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Detection of Adulteration of Ground Meat by Spectral-based Techniques and Artificial Intelligence (2020-2024)

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Abstract

Meat is a significant source of important nutrients and has a vital role in the human diet. Lack of monitoring of the quality and safety of meat can result in posing health threats. Determining safety through chemical methods is costly and time-consuming, without the ability to monitor in real-time. Therefore, nowadays assessing the quality of meat by applying spectral techniques such as spectroscopic and spectral imaging, considered as promising tools and these strategies have recently undergone swift advancements and garnered heightened public attention. Therefore, the purpose of the present review paper is to give an overview of the latest advancements in spectral methods for assessing ground meat safety. The basic working principles, fundamental settings, analysis process, and applications of these techniques are described. By investigating the practical utilization possibilities of spectral detection technologies in the evaluation of meat safety, researchers discussed the present challenges and upcoming research prospects. Furthermore, the newest advances in the application of artificial intelligence accompanied by the mentioned techniques were also discussed.

Keywords: Adulteration, Machine learning, Minced meat, NIR spectroscopy, Spectral imaging

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Introduction

Meat is one of the necessary food products for human diet, which is regularly used by consumers due to its nutritional value and pleasantness. The authenticity of minced meat is among the most important criteria for customers to be considered in their meat purchasing. Some people are willing to pay more for safety certified meat products (Miller, Carr, Ramsey, Crockett, & Hoover, 2001). However, economic profits and easiness of substituting high commercial value meat with cheaper and low quality meat in minced meat increase the possibility of adulteration of meat (Kazemi, Mahmoudi, Veladi, Javanmard, & Khojastehnazhand, 2022). Processing activities on meat like grinding can expose the minced meat to the substitution adulteration. This is due to difficulty of minced meat identification, because of removal of morphological features (Kamruzzaman, Makino, & Oshita, 2016). This enables individuals to potentially commit fraud by replacing or substituting lower-grade meat. Therefore, meat industry has been challenged by some adulteration activities and it is significant to control the authenticity of this product intensively, because of high usage of meat among people and direct relation of its safety to the health of society. In addition to the economic aftermaths, the adulteration of meat species substitution can cause more issues like religious problems (presence of pork in halal meat products or beef in Hindu diets) (López-Maestresalas *et al*., 2019).

Thus, in order to prevent this issue, some traditional chemical methods, instrumental methods, sensory evaluations, and screening techniques have been utilized, over time. Some of the mentioned techniques include immunological detection and DNA-based approaches e.g. enzyme-linked immunosorbent assay (ELISA) and Polymerase Chain Reaction (PCR and real-time PCR) (Edwards *et al*., 2021). Despite their reliability, specificity, and sensitivity features, these authentication methods suffer from various limitations such as being destructive, laborious and costly. Moreover, they need intricate laboratory activities carried out by professional personnel (Edwards, Manley, Hoffman, & Williams, 2021).

The drawbacks of traditional approaches have led to the creation of rapid, non-destructive, precise, and repeatable analytical methods for verifying and detecting contaminants in minced meat items. Recently, there has been considerable attention to the development of a fast and non-destructive technique that can be effectively utilized in a food processing setting.

Currently, researchers have suggested spectral and imaging acquisition methods, along with Artificial Intelligence (AI), to non-destructively assess meat and its products. The application of authentication and/or adulterant detection has been explored through techniques like Near Infrared (NIR) spectroscopy, Raman spectroscopy, Fourier transform infrared spectroscopy, and spectral imaging (Shawky, El-Khair, & Selim, 2020). Nondestructive spectroscopic and spectral imaging methods provide a major advantage in that they allow for measuring the chemical and physical data of foodstuffs while preserving the substance intact. Its superiority over traditional methods is demonstrated by its ease of use, speed, cost-effectiveness, and ability to automate repetitive tasks. Moreover, their ability to conduct analyses quickly and efficiently makes them valuable tools for both online and in-situ detection, which is considered beneficial from industrial perspective.

Some of the reviews have discussed these methods applications for meat assessments. However, these papers have covered various aspects of applications like quality and safety of meat. There is no comprehensive review on the recent applications of spectroscopic and spectral imaging techniques for exclusively minced meat and safety of minced meat. Furthermore, the newest developments of AI including wavelength selection algorithms and deep learning is also discussed in the present review.

The review explores the theoretical foundation and contemporary uses of these emerging methods, along with their distinguishing features and also prospects for future advancements. The present review covers researches performed from 2020 until now, as far as our knowledge a comprehensive review in this era has not been published yet.

Spectroscopic Methods

NIR Spectroscopy

The division of the infrared region in the electromagnetic spectrum includes near-, mid-, and far- infrared (Stark, Luchter, & Margoshes, 1986). Utilizing spectra information combined with statistical algorithms, the NIRs technique has been widely and extensively reported as one of the top optical methods for monitoring meat characteristics.

Near Infrared (NIR) spectroscopy is a fast, nondestructive and highly sensitive method, which eliminates the need for sample preparation and gives qualitative and quantitative information about chemical compositions of sample (Leng *et al*., 2020). The absorption of specific frequencies from the light source by each sample in NIR spectroscopy initiates the occurrence of overtones and vibrational changes within molecules bands, which are basically consisted of CH, OH, CO, and NH groups (Kazemi *et al*., 2022). Thus, the NIR spectrum is formed when molecular vibration transitions occur, crossing from a ground state to a state of higher energy.

In general, NIR spectroscopy has three modes of operation. Reflectance, transmission, and absorbance. Transmission mode can be utilized for detection of transparent liquid like water content and fecal or rumen contamination in minced meat samples (Dixit *et al*., 2017). Reflectance mode is the most common mode in meat analysis and can be used for detection of adulteration and chemical compositions of minced meat (Dixit *et al*., 2017). The NIR system encompasses several key components, including an illuminator, a spectrometer for selecting wavelengths, a sample holder, a photoelectric sensor for evaluating light intensity and converting it into electrical signals, and a computer. After being illuminated by the light source, the sample reflects, transmits, or diffuses its rays which are then detected by an interferometric system. Ultimately, for additional analysis, the collected data from the NIR spectrum will be sent to a computer by the detector.

This technique has its own advantages and disadvantages. The main advantages of this technique is that it is non-destructive and does not require sample preparation. Another merit of NIR spectroscopy is its capability to conduct reflectance measurements, thus making it a feasible choice for measuring inhomogeneous samples (Dixit *et al*., 2017). In addition, with its unique capability to utilize a light-fiber probe and separate the sampling position from the spectrometer, NIR emerges as the most flexible optical technology, perfectly suited for online process monitoring.

A drawback of NIR is that its spectrum is affected by interference from the background, including noise and overlapping bands. This leads to redundant variables and a high degree of collinearity. Furthermore, when recording the reflection spectrum, different light scattering phenomena occur as a result of numerous absorption bands overlapping. This leads to the complexity of the spectral information, and lacks of precise structural composition required for analysis of spectral data. (Guo, Ni, & Kokot, 2016). Therefore, the use of some multivariate analysis is essential for extracting chemically significant information from NIR spectra and create calibration models that connect spectral features with the quality and safety parameters of samples.

Studies have been done to explore meat authentication and the majority of such studies were done in 2020. For example, NIR spectroscopy in the range of 12.500-5400 cm^{-1} was applied to detect pork and duck meat in minced beef. In this study, Discriminant Analysis (DA) and Partial Least Square (PLS) models with various wavelength selection and preprocessing techniques were applied. DA model with selected wavelength and without preprocessing methods had the best performance with 100% and 91.5% for binary and ternary dataset, respectively (Leng *et al*., 2020). In another research, the capability of NIR spectroscopy technique for authentication of turkey meat was investigated by Barbin and coworkers in 2020. The spectral data within the 400 to 2500 nm was collected and analyzed for both raw materials and prepared turkey items, with the goal of using it for quality assurance and verification purposes. PCA and linear discriminant analysis (LDA) models were employed to explore the classification of samples and presented acceptable results (Barbin, Badaro, Honorato, Ida, & Shimokomaki, 2020). Similarly in another study, visible/near-infrared (VIS/NIR) reflectance spectroscopy accompanied with multivariate methods were applied to detect adulteration in minced beef. Deep Convolution Neural Network (DCNN) and PCA models identified the type of adulteration with accuracy of over 99%. In prediction of adulteration levels, Random Forest (RF) model with selected wavelengths had the best results for beef adulterated with pork, and Coefficient of Determination of Prediction (R^2_p) and Root Mean Square Error of Prediction RMSEP were 0.973 and 2.145, respectively (Weng *et al*., 2020). In another research, the evaluation of capability of a portable near-infrared (NIR) spectrometer to detect adulterants in ground meat was explored. For binary mixtures, R^2_c and R^2_p values were between 0.78 and 0.99. Optimal results were obtained when predicting chicken content in beef mixtures (R^2_c = 0.98; R^2_p = 0.99; RMSEC= 4.5 wt%; RMSEP = 3.5 wt%; Limit of Detection (LOD)= 3.4 wt.%, Limit of quantification (LOQ)= 11.2 wt%). For ternary mixtures, analytical outcomes were acceptable only for predicting beef content with the following values: R^2_c= 0.98, R^2_p = 0.93, RMSEC = 3.6 wt.%, RMSEP = 4.7 wt. %, LOD = 4.7 wt.%. and LOQ 15.7% by weight (Silva *et al*., 2020). In another study, a portable VIS-NIR spectrometer (400-1000 nm) and a portable NIR spectrometer (900-1700 nm) were used to distinguish between halal meat types and pork as non-halal meat, and also to distinguish between whole meat and pork. For the application of differentiating between halal and non-halal meat types, the utilized one-class classification (OCC) approach, particularly with the employment of VIS-NIR sensors achieved to the classification rate of 95-100% accuracy (Dashti *et al*., 2021). In a recent study, the adulteration of chicken meat and fat in lamb was explored with VIS/NIR spectroscopy and multivariate methods. Various preprocessing techniques were applied to remove unwanted information from spectral data. PCA model as unsupervised and Support Vector Machine (SVM) and Soft Independent Modeling Class Analogies (SIMCA) as supervised models were employed to detect adulteration in nine and three class datasets. SVM had outcomes of 56.15% and 80.70% for classification of nine and three class datasets (Kazemi, Mahmoudi, Veladi, & Javanmard, 2022). Also, another study by the same research group, reported the classification of pure lamb from adulterated lamb with fat with 5%, 10%, 15%, and 20% (w/w) adulteration levels. Linear Discriminant Analysis (LDA) model with Savitzky-Golay smoothing preprocessing had results of 100% and 86.2% accuracy for two and five class datasets (Kazemi *et al*., 2022). The 2D conventional neural network (CNN) and sized-adaptive online NIRS data were used in the study by Bai et al, to classify minced samples of pure mutton, pork, and duck, as well as adulterated mutton with pork and duck. According to the results, spectral information significantly affected the model's accuracy; for the same validation set, the maximum difference was 12.06%. For all datasets, the accuracy of the CNN model with per-direction average spectral information, Extreme Learning Machine (ELM) classifier, and 7 × 7 convolution kernel was above 99.56% (Bai *et al*., 2022).

Another research focused on testing the possibility of utilizing the fat portion as an indicator of authenticity was performed by NIR spectroscopy. Models for the target class were created using the Data Driven version of Soft Independent Modelling of Class Analogy (DD-

SIMCA), following multivariate exploration. In both calibration and validation, the use of Standard Normal Variate SNV pre-treated data along with 4 PCs achieved outstanding results, yielding a sensitivity and specificity of 100% (Totaro *et al*., 2023).

In another study conducted by Hoffman et al, the evaluation of the performance of portable Near Infrared (NIR) spectroscopy to identify binary mixtures of lamb, emu, camel, and beef sources was explored. The NIR spectra of the meat mixtures were analyzed using principal component analysis (PCA) and partial least squares discriminant analysis (PLS-DA). The cross-validation coefficient of determination (R^2_{cv}) obtained for determining the proportion of species in binary mixtures was above 90%, and the standard error of cross-validation (SECV) ranged from 12.6 to 15% w/w (Hoffman *et al*., 2023).

Two approaches combining deep learning and two-dimensional correlation spectroscopy (2DCOS) methods and Partial Least Square-Discriminant Analysis PLS-DA model have been used to analyze mutton adulteration in beef (Wang *et al*., 2024). Analyzing the effects of different proportions of mixing chicken, duck, pork with beef or mutton through synchronized 2DCOS images reveals different patterns of chemical information changes in spectra under different adulteration scenarios. ResNet's deep learning method can achieve high accuracy (100%) models and has the advantage of effectively extracting 2DCOS feature information. Meanwhile, the accuracy range of the PLS-DA model test set was 32.97% to 50.64, depending on whether the raw or preprocessed spectral data matrix was used.

Fourier Transform Infrared (FTIR) Spectroscopy

Among spectroscopy techniques, FTIR spectroscopy is known as a fast, simple, and economical technique with least sample preparation. In comparison to traditional infrared techniques, this fingerprinting method offers more benefits including ability to detect components of small size samples, high precision and accuracy, data collection ability in controlled temperatures and pressures (Deniz *et al*., 2018). In FTIR spectroscopy, the interference between two IR beams is used to get signal (interferogram), which is based on difference in path length of two beams (Stuart, 2004). The beam splitter receives an incident beam of light that has been collimated from an external polychromatic infrared radiation source. A portion of it is reflected to mobile mirror while another part is transferred to the stationary mirror. The returning beams from mirrors retrace their path and return to the beam splitter and then interfere. Because of interfere, the intensity of each beam returning to the source is different and depends on difference in the path of the beam. This process is done by a Michelson interferometer. The Michelson interferometer is a device that splits an incident light beam in to two perpendicular paths using a beam splitter. Fig.1. displays the Michelson interferometer in its most basic configuration.

The interference is created when two resultant beams are recombined after a path difference. A photodetector can measure the emergent beam's intensity as a function of the path difference, and the path difference can be controlled and modified (Banerjee). The produced signal then is transformed to frequencies that form a signal by Fourier transform algorithms. FTIR spectroscopy technique can be applied to acquire spectral data from solid, liquid, or gas (Chai *et al*., 2020). In order to prepare solid materials to light beam of spectrophotometer, they can be mixed with potassium bromide (KBr) and subsequently pressed to form a small disc. One of the main problems of using this material is the low reproducibility of prepared samples due to some conditions like utilized ratio and homogeneousness required to be the same for all samples.

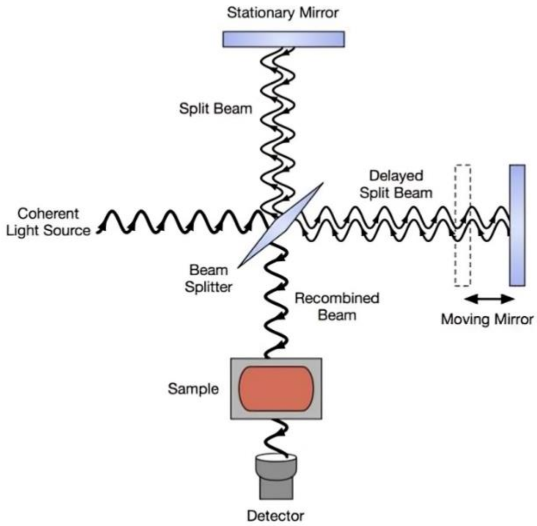

Fig. 1. Schematic diagram of the Michelson interferometer (Banerjee)

Nowadays, Attenuated Total Reflectance (ATR) FTIR has solved this problem which does not require addition of KBr and needs small volume of sample. It also allows for rapid analysis. In spite of some practical applications of FTIR spectroscopy particularly in food safety issues, there are some industrial challenges of this technique like the interpretation of FTIR spectra especially for complicated samples like polysaccharides can be difficult (Hong, Yin, Nie, & Xie, 2021) and sample preparation in this technique can be time-consuming and crucial step.

In a study by Mabood *et al*, FT-NIR spectrophotometer combined with PCA, PLS-DA, and PLSR models was applied to detect and quantify pork meat in other meats. In order to predict the amount of pork meat in other meats, PLSR model was used which had R^2_{cv} = 0.977 and RMSECV = 1.08% (Mabood *et al*., 2020). In another application of ATR-FTIR spectroscopy for meat industry, Keshavarzi et al, applied this technique to explore adulteration of chicken in beef. PCA model was applied for two kinds of data: data without any preprocessing techniques in the whole range of spectra and preprocessed spectral data with focusing on 1700-1070 cm^{-1} range of spectra. Clustering of meat kinds with PCA model on data in transmission mode was successfully done. Furthermore, the preprocessed ATR_FTIR spectrum was used to prepare PLSR and Artificial Neural Network (ANN) models for prediction of adulteration amounts. ANN model outperformed with R^2 of 0.999 for prediction dataset (Keshavarzi, Barzegari Banadkoki, Faizi, Zolghadri, & Shirazi, 2020). In the same year, the research group of Candogan investigated discrimination of pork, horse or donkey meat in beef. Hierarchical Cluster Analysis (HCA) in the region of 1480-1425 cm^{-1} separated all pure beef, pure donkey meat and adulterated samples with sensitivity and specificity of 100% (CANDOĞAN, DENİZ, ALTUNTAŞ, Naşit, & Demiralp, 2020).

In another study, the application of FTIR spectra combined with neural network classifier and different dimensionality reduction techniques was investigated for classification of lamb fat. The feature selection algorithms showed better performance of classification on the dataset collected from dairy lamb carcasses from 89.70% with the full feature set to 91.80% and 93.89% for SVM and PCA, respectively (Alaiz-Rodriguez & Parnell, 2020).

Furthermore, Siddiqui et al, explored application of FTIR spectroscopy for detection of adulteration of beef, chicken, and lamb in lard. PCA model could separate samples with using three principal components. Beef and lamb samples for both adulterated and pure samples had the highest classification accuracy value of 85% with multiclass support vector machine (M-SVM), whereas chicken had the lowest value of 78% for each category (Siddiqui *et al*., 2021). In another investigation, detection of presence of beef liver in beef patties was explored by FTIR spectroscopy. this technique was able to detect adulterated samples at 5% concentration (Abidin, Rosli, Bujang, Nordin, & Nizar, 2021). The feasibility of utilizing portable Fourier transform infrared spectroscopy (FTIR) in combination with multivariate classification techniques was examined by Dashti et al, to classify ground meat, lamb, chicken, and pork samples for the assessment of carnivorous speciation. Examinations were conducted employing Partial Least Squares Discriminant Analysis (PLS-DA) and Support Vector Machines (SVM) with Radial Basis Functions (RBF) serving as the kernel function. SVM performs better than PLS-DA with an overall accuracy of 90% and 98% on ATR-FTIR and DR-FTIR datasets, respectively (Dashti *et al*., 2022).

Raman Spectroscopy

Raman spectroscopy is another nondestructive spectroscopic technique which has proved its capability and includes some advantages like simple operation, no requirements for sample preparation, less interference by water, and ability to provide structural information of chemical elements (Khaled, Parrish, & Adedeji, 2021). This technique is based on inelastic scattering of light on the molecule level. When a sample is illuminated by an external laser beam, molecules are excited by photons and their vibrational energy levels are changed from ground state to unstable state. Then, excited level returns to initial level of energy by photon emission (Pchelkina, Chernukha, Fedulova, & Ilyin, 2022). There are two types of photon scattering based on difference between photons and molecules: elastic scattering and inelastic scattering (Butler *et al*., 2016). Elastic scattering, also known as Rayleigh scattering, happens when there is no energy exchange and the frequency of incident and scattered photons is the same. In contrast, in elastic or Raman scattering, a little amount of energy exchange happens between scattered photons and target molecules (Butler *et al*., 2016). The result of this exchange between sample and light is formation of virtual level. Then, due to the instability of formed virtual level, photons are scattered to a fairly stable level. There is no energy transfer between incident light and scattered light when photons come back to the initial level. This process of elastic collisions is called Rayleigh scattering (Pchelkina *et al*., 2022). The majority of studies that have applied Raman spectroscopy for meat safety are before 2020, and due to the purpose of present review which is based on exploring researches after 2020, we mentioned only two studies after 2020. Table.1, summarizes the research on the safety of minced beef performed by spectroscopic methods between 2020 and 2024. Robert et al, assessed the ability of Raman spectroscopy combined with three chemometric methods (PCA, PLS-DA, and SVM) to differentiate red meat samples (beef, lamb, and vension). The outcomes of linear and non-linear kernels of SVM model were 87% and 90%, respectively (Robert *et al*., 2021). Similarly, Saleem et al, applied Raman spectroscopy technique to differentiate goat, cow, and buffalo fat samples with 532-785 nm. They found that saturated fatty acids at Raman bands of 1060, 1080, and 1440 cm^{-1} were relatively higher in buffalo fats (Saleem, Amin, & Irfan, 2021).

Table 1- Application of spectroscopic methods for meat safety

Technique	Investigated parameter	Chemometrics	Results	References
NIR	Adulteration: Pork and duck meat in minced beef	DA PLSR	R_p=95.80% RMSEP=7.27	(Leng *et al.*, 2020)
NIR	Discrimination: Turkey cuts	PCA LDA	Accuracy=80%	(Barbin *et al.*, 2020)
VIS/NIR	Adulteration: Pork and beef heart in minced beef	SVM RF PLSR DCNN	R^2_p=0.96 RMSEP=2.75	(Weng *et al.*, 2020)
NIR	Adulteration: Chicken/beef; beef/pork;pork/chicken	PLS SVR	R^2_c=0.78 R^2_p=0.99	(Silva *et al.*, 2020)
VIS/NIR and NIR	Distinguish: Halal meat vs. pork	SVM PLS-DA	CCR=95-100%	(Dashti *et al.*, 2021)
VIS/NIR	Adulteration: Chicken and fat in lamb	PCA SVM SIMCA	Accuracy= 80.70%	(Kazemi, Mahmoudi, Veladi, & Javanmard, 2022)
VIS/NIR	Adulteration: Fat in lamb	PCA LDA	Accuracy= 100%	(Kazemi *et al.*, 2022)
NIR	Classification: Mutton, pork, and duck	CNN	Accuracy= 99.56%	(Bai *et al.*, 2022)
NIR	Authenticity= Fat portion	DD-SIMCA	Sensitivity=100%	(Totaro *et al.*, 2023)
NIR	adulteration: adulterants of exotic meat species	PCA PLS-DA	R^2_{cv}= 90% SECV=12.6-15%	(Hoffman *et al.*, 2023)
2DCOS	Adulteration: Mutton in beef	Resnet deep learning PLS-DA	Accuracy=100%	(Wang *et al.*, 2024)
FTIR	Adulteration: Pork meat in other meats	PCA PLS-DA	R^2=0.97 RMSECV=1.08%	(Mabood *et al.*, 2020)
FTIR	Adulteration: Chicken in beef	PCA PLSR ANN	R^2=0.99	(Keshavarzi *et al.*, 2020)
FTIR	Discrimination: Pork, horse, and donkey in beef	HCA	Sensitivity=100%	(CANDOĞAN *et al.*, 2020)
FTIR	Classification of lamb fat	PCA SVM PLS	Accuracy=85.60%	(Alaiz-Rodriguez & Parnell, 2020)
FTIR	Adulteration: Beef, chicken, lamb in lard	M-SVM PCA	Accuracy=85%	(Siddiqui *et al.*, 2021)
FTIR	Adulteration: Beef liver in beef patties	-	-	(Abidin *et al.*, 2021)
FTIR	Classification: Lamb, chicken, and pork	PLS-DA SVM	Accuracy=98%	(Dashti *et al.*, 2022)
Raman	Differentiation: Beef, lamb, vension	PCA PLS-DA SVM	Accuracy=90%	(Robert *et al.*, 2021)
Raman	Differentiation: Goat, cow, and buffalo fat	PCA	-	(Saleem *et al.*, 2021)

In a study by Robert *et al*, the researchers investigated the use of Raman spectroscopy in combination with three chemical analysis techniques to distinguish between beef, lamb, and game samples. They used PLS-DA and SVM classification methods to develop a model for identifying different types of meat, and PCA for exploratory purposes. The results showed that both linear and nonlinear kernel SVM models achieved high sensitivities and specificities, with sensitivities exceeding 87% and 90% respectively, and specificities exceeding 88% when tested against a separate set of samples. The PLS-DA model also demonstrated an accuracy of over 80% in correctly classifying each type of meat (Robert *et al*., 2021).

In order to apply Raman spectroscopy in industrial sector some limitations, like interference of fluorescent with Raman signals which make it difficult to get accurate measurements and requirement of some specialized instrumentation should be solved.

Spectral Imaging

Electromagnetic spectrum includes a wide range of electromagnetic radiation, each with its own unique wavelengths and frequencies. These various types of waves, such as ultraviolet, visible, infrared, microwave, and radio waves, have distinct electromagnetic features like energy levels, propagation traits, and interactions with matter. This makes them necessary for research in different scientific fields. Visible light is an electromagnetic radiation that is visible by human eye and is limited in the range of wavelength between 380 and 780 nanometers. Many well-established methods based on vision and image processing are based on this particular spectral region (Reinhard *et al*., 2010). Recent developments in sensor technology have made it possible to acquire images at a wide scope of electromagnetic wavelengths. These approaches encompass hyperspectral and multi-spectral images, which cover a wider range of spectral bands than the conventional three bands employed in visible spectrum imaging.

In order to get an increased level of spectral resolution, hyperspectral Imaging (HSI) and also Multispectral Imaging (MSI) methods take multitudinous images at compact and adjacent spectral bands encompassing a greater range of electromagnetic spectrum. These developed imaging techniques are known as imaging spectroscopy (Zahra *et al*., 2023).

Spectral sensors are employed to gather information through images, with each image capturing a district portion of the electromagnetic spectrum called a spectral band. There are various ways to collect spectral data, each with its own strengths and weaknesses. The whiskbroom method is a technique that entails installing a line of detectors on a mobile platform; as the platform progresses, the detectors gather information from a small section of the ground, referred to as a swatch. The data that is utilized to generate a visual representation of the scene, where every individual pixel holds specific spectral information (Zahra *et al*., 2023). The pushbroom technique is another approach that involves scanning a single axis and creating an image by either moving the camera or the objects being captured. To prevent spatial distortions in the collected data, the movement should be constant (Zahra *et al*., 2023). By switching out narrow bandpass filters in front of the camera lens or by utilizing electronically tunable filters, wavelength scanning techniques are possible to collect spectral image cubes. A typical NIR-HIS setup consists of a camera, a spectrometer, a detector, a light source, and a movable platform. A spectral image is typically represented as a cube, with the first two dimensions representing spatial information and the third dimension representing a collection of spectral images taken at various wavelengths. The challenge of performing hypercube analysis arises from the application of multivariate statistical methods (Cheng, Nicolai, & Sun, 2017). Moreover, the utilization of hypercube data in classification and prediction models frequently necessitates dimensionality reduction due to their large dimension and size. Preprocessing data from a hypercube often involves various techniques including interference correction, dimensionality reduction, and feature extraction (Oliveri *et al*., 2014). Then, models are used to establish correlations, classifications, prediction, and validations. Table 2 presents the summary of researches for the application of spectral imaging for minced meat safety.

Rady & Adedeji, explored the capability of hyperspectral imaging (400-1000nm) as a nondestructive approach to detect, differentiate, and quantify adulterants sourced from both plants and animals in minced beef and pork.

Table 2- The spectral imaging application for ground meat safety

Application	Technique	Spectral range	Model	Results	Reference
Adulteration: Plant and animal-based adulterants in minced beef and pork	HSI	400-1000nm	SVM LDA PLS-DA	Accuracy= 100%	(Rady & Adedeji, 2020)
Adulteration: Leaf lard in minced pork	HSI	400-1000nm	PCR PLSR	R2p = 0.98 RMSEP = 4.87%	(Jiang *et al*., 2020)
Adulteration: Minced chicken in minced beef	HSI	380-1000nm	GD-RC	R=0.98 RMSEP=0.03	(Zhao *et al*., 2020)
Adulteration: Minced pork jawl in minced pork	NIR-HSI	400-1000nm	PLSR	R2p=0.95 RPD=4.54	(Jiang *et al*., 2020)
Adulteration: Adulterants in minced beef	HSI	350-2500nm	RF	Accuracy=96.87%	(Guo *et al*., 2020)
Distinguish: Pork and duck rolls in mutton roll	HSI	400-1000nm	PLS-DA	Accuracy=100%	(Jiang *et al*., 2021)
Adulteration: SPP in ground beef	HSI	400-1000nm	PLSR	Rp = 0.99 LOD=0.74% RPD=8.45	(Jiang *et al*., 2022)
Adulteration; Duck meat in lamb	VIS-NIR-HSI SWIR-HSI	900-1700nm 400-1000nm	PLSR	R2p=0.98 RMSEP=0.98 RPD=5.62	(Jing-yuan *et al*., 2022)
Authentication of meat samples	VIS-NIR-HSI SWIR-HSI	400-1000nm 1116-1670nm	SVM ANN-BPN	Accuracy=96%	(Dashti *et al*., 2023)
Adulteration: Starch in minced chicken meat	HSI	400-1000nm	SVM CNN	Accuracy=98.6%	(Yang *et al*., 2023)
Adulteration: Minced chicken and turkey and pork in minced beef meat	HSI	400-1000nm	PLSR	R2p=0.96 RMSEP=2.9% RPD=5.4	(Achata *et al*., 2023)
Adulteration of alpacha meat with pork, chicken, and beef	NIR-HSI	-	DD-SIMCA PLSR PCA	Sensitivity=100%	(Cruz-Tirado *et al*., 2024)

The meat and non-meat samples used in our study included beef (chuck rust), pork (Boston butt), chicken thigh, textured vegetable protein (TVP) (Red Mill, Milwaukie, Oregon, USA) that contains 50% soy protein, and wheat gluten (WG) (TruTex RS 65, MGP Atchison, Kansas, USA) with 75% protein. Using the chosen wavelengths from the test set, the classification models produced optimal results with classification rates of 75-100% and 100% for pure and adulterated samples, respectively. Whereas, depending on the type of adulterants, the rates ranged from 83% to 100% (Rady & Adedeji, 2020). In another research, application of hyperspectral imaging (HSI) for detection of adulteration of leaf lard adulteration in minced pork was investigated. The average spectra extracted from regions of interest (ROIs) were subjected to distinct mathematical pre-processing. Then, quantitative calibration models (PCR, PLSR) with various wavelength selection algorithms (Principal Component (PC) loadings, two-dimensional correlation spectroscopy (2D-COS), competitive adaptive reweighted sampling (CARs), and Regression Coefficients (R_C)) were applied. The best outcomes of PLSR model with R_C wavelength selection algorithm were 0.98 and 4.87% for R^2 and RMSEP, respectively (Jiang *et al*., 2020). Zhao et al, employed the combination of hyperspectral imaging and Gaussian distribution of regression coefficient (GD-RC) model to visually detect adulteration of minced chicken in minced beef. The binary GD-RC model performed better than the uniform GD-RC model. The best technique had an average error (ARE) of 2.8%, a correlation coefficient (r) of 0.9831, and a root mean square prediction error (RMSEP) of 0.0319 (Zhao *et al*., 2020).

The combined usage of PLSR and NIR-HIS enabled the detection of minced pork contamination with minced pork jowl meat by collecting data between 400 and 1000 nm. The best performing model, with R^2_p = 0.9549 and residual predicted deviation (RPD)= 4.54, is spectra preprocessed with standard normal variables (SNV), and with partial least squares regression (PLSR) models. Additionally, to precisely choose important wavelengths connected to adulteration identification, principal component (PC) loadings, two-dimensional correlation spectroscopy (2D-COS), and regression coefficients (RC) were applied and yielded acceptable results (Jiang, Cheng, & Shi, 2020).

Similarly, in another research, the capability of hyperspectral reflectance spectroscopy in detection of minced beef adulteration was assessed. Random Forest (RF) model yielded the best accuracy of 96.87% in prediction set with selected wavelengths (Guo *et al*., 2020). Similarly, the potential of use of hyperspectral imaging (HSI) technique to identify any adulteration of offal in ground beef was investigated. PLSR models based on full spectra showed the best performance with R^2_P of 0.98, RMSEP = 4.25%, and Ratio Performance Deviation (RPD) of 7.53 in prediction set (Jiang *et al*., 2020).

Examining the potential of multivariate data analysis alongside HSI, the research done by Jiang et al, investigated the ability to distinguish between raw and cooked mutton rolls with substitutions of pork and duck rolls. The highest rate of 100% classification was achieved in all sets with the application of different models and preprocessing techniques, specifically through the use of the PLS-DA model developed by raw spectra (Jiang, Yang, & Shi, 2021). In another study, the use of hyperspectral imaging technology in conjunction with characteristic variable screening for the quick and nondestructive identification of adulterated fox meat in minced mutton was investigate. When paired with the 2-dimensional correlation- SVR model, hyperspectral imaging can efficiently achieve quantitative detection of contaminated fox meat in minced mutton (Bai et al, 2021). In other study, HSI in spectral range of 400-1000 nm accompanied with multivariate analysis and wavelength selection algorithms was applied to detect soybean protein powder (SPP) in ground beef. The final outcomes displayed that simplified PLSR model based on six selected wavelengths from PC loadings acquired R_P = 0.993, RPD = 8.45, and LOD of 0.74 (Jiang *et al*., 2022).

The visible/near infrared (400-1000nm) and short-wave near-infrared (900-1700 nm) HSI method was employed in another research to detect adulteration of duck meat in lamb. Different models, preprocessing and wavelength selection algorithms were applied and the best outcome was with SNV-SPA-PLSS model in short-wave near infrared band with prediction set (R^2_p = 0.986, RMSEP = 0.058, RPD = 5.62) (Jing-yuan, Jun-qin, Mei, Xing-hai, & Ye-lin, 2022).

Similarly, the effectiveness of visible-near infrared hyperspectral imaging (VIS-NIR-HSI) and shortwave infrared hyperspectral imaging (SWIR-HSI) accompanied with different classification and regression methods were reported for meat authentication by (Dashti *et al*., 2023). the obtained results proved that VIS-NIR-HSI technique outperformed SWIR-HSI. Combination of HSI and transfer learning was employed to detect starch in minced chicken meat (Yang *et al*., 2023). Two classification models were compared. Models were built on acquired hyperspectral data from samples. Additionally, a classification model based on the GoogleNet network pretrained on the ImageNet collection was developed to detect starch in minced chicken meat. The model based on the GoogleNet network showed a better classification accuracy, up to 98.6%, according to the results.

A different study conducted by Achata and colleagues in 2023 examined the use of Hyperspectral imaging (HSI) within a specific spectral range, combined with multivariate analysis. The purpose of this study was to determine if it is possible to create a universal model for detecting the presence of other meats in ground meat samples. To predict the quantity of Minced Beef meat (MBM) in scanned samples, various approaches including different spectral pre-treatments, the partial least squares regression (PLSR) methodology, the ensemble Monte Carlo variable selection method (EMCVS), and combinations of any two of these methods were examined. The researchers used data from MBM contaminated with chicken and turkey meats to create a beef prediction model. They tested the accuracy of the model by using data from MBM contaminated with pork meat at various levels of adulteration. They used a combination of the asymmetric least squares and standard normal variate techniques to analyze the reflectance spectra. The results showed good prediction accuracy with 23 specific wavelengths, achieving an R^2_p value of 0.96, an RMSEP of 2.9%, and an RPD of 5.4 (Achata *et al*., 2023).

The study conducted by Cruz-Tirado et al, utilized the Portable NIR Spectrometer and NIR-HIS methods, which do not involve the use of chemicals, to identify the presence of pork, chicken, and beef in alpaca meat at varying concentrations (0-50% w/w). The samples were classified into pure and non-pure alpaca meat using Principal Component Analysis (PCA), with both instruments providing spectral data. To authenticate pure alpaca meat, a single-class data-driven soft independent class analogy (DD-SIMCA) model was developed and validated. The DD-SIMCA model, using spectra obtained from both instruments, achieved perfect sensitivity and specificity (100%) when applied to an external sample set. Moreover, the NIR-HIS-based partial least squares regression (PLSR) outperformed the portable NIR spectrometer in accurately predicting contaminant concentrations in alpaca meat (Cruz-Tirado *et al*., 2024).

Artificial Intelligence

Data analysis is the keystone that connects the desired sample characteristics to the NIR absorption or transmittance measurements. The primary objective is to enhance both the reliability and accuracy of analytical results. For instance, the combination of spectral data and pattern recognition techniques can effectively address authentication issues in commodities like pharmaceutical, food, and cosmetics (Chophi, Sharma, Jossan, & Singh, 2021). With advancements in artificial intelligence, big data, and cloud computing, new ideas, approaches, and strategies are constantly revitalizing the field of statistical analysis techniques. Fig.2, illustrates how machine learning algorithms convert the NIR absorption data to the necessary outputs. In the realm of machine learning, algorithms include both training and testing phases. Machine learning algorithms use the acquired outcomes as outputs and the light absorption values as inputs during the training phase. In the test step, they predict the intended result based on the supplied light absorption values.

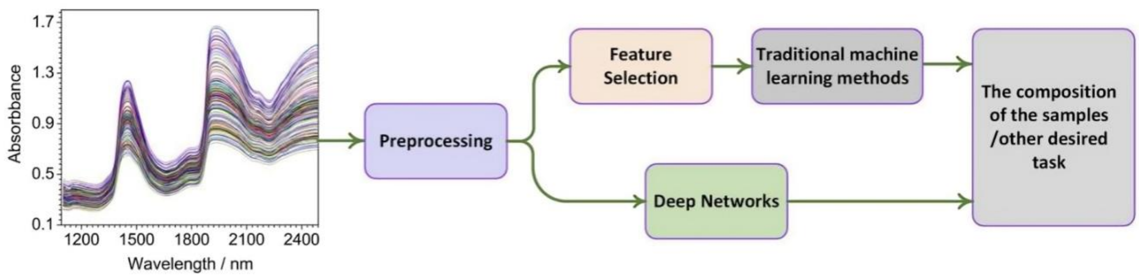

Fig. 2. Architecture of machine learning for NIR spectroscopy (Wenwen Zhang *et al.*, 2022)

Spectral Preprocessing

In addition to the advancement of modeling algorithms, preprocessing algorithms have also made progress. This step is essential in analyzing spectral data as it deals with uninformative spectra caused by light scattering or system noise. In NIR spectroscopy, two commonly used preprocessing methods are spectral normalization and spectral derivatives. Spectral normalization corrects scattering impacts, while spectral derivatives handle peak overlap and baseline drifts (Rinnan, Van Den Berg, & Engelsen, 2009).

The elimination of multiplicative effects in spectral data is challenging, so there is significant interest in developing processing methods to address this issue. To a certain extent, Standard Normal Variate (SNV) along with Multiplicative Scatter Correction (MSC) and extended MSC (EMSC) are common employed techniques for eliminating multiplicative effects, thereby minimizing the impact of solid particle size (light scattering and variance in the effective path length) or scattering effect on spectral data (Wang *et al*., 2022). Furthermore, recently some improved algorithms have been applied. For example, to enhance the SNV preprocessing efficiency, Bi et al, partitioned the NIR spectra in to equally sized and separated sections, and processed with SNV preprocessing for each subinterval (Bi *et al*., 2016). The outcomes demonstrated that this particular local SNV preprocessing method exhibited remarkable efficacy, surpassing the effectiveness of global SNV. In order to account for the varying effects of physical factors on spectral variables, a normalization algorithm called Variable Sorting was created for Normalization (VSN). Before conducting the SNV algorithm, this algorithm assigns varying weights to different wavelength variables. (Rabatel, Marini, Walczak, & Roger, 2020). Denoising refers to the process of improving the signal-to-noise ratio (SNR) by eliminating or reducing random errors that are added to the raw spectral signals. The most used algorithms for denoising include Wavelet Transform (WT), Fourier Transform (FT), Savitzky-Golay (SG), and moving-average. Elimination of noise through these methods can be highly effective. Nevertheless, there is the risk of signal distortion, particularly when dealing with sharp spectra like raman, NMR, and X-ray diffraction.

The proposal of the fact that distorted peak denoising can be attributed to the insufficient sampling, which is a result of frequencies which are being scattered was explored by (Yao, Su, Yao, & Huang, 2021). In order to solve this problem, they suggested an operation method with yield adjustments based on a four-step approach. This method begins by determining the levels of signal and noise in the raw data. It subsequently adjusts the sampling density in areas characterized by high signal levels and improves them using linear interpretation. Next, it performs a smoothing operation to reshape the profile and finally, restores the original shape of the deformed profile. The proposed method demonstrated superior denoising performance when compared to S-G and WT denoising based on the experimental results.

The application of derivative preprocessing techniques, such as S-G derivation, enables efficient elimination of baseline and background interference while also facilitating the resolution of overlapping signals and enhancing spectral resolution and instrumental sensitivity. However, this method frequently introduces unwanted effects in to the frequencies which leads to a low signal-to-noise ratio (SNR). Furthermore, the noise becomes more prominent as the derivative order increases. As a result of this, the WT is commonly used for the computation of high derivatives such as the third or fourth order (Shao, Cui, Wang, & Cai, 2019). Additionally, the singular perturbation Spectra Estimator (SPSE) developed by Li et al is regarded as a reliable technique for calculating higher-order derivatives (Li, Wang, Lv, Ma, & Yang, 2015). In contrast to the derivative spectrum with integer orders, the fractional-order derivative spectrum has a greater ability to accurately depict changes in spectral details according to the derivative order while also addressing the conflict between spectral resolution and signal intensity (Hong *et al*., 2018; Hu *et al*., 2021). Zheng et al applied their novel fractional-Order Savitzky-Golay Derivative (FOSGD) algorithm to preprocess NIR spectral data as an example. They found that this algorithm resulted in improved model performance compared to using the integral order SG derivative (Zheng, Zhang, Tong, Yao, & Du, 2015).

Feature Selection

Due to the issue of including irrelevant or redundant information in spectral data which lead to noise and decreased model performance, application of variable selection is significant in spectral analysis to identify the most informative features. The goal of feature selection is to identify the most reliable, relevant, and unique set of features from a feature vector. Feature selection algorithms are capable of effectively reducing the size of spectral data and eliminating any duplicated information from the spectrum. Feature selection techniques in machine learning are divided in to three groups: filter methods, wrapper methods, and embedded methods (Wang *et al*., 2022). The primary difference of the mentioned techniques is the utilized learning algorithm. The variables in the filter method are assessed individually, disregarding any interdependence among them. Therefore, filter-based approaches ensure that the selected features do not overfit and are ranked based on their importance. The most applied techniques involve correlation coefficient method and analysis of variance (ANOVA) method. By considering the correlation between variables, the wrapper method determines the best combination based on how it affects the model performance. Therefore, wrapper-based characteristics have a tendency to overfit, and the majority of feature selection methods in NIR employ this approach. (Wenwen Zhang, Kasun, Wang, Zheng, & Lin, 2022). From variable selection algorithms of this method, interval PLS (iPLS), successive projections algorithm PLS (SPA-PLS), and genetic algorithm PLS (GA-PLS) can be mentioned. The inclusion of embedded approaches involves the utilization of a model learning factor that assesses the ability of chosen features to generalize. The strategy that is most commonly adopted in this regard is to add regular terms, such as the algorithm for least absolute shrinkage and selection operator, in order to decrease model's complexity (Wang, Bian, Tan, Wang, & Li, 2021). Random Forest (RF) variable selection is one of the most used popular algorithms in embedded method.

Modelling

The literature describes two main types of machine learning architectures for NIR: traditional methods and deep network architectures. Traditional methods involve selecting valuable features from the input data through feature learning and then applying traditional machine learning algorithms. These techniques application in spectroscopy which is called chemometrics is able to predict quantitative and qualitative features.

Multivariate Classification Models

One-class classification (OCC) techniques focus on modeling a single class independently of others, emphasizing the similarities within that class rather than the differences between classes. A widely used OCC technique in chemometrics is Soft Independent Modelling of Class Analogy (SIMCA) (Wold & Sjöström, 1977). SIMCA uses Principal Component Analysis (PCA) on the training data of the target class to create a defined acceptance region in multivariate space. A sample is assigned to a class if its residual distance falls within the statistical limit for that class. Interestingly, a sample can be assigned to more than one class if it meets the criteria for multiple classes (Kazemi *et al*., 2022). In simpler terms, PCA helps analyze the samples of each class and build classification models. If an unknown sample resembles the calibration samples, it will be classified as a member of that class (Basati, Jamshidi, Rasekh, & Abbaspour-Gilandeh, 2018). In contrast, two or multi-class classifiers, known as supervised discriminant methods, are used to establish boundaries between different classes. The most traditional method is Linear Discriminant Analysis (LDA), which identifies linear surfaces (hyperplanes) that effectively separate samples from different categories. This is done based on the relative positions of the groups' centroids and the within-class variance/covariance (Brereton *et al*., 2018). For implementing LDA, the number of training objects must be greater than the number of input variables. Therefore, it is often necessary to reduce the number of variables using PCA before conducting statistical analysis.

Another supervised method is Partial Least Square-Discriminant Analysis (PLS-DA), which aims to maximize the separation between classes while minimizing variability within each class by creating linear decision boundaries (Xu, Xia, Min, & Xiong, 2022). PLS-DA generates new variables, known as Latent Variables (LVs), through linear combinations of the original variables. These LVs maximize the covariance between the predictor matrix (X) and the response matrix (Y). The Y matrix is binary, with as many rows as X and as many columns as there are groups in the dataset. Each column represents group membership using 0/1 variables, where a value of 1 indicates membership in a group, and 0 indicates otherwise (Næs, Isaksson, Fearn, & Davies, 2002). Support Vector Machine classification (SVMc) is another powerful technique based on statistical learning. It works by mapping the original data space into a higher-dimensional feature space using kernel functions, with the goal of finding the best separation between different classes in the training set through a hyperplane. The decision function of SVM is determined by a small number of support vectors located on the margins of the hyperplane. The success of an SVM model largely depends on the appropriate selection of kernel functions (De Girolamo *et al*., 2020).

Multivariate Calibration Models

Through the utilization of a multivariate calibration strategy, the combination of NIR data and reference values obtained from chemical analysis, enables the creation of calibration models with predictive capabilities and quantifiable properties for analogous sets of NIR data. The most commonly applied multivariate calibration models for NIR meat analysis are Principal Component Regression (PCR), Multiple Linear Regression (MLR), and Partial Least Square Regression (PLSR), (Dixit *et al*., 2017). In MLR technique, concentration is linked to absorbance through considering the concentrations of target analytes and other elements that contribute to the overall signal (Blanco & Villarroya, 2002). As an extension of PCA and an inverse calibration technique, PCR is similar to MLR in that it uses PCs from PCA as variables in an MLR model. The first step involves conducting PCA on the calibration data to produce PCA scores and loadings which is then followed by MLR (Gemperline, 2006). The mathematical model employed by PCR and PLSR is indistinguishable, except for how they handle data compression. While PCR focuses only on spectral information, PLS incorporates both spectral and concentration data. Latent Variables (LVs) are the compressed variables that are obtained in PLSR. By utilizing PLSR, the spectral data is mathematically correlated to a matrix of property of interest (chemical or physical properties), along with any other significant spectral components that interfere with the spectrum. (Hemmateenejad, Akhond, & Samari, 2007).

Deep Learning

As it was mentioned, there are two classifications for ML algorithms: traditional machine learning methods and deep network architectures. Unlike traditional machine learning methods, deep network architectures have multiple hidden layers like AlexNet and GoogleNet. Deep network architectures employ raw features unlike traditional machine learning methods that require an expert to engineer appropriate features.

NIR data has been effectively modeled by combining classical chemometric approaches, predominantly PCA and PLS-based techniques, with knowledge-driven spectroscopic preprocessing. For many years, ANNs have been utilized in the chemometric field. Nevertheless, there exists a distinction between the conventional ANNs and more recently developed deep NNs. In order to input data in to ANNs, which are like most Machine Learning (ML) algorithms, pre-extracted features extraction automatically, offering specialized proxies for spectroscopic preprocessing (Fig. 3 b). DL can also include a larger number of layers than ANNs. Training can involve up to hundreds of layers with millions of parameters. This is possible due to the availability of enhanced computational power, graphic processing units (GPUs), refined regularization techniques and advanced model optimization approaches make this attainable (Mishra *et al.*, 2022).

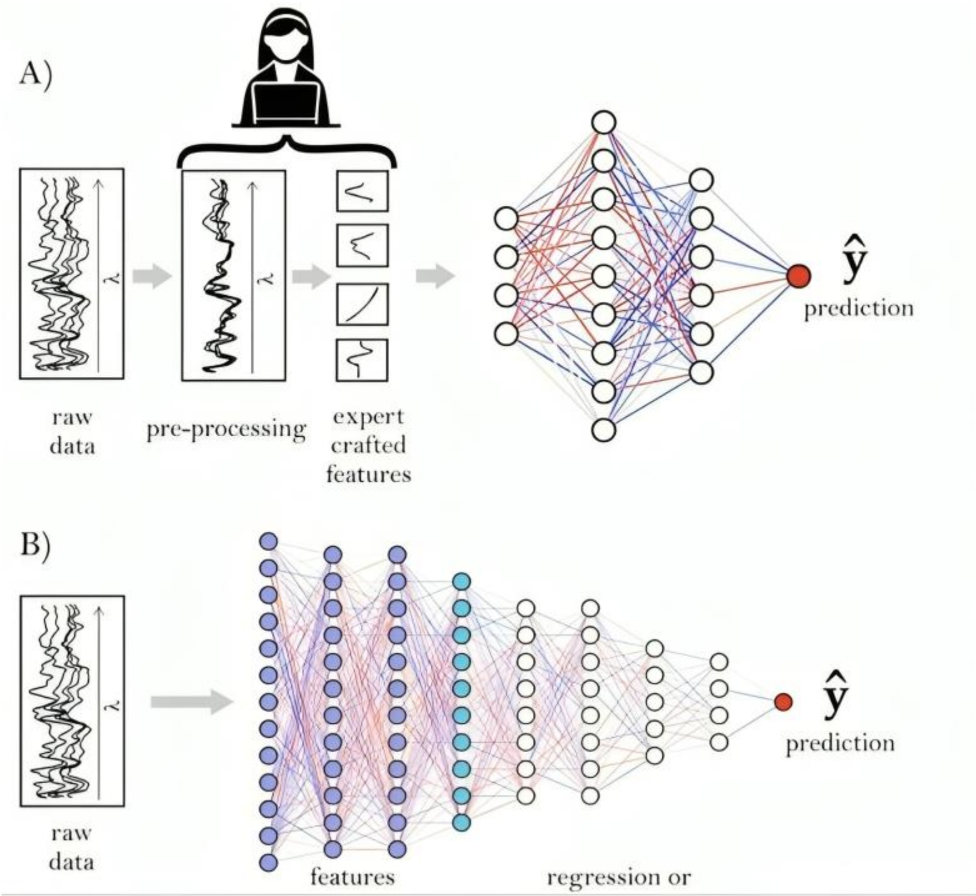

Fig. 3. (A) Classical ANN for data modelling, and (B) DL convolutional neural network (CNN) approach, which includes joint feature extraction and model building (Mishra *et al.*, 2022)

Challenges and Future Outlook

While spectral- and image acquisition techniques have advanced quickly, they still have some challenges when implemented in industrial environments. Firstly, the initial creation of certain models may require a significant investment of both time and money due to the lengthy calibration process. Moreover, the gathering of data is impacted by various acquisition parameters like scanning times and sample to detector distance, as well as environmental factors such as ambient temperature, humidity, illumination conditions, and sample temperature.

However, most testing techniques use a single detection method for a given detection index and provide acceptable predictive results, thus providing multiple pieces of information for a comprehensive evaluation of the sample is required in the future (Xiong, Sun, Pu, Gao, & Dai, 2017). Consequently, it becomes essential to integrate multiple detection methods and indicators, as well as utilize data fusion, for exploring the comprehensive evaluation technique for meat safety.

At this moment, the meat industry requires an online/real-time system for quickly verifying the authenticity of meat products. Despite some initial success, further research is needed to implement online systems effectively. Implementing an online/real-time detection system for the rapid authentication of meat products would indeed have several benefits, but it also comes with its own set of drawbacks: Developing and implementing such a system can be expensive. There are costs associated with research and development, equipment procurement, installation, maintenance, and ongoing operational expenses. These costs may be prohibitive for some companies, particularly smaller businesses in the meat industry. In addition, creating a reliable online detection system for meat authentication requires advanced technology and expertise in areas such as sensor technology, data analysis, and machine learning. The complexity of integrating these components into a seamless and effective system can pose challenges. Furthermore, achieving high levels of accuracy in detecting and authenticating meat products in real-time can be difficult. Factors such as variations in meat composition, processing methods, and environmental conditions can affect the performance of the detection system. Ensuring consistently accurate results is essential for maintaining consumer trust and regulatory compliance. Another weak point is continuous maintenance and calibration of the detection system which are necessary to ensure its ongoing reliability and accuracy. This requires dedicated resources and expertise to address issues such as sensor degradation, software updates, and changes in production practices. Finally, introducing new technology into established meat industry practices may face resistance from stakeholders who are accustomed to traditional methods of authentication. Overcoming this resistance and fostering adoption of the new detection system can be a significant challenge.

Addressing these drawbacks requires careful planning, investment, and collaboration between industry stakeholders, technology developers, and regulatory authorities. Despite the challenges, the potential benefits of an online/real-time detection system for meat authentication make it a worthwhile endeavor for improving food safety and consumer confidence trends.

Despite these drawbacks, these nondestructive spectroscopy and imaging techniques may become more widely used in the future. These methods will continue to evolve as instrument technology improves, the meat industry urgently requires a real-time online system that can quickly authenticate meat products. The development of high-speed computers with sufficient storage capacity and appropriate chemical assays has made this possible. Implementing these fast and non-destructive systems could greatly impact the profitability of the meat industry and may become the leading trend in the future. Even though initial efforts yielded some success, additional investigation is needed to properly implement online systems.

Conclusion

This review provides a comprehensive review of how spectral methods and techniques have been used to swiftly assess the safety of ground meat illuminating the drawbacks of conventional methodologies and underscoring the necessity for enhanced, industry-specific alternatives. The present review paper concentrates on recently done research about the safety of minced meat using some spectral techniques and AI algorithms. Some new issues in application of AI, including feature selection and deep learning, were also discussed. The promising results acquired have highlighted the vast potential for implementation in the meat industry. In conclusion, these techniques could potentially be used in meat as a non-destructive security detection tool. Despite the current limitations, there are still various improvements and research possibilities for successful commercialization, especially for his HSI-based systems.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the author used Tinywow in order to rewrite some sentences. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Author Contributions

Amir Kazemi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing–review & editing, Project administration, Writing-Original Draft, **Asghar Mahmoudi**: Conceptualization, Methodology, Data curation, Visualization, Investigation, Resources, **Mostafa Khojastehnazhand**: Software, Supervision, Validation, Writing-Reviewing, and Editing.

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مقاله مروری

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تشخیص تقلب گوشت چرخ‌کرده با تکنیک‌های طیفی و هوش مصنوعی (۲۰۲۰-۲۰۲٤)

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چکیده

گوشت منبع مهمی از مواد مغذی مهم است و نقش حیاتی در رژیم غذایی انسان دارد. عدم نظارت بر کیفیت و ایمنی گوشت می‌تواند منجر به تهدید سلامتی شود. بررسی ایمنی گوشت با روش‌های شیمیایی پرهزینه و زمان‌بر است، بدون اینکه امکان نظارت به صورت زمان واقعی وجود داشته باشد. بنابراین، امروزه ارزیابی کیفیت گوشت با استفاده از تکنیک‌های طیفی مانند تصویربرداری طیفی و طیف‌سنجی، روش‌هایی امیدوارکننده محسوب می‌شوند و این تکنیک‌ها اخیراً دستخوش پیشرفت‌های سریعی شده و توجه عمومی را به خود جلب کرده است. بنابراین، هدف مقاله مروری حاضر ارائه مروری بر آخرین پیشرفت‌ها در روش‌های طیفی برای ارزیابی ایمنی گوشت چرخ شده است. اصول اولیه کار، فرآیند تحلیل و کاربردهای این تکنیک‌ها شرح داده شده است. محققان با بررسی امکان استفاده عملی از فناوری‌های تشخیص طیفی در ارزیابی ایمنی گوشت، چالش‌های موجود و چشم‌انداز تحقیقاتی آتی را مورد بحث قرار دادند. در ادامه، جدیدترین پیشرفت‌ها در کاربرد هوش مصنوعی همراه با تکنیک‌های ذکر شده نیز مورد بحث قرار گرفت.

واژه‌های کلیدی: تقلب، تصویربرداری طیفی، طیف‌سنجی NIR، گوشت چرخ‌کرده، یادگیری ماشین

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