes based on the characteristic features of objects with the aim of maximizing their similarity within one class and minimizing similarity between classes. Major techniques in cluster analysis can be divided into hierarchical and non-hierarchical methods [135]. Hierarchical clustering structures data in a tree-like fashion, called a dendrogram, which can provide a way of visually showing the relations between data points at a higher level of similarity. This technique finds wide application in the field of food safety. The specifics of the technique followed Medina-García et al. (2024), who, using hierarchical clustering, classified bread pixels into visible–near-infrared spectra and estimated the proportion of wholemeal flour. This technique has proved useful in identifying effectively those pixels related to flour content in heterogeneous food samples [136]. It also showed that when UMAP was combined with hierarchical clustering, both adulterants were suitably identified in food matrices [137].

K-means clustering has assigned data points to a predefined number of clusters based on their features, with the objective of minimizing variance within each cluster [135]. K-means was used to classify Pleurotus eryngii into quality grades during post-harvest storage based on HSI data. The method simplified the work of quality control by clustering the samples efficiently, which provided much assistance in product grading and classification [138]. It was also applied along with self-organizing maps to classify Iranian rice varieties, which proved effective in clustering similar products, with very high accuracy (values of 16.896, 15.7161, and 18.920 in the best total sum of distances of three different varieties) during authenticity verification [139].

FCM clustering is an extension of the traditional clustering method where a sample can be associated with more than one cluster and holds membership values for each cluster. Basically, this has an advantage under situations with data structures that overlap [140]. An experiment could be observed in the work on chia seeds' storage, where NIR-HSI was implemented together with FCM to observe the polyunsaturated fatty acid degradation and build up free fatty acids under the storage conditions [141]. Its capability for the detection of slight changes in composition with time, along with appropriate chemometric techniques like PLSR, made FCM precisely predict the concentrations of the fatty acids and hence demonstrated its capability with regard to food quality and safety during storage.

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) finds density separates areas of data, with noise tolerance, and therefore it can be applied to datasets that have outliers [135]. Lei et al. (2022) and Jiang et al. (2023), respectively, used DBSCAN to remove the outliers in HSI data before further processing. These pre-processing steps enhanced the later models to find the grain type and mixing ratios with higher accuracy. The ability of DBSCAN to identify core samples and label outliers adds significant reliability in unsupervised classification models, especially in the case of food analysis [142,143]. Each one of these clustering methods has its foods and unique advantages relative to quality and safety, be it in differentiating ingredients or identifying adulterants and the authentication of products. It is within cluster analytics techniques that food scientists can then confer effective data management for complex data arising from HSI and other advanced sensing technologies.

3.2.2. Principle Component Analysis (PCA)

Principal component analysis (PCA) transforms a set of potentially correlated variables into a new set of uncorrelated variables, known as principal components. It diminishes the dimensionality of the original data while maintaining the most important information within the dataset [1]. PCA is of great help in reducing the dimensions, which, in turn, allows for faster processing and better visualization in a more comprehensible manner. In this work, critical dimensions from hyperspectral data were selected using PCA and merged with a deep learning model in classification tasks to improve the accuracy of the classification process of sorghum seeds. This study also showed how feature extraction using PCA increased performance to almost 99% correct classification [84]. The application described here highlighted how PCA is very efficient in handling large complex datasets, which usually happens when performing food item inspections. Chemical composition, color, and fat content provided significant compositional markers that enabled the successful classification of all types of cheese by PCA models. This application shows how feature selection through PCA can help improve estimation accuracy in food composition [144]. Indeed, PCA accelerates the processes of qualification in food, including those contributing to consumer safety and product quality by reducing data dimensions and increasing their interpretability.

3.3. Deep Learning

Deep learning is a higher level of machine learning, which involves multi-layer artificial neural networks to interpret large volumes of data for specific purposes, even complex ones. Deep learning addresses training neural networks themselves to extract features from the raw data. Multiple layers interconnected in deep neural networks allow for representing complex relationships between inputs and outputs [145]. Deep learning will further enhance HSI capabilities beyond those provided by conventional methods by modeling complex nonlinear relationships within the spectral data. One such application of deep learning has been with the integration of NIR-HSI to estimate nutrition in foods. The introduction of OptmWave was another approach involving deep learning that coupled the selection of wavelength characteristics with modeling in order to optimize the analysis. Applied to a dataset of scrambled eggs with tomatoes, the OptmWave method returned a high determination coefficient of 0.9913 and a low RMSE of 0.3548 [146].

Applications that can show high potentials for deep learning include microbial detection and food safety. In this regard, deep learning frameworks have been applied to identify and quantify Clostridium sporogenes spores within food matrices. Their comparison of the 1D convolutional neural network against random forest models showed that CNN significantly outperformed the RF model by improving the accuracy in spore quantification up to 8% [147]. While in difficult conditions, such as snapshot HSI systems, the robustness of deep learning forms its essential advantage, where traditional methods often failed. In the meat industry, the use of deep learning was applied by researchers, classifying red meat using hyperspectral images from the 3D convolutional neural network. It introduced novel graph-based post-processing to improve the accuracy. This achieved an over 96% classification accuracy in the meat classification problem with the use of both NIR and visible HSI data [148].

Despite certain challenges, deep learning offers significant advantages over traditional machine learning approaches, including the capability of handling large and complex datasets, making it particularly well-suited for detecting adulteration and ensuring food safety [34] (Table 3). Diverse applications of deep learning can make it useful in different processing methods and different food products like meat, diary, fruits, and vegetables. Overall, as technology continues to advance, deep learning is expected to play an increasingly critical role in the future of food analysis and quality control.

Table 3. AI approach in HSI system.

ML/Deep Learning Method	Preprocessing Method	Wavelength Selection Method	Objective	Result Accuracy	References
MLR	-	SPA	Predicting the oil content of individual corn kernels	RMSECV: 9.5 IU	[101]
				RMSEP: 4.9 IU	
				REP: 9.879%	
				R2pred: 0.976	
				RPDpred: 6.289	
PLS-DA	SNV	-	species discrimination of Brassicas seeds	Classification accuracy: 100%	[103]
PLSR	For hardness, springiness, and meltability: SG_Smoothing	-	predicting low-fat mozzarella texture	Hardness: R^2p = 0.846, RMSEp = 2911.29 Springiness: R^2p = 0.85, RMSEp = 0.0939 Meltability: R^2p = 0.728, RMSEp = 22.08	[104]
	For adhesiveness and free-oil: First Derivative of SG (SG_FD)			Adhesiveness: R^2p = 0.809, RMSEp = 56.39 Free-oil: R^2p = 0.992, RMSEp = 0.442	
	For gumminess: First Derivative of SG (SG_FD)			Gumminess: R^2p = 0.835, RMSEp = 1446.52	
	For chewiness: MSC			Chewiness: R^2p = 0.817, RMSEp = 1186.2 Cohesiveness: R^2p = 0.654, RMSEp = 0.071	
SVM	-	-	Food samples recognition	classification accuracy: 68.74%	[105]

Table 3. *Cont.*

ML/Deep Learning Method	Preprocessing Method	Wavelength Selection Method	Objective	Result Accuracy	References
PLS-DA	-	-	Detection of Physical Hazards in a Variety of Fruit Processed Products	Detection accuracy: 97.6%	[106]
Logistic Regression				Detection accuracy: 97.8%	
Logistic Regression	SG	-	Detection of pesticide residue level in grape	Detection accuracy: 97%	[107]
LDA	MSC	-	detecting adulterants in minced meats	Detection accuracy: 93%	[111]
SVM	-	PCA	identification of foodborne bacteria	Identification accuracy: 92.9%	[112]
1D-CNN	SNV-SG	-	detection of fungal contamination in maize kernel	Average error rate: 3.15	[113]
PLSR, SVMR	-	-	Determination of protein content in single black fly soldier larva	RMSEP values of 1.57–1.66% and RPD values of 2.0–2.5, respectively.	[114]
PLSR	-	CARS, SPA	Prediction of Adulteration Content in Atractylodes chinensis	R^2_T: 99.85%	[115]
				RMSET: 1.25%	
				R^2_P: 98.61%	
				RMSEP: 5.06%	
PLSR			Prediction of Adulteration Content in Atractylodes lancea	R^2_T: 99.92%	
				RMSET: 1.16%	
				R^2_P: 99.00%	
				RMSEP: 2.16%	
DT	PCA	Gray-level co-occurrence matrix (GLCM)	delineating black tea quality	Classification rate: 93.13%	[118]
DT	-	Bootstrap Random Forest	assessing internal quality parameters of apple fruits	For firmness: R^2: 0.881	[119]
				For SSC: R^2: 0.679	
RF	MSC-SNC-SG	CARS	classification of Coix seed storage years	Maximum accuracy: 83.52	[31]
ResNet	MSC-SNV-SG	CARS		Recognition accuracy: 87.27%	[31]
RF	SG-SNV-MSC	CARS	Identification of varieties of sorghum	Precision accuracy: 84.7%	[120]
SEL	MSC	CARS	Detection of wheat saccharification power	R_p^2: 0.9308 RMSE: 0.0081	[121]
			Detection of wheat protein content	R_p^2: 0.9939 RMSE: 0.0116 g kg^{-1}	
SVMR	OSC-SNV	-	prediction of protein content in single chickpea seed	R_p^2: 0.912	[122]
				RMSE: 1.032	
PLSR	external parameter orthogonalization-SNV	-		R_p^2: 0.935	[122]
				RMSE: 0.987	
SVMR	-	-	Assessing the levels of robusta and arabica in roasted ground coffee	R_p^2: 0.956	[123]
				RMSEP: 6.07%	
VGG16-SVM	Continuous Wavelet Transform (CWT)	-	identification of soybean protein in minced chicken meat	Classification accuracy: 98.1%	[124]
LDA	roughness penalty smoothing (RPS)	Wavelet-KNN	moldy tea feature classification	Classification accuracy: 98.33%	[127]
KNN	Normalization	PCA	identifying the authenticity of fresh and cooked mutton kebabs	Classification accuracy: 99.38%	[128]
Naïve Bayes	SNV-SG	-	classification of deoxynivalenol-contaminated oat	Classification accuracy: 63.9%	[130]
RF				Classification accuracy: 77.8%	[130]
SIMCA	SG	-	detection of adulterants in almond powder	Sensitivity: 100%	[131]
				Specificity: 89–100%	
SIMCA	-	-	Detection of nutshells in cumin powder	classification error of 2.2%	[132]

Table 3. *Cont.*

ML/Deep Learning Method	Preprocessing Method	Wavelength Selection Method	Objective	Result Accuracy	References
SIMCA	-	-	Authentication of Gourmet ground roasted coffees	Recognition accuracy: 64%	[133]
Hierarchical Clustering	-	-	authentication of wholemeal bread	Maximum deviation: 0.08	[136]
Hierarchical Clustering	essential spectral pixels (ESPs)	Uniform manifold approximation and projection (UMAP)	identifying minor compounds in food matrix	Not reported numerically. It has been stated that the model is a well-classifier method	[137]
K-means Clustering	-	-	Quality grading for Pleurotus eryngii	Classification accuracy: 91.58%	[138]
				F1 score: 91.36%	
				Precision: 89.65%	
				Recall: 90.60%	
K-means Clustering	MSC	-	Identifying the authenticity and geographical origin of rice	In three rice samples: silhouette coefficient: 0.5169, 0.5433, and 0.4964	[139]
FCM-PLSR	SNV	-	Studying Chia (*Salvia hispanica*) seeds degradation	free fatty acids: 91.7% accuracy	[141]
				oleic acid: 97.4% accuracy	
				linoleic acid: 97.1% accuracy	
				α-linolenic acid: 88.7% accuracy	
BPNN	DBSCAN	PCA	resolution of types and proportions of broken grains	Classification accuracy: 99%	[142]
BPNN	DBSCAN-SG-MSC	CARS	detecting of wheat varieties and mixing ratio	Average accuracy: 92.29%	[143]
				Maximum deviation range: 5%	
PLS-DA	-	PCA	prediction of cheeses composition	For moisture content: RPD > 2.5	[144]
				For fat: 2.0 < RPD < 2.5	
				For protein: ~1.5 < RPD < 2.0	
OptmWave	-	-	food nutrition estimation	R_p^2: 0.9913	[146]
				RMSE: 0.3548	
1D-CNN-RF	-	PCA	quantification of Clostridium sporogenes spores in food products	Overall accuracy: 86%	[147]

4. Application of HSI and AI in the Food Industry

Food in the industry exists in solid and liquid phases. These different phases have specific characteristics with each phase having its own problems in relation to the assessment of quality and safety. Solid foods often undergo spoilage through physical, chemical, and microbiological processes, necessitating rigorous quality management practices such as proper storage and handling to mitigate deterioration. On the other hand, liquid foods are more susceptible to microbial contamination, requiring proper evaluation of their quality parameters to prevent them from spoilage [149]. With the development of HSI integrated with AI, a more accurate and comprehensive analysis is enabled across these phases. HSI detects spatial and chemical properties of solid products, such as grains, fruits, meat, and liquid products, like juices and oils, and boosts AI models in the enhancement of classification and identification of defects. In addition, this supports the lacunars for the real-time monitoring not only of chemical composition but also of contaminant detection, making it a suitable fit through which real-time quality control could be effective for all states of food.

4.1. Solid Products

The areas in which the HSI has also seen increasing adoption include the evaluation of several quality parameters of fruits, such as pH, SSC, TA, and TP.

The studies show that the integration of ANN and PLS with SNV and MSC leads to the non-destructive prediction of apple varieties with a high degree of accuracy (Rcv $\approx$ 0.99) among all quality parameters [150]. Furthermore, in predicting spoiled blueberries, the MT-SIS method used in combination with SPA extracted decaying regions, leading to an accuracy of over 97% for the training set and test set accuracy [151]. The results indicate that the performance of this method is remarkable in the processing of fruits. It is suggested to investigate the AI in different processing steps, such as detecting the pesticide residuals on the surface of different fruits.

In grains, successful classifications of bulk grain samples using modified ResNet architecture have been performed, exploiting both spatial and spectral information from HIS that demonstrated 99.75% accuracy [152]. In the classification of broken grains and calculating the ratios for mixing by HSI using a Back Propagation Neural Network (BPNN), an accuracy of over 99% was shown [138]. As a consequence, AI-based HIS processing can play a key role in the classification of broken and whole grains, which is a very useful tool in terms of quality control for producers, by allowing them to adjust processing parameters to maintain product consistency. The classification of seeds and other grains can be considered in further research.

In the meat industry, the development of a new approach using HSI with a 3D convolutional neural network to classify different classes of minced meat based on myoglobin pigment retention in the meat spectra was introduced. Techniques that included preprocessing schemes before data analysis outcompeted traditional techniques that do not consider features in space at high accuracy in classification [14]. Moreover, the high accuracy of HSI processing in predicting intramuscular fat (IMF) and pH in different red meat species (beef, lamb, and venison) using PLSR and deep convolutional neural networks (DCNN) [153], assessing pork quality characteristics through ANN [154], and observing color changes and freshness quantification [87,155], offers precise classifications of meat authenticity and quality traits. These approaches improve accuracy by incorporating both spectral and spatial data. Future applications in the meat industry could focus on the rapid detection of freshness, the spatial analysis of fat content, and comprehensive models predicting moisture and protein distribution for a variety of meats.

In the case of leafy vegetables, the detection of cadmium (Cd), as a metal with a toxic nature and potential health risks, was predicted accurately through a combination of VNIR HSI with different machine learning models, for example, such as ANN, ensemble learning (EL), and SVM. This achievement was facilitated by considering wavelengths affecting chlorophyll and internal structure changes in the leaves due to cadmium [156]. In another study, the detection of foreign materials in freshly cut vegetables was performed using short-wave infrared (SWIR) data combined with PLS-DA [157]. Finally, the detection of vegetables in complex food matrices was achieved alongside E-nose data and LDA preprocessing, with an accuracy as high as 97.50% [158]. The results highlight AI potential in food safety and external quality control, which are necessary steps for leafy vegetables to ensure their health. The detection of bacteria and toxins is the next step to be considered for vegetables.

The capability of Vis/NIR-HSI for the determination of physicochemical characteristics of dairy powders, which involve tapped density, moisture content, surface free fat, and bulk density, was investigated using different techniques, namely portable, bench-top devices, and HSI systems. PLSR models successfully predicted the various quality attributes with accuracy ranging from moderate to good, proving the flexibility of the Vis–NIR technology for its employment online in dairy powder quality control. Each of these scanning techniques had their own relative advantages for different applications in industries and, therefore, provided flexibility for choosing an appropriate system for fast, non-invasive analysis [159].

The assessment of physicochemical characteristics of dairy powders demonstrating the accurate prediction of attributes like tapped density, moisture content, surface free fat, and bulk density by Vis/Nir-HSI provided moderate to good accuracy, which underscores its potential for online quality control in dairy powder production. This method emphasizes the practical applications and benefits of Vis/NIR-HSI in enhancing dairy powder quality assessment processes. [159]. For further exploration, investigating the use of deep learning models, and extending this approach to predict other complex attributes like shelf life or nutritional content, can be considered.

In another study, determining the end date of the cheese-ripening process using NIR-HSI by using a PLSR model to predict E-index associated with maturation time showed an accuracy of 69.6% [160], demonstrating the good potential of HSI in the detection of cheese ripeness. However, further refinement should be carried out with larger datasets, and repetitive scans, in order to view improvements in predictive capacity at commercial use.

It has been stated that two HSI techniques for egg quality assessment were developed, namely a Hyperspectral Egg Defect Inspection Technique (HEDIT) for factory use and a Hyperspectral Egg Freshness Inspection Technique (HEFIT) for consumers. Both obtained a high accuracy from the CNN architecture, with 99% on freshness and 100% on defects [161], while another approach based on VNIR with XGBoost reached a high precision of egg freshness, $R^2p = 0.91$, with a yolk detection of 97.33% and a crack detection of 93.33% [162]. It has been recommended to optimize AI-based HSI methods for real-time automation, especially for defects like cracks and scattered yolks, in order to develop a rapid and non-destructive method for an efficient egg processing.

4.2. Liquid Products

The versatility of the HSI-AI combination in analyzing liquid products offers non-destructive, real-time, and highly accurate solutions for quality assessment across various liquid food industries. A robust analysis methodology of the composition of alcohols and esters in Baijiu will be developed using HSI and machine learning. Applying PSO, Support Vector Regression and random forest models demonstrated high accuracy for ethanol-ester detection. Specific wavelengths in the NIR region allowed for the highly precise quantification of the compounds, with an Rp^2 above 0.99. This means that when HSI processing is being carried out through AI-based methods, it has the potential to offer a non-destructive, accurate method of assessment of chemical composition as regards alcoholic beverages for quality control and confirmation of authenticity [163]. Since monitoring liquid products is important to preserve them from decontamination and mitigation, it is crucial to develop an HSI method to check the composition, consistently. Furthermore, in some cases like pasteurized milk, models can be developed to check the microorganism activities inside the milk in order to optimize the storage conditions.

This was also carried out for the morphological and moisture content changes in drying droplets of Lonicerae Japonicae Flos extract. Partial least squares regression and artificial neural network analysis, which were integrated with hyperspectral data, enabled the noninvasive monitoring of drying kinetics. This method can be transferred to various other liquid food products, such as milk or fruit juice concentrates, in order to support food manufacturers in the elaboration of optimized processing methods that yield more uniform final products [164]. Another study tested oil adulteration detection by HSI through the use of various machine learning models, including logistic regression and linear discriminant analysis. This study could, hence, establish that HSI has the potential to be a very powerful technique in the detection of the nature of adulteration in oils at various stages of processing. The method is of wider applicability in liquid food products such as edible oils vis-à-vis their authenticity and protection of consumer health [165]. Moreover, this work may present complementary results and point out potential applications of both HSI and machine learning models in the optimization of drying processes for other products, like coffee extracts and plant-based beverages. The fact that this technology allows for the monitoring of dynamic changes in liquid foods with high accuracy makes it a potential tool for enhancing consistency and quality for a wide range of processed products. Further development dealing with integration of HSI into systems for real-time monitoring could further improve processing efficiency in the food industry, especially for liquid matrices of complicated composition.

It can be inferred that the integration of HSI with AI has brought a revolution in the quality control and safety measures at all three phases of the food products, namely solid, solid–liquid, and liquid. The integration showed enormous benefits compared to conventional and statistical methods, as represented in Table 4. For solid products, such as fruits, grains, and meats, the HSI integrated with AI models improved the non-destructive evaluation quality parameters, including spoilage detection and identification of fraud, at an incredible accuracy. Coupling HSI with AI provides powerful solutions for liquid products regarding composition analysis, adulteration detection, and monitoring processing stages. This technological synergy leads to efficiency and accuracy, from real-time, non-invasive inspections to high standards of food safety and quality. In fact, these advances in HSI and AI applications hold quite immense potential for benefiting the entire food industry by making intelligent and dependable quality-control systems a feasible reality.

Table 4. HSI-AI application in the food industry.

Product	Objective	Reason of Application	Model Topology Preprocessing	Feature Selection	ML Model	Reference
Chicken meat	Chemical compositions detection	Simplifies wavelength selection, chemical mapping capabilities	CARS	SGCS	PLS	[58]
Fish	Freshness Visualization	Visualizes freshness distribution, non-invasive detection	SPA	-	PLSR	[87]
Minced chicken meat	Soy protein detection	High classification accuracy, optimized preprocessing	CWT	VGG16	SVM	[124]
Pleurotus eryngii	Quality detection	Improves classification accuracy, generalization ability	K-means Clustering	-	SVM	[138]
Cheese	Identification of types	Predicts composition with imaging, comparable to traditional spectrometry	-	PCA	PLS	[144]
Red Delicious and Golden Delicious apples	Quality detection	Faster, non-destructive, and high accuracy	-	-	PLSR	[150]
Blueberries	Decayed region segmentation	High detection accuracy, multi-source data fusion	SPA	CARS	BPNN	[151]
Bulk grains	Classification	Leverages spatio-spectral data, highest accuracy	-	-	CNN	[152]
Minced meat	Identification of types	Retains spatial-spectral info, nonlinear features	-	-	3D-CNN	[14]
Red meat	Intramuscular fat and pH prediction	High adaptability across species, superior prediction	PLSR	-	DCNN	[153]
Meat	Quality determination	Improves spatial prediction accuracy, rapid assessment			SpecimIQ	[154]
Yellow croaker (*Larimichthys crocea*) filets	Monitoring color changes	Accurate, non-invasive			Feed-forward neural networks	[155]
Fish	Freshness Visualization	spatial visualization	SPA	-	PLSR	[87]
Kale (*Brassica oleracea*) and basil (*Ocimum basilicum*)	Cadmium concentration prediction	Precise detection, robust ML model	-	PCA	ANN	[156]
Freshly cut vegetables	Foreign material detection	Fast, High accuracy	SPA	-	PLS-DA	[157]

Table 4. *Cont.*

Product	Objective	Reason of Application	Model Topology Preprocessing	Feature Selection	ML Model	Reference
Egg pancake	distinguishing green vegetables	Rapid, more accurate through feature vision	-	CARS	LDA	[158]
Dairy powders	Quality assessment	Rapid, Non-invasive, high accuracy	-	-	PLSR	[159]
Cheese	Maturation detection	potential to optimize ripening logistics	SNV	-	PLS	[160]
Chicken eggs	Residual dirt or breakage detection	Real-time inspection, rapid processing time	-	-	CNN	[161]
Egg	quality detection	Accurate detection of egg freshness and high identification accuracy for scattered yolk and eggshell cracks using non-destructive methods	-	-	XGBoost	[162]
Soy Sauce	Analyzing the composition of alcohols and esters	Precise non-invasive detection of alcohol and ester composition inside the solution	EPO	-	RF	[163]
Lonicerae Japonicae Flos extracts	Obtaining information on the morphology and moisture content changes in droplets	Rapid method suitable for real-time monitoring			Faster R-CNN-ANN	[164]
Oils	Adulteration detection	High accuracy offering a robust pipeline for non-invasive food safety and quality control	Various techniques			[165]

5. Challenges, Limitations, and Future Prospects

Application development in hardware and software for hyperspectral imaging in recent years has brought about a promising perspective on food quality and safety assessment. However, there are still some key issues that need to be solved in further studies. Those are mainly connected with the establishment of more efficient, reliable, fast, and low-cost modality that could be traditionally applied both in research functions and practical industrial applications.

The large volume of spectral–spatial data is often characterized by a number of irrelevant or noisy signals that may seriously challenge the processing of the data and the extraction of meaningful information. In general, models are built with limited datasets, acquired under controlled conditions in a laboratory, which may not work well for new samples that will normally be measured in natural environments. Indeed, in this respect, it is of crucial importance to provide these models first with extensive calibration and validation against a wide variability of samples and conditions; this research needs to be carried out within the industry for robust and effective models that will work well in practical situations.

The construction of an effective and robust model should be based on serious insight into light–tissue interactions and also the relationships between spectral–spatial features and the quality attributes under investigation. However, few of them offer in-depth data analysis during the development of the calibration model, a factor that often results in limited generalization among different application scenarios. Future studies should, therefore, be supported with investigations of the mechanisms of light–tissue interaction in hyperspectral imaging, and secondly in the development of more sophisticated methods of data mining to the full advantage of all the spectral–spatial information provided by the technology.

Hyperspectral imaging indeed shows high potential in mapping the quality attributes or chemical composition of food products in both 2D and 3D spatial domains. However, this is confronted with the development of proper models that account for physical and physiological factors. These shall be accompanied by the development of more effective methods of validation and acquisition of accurate ground-truth data at pixel level, enabling higher resolutions of heterogeneities in this spatial domain. Current challenges regarding the application of machine learning models along with hyperspectral imaging include the need for large datasets of high quality and well-labeled to develop robust models, which usually are complicated and time consuming to acquire. In addition, enhancing the visualization and interpretation of hyperspectral data remains a challenge due to the high dimensionality of spectral information. These could be achieved by developing data augmentation techniques to artificially increase the size of a dataset or by using transfer learning through the adaptation of a previously trained model. The development of more efficient dimensionality reduction and feature extraction algorithms is also another possible approach. These kind of ideas may be developed in close collaboration between academic researchers, food industries, and technology developers in these areas; machine learning experts and computational scientists have a key role in model improvements and the development of better visualization tools.

Although there are some challenges in the application of this method and using it widely in the food industry, some remarkable patents have been registered in recent years. Different cases were investigated in order to optimize food processing. Detecting the fertility and gender of unhatched eggs [166] using AI-based HSI can represent the potential of this technology in food quality assessment and increasing the production efficiency of food industries. Furthermore, it has been stated that it is possible to measure the nutrition value of food using HSI and neural network models [167], enabling the better classification of food products. These advancements illustrate the potential of AI-based HSI to solve real-world problems and enhance production efficiency, reduce waste, and improve food safety.

The literature review indicated a reliance on ML algorithms for the analysis of hyperspectral images [24,26,107,119,129,165]. Studies on the use of deep learning algorithms in food products are still at a nascent stage and need further research to realize complete exploitation. Currently, machine learning algorithms in common practice operate in isolation, whereby for a given algorithm execution, one considers training datasets to develop models and does not retain knowledge for future use. Also, most of the studies reviewed have focused on the applications of machine learning in solid products rather than in solid–liquid and liquid products.

6. Conclusions

The review paper explores the potential of combining non-destructive inspection HSI techniques with ML to enhance quality and safety in food, each with a general demonstration of success. However, it would be even stronger in offering a more specific assessment of how such methods apply to real-world food safety scenarios. In this respect, the applicable models and techniques include the use of a convolutional neural network and Support Vector Machine for feature extraction and classification in systems, respectively, due to the high accuracy they present. Other examples of such tasks involve wavelength selection and dimensionality reduction, which are going to be essential in making the models more scalable and efficient for real-time use toward ensuring food safety across the food chain. The control authorities, external and internal, may be contacted in order to show that, through the combination of HSI and AI, this may offer quicker assessment times, more precise, and non-destructive ones, reducing the risk of contamination together with costs related to the recall of food products. In fact, this review will certainly stimulate further research, covering other ML techniques for the non-destructive assessment of food quality.

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