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Hyperspectral Imaging (HSI) for meat quality evaluation across the supply chain: Current and future trends

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ABSTRACT

Meat products are particularly plagued by safety problems because of their complicated structure, various production processes and complex supply chains. Rapid and non-invasive analytical methods to evaluate meat quality have become a priority for the industry over the conventional chemical methods. To achieve rapid analysis of safety and quality parameters of meat products, hyperspectral imaging (HSI) is now widely applied in research studies for detecting the various components of different meat products, but its application in meat production and supply chain integrity as a quality control (QC) solution is still ambiguous. This review presents the fresh look at the current states of HSI research as both the scope and the applicability of the HSI in the meat quality evaluation expanded. The future application scenarios of HSI in the supply chain and the future development of HSI hardware and software are also discussed, by which HSI technology has the potential to enable large scale meat product testing. With a fully adapted for factory setting HSI, the inspection coverage can reliably identify the chemical properties of meat products. With the introduction of Food Industry 4.0, HSI advances can change the meat industry to become from reactive to predictive when facing meat safety issues.

1. Introduction

With the increasing number of population and the demand for a healthy diet, ensuring the safety of food has become an essential topic of discussion. Among these, meat products are particularly troubled by safety and health problems because of their complicated structure and various production processes (Damez and Clerjon, 2013). Meat products are easily perishable and need strict production and storage conditions (Kutsanedzie et al., 2019). Scandals related to meat have occurred in the past and were caused by improper supply chain management, absence of testing, and various operations of meat products. This makes real-time monitoring of production stages extremely important, which not only provides product traceability, but also enhances consumer confidence. It is necessary to adopt novel ways to evaluate meat products leading to the rapid modernisation of the meat industry in the Industry 4.0 era (Sofos, 2008).

Conventional meat quality analysis methods include sensory evaluation, wet chemical methods (moisture, protein, fat etc.), physical methods (pH, colour etc.) and microbiological analysis (culture-based techniques such total viable counts). These require not only a well-prepared sample but also a group of well-trained analysts and testing infrastructure. This type of testing is a high cost and intensive operation in the meat industry especially with the COVID-19 pandemic, causing an immeasurable risk (Rizou et al., 2020). The recent global pandemic seriously impacts the meat supply chain through the random loss of labour which disrupts certain operations (Rude, 2020). Several meat factories in England and Wales closed over the rise in COVID-19 cases while hundreds of workers at a meatpacking plant tested positive in Rheda-Wiedenbrück, Germany (The Guardian, 2020). The meat product supply chain must implement stricter food safety and hygiene control measures for a long time to deal with the food safety risks that may arise from other measures related to the recent pandemic (Nakat and Bou-Mitri, 2020). With these concerns in mind, non-destructive analytical methods are given a new perspective to maintain normal operation in the factory and various places in the supply chain, with less potential labour required. Compared with the conventional, non-destructive technologies such as point-focused mid and near-infrared spectroscopy (MIR, NIR), HSI collects both spatial and spectral information to provide physical and chemical parameters of the meat product (Fu and Chen, 2019). This multidimensional data can be used to determine the intrinsic quality and safety attributes of meat products with two different ways: multi-constituent information of the raw material analysed (meat) and chemical component distribution of

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Abbreviations

AOTF	(acousto-optic tunable filter)
CCD	(Charge Coupled Device)
CMOS	(complementary metal-oxide-semiconductor)
FLD	(Fisher's linear discriminant)
FOV	(field of view)
GLCM	(Gray Level Co-occurrence Matrix)
HSI	(Hyperspectral Imaging)
Light Emitting Diodes	(LED)
LL	(Lifelong learning)
LS-SVM	(Least-squares support-vector machines)
MCR	(multivariate curve resolution)
MCR-ALS	(multivariate curve resolution-alternating least squares)
MLR	(Multiple linear regression)
NIR	(Near-Infrared Spectroscopy)
PLS-DA	(Partial least squares discriminant analysis)
PLS-R	(Partial Least. Squares Regression)
QC	(quality control)
R2	(correlation coefficient)
R2c	(calibration correlation coefficient)
R2p	(prediction correlation coefficient)
RMSE	(root mean square error)
RMSEC	(root mean square error of calibration)
RMSEP	(root mean square error of prediction)
RPD	(ratio of performance to deviation)
SEP	(standard error of prediction)
SPA-PLSR	(Successive projections algorithm- Partial Least. Squares Regression)
SVM	(support vector machine)

this raw material (Kutsanedzie et al., 2019). As an effective analytical method that can be applied to different types of foods, HSI has been widely used in the analysis of different meat products in recent years in both lab and industrial settings. However, the design and operation of the HSI technique can create certain limitations within the current meat production workflow, as discussed later.

As described by Brooks et al. (2017), Bonou et al. (2020), and Soro et al. (2020), Figure A1 shows the flowchart of a conventional meat supply chain. The meat supply chain represents the steps involved in meat production from the farm to fork. This indicates the challenges that technology like HSI can face in the prospect of wide integration into most meat supply chains, which operate at high speeds and face complex logistics. A few review articles have summarised the available literature around the use of HSI technique in detecting quality and safety attributes of meat products in research environment (Pu et al., 2015; Feng et al., 2018; Antequera et al., 2021; Özdoğan et al., 2021). The published papers only describe the limitations of HSI by focusing on the characteristics of the hyperspectral sensors and summarising the practice that has been carried out, but the link the real meat production is not sufficient. Based on the drawbacks of current HSI implementations and the industry's urgent demand for meat process supervision, this paper discusses the latest applications, and also the direction of specific developments around the sensors and software. More specifically, we are reviewing the prospect of high-speed HSI embedding into the industrialised meat production process from a unique supply chain perspective.

2. Recent applications of hyperspectral imaging for meat product evaluation

2.1. Overview of the HSI technique

As can be seen in Figure A2, the main components of the HSI system are the NIR spectrometer with a spectral range of 400–2000 nm coupled with the camera lens and a detector which can be either CCD (Charge Coupled Device) or CMOS (complementary metal-oxide-semiconductor). The setup is illuminated with halogen lamps or Light Emitting Diodes (LED) which provide the appropriate radiation and several moving elements (usually a sample tray) to move the sample across depending on the type of measurement required (Kamruzzaman and Sun, 2016). This allows obtaining the spectral features across a fixed surface where the sample is placed. Both spectral and spatial information are fed into the specialised software. The different configuration in various HSI systems is based on the imaging approaches and common measurements modes. There are four main configurations to obtain hyperspectral images based on the scanning mode: point scan, line scan, wavelength scan, and snapshot (Hsu et al., 2017). These systems provide spectral information with a different resolution by scanning the spectrum of pixels on the sample in a different way (point or line). Hyperspectral images can vary in size according to the optics used, the capacity of the spectral sensor, i.e., the resolution of the digital image and the acquired wavelength channels in every pixel, and the HSI acquisition software (Ngadi and Liu, 2010). This data structure is often referred to as HSI hypercube.

There are two types of HSI hypercube due to the two ways to use the HSI data. Some studies only used the spectral information from HSI system, like the same data structure from conventional spectroscopy based system. Others used both spectral and spatial information from HSI system, which allows the prediction from pixel level. For the next step of HSI hypercube, classification models and multivariate regression models are used for discrimination and numerical predictions. In the case of, the less used, classification models (i.e., country of origin classification), the class prediction metrics used to characterise the models are the correct classification rate and the false positive and negative rates (Zhou et al., 2019). For regression models that quantify (i.e. prediction) specific sample properties, such as certain physicochemical parameters in meat, the prediction performance of the regression model is usually reported as the coefficient of determination, separately of the calibration and prediction set (R2c and R2p), root mean squared errors for calibration and prediction (RMSEC and RMSEP) as well as the ratio of performance to deviation (RPD) are used to calculate, RPD is defined as standard deviation/standard error of prediction (SEP). For the above evaluation indexes, a good calibration model will have lower RMSEs but higher R2 and RPD (Parrini et al., 2019). Both the classification and the regression models are relying on a calibration set populated with many "known examples" to predict "unknown" samples (Ropodi et al., 2016).

Besides, there are many other analytical methods that can be used for rapid non-destructive meat quality and safety control such as Near-Infrared Spectroscopy (NIR), Raman spectroscopy, the standard vision technology (digital RGB photo camera), and the electronic nose (Rodionova and Pomerantsev, 2020). Unlike HSI technique, NIR produce a value of the sample based on the spectrum from multi-scanning, which usually includes a small area of the sample (Kamruzzaman and Sun, 2016). The equipment is probe-based and focuses on single-point detection, which suffices for homogeneous product such as liquid or powdered. Table A1 compares these methods with HSI using several broad criteria such as the difficulty of analysis, data handling, and the cost in the context of meat analysis. For most non-homogeneous products, however, such as fresh-cut steak, bacon, marinated meat, cooked meat, the information provided by previous methods is limited and thus, not representative of the sample's properties because information of overall non-homogeneous sample is lost. Although HSI requires higher capital investment, it offers high resolution, high-level information, and advanced data analytics capable of extracting the characteristic chemical and physical parameters.

Because of the measuring setup, speed, and sensitivity relating to image resolution (Su et al., 2017), the application of HSI technique on meat products in actual meat inspections still has some limitations and lacks widespread application across the meat industry. This mainly relates to the current acquisition mode especially to the special lighting which must be used and specific angles that the instrument should be placed, the amount of raw data produced and relatively slows measuring acquisition time in comparison to the production workflow in the factory. A more specific breakdown for each application is given in detail in the following sections.

2.2. Recent applications of HSI for meat safety and quality evaluation

Table A2 summarises the recent research conducted on the use of HSI for meat safety and quality detection in a variety of meat types, conditions, and specific scenarios. HSI technology was used in studying different types of meat (from fresh meat to processed meat and animal species), in some cases differentiating between different meat types in mixed products or processing systems (fresh vs frozen meat) and determining a variety of meat quality parameters (from marbling score to lipid content). The studies vary from a simple screening of meat products (e.g., as legislation requirement) to determination of a specific parameter according to the objective of the study, e.g., a quality parameter such as marbling score which is useful in detecting if a product requires further processing.

2.2.1. Determination of the colour of fresh meat

Meat colour is the fundamental physical property of food because it has a great correlation with the physical, chemical, and sensory indicators of the product (Francis, 1995). HSI technology has been successfully applied to various kinds of meat products for colour measurement. Kamruzzaman et al. (2016a) used line-scan Visible HSI system (400–1000 nm) to monitor the colour parameters of fresh beef, lamb, pork with the reference value of CIELab colour system. Six characteristic wavelengths were selected to assess the colour parameters, common with all the three kinds of red meat (R2p = 0.88; RMSEP = 1.6). This approach significantly improved the efficiency and comprehensiveness of the detection because the selected characteristic wavelength can shorten the detection time. Moreover, HSI also monitors colour parameters on processed meat products. Feng & Makino (2020) used laboratory based HSI system (380–1000 nm) to analyse the colour change in sausages stuffed in casings, HSI detected the dynamic changing of colour on the sausage by predicting the reference value of CIELAB colour space system. Redness (a*) was predicted by the PLSR model and achieved the acceptable results (R2p = 0.78 and RMSEP = 0.78). HSI detection overcomes problems of insufficient repeatability and accuracy of single-point detection. Meanwhile, using HSI can solve the problem of real-time monitoring of colour distribution on the entire sample.

2.2.2. Determination of the water content of fresh meat

Moisture content directly relates to fresh meat status in the stage of processing, storage, trade and consumption (Cheng and Sun, 2008). Conventional detection method is destructive and time-consuming, HSI technique can provide a rapid method for assessing the moisture content in fresh meat products such as pork (Ma et al., 2016), beef (Zhao et al., 2017), lamb (Kamruzzaman et al., 2012). Advancing in processed meats, Ma et al. (2017) used pushbroom VIS-NIR HSI (328–1115 nm) to predict the moisture content of pork samples under various processing treatments (heated-dehydrated and cool-air-dehydrated) with the help of calibrated PLS-R models (R2p = 0.95; RMSEP = 1.46). To improve detection efficiency in different kinds of meat products and decrease variability related to the selection of characteristic wavelengths according to the type of meat analysed, Kamruzzaman et al. (2016b) developed a parsimonious MLR-based model detecting the moisture content of beef, lamb, and pork within ten characteristic wavelengths (R2p = 0.96; RMSEP = 2.19%) by using line-scan HSI equipment (380–1000 nm). HSI can offer an alternative rapid non-destructive method to determine moisture content certainty for fresh meat product and pork-based processed products with comparable accuracy to the conventional method.

2.2.3. Determination of the biogenic amine index (Bai) of fresh and processed meat

BAI is often used as a chemical indicator of meat freshness because biogenic amine formed during storage is closely related to spoilage (Triki et al., 2018). The detection of BAI with HSI is relatively new and has been tested only in fresh pork and processed beef products. Cheng et al. (2016) used pushbroom HSI system (400–1000 nm) to analyse the BAI in fresh pork and used a variety of regression methods in their modelling. Compared with full wavelength PLS-R model, the optimised MLR model had an excellent result (R2p = 0.96; RMSEP = 4.87). Yang et al. (2017b) used two line-scan HSI systems to quantify the BAI in cooked beef during storage, using two-wavelength ranges (320–1100 nm and 930–2548 nm, separately). The results showed that better performance was in the range of 320–1100 nm with the SVM model (R2p = 0.97; RMSEP = 1.04). Current research progress is still narrow although promising, and some more scientific evidence is needed to prove that the HSI technique can detect the BAI value in an industrial setting using suitable line scan instruments.

2.2.4. Determination of the total viable count (TVC) of fresh and processed meat

TVC is mainly used as a marker to determine the degree of contamination of meat by bacteria to provide a scientific basis for the hygienic evaluation of the tested samples (Skura, 1986). Most of the conventional chemical, physical, and microbiological methods are very time-consuming. HSI-based TVC analysis could provide a modern way to assess microbial load in real-time. TVC has always been a key inspection parameter for HSI testing and has been applied in various fresh meat products such as pork (Huang et al., 2013), chicken (Feng and Sun, 2013) and beef (Peng et al., 2011). HSI has also been considered as a method for rapid detection of TVC in different storage environments, Zheng et al. (2017) predicted the TVC in chilled pork under high oxygen condition by using line-scan Vis-NIR HSI system (400–1000 nm) with the promising outcome (SVR model: R2p = 0.94; SEP = 0.46 with second derivative transforming). Yang et al. (2017a) detected the TVC content in spiced beef product using line-scan HSI technique from range 325–1000 nm (R2p = 0.934; RMSEP = 0.755). The same system was used to predict the TVC value of cooked beef and samples were distinguished with three classes (freshness, medium freshness, and spoilage) based on the value of TVC (correct classification rate = 97.14%) (Yang et al., 2017). Achata et al. (2020) predicted the TVC of the beef Longissimus dorsi muscle with two storage condition by using line-scan Vis-NIR HSI (400–1000 nm, 880–1720 nm), data fusion of both spectral regions was developed for beef samples with storage at 4 °C and 10 °C (R2p = 0.96; RMSEP = 0.58 and R2p = 0.94; RMSEP = 0.97, respectively). Various storage situations brought the complicated circumstance of detecting TVC value and these applications provide broad prospects for real-time monitoring of TVC content. There is enough scientific evidence to support real-time monitoring of TVC in meat at least in the factory especially if the equipment speed of analysis can match the production line speed in the industry.

2.2.5. Determination of the nutritional composition of fresh meat

Consumers expect accurate nutritional information in a label to determine the value of meat, the lipid/fat profile is one of the most requested features (Henchion et al., 2017). A fast and non-destructive model can monitor the fatty acid profile of meat samples at crucial stages of the industry chain to optimise the ability of comprehensive monitoring. Work on fatty acids profiling using HSI in meat products has not been extensive but produced some auspicious results. Wang et al.

(2020) used line-scan NIR-HSI system (900–1700 nm) to detect C16:0 (palmitic acid) and C18:1 n9 (oleic acid), two sets of wavelengths (29 and 22) were selected to build up the prediction model (R2p = 0.91, 0.88 and RMSEP = 0.18, 0.37 respectively). HSI also enabled mapping the distribution of palmitic acid and oleic acid contents in the lamb muscle. Ma and Sun (2020) used line-scan NIR-HSI system (1000–2000 nm) to determine the total content of monounsaturated fatty acids (MUFAs) and polyunsaturated fatty acids (PUFAs) in processed pork meat (R2cv = 0.84, 0.92; RMSECV = 0.79, 0.76 respectively). Considering the practicability, the accuracy of HSI for fatty acids prediction needs to increase, sophisticated equipment and advanced mathematical way will be fulfilled for enhancing the performance of fatty acid prediction.

2.2.6. Detection of meat adulteration of fresh meat

Adulteration has always been a severe problem for the meat processor, whether it is intentional or unintentional, low-value meat is used to replace high-value meat to achieve illegal profit. According to the price of different meat in different regions and food culture, the adulteration of meat is also diverse (Vlachos et al., 2013). HSI technology in meat adulteration mainly focused on different types of meat, and then gradually expanded to the detection of the same species adulteration. Kamruzzaman et al. (2016c) used laboratory-based Vis-NIR HSI system (400–1000 nm) to detect the chicken addition in minced beef, and the results for range 0–50% (w/w) adulteration were excellent (R2p = 0.97; RMSEP = 2.45%). HSI also performed well in measuring the adulteration of minced lamb with duck meat using pushbroom Vis-NIR HSI (400–1000 nm) system (PLSR model: R2p = 0.98, RMSEP = 2.51%) (Zheng et al., 2019). Adulteration of beef mince with duck meat was investigated using line-scan HSI system (380–1012 nm) with outstanding results (R2p = 0.96, RMSEP = 6.58%, limit of detection = 7.59%) based on optimised wavelength selection (Jiang et al., 2019), the researchers also provided a very illustrative visual distribution map of the adulteration. Focusing on same species adulteration, Zhao et al. (2019) successfully used laboratory-based Vis-NIR HSI (400–1000 nm) to detect the meat adulteration on spoiled beef in a fresh beef product (R2p = 0.95; RMSEP = 5.67%). These studies demonstrate that HSI can differentiate between different meats from various sources, future applications could improve on the ability to detect the adulteration of meat products with a specific label such as PDO (Protected designation of origin) meat product, or with a lower proportion of adulteration (<5% LOD). These attempts will achieve the authenticity of localised meat product and delicacy product management.

2.2.7. Determination of gel and water injection of fresh meat

Non-declared injection of water and polysaccharide gels has enormous effects on fresh meat products, reducing the quality and increasing the risk of microbial contamination. The real-time non-destructive method that can verify the externally added water or gel will be a precious asset in the QC workflow in various stages of the meat supply chain. Currently, Vis-NIR HSI technology has been used to detect and quantify adulteration of carrageenan gel in chicken (Zhang et al., 2019). The prediction was based on just ten selected wavelengths from region 400–1000 nm and it showed good prediction results (R2p = 0.85, RMSEP = 0.93). Water injection in meat was detected in beef using a simpler version of the spectral-spatial data set (multispectral imaging technology) demonstrated efficient classification (R2p = 0.923) (Liu et al., 2016). Although there is a small number of studies supporting it and conducted in carefully controlled laboratory conditions using in-house admixtures, there is no doubt that HSI has shown strong potential in this analytical scenario. The next step is for technology to be tested in line scan industrial setups using real samples in a pilot meat processing facility.

2.2.8. Determination of the marbling score of fresh meat

The marbling score is one of the essential indicators to evaluate the meat quality and this score contributes to quality grading in the meat factory or at wholesale (Barbon et al., 2017). HSI has been used to determine the marbling score of different fresh meats. Aredo et al. (2017) predicted the marbling score of fresh beef by using pushbroom HSI system (400–1000 nm) with high correlation coefficient in the PLS-R prediction model (R2p = 0.95, SEP = 0.3), the classification error based on the grade of marbling score reached 0.08% (Velásquez et al., 2017). The marbling score of pork meat can also be demonstrated by HSI technique, Huang et al. (2017a) used line-scan HSI system (900–1700 nm) to evaluate the pork marbling score by using the rib end of the Longissimus thoracis (R2p = 0.89, RMSEP = 0.17). Although different marbling score standards may affect the overall adoption of the HSI technology as an alternative rapid method for marbling score, the weight of the evidence so far is that HSI can offer clear advantages in meat quality grading.

3. Potential applications OF HSI IN the meat supply chain

The meat supply chain has its relatively unique aspects, such as the close connection with land and farm, complex supply chain networks, and its susceptibility to environmental impacts. How to effectively ensure the quality of meat in all aspects and provide real-time monitoring information is becoming a demanding problem. Simplified meat supply chain can be described in four parts: farming, transportation, slaughter and processing plant, and distribution centre. Stages of slaughter plant and distribution are the two main processes when the living animal is transported to slaughterhouse completely. Various meat products are produced rapidly and elaborately in the supply chain after the animals are transported to the environment of industrial operation. Each step is interconnected and the quality problems at key control points are more likely to cause a collapse of the entire production chain. In this case, in-line inspection technology can solve actual production problems such as component evaluation, meat contamination and meat adulteration. There are several studies conducted to promote HSI as the rapid in-line detection tool, HSI technique has been applied from the whole carcass to well-packaged meat product. This section will discuss the future application scenarios of HSI in the supply chain by using several research applications in the field of HSI technology, mainly from two stages: the slaughter and processing plant and the distribution relating to exporting and the food service industry.

3.1. Potential applications of HSI at the stage of slaughter and processing plant

This stage can be separated into two parts: the primary processing (slaughter, fifth quarter removed) and the secondary processing (boning, cutting, packing). Primary processing includes stunning and slaughter, bloodless, scalding, defeathering, evisceration, channel section, finishing and shower channel. Secondary processing includes pieces separation, cuts extraction, filleting chopped, frozen packing, refrigeration, and storage (Noya et al., 2016; Robson et al., 2020). In the slaughterhouse, operation steps such as bloodless, evisceration, shower, frozen and refrigeration have been considered as critical control points because they have a higher possibility for contamination. The pollution caused by improper operation in the meat processing facilities mainly includes abnormal meat caused by improper handling before slaughter, cross-infection caused by microorganisms, abnormal meat colour and obvious trauma, and metal fragments infiltration (Soro et al., 2020). These contaminations bring great difficulties to ensure that the meat is qualified for the next processing step. HSI technology can be used to establish an early warning system before the meat is transported in more critical operations such as separation, freezing, or storage. When abnormal parameters are detected, unqualified samples can be quickly screened out. Further analysis and evaluation will determine whether the unqualified products can return to the production line or need to discard. This potential prospect greatly improves the stability of the manufacturing stage and reduces the probability of recall events. There are not sufficient HSI applications that can be directly used in the manufacturing process although these approaches have achieved promising results, most of which have not been integrated within processing operations due to a lack of knowledge or an unwillingness to implement these into existing processing systems.

Currently, there are some practical applications related to slaughter and processing plants. Konda Naganathan et al. (2015) used a prototype online AOTF (acousto-optic tunable filter) HSI system (450–900 nm) to scan HSI images on the beef carcass instead of cutting a piece of meat from the carcass. The scan time for each carcass was 4 s, and this system achieved a classification success rate of 88% in a true validation set by using Fisher's linear discriminant (FLD) models. This is a novel practice to scan beef carcass directly, which makes HSI technology applicable to the stage of carcass detection. Snapshot VIS-NIR HSI camera was used to detect the pH and IMF of beef in a meat processing pilot plant (Dixit et al., 2021), PLS-R model was used to predict these two parameters accompanied by R2p = 0.72 and 0.77 respectively. Due to the light influence from structural arrangements of the muscle fibers, Kucha et al. (2021) used laboratory-based push-broom HSI to scan three positions of pork for predicting IMF value. This application can fulfill the demand for canning meat under different cutting methods. Regarding various us drying methods, HSI (400–1000 nm) was used to predict the moisture content and colour parameters of dried beef samples (von Gersdorff et al., 2021). This application will enhance the future development of simple and cost-effective tools regarding monitoring systems for beef drying processes (von Gersdorff et al., 2021). Besides, Hitchman et al. (2021) expanded the HSI application on detecting IMF value of lamb storing for one to five years. The results show that the dynamic model based on samples from different periods reveals more spectral variation than the static model, which indicates that a continuously updated model can better suit industrial applications. The prospect of transforming these applications into commercial practice is very high, and these applications also provide the potential for the HSI analysis of other parameters.

3.2. Potential applications of HSI for meat at the stage of distribution centre

When the meat product is cut and transferred to a distribution centre (exporters, the wholesalers, the food service), authentication, classification, and adulteration are three issues that it can face. Weng et al., (2021) used HSI (400–1000 nm) to identify the geographical origin and breed of mutton with effective variables, accuracies of 95.67% for prediction set was obtained. Williams et al. (2020) used a line-scan NIR-HSI setup (950–2500 nm) to classify two species of game meat, Springbok (*Antidorcas marsupialis*) and Blesbok (*Damaliscus pygargus phillipsi*), The PLS-DA model reached 96% of classification accuracy. Three classes of Chinese sausages were used to classify based upon line-scan HSI equipment (874–1734 nm), the classification accuracy is over 90% by running the SVM model (Gong et al., 2017). In addition to meat classification in different categories, prevention of meat adulteration is also necessary. At this stage, various meat adulteration cases frequently occur due to the higher profit margin for illegal replacement fraud. One of the benefits of having both spectral and spatial data in the HSI analysis is that the adulteration can be demonstrated visually in a distribution map of the product itself as it is analysed. Jiang et al. (2020) used pushbroom HSI system (400–1000 nm) to detect the adulterant of jowl meat in pork meat from the homologous body, the R2p is 0.91 and the RMSEP is 14% based on the PLS-R model. The offal adulteration of pork was detected using HSI (400–1000 nm), a simplified PLS-R model was built within 11 characteristic wavelengths which obtained satisfactory results (R2p = 0.98, RMSEP = 4.47%) (Jiang et al., 2021). Besides the adulteration form of the other meat product, the adulteration with plant-based proteins in meat products is also an emerging issue. Pushbroom Vis-NIR HSI equipment (400–1000 nm) has been applied to detect the level of textured vegetable protein adulterated in minced beef and minced pork product and claimed that a 100% classification rate is achieved (Rady and Adedeji, 2020). If the HSI technology is intended to be used in classifying meat products in the actual production stage, the classification model must be extremely accurate. To meet industrial needs, HSI technique should achieve a more than 95% correct classification rate while at the same time the percentage of false-positive or false-negative should be below 5%.

4. Discussion

HSI brings wide prospects in meat quality analysis, such as saving labour costs, and avoiding human subjective errors of quality parameters. However, there are still some limitations that need to be solved in practical applications, The development of instruments limits the scope of detection, while the applied models and algorithms limit the accuracy of detection. This part will discuss the current situation and limitations considering two perspectives: instrumentation and data processing.

4.1. HSI instrumentation

HSI technology is affected by light intensity, speed, and smoothness on the surface of the tested sample, and its repeatability will be affected because of the light attenuation (Ján and Koloman, 2018). Therefore, improving the performance of the spectrometer and simplifying the corresponding hardware should be moving forward. With regards to instrumentation, different suppliers offer various solutions, which include benchtop systems and industrial analysis systems. Benchtop systems are used to acquire HSI image in a laboratory environment, the HSI equipment mainly used in the laboratory is line scanning equipment. The sample is placed directly on the conveyor belt and the HSI image is scanned under a high-intensity light source. Compared with the other two HSI equipments (wavelength scan and snapshot scan), line scanning equipment can obtain higher spectral resolution and relatively fast speed (Wang et al., 2017). By considering the various components of the benchtop system, which are exposed in the external detection environment, such as cameras, lights, conveyor belts, industrial-based HSI systems are integrated custom-made systems capable of operating in a condition of the production line in meat processing environments. However, the actual testing environment, as well as the size, shape, and production stage of the samples from each control point in the supply chain must be considered. Due to the penetration depth of the camera and the image processing speed, real-time HSI acquisition needs to be matched with the high precision of the industrial environment. To ensure that the HSI equipment can perform stable and continuous high-efficiency acquisition, the type and angle of the lighting solution, the distance between the camera and the sample, and the selection of FOV (field of view) require much more time.

In the context of meat production, the image acquisition speed of HSI equipment is an issue worth considering. Although linear scanning equipment can achieve accurate predictions acquisition, the processing speed of a single sample cannot meet the requirements of industrial design. At present, the image acquisition speed still needs to be further improved to adapt to the actual production environment. Recently, new snapshot hyperspectral cameras have been introduced, enabling rapid acquisition of the entire hyperspectral image without the need to move the sample or camera during scanning. Laboratories have gradually begun to use snapshot hyperspectral cameras, Al-Sarayreh et al. (2020) used two snapshot HSI technique (467–639 nm, 673–957 nm) to classify eight types of muscles from three species of meat in lab circumstance, which achieved the overall accuracy of 96.9% and 97.1% by using convolution neural network (CNN) models. Another challenge in HSI implementation in a factory setting is that the meat products going through the production line are not all similar in terms of weight, size, and shape. For example, if the thickness of the sample on the conveyor belt is different, the detected surface of meat scanned by well-prepared light and FOV can vary significantly. These will cause the actual distance between each sample and the camera to be different between measurements, which in turn, will greatly increase the detection error and uncertainty.

The HSI hardware suppliers initially focused on improving the stability of the benchtop system, such as developing a more stable lighting system, wider spectral scanning range, and higher resolution. While improving performance, HSI hardware has been adapted for use in the industry for in-line inspection. SPECIM, RESONON, and Headwall are the three vendors that provide HSI hardware, which will make effort to put HSI equipment into the instrument level under recent developments with faster computers and sophisticated sensors.

4.2. HSI data analysis

Using the HSI technique can generate a large amount of spectral and spatial data for analysis. A database containing pure and adulterated sample data and meta-information that can be used as reference data should be established to obtain a powerful and universal calibration model. The sample size of the model can not only be used to illustrate the feasibility but also to establish a reliable general calibration model. Unfortunately, building a worldwide accessible reference dataset for detection and analysis of meat is challenging, the establishment of meat datasets with sufficient generality and diversity is still greatly needed. Dixit et al. (2021) proposed using eight sets of HSI data from global to construct the IMF and pH prediction models of three types of red meat (beef, lamb, and venison), Different slaughter seasons and detection environments are all considered. The prediction model reached reasonable prediction performance (R2p = 0.86, 0.89 respectively), which illustrated that HSI application can be expanded to global perspective. A good classifier is evaluated by higher R2 and lower RMSE, especially R2 and RMSE of calibration set need special consideration when developing a global dataset, which should include meat under all the scenarios when going through the HSI system. Before putting the well-trained model into real-life meat inspection or along the meat production line, a large batch of products is necessary to verify the model first. The R2p must be as high as possible, and the ratio of R2c and R2p need to be considered as well because the high R2c and low R2p means that the model is overtrained and not suitable for industrial use.

The choice of data analysis method is a challenging problem for constructing a robust and universal calibration model as well. Both linear (PLR-S) and non-linear classifiers (e.g. SVM, random forest) were used according to the analysed parameter. In general, models created with linear classifiers (PLS-DA, PLS-R, LDA) have a strong explanatory ability in prediction, but with lower accuracy in some cases. On the other hand, non-linear models have good accuracy and resolution for analyses such as detection of contamination or discolouration of meat products. Although the data processing methods are contractedly improving, the difficulty of acquiring quality HSI measurements from a sample set remains. Besides, the training process for deep learning takes time, the high complexity of the model and multiple hyperparameters complicate the optimization process. Lifelong learning (LL), which involves reinforcement learning and the use of accumulated knowledge in future problems, is also considered for application in the process of data processing. Over time, LL algorithms gain more knowledge and learn more efficiently, which helps to develop simpler models.

Dimensionality reduction should be carried out to decrease the number of variables needed for modelling, which will speed up the data processing time. The current dimensionality reduction technology mainly uses the PCA method, which is an unsupervised algorithm and only reserved in the view of the main features. It is necessary to develop suitable machine learning methods for dimensionality reduction processing, such as semi-supervised method, and rapid extraction method for characteristic wavelengths. In order to achieve faster processing time, Wan et al. (2020) used line-scan NIR HSI (900–1700 nm) technique predicting three myoglobin content (DeoMb, OxyMb, MetMb) in nitrite-cured mutton (R2p = 0.90 and RMSEP = 2.35, R2p = 0.96 and RMSEP = 2.37, R2p = 0.89 and RMSEP = 3.27, respectively). PLS-R and SVM methods were modelled for each myoglobin form with their characteristic wavelengths. This approach has greatly saved time compared to full-spectrum analysis, but there is still a need for a screening method to use the same set of characteristic wavelengths for three myoglobin forms. As seen previously in the different applications in meat quality assessment, dimensionality reduction is key to the success of the prediction. If a full-spectrum scan is used, HSI equipment will not be suitable for continuous in-line analysis. The current way to increase the speed is to select one of the few characteristic wavelengths from the whole spectrum, but because the characteristic peaks corresponding to different characteristic values are not the same, the lack of representative signals of the spectrum may happen at the same time. Each production stage where HSI is placed needs to be re-modelled and screened for testing, which could bring inconvenience and require more investment.

The classifiers and wavelength selection methods of spectral data, however, are not the final solution to solve the excessive data generated by HSI, which can be an issue in terms of data processing and storage for the average user. This is because, the textural and RGB (colour) information from the HSI camera needed to be analysed as well. Some attempts to automate wavelength selection using data fusion techniques (Li et al., 2015; Yang et al., 2018) and reduce the HSI data (Ghaffari et al., 2020). Data fusion technique obtains comprehensive results by analysing the spectral information and texture information in the HSI data separately. Kucha et al., (2021) used three data fusion methods to predict the IMF content of pork samples, results showed that the data fusion resulted in a higher prediction of IMF. Besides, MCR (multivariate curve resolution) method is also applied to the processing of HSI data differently. MCR unfolds the 3D HSI data into a two-dimensional data matrix and then performs data reduction based on this simplified data set (Ghaffari et al., 2019). Ghaffari et al. (2020) came up with MCR-ALS (multivariate curve resolution alternating least squares) method to compress and reduce HSI data. In the MCR-ALS model, pixels and variables are considered as the rows and columns of a two-dimensional data matrix rather than two independent parts. The joint selection of essential pixels and essential variables greatly reduces the volume of data.

5. Future practice

It should be noted that laboratory based HSI system has no capacity to transfer to actual application directly, instrument and data processor need to adjust according to the working environment and the budget of analysis machine. Price is one of the most important parameters interfere the implementation of HSI, affordable detector developed by the improvements in the electronics and electronic architecture (microprocessor with dedicated cores for machine learning) will bring faster data analysis, and the miniaturisation of the HSI equipment is important as well about looking for the mobile platform. Currently, multispectral imaging technology is leading based on its advantages in capital cost and processing speed, but after the recent developments with faster ICT and sophisticated energy efficient sensors, HSI could be more affordable and accessible for larger or even medium sized meat processors to achieve automation, sample analysis, and traceability of products.

Meanwhile, the barrier expected to be resolved soon is the learning curve using the HSI technology in industrial settings but with untrained staff. In this direction, the instrument vendors are moving at a fast pace. SPECIM developed SpecimONE spectral imaging platform to reduce the operation difficulty of HSI systems in industrial production (Specim, 2020). People without coding or in-depth knowledge of spectral imaging can also use HSI equipment for classification (Viitakoski, 2020). Performing the quality evaluation by analysing several quality indicators will get a more reasonable model with interpretative ability. Zhuang et al. (2022) used fluorescence HSI to predict the TVB-N, pH, colour parameters of frozen meat without thawing, three freshness indicators were determined using one model. A single-quality feature is not sufficient to evaluate the condition of the meat product, but the bid to use the HSI technology should first start from ensuring the accuracy of its evaluation for a single parameter. Sometimes, it is necessary to make a comprehensive measurement of the various single parameters based on the stable performance from HSI equipment. Not does the multi-parameters need to be considered, multi-sensors are also expected to be detected synchronously. The combination of HSI technology and other non-destructive testing equipment (electronic nose, IR or NIR, or Spatially offset Raman spectroscopy) can be considered as a novel way to enlarge the application range of HSI to achieve the analysis of gas and liquid. With this multi-sensory approach, HSI can be used not only for the raw and processed meat product but also for pre-packed meat in various types of packaging.

The development of data processing chips and 5G network, the rise of digital barcode, which will have the capacity to achieve the transient communication across platforms. Network connectivity just as with 5G wireless can connect the HSI system to the cloud for off-loading some of the more intensive and algorithmic processing work to a remote data centre which can be miles away from the factory using secure communication protocols. Continuous improvement of HSI equipment and advanced chemometric methods make HSI technology not only suitable for the process of detecting products, but also involved in the information management systems in the future, such as the decision support systems. Decision support system is a computer application system that can assist decision makers to make decisions through data, models and knowledge (Zhai et al., 2020). HSI in the instrument level enhances the control of industry management such as process automation and safety control systems, which will improve performance management and quality management at the application level. HSI information, like a product's ID of each product, helps decision makers improve the level and quality of decision-making effectively. This system can potentially provide forecast insights about operations and real-time decision-making after continuous corrections. Currently, it is not possible to carry out fully automated analysis without manual intervention because this system needs to rely on a large amount of historical experts' data to verify the feasibility (Pashaei Kamali et al., 2017).

It is important to note that the aim of using HSI as a QC tool in the meat supply chain is not to fully replace the conventional detection methods because the HSI setup needs to update regularly with the reference value to verify the stability of the model. The vision is that the HSI technique can be used as a screening method followed by confirmatory testing using the conventional methods if required. A combination of both methods will help in accelerating detection and reduce costs. Non-destructive, fast real-time technique has been incorporated into instruments, especially for the larger food processing companies with global footprints in the past. Future trends of HSI technique in the meat supply chain can start from the following aspects: building a dataset includes several key scenarios in specific stages; embedding a fast and cost-effective HSI instrument into industrial analysis system; expand the application range of HSI to more steps in meat products chain, such as feeding and customers; user friendly solutions for data management.

6. Conclusion

HSI has clearly shown promising early signs in the non-destructive analysis of meat quality and safety. However, there are some specific challenges in this technique such as the scanning and data analysis speed that involve scaling this technology for use in meat production plants and onwards as a QC tool in the meat supply chain. Here, we reviewed many recent scientific articles related to the use of HSI in meat product analysis and discussed the disadvantages and the implementation of the HSI technique in the proper meat supply chain. The weight of scientific evidence is that HSI technology has the potential to enable large scale meat product testing. Currently, the technology although well-developed for static measurements in terms of instrumentation and analytics, the instrumentation's speed of analysis is still to be adapted for use in an industrial setting where high-speed production lines are moving, and fast-paced decisions must be made. This will allow for more applications in the analysis of meat products to be developed in the future. With a fully adapted for factory setting HSI, the inspection coverage can reach 100% of the target food, and it can reliably identify the chemical properties of food products. Once the HSI, together with other rapid sensor technologies, can successfully be integrated into several key point s of the meat supply chain, the meat industry can start moving from a reactive to predictive mode when facing meat scandals and adulteration issues. This will be translated into fewer recalls, less food fraud occurring in the market, and arguably less waste.

CRediT authorship contribution statement

Wenyang Jia: Conceptualization, Methodology, Writing – review & editing. **Saskia van Ruth:** Writing – review & editing, Reviewing. **Nigel Scollan:** Writing – review & editing, Reviewing. **Anastasios Koidis:** Conceptualization, Reviewing, and, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices.

Table A.1
Summary of the novel non-destructive detection methods

	ELECTRONIC NOSE	NEAR/MID IR SPECTROSCOPY	RAMAN SPECTROSCOPY	VISION TECHNOLOGY	HYPERSPECTRAL IMAGING
Type of Information	Odour	Spectra	Spectra	Image	Spectra and image
Sample size	N/A	Small	Small	Large	Large
Data size	Small	Small	Small	Small	Large
Technical difficulty	Low	High	High	High	Higher
Cost	Low	Low	Low	High	High
Speed	Fast	Fast	Fast	Very fast	Fast
Replicates needed	>5	3–5	3–5	3–5	1

(*continued on next page*)

Table A.1 (*continued*)

	ELECTRONIC NOSE	NEAR/MID IR SPECTROSCOPY	RAMAN SPECTROSCOPY	VISION TECHNOLOGY	HYPERSPECTRAL IMAGING
Suitability for on-line meat inspection (Advantages & Weaknesses)	Sufficient sensor stability buy lacks of absolute calibration	Avoids sample pre-treatment; single-point detection is limiting factor	Avoids sample pre-treatment but has low sensitivity in low concentrations	Non-destructive rapid visual scan but lacks internal analysis	Rich multidimensional information; specific measuring requirements;

Table A.2
Latest applications of Hyperspectral Imaging in meat products (2016–2020)

MEAT	APPLICATIONS/ DETERMINATIONS	EQUIPMENT SET-UP	WAVELENGTH (NM)	SAMPLE NUMBER	ADVANTAGES/WEAKNESSES	REFERENCES
fresh porcine	biogenic amine index (BAI) from longissimus dorsi (LD) muscle	Push broom HSI system	400–1000	210	Pioneering application/Limitation on sample types	Cheng et al. (2016)
	marbling score from loin joints	Line-scan push broom system	900–1700	24	Save cutting time/Less calibration sample	Huang et al. (2017b)
	intramuscular fat (IMF) and peroxide value (PV) from belly muscle cut	Push broom HSI system	400–1000	102	Application of data fusion/Manually wavelength selection	Aheto et al. (2020)
frozen–thawed pork	Monounsaturated and polyunsaturated fatty acids from LD muscle	Line-scan HSI system	1000–2000	192	Detect various processed meat/ Insufficient precision	Ma and Sun (2020)
frozen pork	myofibrils structural deformation from LD muscle	Push broom HSI system	1000–2200	158	Collect under frozen state/ Algorithmic enhancements	Cheng et al. (2018)
boiled pork	sarcoplasmatic and myofibrillar proteins from LD muscle	2 push broom HSI systems	400–2000	104	Reduce data processing time/ Limitation on sample types	Ma et al. (2019)
cured pork	TBARS from pork belly muscle	Line-scan HSI system	400–1000	108	Application on by-products/More data processing time	Aheto et al. (2019)
	NaCl content, water activity (a_w) from belly muscle cut	Line-scan HSI system	400–1000	135	Pioneering application/Less practical on actual production	Aheto et al. (2019)
	salt concentration from LD muscle	2 line-scan HSI systems	450–1664	144	Potentiality of engaging into brining process/Less concentration gradient setting	Achata et al. (2019)
pork sausages	adenosine triphosphate content	N/A	380–1000	75	Pioneering application/Less practical on actual production	Feng et al. (2018)
	Colour change for sausage stuffed in casings	Line-scan push broom HSI system	380–1000	52	Colour dynamic change of processed meat/Limitation on sample types	Feng and Makino (2020)
fresh lamb	myoglobin (DeoMb, OxyMb MetMb) value from LD muscle	Reflectance mode HSI system	400–1000	200	Novel exhibition of HSI on meat product/Incomplete sample range	(Cheng et al., 2019)
	Total viable count (TVC) value from LD muscle	Push broom HSI system	400–1000	150	Selected wavelengths used for packaged meat/Less practical on actual production	Duan et al. (2017)
cured lamb	myoglobin (DeoMb, OxyMb MetMb) form LD muscle	Line-scan HSI system	900–1700	240	Novel wavelength selection method/ Limitation on sample types	Wan et al. (2020)
cooked lamb	metmyoglobin value from LD muscle	Push broom HSI system	400–1000	182	Novel exhibition of HSI on meat product/Underperforming optimization model	Yuan et al. (2020)
fresh beef	TVC from LD muscle	N/A	400-1000; 880-1720	104	Two spectral ranged used for modelling/Relatively high equipment costs	Achata et al. (2020)
	marbling score form LD muscle	Line-scan push broom HSI system	400–1000	58	Expanded the HSI application/ Incomplete marbling standard	Aredo et al. (2017)
spiced beef	TVC	N/A	325–1100	105	Novel chemometrics method for evaluation/potential data overfitting	Yang et al. (2018)
cooked beef	biogenic amines	N/A	400-1000; 1000-1800	105	Pioneering application/Limitation on sample types	Yang et al. (2017)
fresh chicken	Carrageenan adulteration	Line-scan push broom HSI system	400–1000	144	Novel exhibition of HSI on meat product/Adulteration process needs improved	Zhang et al. (2019)

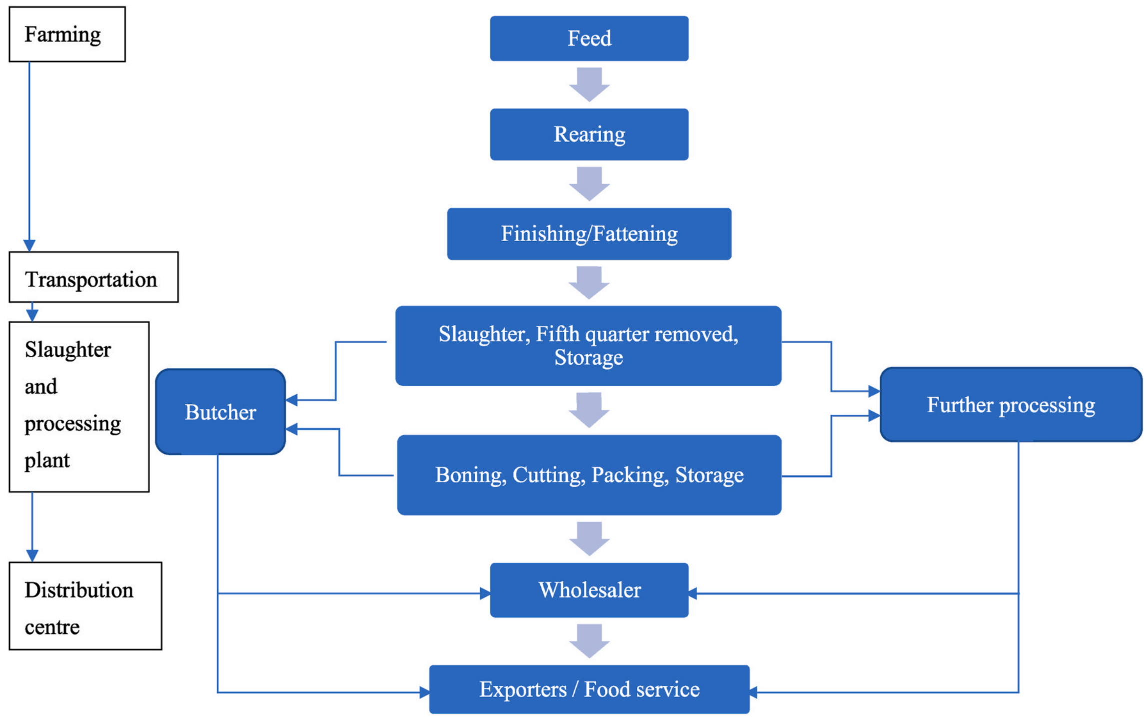

Fig. A.1. Conventional meat supply chain (adapted from Brooks et al., 2017; Bonou et al., 2020; Soro et al., 2020) .

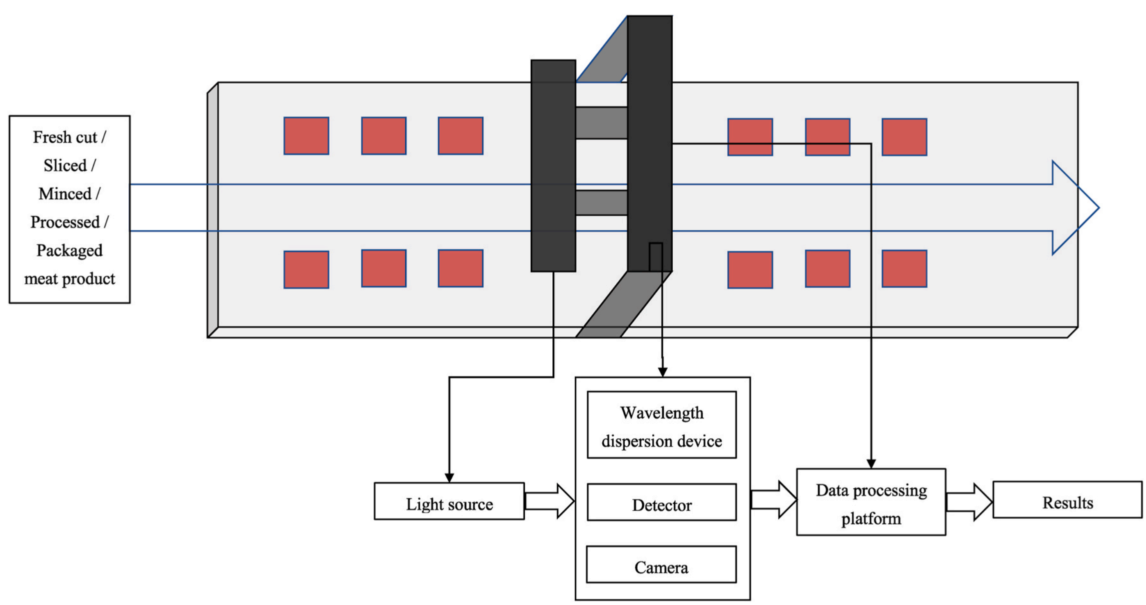

Fig. A.2. Potential implantation of the HSI technique in the meat production line .

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