International Research Journal of Engineering Science, Technology and Innovation Vol. 7(1) pp. 1-14, February, 2021
Available online https://www.interesjournals.org/engineering-science-technologyinnovation.html

Full Length Research Paper

Hyperspectral Imaging for Food Quality Assessment

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Abstract

Consumer concerns regarding the quality and safety of the food they buy and consume, is on the rise with the increasing food miles from farm to fork. Thus, Food Supply Chains (FSC's) need to incorporate advanced technologies such as "Hyperspectral Imaging or Imaging Spectroscopy" towards assuring the quality and safety of foods.

However, the rate of diffusion and adaptation of Hyperspectral Imaging (HSI) within Food Chains is quite slow due to preconceived opinions on the costs associated with acquiring the images and the amount of pre-processing and post-processing requirements for quality assessment.

Therefore, this report attempts to provide an overview of the "Hyperspectral Imaging Process" along with recent developments and applications within the FSC's, to uncover the preconceived opinions on the costs associated with acquiring the hyperspectral images and the complexities related to pre-processing and post-processing of data captured from hyperspectral images, for wisdom enhancement to help gauge the benefits of deploying the full potential of the HSI systems for real-time monitoring of quality and safety of foods.

Keywords: food supply chains, hyperspectral imaging, image pre-processing, image analytics, quality assessment and prediction

INTRODUCTION

Food Supply Chain (FSC), is a complex network, of small to medium-sized farms and processing facilities, that interact and aid multinational firms, with their supply and distribution activities [1]. FSC's provide access to healthy food across the world and are of prominent importance as access to safe and fresh food is vital to human life. Further, instilling customer's confidence in the safety and quality of foods they consume is of vital importance for profit maximizations within the Food Chains [2], thus securing food safety and quality is a matter of international significance for food trade.

Food losses resulting from quality deteriorations account for one-quarter of the produced food supply (614 kcal/cap/day) [3], and quality assessments within food chains aid with curbing food losses through damage reduction, damage prediction, and damage sorting allowing part of the food to be sold within acceptable markets [4].

In response to the quality demands from customers and regulatory bodies, numerous computer vision technologies have been introduced into the food chains for object recognition and information extraction from images for quality evaluation and automatic inspection [5].

However, HSI systems configured through the integration of computer vision and spectroscopy techniques standouts as one of the predominant techniques regarding the amount of data captured for quality assessment. The spectral imagery is three dimensional with two spatial and one spectral dimension providing continuity of data stored in the wavelength domain and Hyperspectral Imaging is one of the spectral imagery techniques that capture images with a great number of continuous wavebands enabling a full spectrum to be extracted from each of the pixels captured [6]. Additionally, HSI systems are configured as an integration of two classical optical sensing technologies (imaging and spectroscopy) towards monitoring both physical and morphological characteristics and intrinsic chemical and molecular information within food products in a swift and non-intrusive manner for quality and safety assessment [7]. In contrast, the Hyperspectral Images captured contain a set of monochromatic images with continuous wavelengths providing redundant information making the data sets highly correlated and complex, requiring new statistical techniques for complexity reduction [8]. However, the development of new and innovative algorithms for processing and analysis of hyperspectral data for usage within food chains, facilitates new avenues for information processing from correlated and complex data sets [9].

Therefore, a greater level of insight into the Hyperspectral Imagery Process, knowledge on recent developments and advances towards efficiency/performance improvements, and applications within various food chains for contaminant detection, defect identification, constituent analysis, etc. along with a holistic understanding of technological innovations in this domain is needful in gauging the benefits and challenges towards configuring the systems for rapid, objective inspection, sorting, and grading, in order to ensure superior, consistent quality of the food to the consumers. However, most of the research in this domain concentrates on the image processing and analysis for quality assessments within FSC's and very few of them concentrate on the holistic understanding of the systems and challenges towards application within food chains [5-8,10,11].

Therefore, this review is undertaken towards a comprehensive understanding of the HSI systems and recent developments to provide an insight into the motivations behind the implementation of HSI systems along with plausible challenges to eliminate the preconceived opinions regarding implementation costs and data management for successful implementation/adaptation of HSI systems within FSC's for Quality Assessments. A systematic literature review process is adopted towards selection, analysis, and synthesis of the relevant articles to understand the state of development in this regard and to identify knowledge gaps that demand a future investigation.

RESEARCH OBJECTIVES

The study aims at synthesizing the fragmented knowledge on HSI systems to fulfill the below research objectives

RO1. To identify the plausible challenges towards successful implementation/adaptation of HSI systems within FSC's for Quality Assessments.

RO2. To provide an overview of the recent developments within the HSI Systems towards deploying the full potential of the HSI systems for real-time monitoring of quality and safety of foods.

RESEARCH METHODOLOGY

A Structured Literature Review (SLR) process was adopted for the study, as it aims at addressing the issues presented through the analysis of ideas proposed to identify knowledge gaps that demand future investigation [12] This process aids in the stimulation of new theories, ideologies, practices, methodologies based on a clear understanding of the progress of work in the domain considered. It also aids in understanding the relationships and patterns between the works under consideration. It fosters a comprehensive search of relevant articles on a specific topic, which can further be used for appraisal and synthesis according to a well-defined explicit method [13]. The review process incorporates multiple stages to comprehensively cover the research area under consideration. The stages included are as described below:

- Searching
- Screening
- Synthesis [14].

Searching

The search aimed at identifying all the possible sources of information related to the research objectives under consideration. The search was executed by identifying a list of keywords from articles that provided a holistic preview of the HSI systems [5-8,10,11]. The list of keywords identified were used as search strings to identify relevant articles from electronic databases such as Science Direct (Elsevier), Emerald Insight, Semantic Scholar, Springer Link, Wiley, WorldCat, Taylor and Francis, Hindawi, and EDP Open. Table 1 lists the keywords used for searching the relevant

Table 1: Keywords and search strings used in the systematic review.

Hyperspectral *Imaging*	AND/OR	*Algorithms*	NOT	
		Analysis		
		Applications		*Astronomy*
		Challenges		*Atmosphere*
		Classification		*Ecology*
		Cost		*Military*
		Detection		*Mineral*
		Developments		*Surveillance*
		Evaluation		*Urban Development*
		Food Authentication		
		Food Quality		
		Food Safety		
		Identification		
		Prediction		
		Processing		

literature from the databases, books, etc. The keywords were then used to construct search strings using Boolean operators "AND, OR, NOT", to identify the relevant titles and abstracts from peer-reviewed journals published within electronic databases.

Screening

A total of 100 articles were identified from the publication portals, books, etc. Based on the criterion defined for inclusion, exclusion as per Table 2, and alignment with regards to research objectives and contribution towards the knowledge on progress of work in the domain considered, only 75 articles were shortlisted. Further, the elimination of redundancies resulted in 60 articles from "thirty eight" reputed journals, 'three" Proceedings, and "six" books for comprehensive analysis.

Synthesis

The selected articles were analysed and synthesized comprehensively based on the classification framework listed in Table 3, to identify the plausible challenges along with recent developments towards adaptation of HSI systems within Food Chains.

Proceeding with the final list of articles identified for the in-depth analysis, the section below provides a brief overview of the significant findings from the articles selected.

RESEARCH ANALYSIS AND FINDINGS

Based on the publication of articles in a myriad of Journals, "Study of non-destructive techniques for Quality Assessments within Food Chains" stands out as a predominant area of research for Academicians, Professionals, and Consultants, as securing food safety and quality is vital for human life and health. The sections below provide an in-depth review of the findings relative to the research objectives under consideration.

Hyperspectral imaging (Inception and Description)

The Hyperspectral Imaging Technology was introduced by Goetz AFH et al., [15] and their research team at the California Institute of Technology during the process of using Airborne Image Spectrometers for Mineral Mapping.

Besides, Hyperspectral remote sensing from airborne and satellite systems has been a prominent source of data for numerous remote sensing applications over the past two decades, as it is capable of assessing individual pixels within the Images for object identification within different areas including agriculture and forestry, ecology, atmosphere studies, geology and mineral exploration, marine, coastal zone management, inland waters and wetlands, urban development, snow and ice for scientific analysis and within

Table 2: Inclusion and exclusion criterion.

Inclusion Criterion	Exclusion Criterion
Structured Literature Reviews, that comprehensively provide a landscape of extant literature and developments within Hyperspectral Imaging Articles Concentrating on Hyperspectral Image Acquisition, Pre-Processing, Classification, Prediction, Applications within Food Chains, Challenges and Recent Developments Articles on Multivariate Techniques used for Hyperspectral Image Analysis.	Articles concentrating on applications other than the Food Industry.

Table 3: Classification framework.

Year	About HSI/ Acquisition	Pre-Processing and Image Analysis	Recent Developments and Applications	Total
Before 2010	Goetz AFH et al. [15]	Gowen AA et al. [10], Rinnan A et al. [34], Robila SA et al. [39], Lee JB et al. [40].	Del Fiore A et al. [55], Gómez-Sanchis J et al. [58], Heia K et al. [59], Ariana DP et al. [62].	9
2011			Siripatrawan U et al. [53]	1
2012	Lorente D et al. [8], Feng YZ et al. [25].	Michael TE et al. [28], Vidal M et al. [33], Lasch P et al. [72].	Elmasry G et al. [49], Wu D et al. [66].	7
2013	Qin J et al. [6], Wu D et al. [7].	Kwan H et al. [9]	Pablo AC et al. [60], Mohammed K et al. [64].	5
2014	Huang H et al. [22], Lu G et al. [26].			2
2015		Qiong D et al. [43]	Gerretzen J et al. [38]	2
2016	Sun DW [5], Shukla A et al. [16], Siche R et al. [17], Kamruzzaman M et al. [18].	Toksöz MA et al. [37]	Lim J et al. [68]	6
2017	Ravikant L et al. [11], Lu Y et al. [24], Mishra P et al. [27].	Arora N et al. [41]	Ricardo V et al. [19], Zhao X et al. [56], Rasool K et al. [61], Lía V et al. [65].	8
2018	Li X et al. [23]	Fordellone M et al. [45], Hu H et al. [73].	Roberts J et al. [50], Ropelewska E et al. [57], Wang Y et al. [67], Qi RZ et al. [69], Abel B et al. [70].	8
2019	Mahajan MP et al. [21]	Yadav H et al. [46], Paoletti ME et al. [47], Gogineni R et al. [48].	Yao X et al. [30], Rizwan Q et al. [31], Michael M et al. [51], Fu X et al. [52], Zu X et al. [63].	9
2020		Lv W et al. [20]	Riggs DR et al. [54], Vazquez JS et al. [71].	3

numerous military applications such as camouflage, littoral zone mapping, and landmine detections, etc. [16].

Besides, spectral imagery includes a stack of images of an object within different spectral bands and classified based on the number and spectral width of the bands into Multispectral, Superspectral, Hyperspectral, and Ultraspectral Imagery wherein the number of bands and spectral resolution increases from Multispectral to Ultra spectral from 1-10 to >1000 and ≈ 100 nm to ≈ 1 nm respectively. Additionally, as the HSI systems are capable of capturing 100-1000 spectral bands with a spectral resolution around ≈ 1 nm, the imaging system stands out as the most powerful spectroscopic technique for non-destructive analysis towards simultaneously providing physical and geometrical characteristics such as shape, size, appearance, and color of the sample, along with the providing the chemical composition of the sample using spectral analysis [17].

Moreover, Imaging techniques lack the capability of analysing the chemical compositions due to the absence of spectral data and spectroscopic techniques lack information on the spatial distribution of constituents within the sample [18]. Hence, Hyperspectral imagery technology was introduced with the integration of two classical optical sensing technologies of conventional imaging and spectroscopy towards capturing both spatial and spectral data from the target sample fostering in-depth evaluation of food safety and quality [6].

Also, the HSI systems capture spectral information (λ wavelengths) along with the two-dimensional spatial information, generating a 3D Hyperspectral Cube or Image Cube with three-dimensional data [7].

Image acquisition

Further, the main principle behind HSI is that materials reflect, scatter, or absorb energy differently when subjected to an electromagnetic radiation source at different wavelength ranges resulting from differences in chemical compositions and physical structures [19]. Therefore, such images are acquired by exposing the food samples at molecular levels to light photons to measure the absorbed or emitted radiation intensities. Additionally, the technique uses a wide range of the light spectrum, causing the light striking each pixel to break down into many different spectral bands capable of providing more information relative to the sample exposed. Furthermore, the parameter configuration within the HSI systems i.e. the selection of an optimal range of wavelengths within the electromagnetic spectrum, employing the right type of the image acquisition mode, and finally employing the right type of the image sensing mode is vital towards capturing the right and needful information from the samples [11].

Likewise, the core components within an HSI system include a source of light to illuminate the object, a lens for focusing and delineating the field view, a spectrograph for splitting the light into different spectral bands, a camera for capturing final spatial-spectral images, and finally a software to monitor the image acquisitions. Besides, the selection of these components is highly crucial to ensure the proper performance of the systems towards acquiring reliable high-quality hyperspectral images [18].

Similarly, the wavelengths within the electromagnetic spectrum used for hyperspectral imaging range from UV light, extend through the visible spectrum, and end in the near-IR or shortwave IR [20]. Besides, the spectral range for an HSI system is defined based on the type of camera, spectrograph, and illumination conditions used [21].

Likewise, the choice of the camera within the hyperspectral image system detector is dependent on the required wavelength, the Quantum Efficiency (QE) representing the sensitivity, and finally the cost. Further, Silicon (Si)-based Charge-Coupled Device (CCD) or Complementary Metal-Oxide-Semiconductor (CMOS) cameras, Indium Gallium Arsenide (InGaAs)-based array detectors, and Mercury Cadmium Telluride (HgCdTe)-based array detectors are most commonly used towards configuring the HSI systems [22].

Besides, HSI systems use three different image acquisition

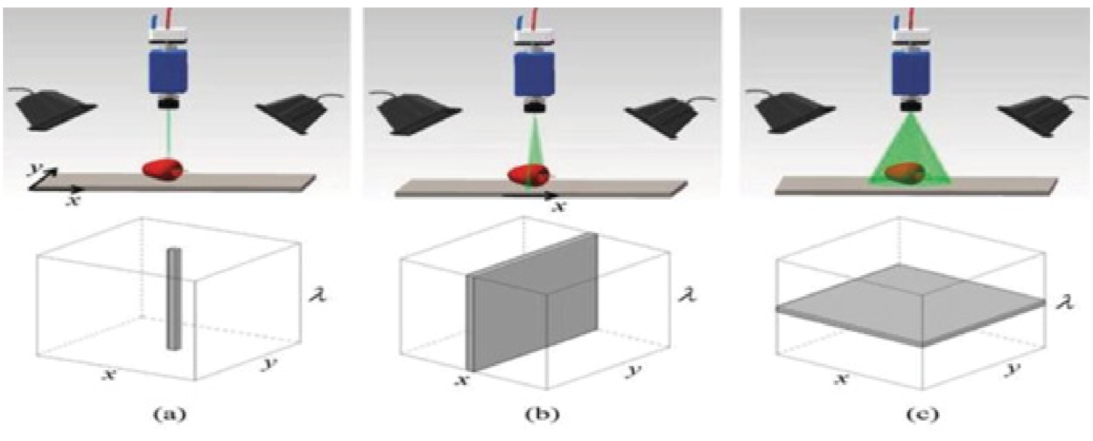

Figure 1: Image acquisition modes.

modes (Point scan, Line Scan, and Area Scan- as illustrated within Figure 1) to capture the data in the form of a 3D Hyperspectral Cube (a). Wherein, the "point scan" system captures the Intensity data for all the wavelengths in a pixel by pixel manner, the "line scan" system (b) captures the Intensity data for all the wavelengths for a row of pixels at a time and finally, the "area scan" system (c) captures the intensity data for each of the wavelengths for all the pixels at a time [7, 6, 11, 23].

Additionally, the HSI systems use different sensing modes for data acquisition depending on the properties of the sample being analysed. Furthermore, the three common sensing modes used (Figure 2) within the HSI systems can be classified as reflectance, transmittance, and interactance based on the different lighting and detector configurations used to capture dissimilar effects of data acquisition from the same sample. [18].

Wherein, the reflectance mode (a) positions the detector and light source above the sample facilitating the detection of external quality characteristics such as color, size, shape, and surface defects. In contrast, the transmittance mode (b) facilitates the evaluation of internal quality parameters as the detector and light source are positioned on opposite sides of the sample. On the contrary, the interactance mode (c) facilitates the assessment of the sample properties within a minimum distance from the surface, as it integrates both reflectance and transmittance through the placement of detector and light source on the same side of the sample separated by a light shield [11,23,24].

Ultimately, the final output (Figure 3) from the Image Acquisition process, is a 3-D cube with a series of narrowband sub-images arranged across the reflectance spectrum (amount of energy reflected by the surface at a specific wavelength) providing two spatial dimensions (x, y), one spectral dimension (λ), along with the intensity values of the pixels characterizing their unique spectral footprints [17, 25-27].

Besides, the image reliability within HSI systems is highly dependent on the system configurations, as minute variations within the configurations result in variations

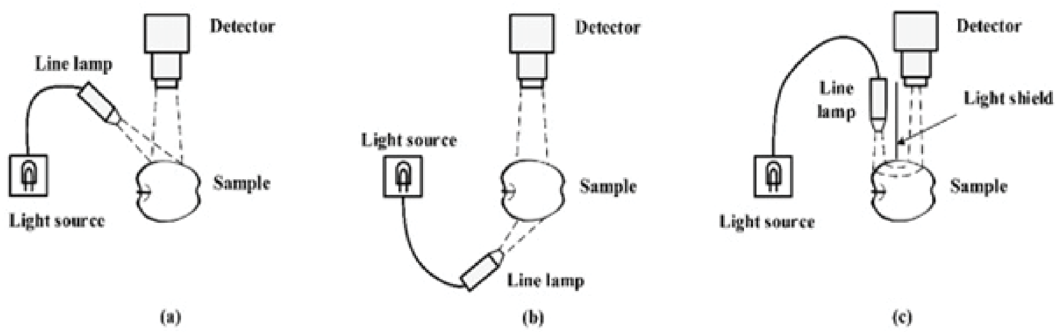

Figure 2: Image sensing modes.

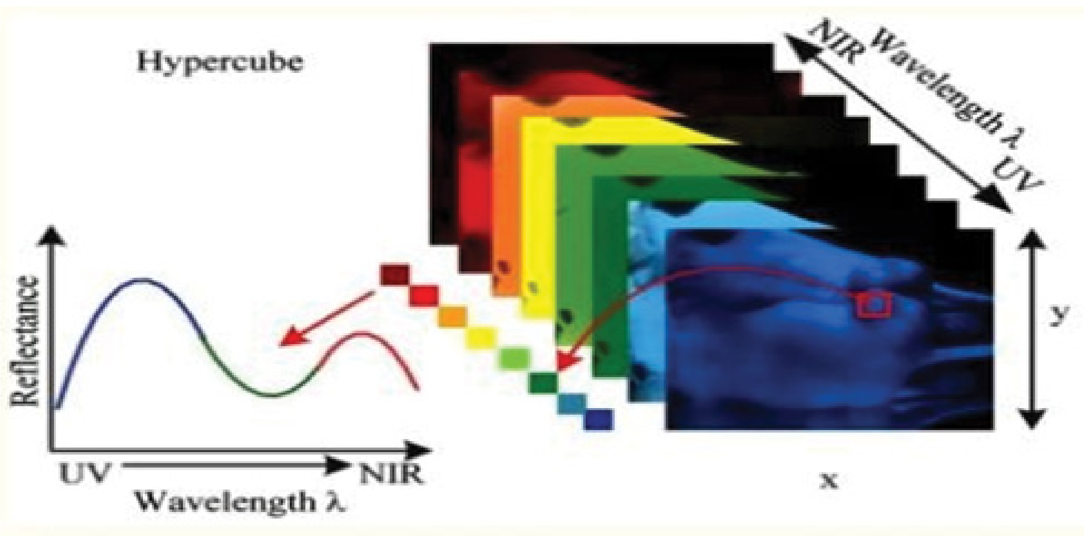

Figure 3: 3-D cube and spectral footprints.

within the spectral profiles of reference spectra obtained from a sample. Hence, it is highly essential to eliminate the variability through the usage of standardized/objective calibration and validation protocols that aim at standardizing the spectral and spatial axes of the hyperspectral image to validate the acceptability and reliability of the extracted spectral and spatial data. Thus, Wavelength Calibration (to identify each pixel along the spectral dimension with a specific wavelength), Spatial Calibration (to determine the range and the resolution of the spatial information), Spectral Calibration (to determine the spectral band centre's for all samples within a hyperspectral data cube), Curvature Calibration (to correct the reflection effect of light on food with spherical geometries using the angle of light incidence), and Reflectance Calibration (to calibrate the raw intensity image into reflectance or absorbance image with black (D) and white (W) reference images) are generally used within the HSI systems towards ensuring the consistency and reliability of the acquired hyperspectral image data [7,6,22,23,25,28, 29].

Challenges: However, the traditional HSI systems are relatively expensive and bulky as they require high precision scanning optomechanics elements and computer controls, thus making them inconvenient for handling and usage within the Food Chains for Quality Assessments [30]. Further, abrupt behaviour of instrument, environment, or imperfections within the electronic circuitry result in variations within the "signal to noise" ratio within certain wavelength bands impacting the quality of the Hyperspectral image acquired [31].

Likewise, the addition of a third dimension containing spectral or band information to the conventional 2D image framework within the Hyperspectral 3D Imagery, induces complexity within the calibration framework towards dealing with the variations within the spectral profiles of reference spectra obtained from the sample [23]. Similarly, the calibration requirements are different for different food products, calling out for in-depth product-specific knowledge to correlate the spectral information from the Hyperspectral Cube to the desired measurement metric [32].

Image pre-processing

Nonetheless, HSI systems can capture both spatial and spectral information, the data extracted from these images need corrections on effects induced from random noise, length variation of the light path, and light scattering [10]. Additionally, the hyperspectral imaging is subjected to variations resulting from external factors, system components, and complexities within the foods, as the food samples are characterized with surface inhomogeneities resulting in variations within the collected data. Besides, the light incident on the food material also experiences scattering due to physical properties of food material like cellular structure, particle size, density, etc., and absorption resulting from chemical composition like carbohydrates, protein, fat, etc, within the foods [11]. Further, to convene spectroscopic analysis, the regions of interest are to be selected by thresholding the image at a single waveband or a ratio and/or difference image, and to convene image analysis limited number of images are to be selected from massive images available for fast computation [25]. Hence, image pre-processing is vital towards building robust prediction and classification models for Quality Assessment. Though several techniques and algorithms are available for image pre-processing, their application and performance are highly dependent on further processing and analysis requirements. Therefore, the selection of the right pre-processing is done iteratively towards the development of a robust model with the best predicting ability [18,23,33].

Whilst, a detailed review of all the available pre-processing methods is presented by [34], only a few of the important and commonly used pre-processing methods such as Averaging, Smoothing, Normalization, Standard Normal Variates, Multiplicative Scatter Correction, Derivative Correction, Transformation, Baseline correction, Dimensionality Reduction, Nearest Neighbourhood Comparison, and Thresholding/Masking are presented in the Table 4 below.

Challenges: Although several techniques and algorithms are available for image pre-processing, the selection of an optimal pre-processing is among the main bottlenecks within the HSI analysis. Based on the multitude of pre-processing methods available for baseline correction, smoothing, and alignment, etc. pre-determined clarity on the method to be used for each of the data set generated is nearly absent-leading the analysts to select the right option through trial and error fashion [38].

Feature extraction

Finally, a Region of Interest (ROI) that excludes redundant background information within the combined or original calibrated image is generated after image pre-processing. In addition to the image pre-processing techniques, several image analysis techniques are further employed to extract useful image features from the Hyperspectral Image data for further analysis. Few of the feature extraction techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Minimum noise fraction, Gabor filter, Grey Level Co-Occurrence Matrix (GLCM), Wavelet transform, Wide line detector, etc. presented in the Table 5 below, are generally employed to extract image features effectively [22].

Challenges: However, the choice of the feature selection algorithms is dependent on the size of the dataset, the nature of the problem, prediction accuracy, and complexity levels [43].

Data modelling and post-processing

Additionally, hyperspectral imaging for food monitoring and assessment calls out for real-time classification of the

Hyperspectral cube, which involves the prediction of the class of the item. Additionally, the Hyperspectral image classification aims at assigning a pixel (or a spectrum) to one of a certain set of predefined classes. Further, based on the usage of the training sample, the HSI classification algorithms are generally classified into unsupervise and supervised classifications. However, the pixel-wise classification techniques face discrimination problems in situations with high intraclass spectrum variability and low interclass spectral variability, therefore spatial-spectral classification methods are employed that explore additional information of spatial dependency for classification. In addition to the classification, Hyperspectral Image Regression enables the prediction of constituent concentration in a sample at the pixel level, thus facilitating spatial distribution or mapping of a particular component in a sample to be visualized, hence several regression models are developed to predict the quality features using the data within the 3D spectral cube.

Supervised-Classification: Within the supervised classification, the input data is classified into different classes based on a representative set of samples known as training samples. Further, the discriminant function for classification is calculated based on a discriminant criterion defined based on the known sample category and prior knowledge. However, the power of supervised classification reduces with an increase in feature dimensions and limited availability of trained samples [44]. Hence, feature extraction techniques are often employed for dimensionality reduction-prior to supervised classification. In general, as presented in Table 6 below, the support vector machine method, artificial neural network classification method, decision tree classification method, and maximum likelihood classification method are employed for supervised classification [20].

Unsupervised Classification: Besides, the unsupervised classification algorithms or methods are often employed to group pixels with similar spectral characteristics inherent in the image into unique clusters based on some predefined statistical criterion. Further, within the unsupervised classification, as there is no output variable to guide the learning process, the data is explored by algorithms to find patterns. In general, as presented in Table 7 below, the most common algorithms employed for unsupervised classification are K-Means Clustering, Iterative Self Organizing Method, etc. [46].

Table 4: Pre-processing methods.

Averaging	Used to reduce the thermal noise and smoothen the spectrum (Li et al.) [23].
Smoothing	Carried out to reduce the noise levels (random variations in intensity) from spectral data without reducing the number of spectral variables (Savitzky et al.) [35], (Wu. D et al.) [7], (Kamruzzaman et al.) [18].
Normalization	Used to correct the spectra affected by differences in optical path lengths.
Standard Normal Variate	Row-oriented transformation method that aids with the removal of scatter effects within the spectra through centering and scaling of each individual spectrum (Barnes et al.) [36].
Multiplicative Scatter Correction	Used to reduce multiplicate problems or deviations caused by particle size and scattering (Li et al.) [23].
Derivatives	Employed to remove overlapping peaks and baseline shifts resulting from the variation of particle sizes and instrumental conditions (Savitzky et al.) [35].
Transformation	Used to separate noise from the spectra in the frequency domains through the decomposition of the original spectra into various frequency domains (Ravikanth et al.) [11].
Baseline correction	Aims at removing the background noises from the spectral data.
Dimensionality Reduction	Band Selection and Orthogonal Transformation are generally used to reduce the redundancy by decorrelating the band images.
Nearest Neighbourhood Comparison	Used to eliminate the spikes (sudden rise followed by a sharp fall in the observed energy within a local region of a band) resulting from the abrupt behaviour of instrument, environment, or imperfections within the electronic circuitry (Qureshi et al.) [31].
Thresholding or Masking	Used to segment the targeted object to eliminate redundant information (Toksöz et al.) [37].

Table 5: Feature extraction methods.

PCA	Used to reduce redundant features, extract key features and key wavelengths within the Hyperspectral Imagery Feng et al., Qin et al.) [25,6].
Independent Component Analysis	Generalized version of PCA, used to obtain the class information within different bands when applied to a full hyperspectral data set (Robila et al.) [39].
Minimum noise fraction	To filter or remove the bands that generate a high nose (Lee et al.) [40].
Gabor Filter	Used for edge detection, texture analysis, and feature extraction within Hyperspectral Imagery (Arora et al.) [41].
Grey level co-occurrence matrix	A statistical method for texture analysis considering the spatial relationships of pixels (Sebastian et al.) [42].
Wavelet transform	Employed to transform the image from the spatial domain into a time-frequency or wavelet domain instead of just a frequency domain
Wide Line Detection	Used for edge detection to detect the presence of lines of a particular width “n” at a particular orientation “θ” (Huang et al.) [22].

Spatial-spectral classification: Despite the fact, that supervised classification techniques are based on a set of representative samples for training, they often face problems due to the high dimensionality of the data and limited availability of training samples. Also, issues resulting from high intraclass variability hamper the power and effectiveness of their classification. Hence, Spatial spectral classifiers, that use both spatial and spectral information simultaneously are employed for the classification of Hyperspectral Imagery Data. Additionally, Deep learning includes a set of algorithms within machine learning that attempt to model high-level abstractions within data employing architectures composed of multiple non-linear transformations. Also, Deep learning models such as Convolution Neural Networks, Deep Belief Networks fall under the category of Spatial-spectral classifiers [47,48]. Generally employed Spatial-spectral classifiers are presented in the table 8 below.

Regression Models: Likewise, Hyperspectral Regression models are formulated to predict the quality parameters within foods, however, the model formulations call out for a representative calibration set containing the spectra with corresponding accurate reference values for each of the quality parameters to be assessed. Generally employed Regression Models are presented in the Table 9 below.

Challenges: In contrast, the HSI systems or Innovative Hyperspectral Imaging Systems are often developed within laboratory or research environments, with slow-moving trays for food classification. However, to be employed within food chains for real-time classification, they need to match with the speed of high throughput conveyors to sort food analysing data within a hyperspectral cube of sizes around 1 GB in less than a second [7,24].

Applications

Besides, food industry is one of the crucial areas where traceability, quality, and safety are of the highest importance to all the stakeholders within the supply chain including the consumers, as access to healthy and safe food is the need of the hour. Thus, ensuring both quality and safety of food is vital towards curtailing increasing morbidity, mortality, human suffering resulting from poor-quality foods and economic burden resulting from food losses, etc. across the world.

Hence, advanced analytical techniques have been developed

Table 6: Supervised classification methods.

Support Vector Machine Method	It employs a Kernel trick to transform the input data i.e. transformation from a non-linear decision surface to a linear equationin a higher number of dimension spaces and then uses the transformeddata to identify an optimal boundary between the possible outcomes (Mario et al.) [45].
Artificial neural network classification method	ANN's are crude networks of neurons that mimic the neural structureof the brain, trained iteratively with known records to adjust the connection weights within the hidden layer to convene the prediction of the correct class label for classification of the real image data.
Decision Tree Method	It mimics the tree structure, wherein a set of if-then rules are used to classify the input data records, the rules are learned sequentially usingthe training data set to convene classification of the real image data.
Maximum Likelihood Method	It employs the Bayes Classification, to classify each pixel within theHyperspectral Imagery into a category with the highest probability.
K-nearest Neighbourhood	Classifies data points through analysing its nearest neighbors from thetraining data set and assigns current data points to a class most commonly found among its neighbours.
Linear Discriminant Analysis (LDA)	It employs a linear combination of features or characteristics to separate or discriminate data into classes or groups by reducing the dimensionality to maximize the separability between the classes (Huang et al.) [22].
Partial Least Square Discriminant Analysis (PLS-DA)	Compromise between discriminant analysis and discriminant analysison the principal components of the predictor variables to convene dimensionality reduction for classification of data within the hyperspectral cube (Mario et al.) [45].

Table 7: Unsupervised classification methods.

K-Means Clustering	Employs an iterative refinement method to define the final clusteringbased on the defined number of clusters (K).
Iterative Self Organizing Method	An alternative to K-Means, adjusts the number of clusters automatically during the iterations by merging similar clusters or by splitting clusterswith large standard deviations.

Table 8: Spatial-spectral classifiers.

Convolution Neural Networks (CNN)	Formulated as a special class of Artificial NeuralNetworks, to aid with the extraction of deep and robust features for classification based on both spatial and spectral information.
Deep Belief Networks (DBN)	Formulated as a class of deep neural networks composed of multiple layers of latent variables,with connections established between the layers but not between the units within the layers, employed to learn both spatial and spectral features from the Hyperspectral cube for superior classification performance.

to assess the composition, physicochemical properties, and sensory characteristics of food. However, the established techniques are often challenged with requirements for cost efficiency and environmental sustainability. Consequently, non-invasive technologies such as HSI have come into existence to meet the expectations for high speed and low-cost quality assessments within food chains [50]. Further, the availability of both spatial and spectral data on food from HSI systems, makes them attractive to assess biological attributes such as bacteria counts, etc, physical attributes such as texture, color, marbling, tenderness, etc. and even chemical attributes such as fat content, moisture, protein content, pH, drip loss, etc. [22]. Besides, the information within the hyperspectral cube can be employed towards the assessment of Microbiological contamination such as bacterial determination, fungal contamination, parasite infections, etc. Physical contamination and defects such as Fecal contamination within fruits, Fecal/Ingesta Contamination within the meat, detection of foreign materials, detection of defects, etc. and even chemical contamination such as adulteration of melamine, pesticide residues, etc. [25].

1. Microbiological contamination: Has been identified as one of the major determinants of 10%-50% of losses within agricultural production and the reason behind 42% of foodborne illnesses. Also, commonly employed techniques such as plate count, visual inspection, microscopy, Polymerase Chain Reaction (PCR), fluorescence, ultrasound, etc. for bacteria, parasite, pathogens, and fungal detection are found to be invasive/destructive, laboratory driven, expensive, labor-intensive, time-consuming, sometimes erroneous and dependent on culture and colony counting methods [25,19]. Thus, HSI is often employed towards bacterial determination, fungal contamination, and detection of parasite infections.

Bacterial determination: Is crucial towards determining the presence and concentration of specific bacteria within foods to reduce the potential for spoilage, maintain the essential/correct product characteristics, and further to control safety hazards. Besides, the process of bacterial determination within food involves independent growth of different bacterial strains followed by the capture of HSI images of the cells from the isolated colonies to generate hyperspectral graphs of the respective bacterial cells for the reference library that is further employed along with the classification algorithms to determine the class of bacteria within the food [51]. Table 10 briefly summarizes the application of HSI systems for Bacterial Determination.

Fungal determination: Further, HSI stands out as one of the best alternatives towards the identification of different fungal species as it is capable of extracting a spectral signature for each of the species, thus the extracted spectral signature can be used to compare with the referential spectra to detect fungal contamination in food along with the determination of unknown fungal species [55]. Table 11 briefly summarizes the application of HSI systems for Fungal Determination.

Parasite infection: Besides, HSI systems be easily employed for parasite detection within foods as parasite presence leaves a distinctive spectral footprint within foods compared to normal foods [19]. Table 12 briefly summarizes the application of HSI systems for the detection of parasite infections.

2. Physical features and chemical composition: As Hyperspectral imaging is based on light reflectance from the exposed food surfaces facilitating the capture of spectral signatures based on the characteristic wavelengths at

Table 9: Regression models.

Multiple Linear Regressions-MLR	Anticipates the result on a response variable using a few illustrative factors through building a linear relationship between response variables and explanatory variables.
Principal Component Regression-PCR	Based out of PCA, wherein the main spectral variation isdefined by several orthogonal regression factors that are further used to develop estimation models.
Partial Least Square Regression (PLSR)	Aims at building linear models of prediction between spectral data and the values of the quality parameters obtained from the traditional measurements, such that thequality attributes can be predicted in the future directly from the measured spectra. It is often employed to predicta set of dependent variables from a set of independent variables or predictors (Gamal et al.) [49].

Table 10: Application of HSI systems for bacterial determination.

Type of Bacteria Assessed	Type of Food Assessed	Analytical Methods Employed	Reference
Salmonella	Chicken Meat	PCA, ANN, PLS-DA, KNN, K-means	Fu et al. [52]
Escherichia coli	Fresh Vegetables	PCA, ANN	Siripatrawan et al. [53]
Listeria	Milk & Dairy	PCA, K- Means, CNN	Riggs DR et al. [54]

Table 11: Application of HSI systems for fungal determination.

Type of Fungi Assessed	Type of Food Assessed	Analytical Methods Employed	Reference
Aspergillus	Maize	PCA, SVM	Zhao et al. [56]
Fusarium	Wheat Kernels	LDA, Decision Tree	Ropelewsk et al. [57]
Penicillium	Mandarins	LDA, Decision Tree (CART)	Gómez-Sanchis et al. [58]

absorption peaks. Further, the strength and wavelength of absorption depend on the physical and chemical states of the food.

Thus, the hyperspectral images enable the determination of physical parameters of interest such as texture, color, tenderness, defects (bruises, chilling injuries, canker, and rottenness), foreign material presence, etc and chemical compositions parameters such as fat content, moisture, protein content, etc to be quantified based on the features extracted from the information captured within the 3D spectral cube [22, 23].

Physical parameters: Besides, knowledge on physical parameters aids with determining the status of food quality facilitating efficient and reliable monitoring and control of important steps within the food chains to curb the degradation of food [50]. Further, texture identification within fruits aids with the classification of fruits into unripe, ripe, and overripe categories [61].

Also, prior knowledge on quality traits facilitates quality class prediction of food samples enabling segregation of good samples from defective samples characterized with bruises, chill injuries, rotten areas, etc. [25]. Table 13 briefly summarizes the application of HSI systems for physical parameter identification.

Chemical composition: As the hyperspectral imagery combines both digital imaging and spectral information within each of the image pixels captured, it enables composition mapping within foods based on the differences within the spectral signatures of the chemical ingredients within the samples tested.

Thus, HSI is often employed to assess the chemical quality attributes within foods such as solid content, protein, moisture, etc. that also impact other sensory characteristics such as hardness, etc. [11]. Table 14 briefly summarizes the application of HSI systems for chemical composition assessment.

Challenges: Although HSI integrates both the traditional spectral and image techniques to characterize the intrinsic and extrinsic properties of foods, it calls out for sophisticated data mining techniques to realize the prediction of quality attributes [43]. Further, a commercial HSI system costs around $28,000 limiting its application within the food supply chain for quality assessments [10,71]. Even though, Hyperspectral Imagery Techniques aid with assessing the composition, physiochemical properties, and sensory characteristics of food, lack of commercial and robust instrumentation along with lack of academic training stand as potential barriers for the worldwide application of these technologies at the Industry level [50]. Besides, the potential of hyperspectral imaging for food quality and safety analysis within food processing and packaging is heavily influenced by the sensitivity and resolution of the cameras used and the data processing methods employed [22].

Recent developments

In contrast, technological advancements within data mining and the availability of advanced computing technology/ hardware platforms facilitated a reduction in computational times and expenses. Consequently, algorithms such as Nearest Neighbourhood, Smoothing, etc., got introduced as affordable solutions for noise reduction to cope up

Table 12: Application of HSI systems for parasite detection.

Type of Parasite Assessed	Type of Food Assessed	Analytical Methods Employed	Reference
Gadus morhua	Fish Fillets	PLS-DA	Heia et al. [59]
Edotea magellanica	Shell Free Cooked Clam	Algorithms based onClustering and Discriminant Methods	Pablo et al. [60]

Table 13: Application of HSI systems for physical parameter identification.

Physical Parameter Assessed	Type of Food Assessed	Analytical Methods Employed	Reference
Texture	Pear	PLS-DA, LDA	Rasool et al. [61]
Defects (carpel suture separation or hollowness)	Pickling Cucumbers	PLS-DA	Ariana et al. [62]
Color and Tenderness	Fresh Beef	PCA & PLSR	Gamal et al. [49]
Bruises	Apples	PLS-DA, Decision Tree (CART)	Zu et al. [63]
Adulteration	Minced lab with Minced Pork	PLSR	Mohammed et al. [64]
Marbling	Beef	DT	Lía et al. [65]

Table 14: Application of HSI systems for chemical composition assessment.

Chemical Constituent Assessed	Type of Food Assessed	Analytical Methods Employed	Reference
Moisture	Dehydrated Prawns	PLSR	Wu et al. [66]
pH	Fresh Beef	PCA & PLSR	Gamal et al. [49]
Protein	Peanuts	PLSR	Wang et al. [67]
Adulteration ofMelamine	Milk products	PLSR	Lim et al. [68]
Pesticide Residues of Dimethoate	Spinach	PCA, KNN, DT,LDA,	Qi et al. [69]
Starch Content	Adulterated freshcheese	PLSR	Abel et al. [70]

with variations within the "signal to noise ratios" resulting from abrupt behaviour of instruments, environment, or imperfections within the electronic circuitry during image acquisition [31].

Also, the availability of high-resolution cameras, electronics, and optics facilitated the development of robust, low-cost HSI devices with high data quality and with low spatial and spectral distortions at around 2% of the cost of commercial devices that weigh about 300 g and characterized with a built-in capability to detect wavelengths within the range of 400 nm-1052 nm, with high spectral accuracy within controlled light as well as ambient light conditions, capable of generating 315 different wavebands with a spectral resolution up to 2.0698 nm and spatial resolution of 116 pixels × 110 pixels providing the convenience for handling and usage within the Food Chains for Quality Assessments fostering large scale applicability and also aiding with the evaluation of new algorithms for Hyperspectral image analysis. Besides, the introduction of line-scan spectral imaging systems built to acquire hundreds of lines per second facilitated the adaptation of the systems for online inspections within food processing plants. Further, the market availability of Imaging spectrographs with capabilities to scan more than 1000 lines per second, continuous introduction of new hardware design concepts for building high-performance systems, and enhancements within computation capacities of computers facilitated the real-time handling and processing of large data files generated from spectral processing (6, 71].

Besides, multiple firms are currently working towards the development of softwares using computer vision and machine learning in partnership with food chains facilitating the acquisition of in-depth product specific knowledge needful to correlate the spectral information from the Hyperspectral Cube to the desired measurement metrics to convene the development of calibration standards for different food products [32].

Further, the development of web-based applications and Design of Experiments facilitated the automation of the procedures for selecting optimal pre-processing and post-processing algorithms for Hyperspectral Image analysis convening the analysts to select the right algorithms for pre-processing and post-processing without trial and error methods [38,50].

Likewise, reduction in data computational times and expenses also facilitated the integration of different classification methods towards achieving the desired classification effects for real-time classification of different food products through analysis of large amounts of Hyperspectral data within time frames of the fraction of seconds [20]. Further, advancements within the Deep Learning methods/Machine Learning Algorithms/ensemble-based learning systems convened the development of advanced and powerful tools for processing high dimensional Hyperspectral data facilitating the development and fine-tuning of classification/prediction models within reasonable time frames [50,47]. Similarly, the development of low-cost and portable hyperspectral scanners characterized by push-broom scanning facilitated rapid and non-invasive acquisition of reflectance spectra [30].

RESEARCH GAPS

Though the rapid developments within the hardware and software platforms aided the evolution of the HSI systems from a research platform into a useful tool for many practical applications within the food industry, there exists a need to further enhance the potential of the current systems with extensive research to widen the platform of image spectroscopy by introducing different spectral profiles such as NIR, Raman, Fluorescence Spectra, etc., in order to capture additional features for enhanced Food Quality and Safety assessment [25]. Further, interdisciplinary research within the Physics and Computer Science domains can be enhanced to foster constant price reduction of the components used within the HSI systems and enhancements of computation speeds towards the rapid adaptation of HSI systems for real-time food authentication [8].

Likewise, formalized methodologies can be developed for optimally selecting the spectral information to convene automatic on-line parasite detection within cooked foods based on the spectral features [60]. Similarly, there exists a need to integrate the existing feature selection methods to take advantage of the combined potential towards extracting intricate features within the food samples. Moreover, future works in this domain can concentrate on expanding the range of applicable food products [22].

Additionally, studies should also focus on defining the optimal wavelengths for each food and food constituents such that the HSI systems can be fine-tuned to obtain real-time information on features measured to facilitate decisions on compliance with food quality and safety standards [17]. Also, Innovative hyperspectral imaging systems (combing different spectral technologies such as Multispectral & Hyperspectral, etc.) can be further explored beyond laboratory levels towards assessing internal quality features of fruits and vegetables and the current processing methods can be further explored to drive superior results within inspection speeds and accuracies [24].

Although, research studies have demonstrated successful application of HSI systems for quick, effective, and non-destructive classification of marbling in beef using few of the available samples, on-the-contrary there exists a need to evaluate all the marbling degrees contemplated within the Japanese standard BMS, through the collection of samples from different geographical areas, different breeds and different feeding regimes [65]. Currently, the evaluation of biological contaminants within food is limited to solid foods, hence there exists a need to explore the evaluation of biological contaminants within liquid foods [19]. Based on the literature it is evident that the HSI systems are good at classifying bruised specimens from good ones, but future works need to explore the degree of the bruise to help decide on the quality level and reduced pricing levels for bruised foods [63]. Moreover, research on High-Performance Computing is the need of the hour, as it can serve as an efficient mechanism to cater to the huge computational requirements of the deep learning algorithms used for processing HSI data, as the acquisition ratios of imaging spectrometers and the volume of future available repositories are expected to rise tremendously with real-time quality monitoring of food [47]. Similarly, the Hyperspectral image classification methods can be further explored towards classifying complicated images with high classification accuracies [20]. Further, partnerships between Industry and Academic Fraternity is the need of the hour to develop tailored systems to match with the unique application requirements at low costs to convene large scale implementations of the much capable HSI technology within the food Industry to extract its maximum potential towards enhancing the quality and safety and reducing the food losses within the whole chain. Besides, the generation of standardized practices and procedures for raw-data processing and feature classification would be needful in reducing the complexity of data-processing and feature identification within the foods.

CONCLUSION

The surveyed literature, aided to uncover the preconceived opinions on the costs associated with acquiring the hyperspectral images and the complexities related to pre-processing and post-processing of data captured from hyperspectral images by providing the needed wisdom to gauge the benefits of deploying the full potential of the HSI systems for real-time monitoring of quality and safety of foods. Additionally, the review also provided substantial evidence relative to the recent developments and success stories concerning the application of the technology for assessing biological attributes such as bacteria counts, fungal contaminations, parasite infections, etc, physical attributes such as texture, color, marbling, tenderness, etc. and even chemical attributes such as fat content, moisture, protein content, pH, drip loss, etc. within the foods. Therefore, with the advent of low-cost equipment's for data capture and systems with high computational power for data analysis, it is highly desirable to increasingly adopt the HSI systems for rapid, low cost and non-destructive assessment of foods towards curtailing increasing morbidity, mortality, human suffering resulting from poor-quality foods and economic burden resulting from food losses, etc. across the world.

ACKNOWLEDGMENTS

I would like to thank Dr. Mahmoud Awad, Associate Professor, Department of Industrial Engineering, College of Engineering, American University of Sharjah, for his continuous guidance and support towards conducting the Systematic Literature Review.

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