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A concise review on food quality assessment using digital image processing

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ABSTRACT

Background: Recent advances in signal processing technology and computational power have increased the attention towards computer vision-based techniques in diverse applications such as agriculture, food processing, biomedical, and military. Especially in agricultural and food processing, computer vision can replace most of the manual methods for screening of seed, grain and food quality.

Scope and approach: The objective of present study is to review the recent advancements in computer vision techniques for predicting quality of various raw materials and food products. This review paper is focused on the quality determination of grains, vegetables, fruits, beverages, meat, sea food and edible oils using Digital Image Processing (DIP). Several studies have reported the successful applications of DIP techniques for feature extraction, classification and quality prediction of foods. DIP algorithms are used to extract the significant features from images which are further used as input for machine learning (ML) algorithms to classify them based on different criteria. These feature extraction methods have been improved by Deep Learning (DL) algorithms. Features can be automatically extracted by DL algorithms resulting in higher accuracy. DL algorithms require huge data management and computational resources which can be a major limitation.

Key findings and conclusion: A significant literature is available for quality estimation of food products by using computer vision algorithms, but they lack commercial exploitation. Android based applications have not yet been developed for this specific purpose. User friendly, low cost and portable devices equipped for quality estimation would be helpful for rapid quality measurement of food products in real time.

1. Introduction

Recently, computer vision and machine learning (ML)-based techniques are frequently employed in broad range of applications such as face recognition, object detection, autonomous vehicles and defect detection. The development of new and improved algorithms for ML as well as for image processing has led to their successful adoption in many fields (Fujiyoshi, Hirakawa, & Yamashita, 2019). Image processing for food quality inspection is gaining increased popularity because of its inherent advantages over the conventional techniques (Botelho, De Assis, & Sena, 2014; Franco, Suarez, dos Santos, & Resque, 2021; Li et al., 2021; Minz, Sawhney, & Saini, 2020).

Food is one of the major factors that determine human health and well-being. The poor quality of food can cause nutritional deficiencies and several life-threatening diseases. In addition, adulteration in the form of pesticides, heavy metals also exhibit adverse effect on human health. Likewise, the presence of microbial contamination of food products also causes several acute or chronic disorders. Thus, food quality assessment is one of the crucial steps to meet the consumers demand for high quality and safe food products (Meenu, Guha, & Mishra, 2018; Orlandi, Calvini, Foca, & Ulrici, 2018; Xu, Meenu, & Xu, 2020).

Conventional quality assessment majorly includes chemical and microbiological analysis (Meenu et al., 2018; Xu, Meenu, & Xu, 2020; Xu, Meenu, Chen, & Xu, 2020; Yu, Meenu, Xu, & Yu, 2021). The chemical analysis involves determination of chemical composition of

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particular food product that can be present in it naturally, added to foods to increase its nutritional value or a chemical adulterant deliberately added to food by fraudsters (Meenu, Cai, & Xu, 2019; Meenu, Decker, & Xu, 2021; Wu, Meenu, & Xu, 2021). The microbiological examination involves the detection of certain microorganisms in food items that may be harmful to humans and usually used employed as a significant quality control tool (Meenu et al., 2018).

Both chemical and microbiological analysis are destructive in nature. These methods require large amount of food sample for analysis. Thus, that food product cannot be collected and consumed afterwards. More importantly, these analysis methods are time-consuming, laborious and require a lot of chemicals (Meenu, Guha, & Mishra, 2017; Meenu, Kamboj, Sharma, Guha, & Mishra, 2016; Meenu, Sharma, Guha, & Mishra, 2016; Meenu & Xu, 2019; Xu, Meenu, Chen, & Xu, 2020). Therefore, these conventional methods are not suitable at the time when a consumer immediately need to analyse the quality of a food product before buying. On the contrary, computer-vision based techniques are non-invasive and non-destructive. Also, they can predict the quality of a large quantity of a particular food product on-site immediately in a short time (Botelho, Dantas, & Sena, 2017; Jung, Heo, Lee, Deering, & Bae, 2020; Soponar, Moţ, & Sârbu, 2008; Wongthanyakram, Harfield, & Masawat, 2019).

The sensory evaluation is another important quality parameter of food product that involves the manual testing of the food item by a panel of experts. This is generally a tedious process, especially when large number of food products have to be evaluated. The accuracy and repeatability of analysis is less and frequently influenced by several factors such as mood of experts, their perception and fatigue. The manual inspection of sensory and physical parameters of food is subjective in nature, and the results may vary depending on the persons inspecting the food items (Laddi, Sharma, Kumar, & Kapur, 2013; Li et al., 2021). Hence, manual inspection is more error-prone compared to the image-processing techniques. The quality analysis of various food products using image processing primarily used to determine physical damage, adulteration, classification of various grains, fruits and vegetable for prediction of nutritional contents.

Overall, the image processing applications for food quality determination has the following advantages:

- Non-destructive and non-invasive measurement
- Safe and eco-friendly applications
- User friendly
- Energy efficiency
- Rapid data collection and processing
- Low-cost instrumentation
- Does not require highly skilled personnel for data collection
- Reduces human error
- Has high precision

In this paper, various online and offline image processing techniques published since 2011 were reviewed for quality assessment involving different types of food and ingredients. The total number yearly papers related to this topic from 1988 to 2021 as cited by Science Direct are shown in Fig. 1.

Online techniques are more popular in case of large and continuous monitoring of food quality, for example, using a conveyor belt and an image capturing module to capture a continuous stream of images (Wang et al., 2018). Offline techniques involve classification based on individually captured images, generally from batches of samples, and these can potentially be transformed for mass use, via consumer applications (Song, Jiang, Wang, & Vincent, 2020). In both cases, the image capturing setup generally involves a camera module to capture the test images. The most common approach involves capturing RGB (Red Green Blue) color images using Charged Coupled Devices (CCD) cameras. RGB color space can also be converted to HSV (Heu Saturation Value) or CIELAB (device-independent color space; L*, a*, b*, C*ab and Hab) color space (Stinco et al., 2013), to extract useful information (Fig. 2). Apart from these, depth images for volume estimation, IR images (Pamornnak, Limsiroratana, Khaorapapong, Chongcheawchamnan, & Ruckelshausen, 2017), hyperspectral images (Su et al., 2018) were also explored depending on the individual test requirements. To maintain constant light conditions during the image acquisition process, standard illumination systems were used.

The next step is a pre-processing step, which involves elimination of noise from the input image, as well as segmentation of the region of interests (ROI) from background. Generally, intensity thresholding and connected component analysis are the methods used for ROI segmentation. Further, it is also important to separate touching food items in case of grains, fruits or vegetables. Algorithms like Watershed algorithm or Elliptic Fourier series approximation can be used for this purpose (Mebatsion & Paliwal, 2011).

The next step is the feature (variables) extraction, which involves several image processing techniques to obtain useful and relevant information from the images. These involve features based on color, texture, morphological features or geometry of food items. Color features generally include statistical parameters relevant to the color channels in the input image. Normalised histograms are also useful. The Local Binary Pattern (LBP), Noise Reductant Local Binary Pattern (NRLBP), Completed Local Binary Pattern (CLBP) (Mohapatra, Shanmugasundaram, & Malmathanraj, 2017) or the Gray Level Co-occurrence Matrix (GLCM) (Khojastehnazhand & Ramezani, 2020) are generally used to obtain the textural information from input images. Geometric features include parameters related to the shape of the food item, such as area, perimeter, length, width, aspect ratio and various

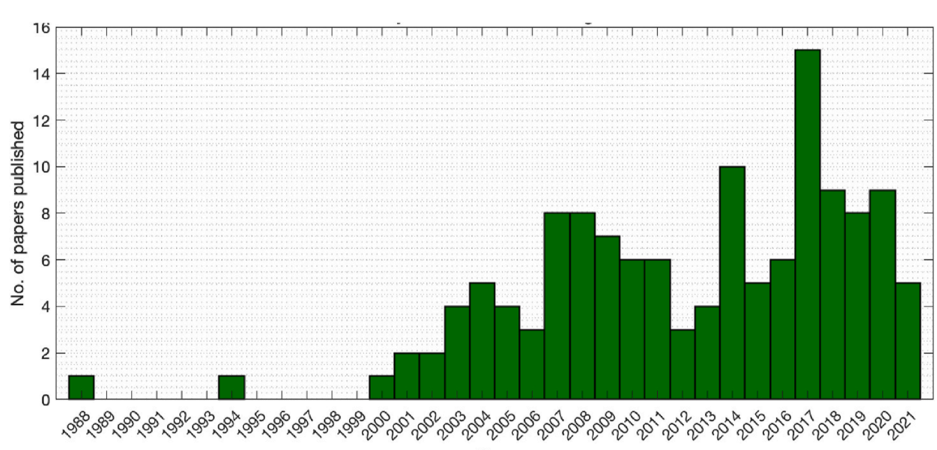

Fig. 1. Total number of papers per year related to food quality analysis using DIP (Data retrieved from Science Direct).

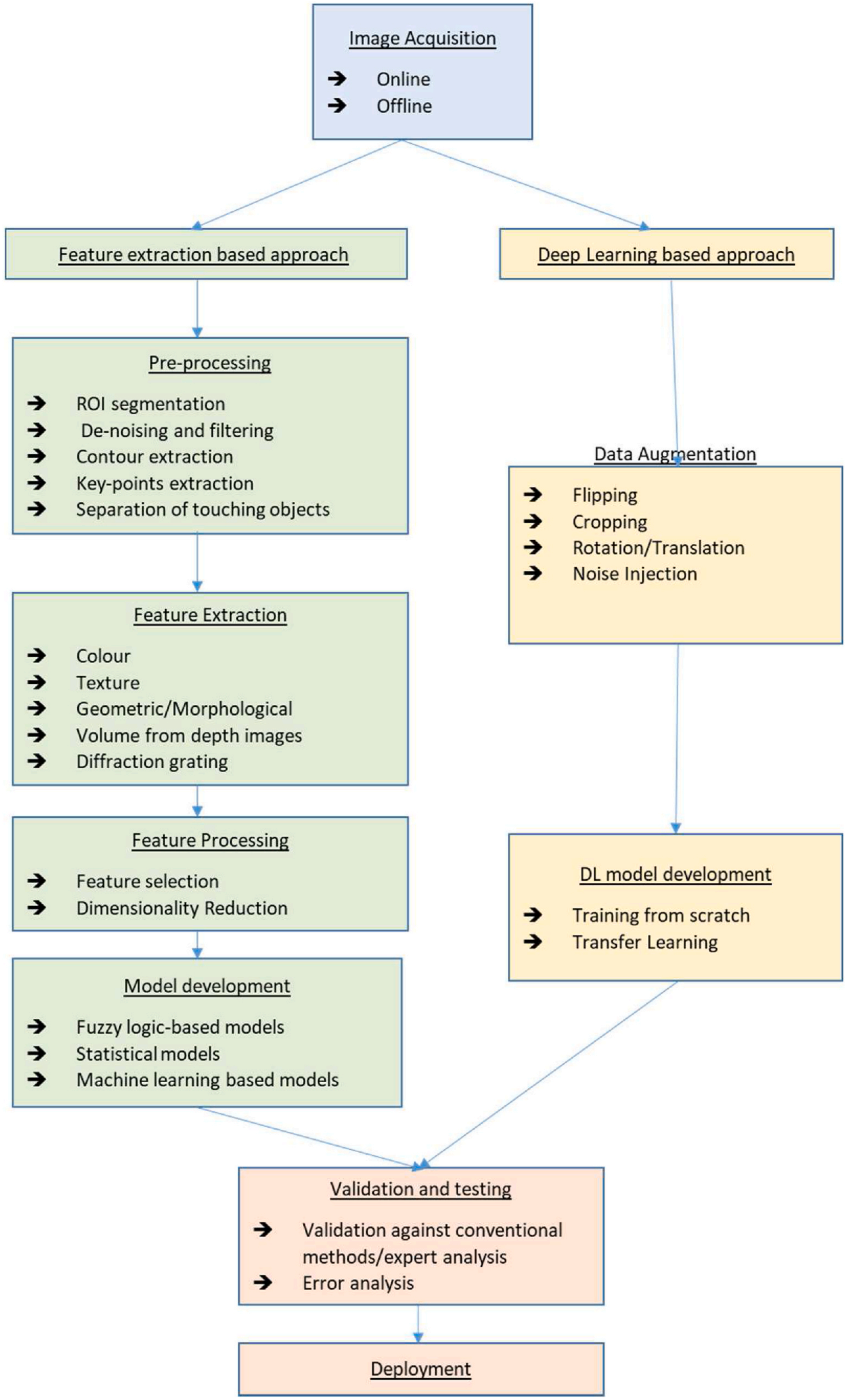

Fig. 2. Methodology and steps involved for quality estimation of food products using Machine Learning and Deep Learning Algorithms.

shape factors (Koklu & Ozkan, 2020). Apart from these, fractal features (Wu, Lin, Chen, Wu, & Xiao, 2012), as well as certain external information like temperature, humidity, atmospheric pressure and weight can also be used (De La Iglesia, González, García, Rivero, & De Paz, 2020).

Further, the classification of food items based on their quality can be done by employing either statistical methods or ML techniques. Statistical methods are generally preferred when the number of explanatory variables are less, whereas ML is preferred in those cases where the number of features are large. Statistical models employed for DIP majorly include the Linear Discriminant Analysis (LDA) (Manickavasagan, Al-Mezeini, & Al-Shekaili, 2014), Quadratic Discriminant Analysis (QDA) (Khojastehnazhand, Mohammadi, & Minaei, 2019), Linear regression, Logistic Regression, Partial Least Square (PLS) regression (Elsayed, Galal, Allam, & Schmidhalter, 2016), Binomial modelling (Wu et al., 2012), Principal Component Analysis (PCA) (Caro, Alaiz-Rodríguez, González-Castro, Quinto, & Mateo, 2018), Pearson correlation test, Welch's *t*-test (Romano, Argyropoulos, Nagle, Khan, &

Table 1
Summary of observations related to the application of digital image processing in grains.

Product	Image type and image size	Dataset size	Studied property	Feature exploited	Model used	Performance	Reference
Spring and winter wheat varieties in various quality classes	2673 × 4031 resolution, 400 dpi, 24-bit depth	552 images for each Kernel	Humidity	Texture, seven different channels (R, G, B, Y, S, U, V)	Discriminant analysis and neural networks	82–89% classification accuracy.	Zapotoczny (2011)
Grain verities: Barley, oats, rye, Canada Western Amber Durum wheat, Canada West Red Spring wheat	2816 × 2112 pixels	NA	Separation of touching kernels in digital images	Edge features	Elliptic Fourier series approximation	Separated more than 98% of the touching grains	Mebatsion and Paliwal (2011)
Freshly harvested rice	Horizontal sectioning and scanning electron microscopy (SEM).	NA	Retrogradation of rice starch	Fractal features edges using high pass filter	Binomial model	$R^2 = 0.9976$	Wu et al. (2012)
Cereals - barley, oat, rye and wheat	512 × 480 pixels	Barley:7440, CWAD: 6918, CWRS:7200, Oats: 5340, Rye: 7200	Cereal classification	Colour features, Morphological features	Least squares classifier	Barley:98.46CWAD: 100; Oats: 99.92; CWRS: 99.97; Rye:100	Mebatsion et al. (2013)
Lentils	NA	1000 to 3500 seeds	Length, single-seed mass, bulk-sample mass and seed size index	Physical features	Morphological feature extraction (DIP)	10% misclassification rate	Lemasurier et al. (2014)
Sprouted Wheat kernels	752 × 480 pixels	600 wheat kernels	Sprout damage due to alpha- amylase	Color, texture, and shape and size	Morphological feature extraction feed to ANN	SND:89.3, SPTD: 62.5, SEVSPTD:66.7	Shrestha, Kang, and Baik (2016)
Coffee beans- four groups: green, whitish, cane green, and bluish-green	NA	120 50g samples (30 per color)	Commission Internationale d'Eclairage (CIE) L*a*b* measurements of green coffee beans	L* or luminescence, a* - the red-green axis and b* - the blue-yellow axis	Artificial Neural Networks and Bayes classifier	Error of 1.15% ± 1.01% for transformation model 100% accuracy for classification	De Oliveira et al. (2016)
Coffee beans	640 × 480 pixels	NA	Color during roasting in a spouted bed	Color parameters- brightness (L*), browning index (BI) and the distance to a defined standard (E)	Neuro Fuzzy model	An updated Schwarz-Rissanen knowledge criterion of 0.98, RMSE: 0.002, R^2:0.98	Virgen-Navarro et al. (2016)
Canadian Western Red Spring wheat	752 × 480 pixels	600 sprout damaged kernels prepared in lab	Sound, sprout-damaged, or severely sprout-damaged classes	Sixteen features comprising of texture, color, shape and size	Neural network model	Segmentation accuracy: 95% Classification accuracy of 72.8%.	Shrestha, Kang, Yu, and Baik (2016)
Maize	24 bit, 4000 × 3000 pixels	332 RGB images of 83 mixtures	Percentage of defective maize (% DM)	R,G,B, Lightness, relative colors, HSI, score vectors from PCA of RGB data	PCA, PLS, iPLS	RMSE = 2.6%	Orlandi et al. (2018)
Sterilized whole corn	500D, Canon	500 corn samples	Grading system	Edge features, Texture, Colour	FCM clustering	C-Value: 3.0; m-value:1.15	Park et al. (2019)
15 rice varieties	1280 × 720 pixels	150 total images	Assessment of rice quality	Geometric/ Morphological features	SVM	93% accuracy, time = 2.4 s	Mittal et al. (2019)
Dry beans	2048 × 1088 pixels	13,611 grains of 7 different registered dry beans	Appearance, size, color, internal health and diversity	16 features; 12 dimension and 4 shape forms	MLP, SVM, kNN, DT classification models	CCR of 91.73%, 93.13%, 87.92% and 92.52% for MLP, SVM, kNN and DT, respectively	Koklu and Ozkan (2020)
5 types of rice	5,416 × 3,264 pixels	27,000 images	Authenticate variety of rice	NA	CNN	Accuracy ranging from 93 to 99%	Izquierdo et al. (2020)

ANN: Artificial neural Network, CNN: Convolutional Neural Network, CIE: Commission Internationale d'Eclairage, HSI: Hue Saturation Intensity, PCA: Principle Component Analysis, FCM: Fuzzy-C- means, SVM: Support Vector Machine, CCD: Charged Coupled device, MLP: Multi Layered Perceptron, KNN: K- nearest neighbour, NA: Not Available; MLP, Multilayer perceptron; SVM, Support Vector Machine; kNN, k-Nearest Neighbors; DT, Decision Tree; FCM, Fuzzy c-mean; PCA, Principal Component Analysis; PLS, Partial Least Square regression; iPLS, interval PLS.

Müller, 2012), Canonical Correspondence Analysis (CCA), and LASSO Regression (Pabiou et al., 2011), Bayes Classifier (De Oliveira, Leme, Barbosa, Rodarte, & Alvarenga Pereira, 2016). Whereas various ML techniques include Support Vector Machine (SVM) with linear as well as nonlinear kernels (Mittal, Dutta, & Issac, 2019), Feedforward Artificial Neural Networks(Baiocco et al., 2020), Multilayer Perceptron, Decision Trees, k-Nearest Neighbors (Koklu & Ozkan, 2020) and ensemble techniques such as Random Forest Classifier (Pereira, Barbon, Valous, & Barbin, 2018). Apart from the approach based on feature extraction, certain approaches based on the Convolutional Neural Networks (CNNs) (Izquierdo et al., 2020) have also been explored. These models, however, require huge amounts of images as input data, generally ranging in tens of thousands. Some of the model architectures employed include AlexNet, GoogLeNet, ResNet50 (Raikar, Meena, Kuchanur, Girraddi, & Benagi, 2020), Mask R–CNN (Vo, Scanlan, & Turner, 2020). The selection of an appropriate model is determined based on the number and type of features/variables, as well as required accuracy and the processing time. The developed model should be robust enough to generate same results when employed in real time applications. Hence, they must be adaptable to external factors such as lighting conditions, poor focusing, motion blur, lens distortion, etc. Also, an appropriate software interface must be developed to enable interaction and easy access to the end-user.

Fig. 2 presents different steps and methodologies used for the quality estimation of food products by using feature extraction methods namely, ML and Digital Image Processing (DIP) and automatic methods such as Deep Learning (DL) methods. Various pre/post processing steps are required to enhance the results. Features are extracted by heuristic algorithms using DIP tools. Quality prediction is done by feeding these extracted features to neural networks. Whereas DL algorithms extract features automatically from the convolution layer and are feed to neural networks. DL algorithms require a huge dataset and high computation power to generate accurate results. Various research articles on the quality estimation of food products by employing computer vision have been retrieved using different database searches such as google scholar, PubMed, Web of Science and Scopus. Then, the duplicate articles were removed by matching their titles and abstracts followed by identification of potentially relevant articles based on the inclusion and exclusion criteria. These potentially relevant articles are further reviewed and summarized in Tables 1–4 and Supplementary Tables S1 and S2.

2. Digital Image Processing in grain quality estimation

Previously, DIP was efficiently employed for the discrimination of different varieties of wheat depending on the texture of 20 grain samples computed for seven channels namely, R, G, B, Y, S, U and V. The best classification of wheat varieties (100%) was reported with neural network models (Zapotoczny, 2011). During the DIP of grains, touching kernels presents the problem of false prediction or misclassification of samples. Thus, to address this problem elliptic Fourier series approximation was employed that smoothen the periphery contour of kernel images. Then, the curvature along the boundary of images was estimated using nodal points followed by the drawing of segmentation lines by applying a radian critical distance difference of chain-coded boundary point criteria and nearest-neighbour based algorithms. They reported that this method was >98% efficient in separating the touching kernels. (Mebatsion & Paliwal, 2011).

Researchers have also explored (Mebatsion, Paliwal, & Jayas, 2013; Wu et al., 2012) application of DIP to effectively study the extent of retrogradation of rice starch (RS) based on its scanning electron microscope images. The fractal characteristics of retrograded RS samples were provided by fractal analysis and the fractal features were obtained by employing an image processing method. An increase in the fractal dimensions was reported with an increase in the extent of retrogradation. The fitted binomial model was also reported to yield a high correlation ($R^2 = 0.9976$) between retrogradation enthalpies and fractal dimensions of retrograded samples (Wu et al., 2012). Mebatsion et al. (2013) reported the classification of various types of non-touching cereal grains by employing color and morphological features of grain images by applying Elliptic Fourier Descriptors. A combined model described by geometric feature namely, symmetrical Fourier index (SFX), major diameter (MD), aspect ratio (AR) and roundness (Ceq) along with color features was reported to present 98.5–100% classification accuracy for different kinds of cereals. Another study has reported the use of 3D image processing of a single kernel for the assessment of lentil size grading. An efficient grading of lentils was observed based on their size (10% misclassification). In addition, physically measured length (0.98), bulk-sample mass (>0.99) single-seed mass (0.97) and seed size index (>0.99) presented a high correlation with the predicted values obtained by image processing (Lemasurier, Panozzo, & Walker, 2014). Recently, researchers have efficiently used DIP for estimation of the moisture content of coffee beans during roasting by applying a neuro-fuzzy model. The change in moisture content of grains was described as a function of the brightness (L*), browning index (BI) and distance to the defined standard (E). The performance of the model was found to be superior compared to the conventional methods as presented by a high coefficient of determination of 0.98, low root mean square error less than 0.002 and also in terms of altered Schwarz-Rissanen information criterion (<0) (Virgen-Navarro, Herrera-López, Corona--González, Arriola-Guevara, & Guatemala-Morales, 2016). The color of green coffee beans has also been determined by employing DIP and Artificial Neural Network (ANN). ANN was used as a transformation model that resulted in 1.15% of generalization error. Whereas, the Bayes classifier was resulted in 100% accurate classification of coffee beans into different groups based on the L*a*b* measurements (De Oliveira et al., 2016). Such a method can efficiently be used by coffee producers and food industries for efficient color-based classification of coffee beans.

The alpha-amylase enzyme present in damaged wheat kernels results in the poor baking quality of wheat and low-quality end-products. This problem of damaged wheat sprout kernels and associated α-amylase activity has been evaluated by applying two-camera machine vision approach. The neural network model was employing by using visual properties as an inputs and α-amylase activity as an output. The resulted model was reported to present satisfactory performance with low RMSE and high R^2 (0.72) in case of wheat samples exhibiting α-amylase activity 178 U/L to 28935 U/L (Shrestha, Kang, & Baik, 2016). In a further study (Shrestha, Kang, Yu, & Baik, 2016), the same researchers have again used two camera-based machine vision system to classify sprouted wheat kernels into three different classes namely, severely sprout-damaged, sprout-damaged and sound kernels. The clustered kernels were separated by employing the watershed segmentation technique with an accuracy of 95%. Sixteen features including shape, size, color and texture were used as input and α-amylase activities were employed as output for developing neural network model. Further, this model was employed to classify the sprouted wheat kernels with 72.8% accuracy. Mycotoxins are also a major concern to the food industry and consumers due to their potential health hazards to humans as well as farm animals. In this context, an attempt has been done to quantify percentage of defective maize (%DM) based on the multivariate image analysis that, in turn, represented high levels of mycotoxin deoxynivalenol (DON). DON content was estimated by employing a commercial ELISA kit and maize kernel images were converted into a signal (colorgram). The colorgrams were explored by employing PCA and the calibration models for %DM values were established by empolying partial PLS and interval-PLS (iPLS) approaches. The best prediction of % DM values of external test samples was observed in case of iPLS with a RMSE of 2.6%. Additionally, this approach could efficiently highlight a particular area in the image with a defective-maize kernel (Orlandi et al., 2018).

Recently, rice classification has been carried out based on their commercial value using DIP in conjunction with discriminative feature

Table 2
Summary of observations related to the application of digital image processing in vegetables.

Product	Image capturing instrument	Image type and image size	Dataset size	Studied property	Feature exploited	Model used	Performance	Reference
Red, yellow and green bell pepper	digital CCD camera (PAX Cam P1-CMO, Villa Park IL, USA)	1280 × 1024 pixels	NA	Moisture content	Light intensity and scattering area	Pearson correlation test and Welch's *t*-test	R = 0.93 and RMSE = 7.28 for yellow, (R = 0.33 and RMSE >22) for red and green	Romano et al. (2012)
Tomatoes	CAS 140 B spectroradiometer (Instrument Systems, Germany) & Nikon D-80	NA	52 tomato products	Levels of LYC isomers in processed vs fresh tomato products	CIELAB (L*, a*, b*, C*ab and hab)	DIA and SPR	DIP result in efficient color determination	Stinco et al. (2013)
Broccoli	Sony DSC-W55, 7.5 pixels digital camera	NA	NA	Appearance, aroma and flavor acceptability	NA	ANOVA and quality scoring method	Consumer acceptance towards real broccoli and corresponding image was same	Garitta et al. (2013)
Green beans (*Phaseolus vulgaris* L.)	Digital camera (Go – 5, Qimaging Ltd)	2592 × 1944 pixels	NA	Green color, color change after heat and acid treatments	L*a*b*	Oneway ANOVA	DIP set up mentioned in study efficiently determine the color change in green bean during heat treatment.	Manninen et al. (2015)
Tomatoes variety Cappricia	NIKOND7000 digital camera with NIKKOR AF-S DX 18–105 mm f/3.5–5.6VR ED lens	NA	NA	Color	Geometric and color features	ANN	Classification neural model RBF 22:22–20–2:2 resulted in fast and accurate quality evaluation of tomatoes	Zaborowicz et al. (2017)
Potatoes	Primesense Camine 1.09	NA	110 potatoes	Length, width, mass, interior and extrerior defects, bent shape, bumps, and hollow	Depth images	3D Shape analysis	Accuracy 90% for volume model and 88% for appearance grading	Su et al. (2018)
White button mushrooms	Line scan camera MV-LC2K40	NA	NA	Diameter of the pileus	Morphological features	Watershed method, Canny operator	Average maximum grading speed was 102.41 mushrooms/minute, accuracy of grading was 97.42%, damage rate was 0.05%, and undetected rate was 0.96%.	(F. Wang et al., 2018)
Carrots	MinTe U2-YW500	2592 × 1944 pixels	300 carrots	Physical parameters	Shape parameters, color parameters on R, G, B, H, S and V components	BPNN, SVM, ELM	Accuracy: 96.67%	Xie, Wang, and Yang (2019)
Cauliflower	Digital CCD camera (Model: Microsoft Life Cam studioTM, China)	1920 × 1080 pixels	75 samples	Effects of modified atmosphere packaging (MAP) on shelf-life and the quality	NA	Multi-layer perceptron (MLP)	MSE and R^2 of the optimum network were 0.0095 and 0.990	Alden et al. (2019)
Okra (*Hibiscus esculentus*)	Mobile camera - 13 MP	NA	3200	Freshness, tenderness, color, shape,decay, scarred, bruised, cuts,insects, dirt,wormhole, trim	Length of the pod	AlexNet, GoogLeNet, ResNet50	63.45% for AlexNet, 68.99% for GoogLeNet model and 99%	Raikar et al. (2020)

CIE: Commission Internationale d'Eclairage, CCD: Charged Coupled device, RMSE: Root Mean Square Error, ANN: Artificial neural Network, BPNN: Back propagation neural network, ELM: extreme learning machine, MLP: Multi Layered Perceptron, KNN: K- nearest neighbour, MSE: Mean Square error, NA: Not Available; ANOVA, analysis of variance; BPNN, Back propagation neural network; SVM, support vector machine; ELM, extreme learning machine.

Table 3
Summary of observations related to the application of digital image processing in fruits.

Product	Image capturing instrument	Image type and image size	Dataset size	Studied property	Feature exploited	Model used	Performance	Reference
Four varieties of seedless raisins	Microvision MV-VS078FM/FC industrial CCD digital camera (MV-VS series 1394 interface CCD industrial camera, China)	768 × 1024 pixels	300	Physical Properties	Morphological, colour and texture features	PLS, LDA, SIMCA, LS-SVM, RBF	Best correct answer rates (CAR) of 99%	Wang et al. (2012)
Apple	CCD color camera (Fire-I Digital Camera, Unibrain Inc., California, USA)	640 × 480 pixels	300	Segmentation of colour images	Colour features	LSVM and Otsu's thresholding method	Segmentation error from 3% to 25% for the fixed SVM, while the adjustable SVM achieved acceptable results for training set with the segmentation error <2%	Mizushima and Lu (2013)
18 types of fruits	Digital camera	256 × 256 pixels	1653 color fruit images from the 18 categories	Fruit classification	Color, texture, shape features	FSCABC, FNN	accuracy of 89.1%	Zhang et al. (2014)
Three varieties of dates (Fard, Khalas, Naghal)	EOS 550D, Canon Inc., Japan	5184 × 3456 pixels	3300	Hardness	39 features (13 features in each R, G and B channel)	LDA with all features and SDA with selected features	Overall classification accuracy was 69%, 87% and 82% for Fard, Khalas and Naghal varieties, respectively, using LDA	Manickavasagan et al. (2014)
Figs	Hi-Peak camera (HPK-6308/4)	750 × 540 pixels	NA	Grading of figs	Split area, equivalent diameter, and color intensity	Grading algorithm was coded in Lab-VIEW	Sorting accuracy for all the classes up to 95.2%, mean rate was 90 kg/h	Baigvand et al. (2015)
Mango fruits of the Zabdia cultivar	Kodak D5100 reflex camera with a 14-mega-pixel resolution	NA	NA	Ripening	(i) Spectral reflectance information (500–900 nm), (ii) selected spectral indices, (iii) selected RGB indices from digital image analysis, and (iv) the combination of spectral reflectance indices and RGB indices information	SLR, PLSR	PLSR analysis based on the combination of six spectral reflectance indices and six RGB image analyses result in best prediction of mango quality	Elsayed et al. (2016)
Oranges	DSC 2000 Sony Camera in VGA mode (640 × 480),	640 × 480 pixels	160	Maturity, size, quality and breeds	Tot_pixel, Ravg, Gavg and Bavg	EMSNNT, LRA	Classification accuracy ranges from 90 to 98%.	Jhawar (2016)
Grapes	NIKON D7000	4928 × 3264 pixels	72	Identification of pesticide in grapes	Features are extracted in frequency domain using Haar filter	SVM classifier	100% accuracy, sensitivity and specificity	Dutta, Sengar, et al. (2016)
Apple	NA	360 × 360 pixels	120	Grading of apples	Statistical, textural and geometric features	SVM, MLP, KNN classifiers	Recognition rate of 92.5% and 89.2% for healthy and defected samples	Moallem et al. (2017)
Mango	XGA format 1/2" Sony CCD ICX205AK	980 × 880 pixels	120	Grading of mangos (geometry and shape)	Projected area, perimeter, and roundness features	Morphological analysis using STATA (Stata Corp. LLC, Version 14, TX, USA)	Accuracy of 97% for projected area and Feret diameter, 79% for perimeter, and 36% for roundness	Momin et al. (2017)
Red banana	SONY Cyber-shot DSC-W570	NA	140	Dielectric properties to measure ripening stages of red banana	NRLBP, LBP, CLBP	Chi-Square distance/nearest neighbour and FCM clustering	NA	Mohapatra et al. (2017)
Papaya		NA			Color features	Random forests		Pereira et al. (2018)

(continued on next page)

Table 3 (*continued*)

Product	Image capturing instrument	Image type and image size	Dataset size	Studied property	Feature exploited	Model used	Performance	Reference
	Digital camera (Sony, Japan)		114 samples from 57 fruits	Ripening of the papaya fruit			Classification accuracy: 94.7%	
Mangoes	Canon Digital IXUS 400.	500 × 1000 pixels	>100 mangoes at different maturity stages	Maturity skin color	A total of 24 image features	Decision tree	Classification accuracy: 96%	Mim et al. (2018)
Cashew	Digital single-lens reflex (DSLR) camera (Model: Nikon D5100, Nikon Corp., Japan)	NA	NA	Classification of whole and split cashews	Several features derived from grayscale-intensity-profile	Surface grayscale-intensity-profile for split-up cashews and object shadows for split-down and whole cashews	Accuracy:100%	Sunoj et al. (2018)
Banana	Logitech, model C920, China	2048 × 1536 pixels	200	POD and PPO enzymes		GP modeling	Correlation coefficients between measured values and predicted values for PPO and POD enzymes were 0.98 and 0.97, respectively	Nadafzadeh et al. (2018)
Mango cultivar 'Nam Dokmai	Logitech C920 USB HD Pro	1920 × 1080 pixels	61 randomly selected mangoes	Mass	Length, width, and thickness	ANN	Highest success rates of 97% and highest coefficient of efficiencies of 0.99	Utai et al. (2019)
White nectarine stored at 4 °C for 50 days	Nikon D7100, Nikon Corp., Tokyo, Japan	2200 × 1900 pixels	150	Weight loss, pH, TSS, in-package gas concentration, decay rate, color, texture, FT-NIR	Color and morphological characteristics	Series of codes prepared in Matlab (R2016a, MathWorks, Natick, Mass., USA)	Efficient determination of quality of nectarine followed by ultrasonic treatment	Temizkan et al. (2019)
Apricot	Canon PC1438, Canon Inc., Japan	NA	104	Maturity stages (i.e. unripe, ripe, and overripe)	Relative R, G, B channels, gray-scale, L*, a*, and b*	LDA and QDA classifiers	Accuracy of 0.904 and 0.923 for LDA and QDA classifiers, respectively	Khojastehnazhand et al. (2019)
Tomatoes	HikvisionMini Camera (DS-2CD2D14WD/M4MM),	1280 × 720 pixels	200	Calyx and stalk scar detection	Histogram thresholding based on the mean g-r value of these regions of interest	RBF-SVM	Average accuracy of grading was 0.9515	Ireri et al. (2019)
Pomegranate	Canon PowerShot SX220 Camera (12 MP)	3000 × 4000 pixels	200	Relationship between color of fruit and size of arils	465 inputs extracted from 31 monochrome chanels	ANN	Accuracy of 98% with correlation coefficient of 0.943 and a MSE of 0.008	Fashi et al. (2019)
Pomegranate	EOS 550D, Canon Inc., Japan	3456 × 2304 pixels	NA	NA	Features extracted by traditional 2DLDA, Fractional 2DLDA, Fuzzy 2DLDA and FF2DLDA	FF2DLDA	FF2DLDA presented accuracy = 0.97, Precision = 1, F-score = 0.965	Gurubelli et al. (2019)
Brazilian Amazon native and exotic fruits-	Smartphone Samsung Galaxy S4 Mini with an 8.0 megapixel resolution	NA	NA	Ascorbic acid determination	Colorimetric reaction by iodometric titration	Image analysis analysis using ImageJ software, paired *t*-test	Proposed DIP based method exhibit good accuracy and precision in comparison with results from a standard method.	(dos Santos et al., 2019)
Khalal, Rutab, Tamar, and defective date	Smartphone camera	NA	1357	Healthy date fruit, ripening stage of the healthy dates	NA	Deep CNN	Overall classification accuracy of 96.98%	Nasiri et al. (2019)
Mulberry fruit	Casio EX-H20 G 14.1 MP CCD digital camera	NA	577 mulberries	Ripeness	Geometrical properties, color, and texture characteristics	ANN, SVM	Accuracy of 100%, 100%, and 99.1% and least MSE of 9.2 × 10-10, 3.0 × 10-6, and 2.9 × 10-3 for training,	Azarmdel et al. (2020)

(*continued on next page*)

Table 3 (*continued*)

Product	Image capturing instrument	Image type and image size	Dataset size	Studied property	Feature exploited	Model used	Performance	Reference
							validation, and test sets	
Cherries	PIXERA Mod 150 ES	1392 × 1040 pixels	2520 pictures	NA	Histograms	Feedforward ANN	Accuracy: 92.3%.	Baiocco et al. (2020)
Lemons	NA	4320 × 3240 pixels	341 sour lemon samples	Apparent defects of sour lemon fruit	NA	Improved CNN	Accuracy:100%	Jahanbakhshi et al. (2020)
Bulk raisin	CMOS Logitech C920 HD pro Webcam	480 × 640 pixels	750 (50 images x 15 class).	NA	Texture feature	SVM classifier using GLRM features	Classification accuracy of modes I (6 classes of good and bad raisin) and II (15 classes) was obtained 85.55% and 69.78%, respectively	Khojastehnazhand and Ramezani (2020)
Apple	Smartphone camera	NA	150	Differentiating organic apples from conventional ones	NA	PLS-DA, SVM, LW-PLSC	Classification accuracies of 93–100%	Song, Jiang, Wang, and Guo (2020)

PLS, Partial Least Square; LDA, Linear Discriminant Analysis; SIMCA, Soft Independent Modelling of Class Analogy (SIMCA); LS-SVM, Least Squares Support Vector Machine; RBF, Radial Basis Function; CAR, Correct answer rate; SVM, Support Vector Machine; CCD, Charged Coupled device; LDA, linear discriminant analysis; SDA, stepwise discriminant analysis; PLSR, Partial Least Square Regression; MLP, Multi Layered Perceptron; KNN, K- nearest neighbour; FCM, Fuzzy-C-means; NRLBP, Noise Reductant Local Binary Pattern; LBP, Local Binary Pattern; CLBP, Completed Local Binary Pattern; GP, Genetic Programing; ANN, Artificial neural Network; FT-NIR, Fourier transform near-infrared; NA, Not Available; CNN, Convolutional Neural Network; PLS-DA, Partial least squares discriminant analysis; LW-PLSC, Locally weighted partial least squares classifier; GLRM, Gray Level Run Length Matrix; FF2DLDA, Fractional fuzzy two-dimensional linear discriminant analysis; LSVM, Linear support vector machine; FNN, Feedforward neural network; FSCABC, Fitness-scaled chaotic artificial bee colony; SLR, Simple linear regression; SVM, Support Vector Machine; EMSNNT, Edited Multi Seed Nearest Neighbour technique; LRA, Linear regression analysis; FT-NIR, Fourier transform near-infrared; TSS, total soluble solids; MSE, mean square error; NRLBP, Noise Reductant Local Binary Pattern; LBP, Local Binary Pattern; CLBP, Completed Local Binary Pattern.

extraction. The geometrical features of rice were obtained in the spatial domain and used as input to SVM for classification of rice samples (Mittal et al., 2019). This method was mentioned to classify rice samples with 93% accuracy, a level considered significant for rice quality assessment. Izquierdo et al. (2020) authenticated rice varieties and their flours based on visible imaging. In this study, images of five varieties of rice were processed by employing CNNs. This model was trained and optimized for identification of different varieties of rice followed by validation by using imaging which was initially isolated from the training set. Best classification results were reported in the case of flours and based on the different algorithms used in this study, the classification accuracy for rice grain was increased from 93 to 99%.

Furthermore, image processing along with fuzzy c-mean (FCM) clustering was employed by Park, Yoo, Jung, and Yoon (2019) to achieve a uniform quality of sterilized whole corn. The geometric feature of corn was extracted from images of ears and fed as inputs to fuzzy c-mean (FCM) clustering. These were used to categorise corn into three grades and further employed to design sterilization process for whole corn ear. Based on the analysis of texture properties of the sample, 121.1 °C was reported as the optimum temperature for the sterilization Recently, researchers have also applied an image processing technique to obtain a uniform seed variety of dry beans. The beans images were acquired by a computer vision system followed by segmentation and extraction of features. Furthermore, 4 different shapes, 12 dimensions and 16 features were used to develop four different classification models. Among these models, SVM exhibit the highest classification rate (93.13%). This model was reported to classify different genotypes of dry beans with an accuracy ranging from 86 to 100% (Koklu & Ozkan, 2020). The detailed description of grain samples, image capturing instrument, image type, image size, dataset size, properties explored, features exploited, model employed along with their performance are shown in Table 1.

3. Role of computer vision in vegetable quality prediction

Several studies have used artificial intelligence techniques for predicting the quality of fruits and vegetable-based on various quality-related parameters using hyper-spectral approaches. Romano et al. (2012) predicted the moisture content of green, red and yellow bell pepper while drying by employed DIP using a CCD camera with laser diodes. Light source of wavelength 532 nm and 635 nm were used and the intensity of light and scattering area from the samples were determined. The correlation among the light intensity and moisture content was determined by using Pearson correlation and Welch's *t*-test. The highest direct relationship was observed for yellow samples ($R^2 = 0.95$), with lower correlations for red and green with R^2 0.63 and 0.58, respectively. The logarithmic models were used to predict the relationship between moisture content and scattering area, and satisfactory R^2 values were observed for yellow bell pepper at both wavelengths (0.89 and 0.93), red bell pepper at 635 nm (0.90) and also for green bell pepper at 532 nm (0.89). Consumers use 'appearance' as a critical attribute for market purchases of vegetables. Garitta, Hough, and Chaves (2013) used the quality scoring method (QSM) with a panel of 8 experts and assessed the broccoli samples and correlated them with digital images of broccoli samples, at varying storage times. Using ANOVA, they showed that appearance was the only attribute correlated with deterioration pattern with increasing storage time.

DIP as well as a spectro-radiometer (SPR) was used by Stinco et al. (2013) to determine lycopene (LYC) isomers in fresh vs processed tomatoes. Statistical analysis including ANOVA and PCA was carried out to discriminate between fresh and processed tomatoes. Both simple and multiple regression were employed to study the relation between color parameters and LYC content. They reported satisfactory correlation between LYC and L* ($r = 0.97$), LYC and a* ($r = 0.86$) as well as LYC and C*ab ($r = 0.85$) and a high correlation was also observed in case of parameters achieved by SPR and DIA ($p < 0.05$). However, better

Table 4
Summary of observations related to the application of digital image processing in beverages and drinks.

Product	Image capturing instrument	Image type and image size	Dataset size	Studied property	Feature exploited	Model used	Performance	Reference
Indian black (CTC) tea samples	3CCD color camera (JAI Manufacturing, Japan)	NA	Ten graded tea samples	Types of tea samples	Five textural features were 'entropy', 'contrast', 'homogeneity', 'correlation' and energy	PCA, ANN, Fuzzy logic	Variance: 96%	Laddi et al. (2013)
Soft beverages	CanoScan LiDE 110 (Tokyo, Japan)	NA	Eighty-three samples of commercial beverages	artificial dye, sunset yellow (SY)	Histograms of R, G and B	PLS	Relative prediction errors lower than 10%	Botelho et al. (2014)
Distilled beverages	Samsung Galaxy J7 smartphone	NA	NA	Ethanol content	Colour intensities	Linear regression	Linear response from 10.0 to 70.0% (v/v) ethanol (r = 0.998, n = 7), a coefficient of variation of 1.2% (n = 8) and a limit of detection (99.7% confidence level)	Marinho et al. (2019)
Milk	LG K10 Pro	4128 × 2096 pixels	NA	Protein content	NA	Smartphone-based digital colorimetry	Sample throughput of 32 assays/h, coefficient of variation = 3.0%, n = 20, 95% confidence level	Silva and Rocha (2020)
Milk	Smartphone camera, video of reflected light of different colors from food samples 32-bit	960 × 720 pixels 138 frames per video	160 unadulterated and adulterated olive oil samples	Adulteration of skimmed, semi-skimmed and whole milk	Vector of 414 variables in RGB channels by averaging color levels	SVM, RF, PLS-DA, LW-PLS	Test accuracies of 100% were achieved milk authentication.	Song, Jiang, Wang, and Vincent (2020)
Geopropolis (EEGs) from Brazilian native bees	Smartphone camera	NA	NA	antioxidant capacity (AC) and Total Flavonoid Content (TFC)	Statistical features	PLS	R^2 for calibration ≥0.74 R^2 > 0.80 together with low RMSEP	Turco et al. (2020)
Milk	Smartphone camera	NA	Seven brands of milk	Milk adulterants - hydrogen peroxide, sodium hypochlorite, and starch	Histograms of the red green- blue images	PLS	$R^2 = 0.9997$ for H_2O_2, R^2=0.9929 for NaClO, and 0.9974 for starch by using PhotoMetrix® and 0.9785, 0.9653 and 0.9777 for RedGIM	Costa et al. (2020)
Red wines	Nokia Lumia 710	1944 × 2592 pixels	93 commercial red wine samples	Geographic origin, winemaker, and grape variety	Colour histograms	PCA-LDA coupled with HSI histograms	100% accuracy in test set	de Lima et al. (2020)
Milk powder	Canon PowerShot A3400 IS	2500 × 2500 pixels	NA	Processing of food colorimetry images	CIE Lab colorimetric parameters	A two-step image cropping algorithm	Developed algorithm was successfully applied for HD image analysis of skim milk powder to measure colour values.	Minz et al. (2020)
Keemun black tea	Huawei Honor 10 GT smartphone	5632 × 4224 pixels	105 Keemun black tea samples	Quality grades	Eight texture characteristics	PCA, SVM	SVM based on NIR and DIP resulted in 100 and 94.29% accuracy in calibration and prediction set.	Li et al. (2021)
Cachaça	Asus ZenFone 3 smartphone	NA	12	Reducing sugars - adulteration	Color intensity	Paired *t*-test	Efficient method to detect reducing sugar in Cachaça	Franco et al. (2021)

PCA; principal component analysis, SVM; support vector machine, LDA; Linear discriminant analysis, PLS; partial least square regression, SVM; support vector machine, RF; random forest, PLS-DA; partial least squares discriminant analysis, LW-PLS; locally weighted partial least squares, ANN; artificial neural network, NA; Not Available; NIR, Near Infrared spectroscopy.

differentiation of samples was provided by SPR considering the PCA data (97%). Researchers have also used DIP to assess color change in green vegetables as influenced by heat and acid treatments. The CIELAB-coordinates (L*, a*, b*) were employed to measure color of samples. They documented color differences between green vegetables including beans, leaf lettuce, cucumber, green peas and basil, and concluded that the technique may have the potential to discriminate the different batches of green vegetables. (Manninen, Paakki, Hopia, & Franzén, 2015).

An automatic in-line sorting system using DIP was developed by Wang et al. (2018) for grading white button mushrooms according to their pileus diameter. The hardware, in this case, consisted of the image acquisition setup, conveyor mechanism, actuators and a control module. An algorithm based on the Canny operator, watershed method, closed operation and OR operation was developed to predict the pileus diameter. Further, a control strategy was developed to optimize processing time. The experimental average maximum grading speed was about 102 mushrooms/min with high accuracy of grading (97.4%) and low damage rate (0.05%) and failure rate (0.96%). It was observed that the grading speed as well as accuracy improved by 38.9% and 6.84%, respectively, as compared to manual grading. For quality grading of potatoes, Su et al. (2018) used a depth camera to acquire depth images of 110 potatoes and mass was estimated from the depth images by employing volume linear regression model. The appearance defects were determined by image processing approaches and were classified as normal or abnormal. The developed models were reported to have an accuracy of 90% for mass prediction, and 88% for appearance detection. Researchers have also explored DL techniques for okra (*Hibiscus esculentus*) grading based on their size, into 4 categories. 3200 images were taken and CNN architectures including AlexNet, GoogLeNet and ResNet50 were explored for the classification task. The ResNet50 model gave the best accuracy of 99%, compared to AlexNet (63.5%) and GoogLeNet (69.0%) (Raikar et al., 2020).

A smartphone application (APP) was developed to identify cold damage in zucchini based on DIP approaches (Novas, Alvarez-Bermejo, Valenzuela, Gázquez, & Manzano-Agugliaro, 2019). Hyper-spectral images of 4 varieties of zucchini were obtained and were adjusted based on hue and saturation according to the respective variety. Further, Canny edge detection and point of interest analysis using the Hessian Affine algorithm were performed, and an algorithm was developed to obtain the percent surface damage on a zucchini. The difference in damage determined by the APP as compared to the standard method ranged from −0.31% to 7.17%. Alden, Omid, Rajabipour, Tajeddin, and Firouz (2019) compared the impact of regular air packaging and modified atmosphere packaging (MAP) on the shelf life of cauliflowers packed in polypropylene (PP) and polyethylene (PE) pouches. The mechanical properties including hardness, firmness of the flower head, and peak shear force for the stem were measured. Color changes based on the CIELab color space. PE pouches with MAP were reported to give the best results in terms of shelf life with a marketing capability of 50 days.

Arakeri and Lakshmana (2016) applied computer vision techniques to develop an automatic grading system for tomatoes, and to analyse the defects and ripeness. Color features, as well as texture features including energy, homogeneity, contrast and correlation were extracted. Then, a 3-layer feed-forward neural network were employed to classify tomatoes and the Leave One Out (LOO) cross-validation was conducted. It results in 100% and 96.5% of classification accuracy with these two models respectively. Artificial neural modelling based approaches have also been explored to assess the quality of greenhouse tomatoes. Image acquisition and empirical data (mass, hardness, height, length, width) acquisition was carried out throughout the entire growing season. A total of 41 features, including 8 empirical features and 33 features from image analysis, were obtained. Several neural networks were tested, and the RBF network with 22 input variables and 2 outputs (color and hardness) were reported to provide the best results (Zaborowicz, Boniecki, Koszela, Przybylak, & Przybył, 2017). An effective grading system for tomatoes has been designed based on DIP and ML technique (Ireri, Belal, Okinda, Makange, & Ji, 2019). The ROI was segmented from the captured RGB images and calyx, stalk scar detection was carried out using histogram thresholding techniques. The LAB color space was used to generate color statistical features. Also, several textural features and geometric features were extracted, and a defect grading model was developed. Several models including SVM, ANN and Random forest models (RFM) were tested to classify the healthy and defected categories of tomatoes. It was concluded that RBF-SVM model result in highest accuracy of 0.9709. Further, in order to grades and separate the defective tomatoes, a microcontroller-based three-stage system was developed. In the first stage, the tomatoes were separated from other species. Further, separated tomatoes were classified as good or defective, based on the Gabor wavelet transform. In the third stage, a cascade of two SVM classifiers was developed to classify the defective tomatoes into three categories based on defects, namely black spot, canker and melanose. The first two stages performed perfect classification with no error. For the third stage, the mean values of accuracy was 0.9774, specificity was 0.9938, whereas, the sensitivity and precision were 0.9655 and 0.9824, respectively (Kumar, Esakkirajan, Bama, & Keerthiveena, 2020). Table 2 described the different types of vegetables, their properties under investigation, image capturing instrument, image type, image size, dataset size, features exploited, model employed and their performance.

4. Computer vision for fruits quality estimation

DIP and ML-based approach has also been used to predict fruit quality and classification. Wang, Liu, Yu, Wu, and He (2012) employed such a method to classify seedless raisins into their four respective types by extracting 74 morphological, color and texture features and ML models with five classifiers - PLS, LDA, soft independent modeling of class analogy (SIMCA) and least squares support vector machine (LS-SVM) along with linear and radial basis function kernels. The best results (99%) were obtained with LDA based on the morphological, color and texture feature set. Furthermore, an automatic and adjustable algorithm was developed for the classification of apples by Mizushima and Lu (2013) using linear SVM and Otsu's segmentation. In the training phase, the apple and background are manually selected and SVM was used to calculate a separation hyperplane to generate a contrast-enhanced image and then used to separate apples from the background using Otsu's algorithm. Apples with differing color characteristics were segregated with an error less than 2%. An in-line system consist of a feeder, a machine vision unit and a grading unit has been developed for grading of figs (Baigvand, Banakar, Minaei, Khodaei, & Behroozi-Khazaei, 2015). Figs were graded based on three quality parameters namely, size, color and split size, which were classified into 5 classes by experts. Otsu's algorithm was used to segment the figs by considering size, color and split indexes mentioned in terms of the equivalent diameter, gray color, and split area respectively. The developed grading algorithm achieved an accuracy of 95.2% and the mean grading and classification rate was 90 kg/h (Mizushima & Lu, 2013).

Classification of fruits into 18 different categories was also done using DIP and ML with split-and-merge algorithm to segment background and for extracting color histogram, shape and texture features (Zhang, Wang, Ji, & Phillips, 2014). PCA was used to reduce the dimensionality of data. A feedforward neural network (FNN) along with fitness-scaled chaotic artificial bee colony algorithm was used to train its weights and classification task. The classification accuracy obtained was 89.1%, which was better than several other algorithms that were explored, including kernel SVM (88.2%), Particle Swarm Optimization–FNN (PSO–FNN) (87.9%), ABC–FNN (85.4%) and Genetic Algorithm–FNN (GA–FNN) (84.8%). Manickavasagan et al. (2014) study focused on using RGB images to classify a total of 3300 samples of dates into three different categories based on 39 GLCM features of color and hardness. Then LDA was performed with all features and stepwise discriminant analysis was conducted with selected features. The overall classification accuracy was reported to be 87%, 82%, 69%, using LDA, and 86%, 81%, 68% using SDA for Khalas, Naghal and Fard varieties, respectively. A DIP-based grading algorithm for mangoes was used by Momin et al. (2017) based on the perimeter, projected area, and roundness features. The RGB color model was converted into HIS for thresholding. The system designed for grading based on projected area and Feret diameter exhibit highest accuracy (97%) followed by perimeter (79%) and roundness (36%), respectively.

A DIP and ML-based 6 stage technique was used for the apple grading process by Moallem, Serajoddin, and Pourghassem (2017). After ROI segmentation, the stem end was detected using morphological methods and Mahalanobis distant classifier and clayx were detected by employing K means clustering on Cb component in YCbCr color space.

Subsequently, defect segmentation was done using MLP. Further, statistical, texture and geometrical features are extracted and SVM and KNN based classifiers are developed for apple grading. Two different tasks – healthy vs defected and the first rank vs the second rank vs rejected, are performed. The SVM model achieved the best recognition rate of 92.5% and 89.2% for the two classed respectively.

Researchers developed a DIP and ML-based model Pereira et al. (2018) classified papaya fruits based on ripeness using pulp firmness as an indicator. Twenty-one statistical color features were extracted from HSV, RGB and CIE L*a*b* color spaces and a Random Forest classifier with 500 decision trees to classify the fruits into 3 maturity classes. The success rate was reported to be 94.7%. Utai et al. (2019) classified 'Nam Dokmai' mango fruits into 3 classed based on their weight extracting features from the length, width and thickness of the bounding box and area. They reported a success rate of 97%. In another mango classification study, 24 statistical features in the RGB and HSI color space were extracted from over 100 images of six different ripeness stages, and a Decision Tree-based classifier was used for random prediction of mango ripeness with 96% accuracy (Mim, Galib, Hasan, & Jerin, 2018). Maturity-based classification of mulberry fruits into three categories namely, overripe, ripe and unripe was reported by Azarmdel, Jahanbakhshi, Mohtasebi, and Muñoz (2020). Several geometrical, color and texture features were extracted by employing image processing techniques, and feature reduction techniques including Correlation-based Feature Selection subset (CFS) and Consistency subset were employed to select significant features. Both ANN and SVM models were evaluated, and the ANN model with CFS was reported as the best with 99.1% accuracy. Hossain, Muhammad, and Amin (2018) developed an automatic date fruit classifier framework using 5G technology with DL. Transfer learning was used with CaffeNet architecture. The training images were scraped from the internet, and images of four classes namely, mabroom, ajwa, sukkary and sagai were obtained. Data augmentation was conducted to enhance the number of samples from 1000 to 2000 per class. The proposed model was reported to achieve an accuracy of 99% after refinement of CNN model. More recently, Khojastehnazhand and Ramezani (2020) classified bulk raisins as good or bad based on the quality using textural features extracted using GLCM, GLRM and LBP techniques and created a database consisting of good and bad raisins. Unsupervised classification using PCA and supervised classification using LDA and SVM was performed, and classification accuracy of up to 85% was reported.

A novel approach to classify cashew nuts into whole vs split was proposed by Sunoj, Igathinathane, and Jenicka (2018) using surface grayscale intensity and object shadows. The surface grayscale intensity was used to differentiate split-up samples from split-down or whole samples. Furthermore, the shadow ratio, obtained as a result of a light source at an angle to the camera, is used to differentiate between split down and whole cashews. The proposed method achieved an accuracy of 100% to classify whole vs split cashews. For detecting healthy vs defective date fruits, Nasiri, Taheri-Garavand, and Zhang (2019) also used a Deep CNN-based approach model. A VGG-16 based architecture, followed by max-pooling, dropout and dense layers was developed for the classification the dates into 4 classes, namely Khalal, Tamar, Rutab and defective dates. The model exhibit high classification accuracy (96.98%) and outperformed the classification methods based on feature engineering. In another attempt to classify pomegranate fruits based on size and color of their arils, DIP and AI-based models were developed. Images of 200 fruits were obtained and converted into several color channels from which 482 features were extracted. Furthermore, ANN, Adaptive Neuro-Fuzzy Inference System and Response Surface Methodology were explored for classification purpose and the ANN model was reported exhibit highest accuracy (98%) (Fashi, Naderloo, & Javadikia, 2019). Other researchers have also employed the CNN-based approach for classification of sour lemons into healthy and defective samples. In total, 1637 sample images were obtained and 30% was used for validation. The histogram of oriented gradients (HOG) and LBP feature extraction along with ANN, KNN, SVM, Fuzzy and DT algorithms were employed for classification. The CNN-based algorithm was reported to exhibit satisfactory accuracy of 100% (Jahanbakhshi, Momeny, Mahmoudi, & Zhang, 2020). A homemade sensor system using DIP and a ML-based model for apple authentication was developed Song, Jiang, Wang, and Guo (2020) using a diffraction grating. Two diffraction grating sheets were placed on either side of apple and images were acquired with a smartphone camera. Several ML models were employed, among them SVM and locally weighted partial least squares classifier (LW-PLSC) were reported to be most effective, with the classification accuracies ranging from 93 to 100%.

Gurubelli, Ramanathan, and Ponnusamy (2019) used special feature extraction techniques using various two-dimensional linear discriminant analysis variants including fractional fuzzy two-dimensional linear discriminant analysis (FF2DLDA) to facilitate pomegranate fruit grading. Kernel support vector machine (KSVM) was employed for the classification of pomegranates based on these features. The FF2DLDA based model was reported to achieve the highest accuracy. Temizkan, Atan, Büyükcan, and Caner (2019) used DIP for quality estimation of white nectarine based on physiochemical analysis in order to evaluate the efficiency of ultrasonic treatment to improve the shelf life of fruits. Color parameters in HSV, RGB, YCbCr, L*a*b* color spaces were obtained, along with morphological parameters for qualitative evaluation. They reported that ultrasound treatment at 300 W resulted in the color, shape, size being maintained for a longer period. In another similar study, DIP and statistical models were employed to classify the maturity stages of apricots in to unripe, ripe or overripe, as well as the volume (Khojastehnazhand et al., 2019). Features in RGB, grayscale and L*a*b* color spaces were extracted and employed to develop the LDA and QDA classification models. Both models are reported to result in accurate predictions.

Dutta, Sengar, et al. (2016) employed a DIP based approach to identify pesticide-treated grapes versus untreated/fresh grapes. After ROI segmentation, statistical features in the spatial domain were extracted using GLCM and Run Length matrix. Additionally, features in the frequency domain were extracted using Haar filter with 2D Discrete Wavelet Transform (DWT) implemented via the Mallat's tree algorithm, and then SVM classifier was employed to identify the pesticide content in grapes. The classifier achieved an accuracy of 100%, suggesting that the proposed method is efficient in identifying pesticide-treated grapes. Another similar study was used to determine four common food dyes, namely, sunset yellow, carmoisine, quinoline yellow and brilliant blue, in binary mixtures in commercial products. The output was validated against a standard high-performance liquid chromatography (HPLC) method. The method provided correlation coefficients >0.998 under optimal conditions. (Sorouraddin, Saadati, & Mirabi, 2015).

Another study employed DIP and statistical methods including simple linear regression and multivariate analysis PLS regression to determine chlorophyll *a*, chlorophyll *b*, total chlorophyll t, chlorophyll meter readings, carotenoids, titratable acidity and soluble solids content in mango fruits. PSLR models were developed for spectral indices and six RGB indices. The multivariate analysis PLS regression result in improved and more robust analysis of various biochemical parameters (Elsayed et al., 2016). An automatic system for grading oranges based on their ripeness and size was developed using an image processing approach to classify them into 4 classes based on ripeness and 3 classes based on size. Novel pattern recognition techniques using Edited Multi-Seed Nearest Neighbour and Linear Regression are proposed. The experimental success rate ranged from 90% to 97% for the linear regression-based technique (Jhawar, 2016). Mohapatra et al. (2017) used the DIP based model to study the dielectric properties of red banana fruits at various stages of ripening with ROI segmentation conducted by employing Tsallis entropy-based thresholding. For feature extraction, LBP, CLBP and NRLBP based methods were employed. Chi-Square distance/nearest neighbour and FCM clustering are employed for the classification. The NRLBP + FCM based technique reported to exhibit highest average accuracy of 97.61%. DIP and statistical analysis have been used for ascorbic acid (AA) content in Brazilian Amazon native fruits (dos Santos, da Silva, de Oliveira, & Suarez, 2019). Images from a colorimetric spot test were captured using a smartphone and the RGB values were analysed using the ImageJ software. The results were compared with iodometric titration using a paired *t*-test with 95% confidence level.

DIP has also been used to predict enzyme activity in ripening bananas. Peroxidase (POD) and polyphenol oxidase (PPO) enzymes are responsible for enzymatic browning of banana fruits. Nadafzadeh, Abdanan Mehdizadeh, and Soltanikazemi (2018) extracted 17 color parameters from each image and used genetic programming (GP) modelling is used to predict PPO and POD enzyme activity after 9 days and compared the results with laboratory methods. The model was reported efficiently predict PPO and POD enzymes with correlation coefficients of 0.98 and 0.97, respectively. The detail regarding different types of fruits along with their properties under investigation, image capturing instrument, image type, image size, dataset size, features exploited, model employed and their performance are summarized in Table 3.

5. Computer vision for beverages and drinks

The beverage industry has significant number of AI applications for quality prediction and grading of different types of beverages. DIP was employed to classify different grades of tea samples based on their textural features under Darkfield and Brightfield type of illumination. Laddi et al. (2013) found from a PCA analysis of textural features of samples that Darkfield illumination led to the best discrimination of samples with a variance of 96% while the Brightfield illumination resulted in only 83% discrimination. More recently, Li et al. (2021) developed an economical method to predict tea quality using smartphone imaging in conjunction with a micro-near-infrared (NIR) spectrometer. The texture, color and spectral features were obtained from the captured images, and data fusion techniques namely, low-level, mid-level and high-level fusion were explored. PCA was used for dimensionality reduction and an SVM model was used for classifying tea samples based on grades. The mid-level data fusion technique result in classification of different grade of tea samples with accuracy (94%).

A multivariate calibration method in conjunction with RGB histograms acquired from digital images were used by Botelho et al. (2014) for determination of an artificial dye (sunset yellow) in orange beverages. This method was mentioned to quantify sunset yellow in orange beverages in the range of 7.8–39.7 mg/L and relative prediction errors $<$10%. This method was later validated against standard guidelines and reported to be linear, accurate, unbiased and this method can also be used as an official method to estimate artificial dyes in beverages. Other researchers have developed a novel sensor system to authenticate milk sample based on computer vision and pattern recognition (Song, Jiang, Wang, & Vincent, 2020). The sensor system used a smartphone camera to record video of the samples followed by the extraction of spectral from these videos via image processing. The SVM, RF and PLS-DA based models were employed for the classification. The PLS-DA and LW-PLSC models were reported to classify milk samples with 100% accuracy.

In another study, Marinho, Lima, Rocha, Reis, and Kamogawa (2019) developed a fast and environment-friendly method to detect ethanol concentration in distilled beverages using phenolphthalein as an indicator and a smartphone camera. The color intensity of the solution was measured and monitored by a smartphone camera with a free smartphone application. They reported experimental results and AOAC reference procedures to agree with a confidence level of 95%. A machine vision system was developed to rapidly analyse high-definition images for food colorimetry applications (Minz et al., 2020). A two-step algorithm was employed for ROI segmentation, and subsequently, the color features were obtained for the cropped region by converting the RGB image to CIE Lab image using the Scilab program. The DIP system was tested with skim milk powder at various cropping size of the ROI. At 1100×1100 resolution, the software was able to achieve stable conditions and the RAM, CPU and Disk usage was 87%, 53% and 12%, respectively. A combination of RGB, HIS and grayscale histograms was employed for the classification of red wine produced in the São Francisco valley based on grape variety, geographic origin and winemaker (de Lima et al., 2020).

Various multivariate classifier models including PLS-DA, PCA-LDA and SPA-LDA were explored and their results were compared for each of the three tasks, based on precision, sensitivity and specificity. The PCA-LDA models in conjunction with HSI histograms was reported to be most efficient in classifying the red wine based on geographical region, whereas SPA-LDA was more efficient for classification based on winemakers and grape variety using Grayscale + HSI histogram and RGB histogram respectively. A colorimetric method using a smartphone camera was developed to detect milk adulterants including starch, sodium hypochlorite and hydrogen peroxide (Costa et al., 2020). Histograms of the captured RGB images were obtained, and PLSR was used to predict the respective concentrations of starch, H_2O_2, and NaClO in the sample milk with high mean R^2 values for starch (0.9974), H_2O_2 (0.9997), and NaClO (0.9929).

Turco, do Nascimento, de Lima, and Torres (2020) used a multi-imaging analysis in conjunction with NIR spectra to determine the antioxidant capacity (AC) and Total Flavonoid Content (TFC) of geopropolis (EEGs) from Brazilian native bees. The standard spectrophotometric assays were carried out to determine the TFC and AC. Further, the digital images and NIR spectra was used to establish PLS regression model for calibration. The results of digital image and NIR data were compared with the data obtained from reference assays. The color-based PLS models were reported to result in the best performance with low RMSEC and RMSECV. Silva and Rocha (2020) developed a novel method to detect milk adulteration using smartphone-based digital colorimetry. The proposed method was reported to perform 32 assays per hour and accurate with coefficient of variation = 3.0% (n = 20) and allowed the detection of even 1.0% v/v water in adulterated milk sample. This proposed method is an accurate, fast and environment-friendly alternative to detect milk adulteration. More recently, Franco et al. (2021) proposed a method to determine reducing sugars in cachaça using colometry by employing a smartphone camera. The method was based on the formation of a colored Cu(I)-Neocuproine complex due to the reduction of Cu(II) to Cu(I) by sugars. The results obtained were compared with the reference method using statistical tests including F-test, with confidence level of 95%. Table 4 summarizes the detail regarding different types of beverages and drinks, their properties under investigation, image capturing instrument, image type, image size, dataset size, features exploited, model employed along with their performance.

6. Computer vision for meat and seafood quality estimation

Like in other situations, some research has been focused on quality evaluation, prediction and monitoring in the area of meats and seafood. Pabiou et al. (2011) developed a video image analysis (VIA) based model to classify cattle carcass cuts based on their quality. Statistical models including stepwise regression, PLS, LASSO, PCA and CCA were developed based on carcass weight, EUROP carcass classification and VIA parameters. They reported that the models developed using carcass weight and VIA parameters had the lowest RMSE and error of prediction across traits. More recently, De La Iglesia et al. (2020) used an automated system consisting of visual and sensory components for improving the automation and grading of beef carcasses. The sensory system consisted of a weight sensor, as well as temperature and humidity sensors. After image acquisition, segmentation was performed using landmark detection. Subsequently, DIP techniques were used to identify the fat content, which was used in the classification process. They reported that the developed system was up to 10 times faster than a human expert.

An automatic fish grading system based on its freshness was proposed by Dutta, Issac, Minhas, and Sarkar (2016) using DIP and statistical methods. The L*a*b* color space was obtained from capture images and ROI segmentation was performed. The Haar filter was employed to extract the features in the wavelet domain. The third level of the wavelet transform of the segmented image was used for classification into 3 categories based on freshness. Miranda and Romero (2017) used an online system to measure the length of rainbow trout fish using DIP. A water channel was developed with a computer vision component to acquire fish images as it crosses a control point. Connected component analysis followed by third-order regression curve fitting was the employed to determine fish length. The system was reported to achieve an MAE of 1.413 cm in the experimental evaluation. Vo et al. (2020) developed a low-cost biometric identification system based on CNN and DIP for tracking lobsters from catch to table. The ROI segmentation of the captured lobster images was carried out by using a pre-trained Mask-RCNN model and the carapace area was extracted. This CNN based method eliminated the problems arising due to non-uniform background and lighting conditions. The grading attributes including weight, size and color were determined and this data was used as an input for the follow-up research to identify individual lobsters. This method was successfully tested using a mobile application at a lobster processor.

Caro et al. (2018) used DIP and statistical methods to compare the suckling lamb carcasses of three sheep breeds. A total of 161 images were used to extract various length features in the dorsal and side view. General linear model univariate analysis, as well as PCA, were performed. In general, the analysis of side-view images was shown to result in better performance than that of dorsal images. An eco-friendly system to determine the fat in chicken hamburgers was developed by Fernandes et al. (2019). Color histogram features in the HIS, RGB and grayscale channels were used and the samples with more than 20% (w/w) fat content were considered as adulterated. Qualitative as well as quantitative analysis were performed and models including PLS, PCA, PLS-DA, PLA- LDA, SPA-LDA were explored along with different feature combinations. PLS with HSI features were reported to present best results ($R^2 = 0.95$) in prediction set, whereas SPA-LDA/Grayscale + HIS exhibit best results in test set, with only one sample misclassified out of 24 samples.

A computer vision system was developed to measure the color attributes of poultry chicken by Barbin et al. (2016). The CIELab components of images were compared with the analytical reference measurements of a colorimeter. Illumination normalization was performed to reduce the bright spots or shadow effects. Subsequently, RGB image was transformed to CIEL*a*b* color space. The R^2 values for L*, a* and b* were reported to be high 0.99, 0.74 and 0.88, respectively. A safe and feasible high-confidence indicator was developed by Lee, Baek, et al. (2019) to detect freshness vs spoilage in chicken breasts. A three-layered indicator was constructed by using Tyvek® sheet with high gas and vapor permeability as the inner layer. BCG-immobilized with binding polymer act as the color changing layer, and a low-density polyethylene film used as the outer layer that turned yellow from green when spoilage occurred with TMA used as a simulant. Subsequently, RGB images were used to quantify this change. The CO_2, total volatile basic nitrogen and bacteria content were correlated with the color changes. Another freshness indicator to monitor chicken breast spoilage was developed by Lee, Park, et al. (2019) consist of an inner poly(ether-block-amide) film, a color-changing layer of polymer-immobilized pH dyes, and an outer layer of poly(ethylene terephthalate). This indicator was employed to detect the freshness of packaged chicken breasts, by applying it to the packaging. Subsequently, the color changes were observed with smartphone camera, over the storage time. Melanosisin snow crab (*Chionoecetes opilio*) clusters were detected using DIP and statistical analysis methods (Rotabakk, Heia, Rode, Lian, & Lorentzen, 2020). The acquired images were used to extract L* and b* values after ROI segmentation, which were then used to obtain a 'chromatic melanosis value'. This was then used to develop the linear regression model and was compared with the results of a panel of 3 expert examiners. The model achieved $R^2 = 0.7984$ with $p < 0.001$.

Muñoz, Rubio-Celorio, Garcia-Gil, Guàrdia, and Fulladosa (2015) developed an automatic classification system for grading dry-cured ham depending on marbling. A sensory marbling grading scale established by experts was used for this process. ROI segmentation followed by feature extraction – 30 geometric and 18 textural was performed. Several classifiers including SVM and NN were tested, along with feature selection algorithms. The best model (SVM with linear kernel and Plus-L Minus-R Selection (RLS)) was reported to achieve a correct classification rate of 89%. More recently, another automatic computer vision-based dual stage image analysis (DSIA) system to detect dry-cured ham veining defects was developed by Lopes et al. (2020). The first stage consisted of ROI segmentation and detection of veining. In the second stage, the level of veining defects was determined. Features including color, texture, border, histogram and intensity, were used and SVM and RFM were explored. The RF model achieved 88.10% accuracy with DSIA, and 63.10% without it.

Researchers have developed an egg grading system to detect various defects by employing fuzzy logic and machine vision (Omid, Soltani, Dehrouyeh, Mohtasebi, & Ahmadi, 2013). The defects included cracks, internal blood spots, and breakages of eggshell. The features in the HSV color space were extracted using DIP, and a fuzzy inference system was established to determine the size, as well as the defects. The experimental CCR was 95%, 94.5% and 98% for size detection, crack detection and breakage detection respectively. Egg occlusion (multiple eggs in a single frame) make it difficult to accurately determine the volume. Hence, a simple and fast depth image-based system was developed to address this issue (Okinda et al., 2020). ROI segmentation was performed with k-closest M-circlecenter algorithms and contour curvature analysis. The Exponential Gaussian Process Regression, out of several tested, performed the best, with RMSE of 1.294 cm3, 1.175 and 1.080 and for a complex occlusion, single egg and simple occlusion, respectively. Further, Ruedt, Gibis, and Weiss (2020) developed a cost-effective method to analyse surface iridescence in meat using DIP techniques. Global thresholding, as well as k-means clustering, were explored for ROI segmentation, with k-means providing slightly higher iridescence areas. The results were compared with a conventional method with a panel of 20 experts. The proposed method achieved an almost perfect agreement with $\kappa = 0.800$ and $p = 0.001$. The consolidated summary of different studies including different types of meats and seafood along with their properties under investigation, image capturing instrument, image type, image size, dataset size, features exploited, model employed and resultant their performance is given in Supplementary Table S1.

7. Computer vision for edible oil quality estimation

Milanez and Pontes (2014) suggested a simple and economical method to predict the shelf life and type of vegetable oils by using digital images and pattern recognition techniques. The selected variables were used to develop LDA based classification models. The and stepwise (SW) formulation and successive projection algorithm (SPA) were employed for variable selection. The type of oils was classified accurately by employing LDA/SW (90%) and LDA/SPA (95%) models. However, the best classification of expired and non-expired samples was achieved by LDA/SPA models in case of sunflower (97%), soybean (94%) and canola oils (93%), while the corn oil data were accurately classified (100%) based on the shelf life with LDA/SW. The quality and market price of palm oil depends on the freshness of the fresh fruit bunch. Pamornnak et al. (2017) reported a rapid and automatic method for grading of palm bunch based on its quality using a Kinect camera. For this purpose, an algorithm based on a volume integration scheme was employed to determine relative volume of the palm bunch. another algorithm was used to classify the bunches based on the oil content into H-Grade, M-Grade and L-Grade. The reported accuracy was 83% with a running time of 6 s per sample. The production of high-grade olive oil is also mainly dependent on the quality of olives used.

Pariente, Cancilla, Wierzchos, and Torrecilla (2018) classified olives based on the quality by using image processing in conjunction with mathematical modelling. For grading of olives, the average color channels of olives obtained from their images and employed as input to develop PLS and ANN-based models. The PLS model had a 70–75% correct classification rate while the ANN gave a better rate (90–93%) with a misclassification percentage less than 13%. Recently, Singkhonrat, Sriprai, Hirunwatthanakasem, Angkuratipakorn, and Preechaburana (2019) the digital image colorimetry was used to predict lipid oxidation in oils and oil-in-water emulsions. These digital images were processed using Image-J software into signals based on the RGB model. The Image-J method was reported to present accuracy similar to the standard titration method and UV–Vis spectroscopic methods. A good correlation between the methods was also observed over the peroxide value (PV) from 3 to 14 meq.O_2/kg.

Recently, Song, Jiang, Wang, and Vincent (2020) used smartphone video in conjunction with pattern recognition techniques to detect adulteration in olive oil. The video was processed by employing computer vision techniques, converted to sensor data and analysed for pattern recognition. The PLS-DA and LW-PLSC models were reported to identify the minimum level of 10% adulterant in olive oil with a classification accuracy of 96.2%. Further, Parsaeian, Shahabi, and Hassanpour (2020) measured these fatty acids composition using digital images of sesame seeds. Fatty acid composition is a critical parameter to determine the quality of sesame oil. Oleic, stearic palmitic and linoleic acids are the major fatty acids present in sesame oil. Certain features of seeds namely, color, length/width ratio, and texture were obtained from the images and used as input to develop mathematical models. A multilayer perceptron (MLP) artificial neural network result in an accurate estimation of oleic, palmitic, linoleic and stearic acids.

Supplementary Table S2 summarizes the detail about different types of oils, image capturing instrument, image type, image size, dataset size, properties explored, features explored, models employed and resulting performance.

8. Computer vision for other food products quality estimation

DIP has been applied to monitor the density and volume of dough during fermentation process. Pour-Damanab and Rafiee (2011) captured the side view pictures and segmented the ROI based on the threshold value obtained from grayscale histograms. Further, the volume was derived using the height values at different parts and was correlated with the humidity and temperature of the fermentation oven. They demonstrated that the density was significantly more influenced by temperature than the relative humidity. In a different study, DIP was used to monitor the industrial baking process states including the color and size of the baking goods (Paquet-Durand, Solle, Schirmer, Becker, & Hitzmann, 2012). Images were captured continuously from inside the baking oven in an online system. A modified Viola-Jones algorithm is used to identify the kind of baking goods, and an automated method is used to determine the width and height of the baking goods, with an error of 5.6 and 4%, respectively, for the two processes. Further, the lightness and color were calculated using neural networks to obtain relevant information about the baking process.

Researchers have also used digital color imaging (DCI) to determine the quality of binary powders, by quantifying the color variance of the mixture (Shenoy et al., 2014). Three different mixtures with ingredients including paprika, salt, black pepper and onion were explored. The potential of assessing mixture quality was found to depend on whether the color difference between the mixtures and individual powders is significant. In a further study, Shenoy, Innings, Tammel, Fitzpatrick, and Ahrné (2015) used DCI to determine the powder mixture quality of two binary and quaternary mixtures and the results of DCI were compared to the salt conductivity method. The coefficient of variation was employed to assess the homogeneity of mixtures. The mixtures containing similar colored particles or segregating particles were relatively difficult for the DCI based method to determine the mixture quality. DIP was also used to study the porosity characteristics of baked food items made up of five different types of flours (Rahimi, Baur, & Singh, 2020). The captured images were de-noised and binarized followed by determination of mean area, number of pores and largest area for all the flour types. Further, fractal features were also determined to measure the surface irregularities. Amaranth flour exhibited the highest porosity of 8.23%, whereas wheat exhibited the lowest with 1.41%.

In a different study, Yin, Xiao, and Yu (2015) graded tobacco leaves using DIP and statistical methods. Seven light sources were considered and features for all individual samples were calculated. Further, the mutual information between the two samples was also calculated. These were used to select the grading images, with cyan color giving the best results. Further 18 color and 13 texture features were calculated and a Fisher discriminant analysis (FDA) was used to classify the sample images. Botelho et al. (2017) used a homemade low-cost image analysis system to determine level of azo dye allura red in the hard candies. For the same, 238 candies of four different flavours, brands and batches were employed. 2D Fast Fourier transform was used for pre-processing and multi-way calibration by employing N-way PLS. A multivariate analysis was performed and the analytical range was mentioned between 22.9 and 78.8 mg.kg-1 of allura red with RMSEC and RMSEP values were 4.8 and 6.1 mg kg^{-1} respectively.

Mollazade and Arefi (2017) developed a "LightScatter", a MATLAB based software package for monitoring horticulture food products using DIP techniques. A user-friendly GUI was developed which enables the user to acquire images and perform image pre-processing (using various spatial domain fitting functions), feature extraction (texture, wavelet, Gabor, SAR) and model generation (MLP, ANIFS, PLSR, PCR) for classification or prediction. Vidal, Garcia-Arrona, Bordagaray, Ostra, and Albizu (2018) used A low cost, non-toxic and quick method for quantification of allura red (E129) and tartrazine (E102) yellow colorants in food samples was developed using DIP. Up to 92 samples can be measured simultaneously in a single image. The images were switched from RGB to CIELab and YC_BC_R color spaces to obtain 'color-fingerprint'. Further, PLS models are used to identify individual colorant. RMSE values of 1.1 and 1.2 for allura red and 3.3 and 3.0 for tartrazine were reported in case of cross-validation and external validation sets respectively.

A fast and automatic method to detect acrylamide in fried potato chips was mentioned by Yadav, Sengar, Issac, and Dutta (2018) using DIP and statistical methods. ROI segmentation was followed by feature extraction by the Morlet wavelet transform, that was fed to LOOCV based SVM classifier to detect acrylamide in the chips. The experimental accuracy and specificity were 98.3% and 100%, respectively. Wongthanyakram et al. (2019) used DIC to determine curcumin in turmeric based on RGB color images. The proposed method was reported to exhibit 0.48 mg/L of limit of detection (LOD) and 1.61 mg/L of limit of quantitation (LOQ). The results were compared with data obtained from UltraViolet-Visible microplate reader (UV–Vis MR) and HPLC with no significant differences in results.

A DIP based method was used to detect key features including perimeter, area, curvature, length and width of horticultural crops with irregular shapes - focusing on Anthurium flowers (Soleimanipour, Chegini, Massah, & Zarafshan, 2019). Canny edge detection is used to detect the boundary to fit a B-spline curve. This was then used for detecting geometrical key points, which were in turn used to determine the geometrical features. The proposed model achieved less than 2% error in detecting the geometric features of rotated flowers. Another smartphone-based application to monitor the bacteria *E Coli* O157:H7 in food using lateral flow immunoassays was developed by Jung et al. (2020). The color change of the nitrocellulose pad was quantitatively measured using DIP, and a regression model based on these color values was developed. The tests were conducted on spinach food matrices and ground beef indicated that the developed system could detect 10^4–10^5 CFU/ml of *E. coli* as a model organism.

Computer vision (CV) coupled with statistical analysis was used to determine adulteration and dyeing of safflower (*Carthamus tinctorius* L.) by Lin et al. (2020). A total of 32 color features using the RGB, HSV and CIELab color models were extracted. Subsequently, a PLS-DA model was employed for the classification of safflowers as dyed or undyed. Further, PLS models were used to measure the hydroxy safflower yellow pigment A and water extract of undyed safflower. A high discrimination rate of 100% was achieved with PLS-DA model. Further, Narushin, Romanov, Lu, Cugley, and Griffin (2020) reported a DIP based system for the grading of chicken eggs based on their volume and surface area calculation. Hugelschaffer's equation was used for this purpose, which deduced the egg profile by transforming it from an ellipse. In an attempt to identify a carcinogenic, mutagenic and genotoxic dye – Sudan I in ketchup, a DIP based approach using color histograms and multivariate analysis was suggested (Reile et al., 2020). Histogram features using a combination of RGB, HSI and grayscale features were computed and subsequently SPA-LDA and SPA-PLS models were developed for classification and quantification respectively. The SPA-LDA model was reported to classify all the samples correctly, whereas RMSEP, R^2, RPD, REP and LOD values for the SPA-PLS model were 11.64 mg kg-1, 0.96, 5.28 13.63% 39.45 mg kg-1, respectively. In another similar study, to detect the presence of pesticides in the wash water of fruits or vegetables, a paper-based device (PBD) was developed by Sankar et al. (2020) using Whatman No.1 paper, *p*-nitrophenol palmitate and *Rhizopus niveus* lipase as support matrix, a substrate and an enzyme, respectively. Digital images of the PBD after testing were captured and several color space models including HSV, RGB and YCbCr were explored. The Cb component giving the highest correlation ($R^2 = 0.988$) with the actual values measured using microtiter plate assay. Recently, artificial intelligence technique has been used to find out-of-stock products in a grocery store-based images of store shelves. The semi-supervised and deep learning algorithms such as RetinaNet, You Only Look Once (Version 3 - YOLOv3), and You Only Look Once (Version 4 - YOLOv4) were applied to detect the on-shelf availability of products. It was reported that YOLOv4 deep learning architecture outperformed RetinaNet and YOLOv3 approaches which, in turn, significantly reduced the manual efforts of storekeepers (Yilmazer & Birant, 2021).

9. Conclusion and future perspective

DIP techniques have been employed widely for classification and quality prediction of different types of food products, raw materials such as grains, fruits, vegetables, meat, seafood, beverages, drinks and oils. DIP technique reported to efficiently classify a diverse range of food materials and prediction of various quality parameters. However, comparison of prediction capability and classification ability between different studies was not possible. It is because different researchers have explored the capability of DIP techniques to determine different quality parameters of different types of food materials by employing various types of the experimental setup and by employing a diverse range of ML and DL approaches.

In literature, two different approaches have been explored extensively namely, feature extraction-based approach, and DL-based approach. The choice of approach for a particular task depends on the size of the dataset available. DL methods were used to explore large datasets. In order to improve the efficiency of results for the feature extraction-based approach several pre-processing techniques, as well as feature processing and feature selection techniques, are rigorously employed, in conjunction with the image acquisition setup. Subsequently, several ML and DL-based models were also used for classification, regression and clustering of food products based on their quality parameters.

The advancements in image processing algorithms, as well as statistical methods such as ML and DL techniques, offers new opportunities to control the quality of food products and raw material using computer vision. Such applications to automate and speed up the conventional methods are more objective and generally more accurate than existing methods involving human examiners. Despite the availability of huge literature related to quality control of food products by using computer vision algorithms, commercialization of DIP based tools and techniques are scarce. There is an immediate need to develop android-based applications for real-time authentication of food and quality assessment. User friendly, low cost and portable devices based on DIP techniques are the urgent requirements of the market. Availability of these types of devices will help the consumers to perform real-time food testing on a day-to-day basis. That, in turn, will satisfy the consumer's demand for high quality and safe food products.

Furthermore, the image acquisition during food quality estimation could be challenging. It is desirable to use the best quality acquisition setup with high-resolution cameras. The design of experiments for image acquisition should consider proper lighting and reflecting conditions. Improper image acquisition set-up may lead to poor quality of images including blurring and different types of noises in the image and poor calibration. Pre-processing algorithms can be employed for the correction of these noises which in turn may require extra computational power. Inherently, DL algorithms require a large amount of data for the prediction of food quality. Smaller data sets may lead to the unsatisfactory quality predictions. Thus, ML and DL algorithms make use of high computational power for processing. Developing algorithms or programming for efficient utilization of available computational power can also be challenging.

Thus overall, good quality image acquisition systems assuring the proper visibility of relevant features, generation of large database including different options such as scaling and rotation, effective design of experiment for different types of foods based on the need based food characteristics, and effective utilization of computational resources are required. Therefore, challenges vary depending on the end use and demand significant considerations.

Declaration of Competing interest

None.

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Aspect Ration
CCD	Charged Couple Devices
CFS	Correlation-based Feature Selection subset
CLBP	Completed Local Binary Pattern
CIELAB	Device-independent color space
CNN	Convolutional Neural Networks
CV	Computer vision
CFS	Correlation-based Feature Selection subset
DCI	Digital color imaging
DIP	Digital Image Processing
DL	Deep Learning
DSIA	Dual stage image analysis
DT	Decision Tree
DWT	Discrete Wavelet Transform
FCM	Fuzzy C Mean
FNN	Feed forward network
GA	Genetic Algorithm

GLCM Gray Level Co-occurrence Matrix
HPLC High-Performance Liquid Chromatography
HSV Heu Saturation Value
HOG Histogram of oriented gradients
iPLS interval Partial Least Squares
KNN K-Nearest Neighbour
LBP Local Binary pattern
LW-PLSC Locally weighted partial least squares classifier
LDA Linear Discriminant Analysis
LOO Leave One Out
ML Machine Learning
NIR Near Infra Red
NRLBP Noise Reductant Local Binary Pattern
PCA Principle Component Analysis
PLS Partial Least Squares
POD Peroxidase
PPO Polyphenol oxidase
PSO Particle Swam Optimization
QSM Quality Scoring Method
QDA quadratic discriminant analysis
RBF Radial Basis Function
RGB Red Green Blue
RL Reinforcement Learning
RMSE Root Mean Square Error
ROI Region of Interest
SDA Stepwise Discriminent Analysis
SPR Spectroradiometer
SVM Support Vector Machine
VIA Video image analysis
YOLOv3 You Only Look Once, Version 3
YOLOv4 You Only Look Once, Version 4

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tifs.2021.09.014.

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