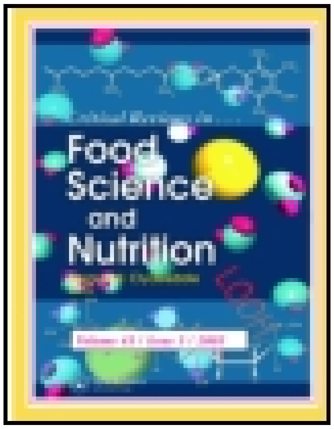

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Applications of computer vision for assessing quality of agri-food products: a review of recent research advances

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Applications of computer vision for assessing quality of agri-food products: a review of recent research advances

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Abstract

With consumer concerns increasing over food quality and safety, the food industry has begun to pay much more attention to the development of rapid and reliable food evaluation systems over the years. As a result, there is a great need for manufacturers and retailers to operate real-time effective assessments for food quality and safety during food producing and processing. Computer vision, as a non-destructive detecting approach, has the aptitude to estimate the characteristics of food products due to its advantages of fast speed, ease of use, and minimal sample preparation. Precisely, computer vision systems are feasible to classify food products into specific grades, detect defects and estimate properties such as color, shape, size, surface defects, and contamination. Thereof, in order to track the latest research developments of this technology in the agri-food industry, this review aims to present the fundamentals and instrumentation of computer vision systems, details of applications in quality assessment of agri-food products from the years 2007 to 2013, and also discuss its future trends in combination with spectroscopy.

Keywords: Computer vision, image processing, quality and safety, applications, agri-food products, hyperspectral imaging, 3D, sonar.

Contents

1. Introduction

Food quality and safety problems are frequently confronted in our daily life, and there has been a growing demand for food of high-quality from the public. For consumers, they tend to consider the price, appearance, freshness, as well as nutritional values at first sight of products. Therefore, in order to provide consumers with tasty, nice-looking, and trustworthy foods and attain their expectation, the food industry must be more careful and cautious about every step in food production and processing (Müller and Steinhart, 2007). Food recognition, identification, and classification are significant items in food processing and evaluating, and these steps are usually performed by proficient workers. Such procedures are laborious, time-consuming, costly, and subject to human error. Therefore, a novel technique is in urgent need, which is rapid, accurate and non-destructive, and can make processing more efficient and economical. Particularly, computer vision technology, which is one of the detection means for food evaluation, has proved to be effective to achieve this goal (Sun, 2011).

Computer vision has the ability to inspect samples and analyze differences among samples or regions within a sample. Although originated in the 1960s (Baxes, 1994), computer vision is a relatively new technology for food industry. In recent years, with improvement in computer development, numerous applications have been successfully achieved, which motivate more further and supplementary researches (Antequera *et al.* 2007; Chmiel *et al.* 2011a; Jackman *et al.*, 2009a; Wang *et al.*, 2007; Blasco *et al.* 2007b; Zou *et al.*, 2010; Jin *et al.*, 2008; Mathanker *et al.*, 2011; Lei *et al.*, 2007; Igathinathane *et al.*, 2009; Sun, 2012).

Computer vision is capable of estimating shape, size, and position consistently and rapidly. With the recent developments of algorithms and the improvement of computer hardware, the sensitivity and ranges have been widened for samples of larger size and more complicated shape. Therefore, computer vision has been extensively applied for food quality assessment, including meat and meat products (Antequera *et al.* 2007; Chmiel *et al.* 2011a; Jackman *et al.*, 2009a), fruits and vegetables (Wang *et al.*, 2007; Blasco *et al.* 2007b; Zou *et al.*, 2010), nuts (Jin *et al.*, 2008; Mathanker *et al.*, 2011; Wang *et al.*, 2011), cheese (Jeliński *et al.*, 2007), as well as grains (Lei *et al.*, 2007; Igathinathane *et al.*, 2009; Szczypiński and Zapotoczny 2012). Besides providing a brief introduction to the principles of computer vision, this review focuses mainly on recent developments in agri-food applications from 2007 to 2013 involving meat and meat products, fruits and vegetables, nuts, cheese, grains and some other sorts of foods.

2. Principles of computer vision technology

The technology involved in computer vision normally consists of three parts: hardware of computer vision, other types of imaging equipment, as well as image acquisition and processing. Computer hardware is required for acquiring the images of agri-food products, while image processing is to extract useful information from the images for quality analysis and process control.

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2.1 Hardware of computer vision

A computer-based vision system commonly consists of five parts: illumination, a camera, an image capture board (frame grabber or digitizer), computer hardware, and software (Wang and Sun, 2002) as depicted in Figure 1.

A well-designed illumination system and appropriate light source can help to reduce reflection, shadow and some noise to provide a high-quality image, and decrease the subsequent image processing time. Thus in the food industry, location, lamp type, and color quality for the illumination system must be designed elaborately. The selection of a lamp can affect image quality and analysis results. There are many types of lamps to choose from: incandescent, fluorescent, lasers, X-ray tubes, and infrared lamps (Bachelor, 1985). Meanwhile, modern systems have been built in compensatory circuitry to eliminate the effects of natural light during image acquisition (Brosnan and Sun, 2004).

A vision processor board, called digitizer or frame grabber, is a device for capturing individual still frames from an analog video signal or digital still frames in a digital video stream. In this process, an image is divided into a small region of two-dimensional grids (Brosnan and Sun, 2004).

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2.2 Other types of imaging devices

Additionally, the varieties of other vision system are growing at an inspiring speed, such as ultrasound, infrared, computed tomography, magnetic resonance imaging. The use of ultrasound for food quality assessment is based on the information obtained from the reflection or transmission, refraction, absorption, as well as scattering of sound waves, e.g., estimation of the intramuscular fat content of the *longissimus* muscle of pork (Mörlein *et al.*, 2005) due to the nature that the acoustic variation can be related to density changes in food products. Moreover, recent studies have proved that the characteristics of ultrasonic velocity can be applied to predict components like fats, water and proteins in meat products (Simal *et al.*, 2003).

Infrared (IR) in the region of 700-1000 nm is another promising and unique vision technology, which allows IR thermal radiation detection and acquirement of spectral reflectance of the tested product, thereby more information about material structures can be obtained. IR imaging has been applied in the food industry (Gómez *et al.*, 2006; Ginesu *et al.*, 2004) as the thermographic signatures are highly related to many physiochemical properties of food such as shelf life, fatty acids, firmness, etc. However, the image process is relatively complex.

In addition, tomographic imaging is another special and popular technique due to its capability of examining the internal quality of target objects. Nuclear tomography utilizes the nuclear energy for imaging and there are two classes of source of radiation. Computed tomography (CT) is categorized into "remote sensing", which consists of exterior sources. Modern CT system employs a fan-beam arrangement and the size can be enlarged to cover the whole field of view of the object. Therefore, the acquisition time is shortened directly. However, the dependence of X-rays has limited its application to calcified objects whereas food objects are usually soft or semi-fluid. Encouragingly, with the advancement of software and hardware development, CT coupled with proper image analyses has been successfully used to detect the magnitude and spatial location of salt gradients in dry-cured ham (Vestergaard *et al.*, 2005). On the other hand, unlike CT, magnetic resonance imaging (MRI) is possible for visualizing most food objects and suitable for both non-invasive and real-time monitoring during different food processing operations. Based on an external magnetic field, MRI detects the sample in the whole area by emitting a typical nuclear magnetic resonance frequency. The hydrogen nuclei will preferentially line up their spin toward the magnetic field, which is termed as the Lamor effect (McCarthy, 1994). Thus, MRI can determine both the quantity and the structural dynamic characteristics of water present. Many studies have applied MRI for food detection as water exists in most food products. In the research of Borompichaichartkul *et al.* (2005), images of corn kernels during the freezing process were captured by MRI and the location and state of water in the frozen corn was visualized. However, the cost associated with MRI technology is high, which limits its wide-spread application in the food industry to a large extent.

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2.3 Basic image processing steps

Basic image processing steps include image acquisition, preprocessing, segmentation, and advanced image processing as shown in Figure 2. These steps form the entire imaging analysis procedure, of which every step of the results will have an impact on the subsequent steps (Gunasekaran, 1996). These steps must be taken seriously, in order to minimize errors and ensure high accuracy. Image acquisition is the first step of all processing, involving preparation, illumination, noise reduction, and alleviation of specular reflection, which is essential to improve the accuracy and guarantee data quality (Brosnan and Sun, 2004).

Pretreatment can help to obtain high-quality images. The quality of the images is often affected by distortion, noise, and the electronic input device. Correction of geometric distortions, removal of noise, gray level correction, correction for blurring, and defocus correction (Brosnan and Sun, 2004) are the main approaches for image pre-processing and usually used alone or combined.

Image segmentation plays a significant role in image processing. Three different techniques used for segmentation involve thresholding, edge-based segmentation, and region-based segmentation (Brosnan and Sun, 2004). Based on light absorption and reflection of sample surface, characteristics of the image areas can be exposed quickly by the simple thresholding technique. Edge-based segmentations rely on edges found in an image by edge detecting operators. These edges mark image locations of discontinuities in gray level, color, texture, and so on. Region-based segmentation methods attempt to partition or group regions according to common

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image properties. The segmentation image is made up of a boundary and a region as a kind of representation. The boundary can be used as the basis for analyzing sample size and shape, and regional characteristics can be used to assess the texture and defects (Brosnan and Sun, 2004). With the continuous improvement in the variety of algorithms, the quantitative information of the segmented image can be better described so that subsequent recognition and classification can be achieved.

Advanced image processing includes recognition and classification so as to meet the ultimate purpose of computer vision for process monitoring and control. Gunasekaran and Ding (1994) and Sun (2000) outlined a systematic classification for the steps mentioned above, among which there exist three processing levels: low-level processing including image acquisition and preprocessing, intermediate-level processing as well as high-level processing containing recognition, and classification as described in Figure 3.

3. Applications of computer vision in the food area

In today's highly competitive market, for manufacturers and retailers, the major factor is to provide high-quality products. Therefore, producers of different types of foods need to improve food quality to meet consumer demands. However, it is difficult to have a standard inspection method to detect all types of food, which are diverse in size, shape, appearance, and other characteristics. Computer vision has demonstrated to have enormous potential for quality prediction and assessment of a variety of foodstuffs. Figure 4 presents the extent of published articles quoted in this paper in recent years involving different applications in the food area and the literatures were cited from ScienceDirect.

3.1 Meats and meat products

Meats and meat products play an essential role in people's daily life on account of their high nutritional values, which can not only provide proteins, but can also be an important source of fat, minerals, as well as vitamins. As a result, most developed countries are in high demand for meat and in some developing countries requirements for the amount of meat are also increasing at a high rate. However, the quality of meat varies in close relation with the species, age, gender, weight, living conditions, feed, and patterns of slaughtering of animals (Jackman *et al.* 2011). Besides, the quality of meats and meat products is also seriously affected by the conditions of transportation, storage periods and temperature. Therefore, it is important to conduct quality evaluation, classification and reasonable pricing to meet consumer requirements. Different techniques such as chemical procedures, instrumental methods, sensory analysis, and screening methods have already been applied to determine the attributes of meat, which is, however, destructive, time-consuming, manual, and subject to human errors. Compared with traditional inspection methods, computer vision is a rapid, simple, non-destructive, and sensitive detecting approach and has been utilized in the quality assessment for meats and meat products.

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3.1.1 Beef

Beef palatability needs to be measured at the slaughterhouse so as to be transported to appropriate markets afterwards. The quality of beef is mainly determined by estimating the properties involving color, marbling, and surface texture. Beef *longissimus dorsi* muscle is particularly valuable due to its superior palatability. Consequently, research about quality evaluation of beef *longissimus dorsi* is one of the most outstanding issues among numerous applications in computer vision. Experienced grading equipment can use color, surface texture, and marbling of beef *longissimus dorsi* as indicators for palatability, which are also the main properties used to classify beef carcasses by expert graders. Computer vision systems can provide an instantaneous, non-destructive and rapid assessment of beef quality. Thus, many scientists have performed relevant research to evaluate the features of beef *longissimus dorsi* including acceptability, tenderness, hardness, juiciness, as well as flavor (Table 1). Figure 5 shows an example of beef images after different image processing steps used in computer vision.

Imaging at high magnification has been used for beef quality detection. With common images, prediction of beef surface texture alone for beef palatability is quite effective, imaging based on the high magnification model attained higher detection efficiency (r=0.93) with the combination of color and marbling characteristics for *longissimus dorsi* compared with that of surface texture alone (Jackman *et al.*, 2009d). Also, Jackman *et al.* (2009a) employed images at high magnification combined with sensory acceptability and WBSF (Warner-Bratzler shear force)

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measurements as an accurate model to determine surface color, marbling, and wavelet texture features with an accuracy of 90%. Moreover, an alternative grayscale (Jackman *et al.*, 2010a) and a broad range of colors and marbling fat features (Jackman *et al.*, 2008) were combined with high magnification images to develop surface texture features with good results. Based on these experiments, the results showed that linear models proved to be better than non-linear models. Additionally, Zheng *et al.* (2007) conducted a study for evaluating beef *triceps brachii* muscles. Using computer vision, 25 beef samples before and after cooking were imaged and tested items included up to 15 factors. The prediction coefficients (R^2) of volume shrinkage, surface area, and major axis were 0.684, 0.674, and 0.745, respectively. The color scores of beef fat were obtained using computer vision and a support vector machine (SVM) by Chen *et al.* (2010), who selected 120 beef rib eye steaks for sensory evaluation and image processing. By boundary tracking, morphological operations, and thresholding, subcutaneous fat of rib eye were successfully segmented. A classification rate of 97.4% turned out to be possible to assess fat color scores using SVM. Jackman *et al.* (2009c) reported correlation coefficients for beef palatability (acceptability = 0.79, tenderness = 0.64, juiciness = 0.71, flavor = 0.82) based on employing all kinds of wavelet decompositions, while similar correlation coefficients (acceptability = 0.79, tenderness = 0.69, juiciness = 0.76, flavor = 0.78) were reported by Jackman *et al.* (2010b) based on partial least squares regression and genetic algorithms. On the other hand, Du *et al.* (2008) developed an automatic evaluation system to estimate intramuscular fat content in beef

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longissimus dorsi by using a series of image processing algorithms. Five IMF (intramuscular fat) characteristics (CDMiddle, CDLarge, ADMiddle, ADLarge, and AD) were meaningfully correlated with the fat content (the highest coefficient was 0.852 for CDLarge). Later, an algorithm was developed for automatic segmentation of beef *longissimus dorsi* muscle and marbling by Jackman *et al.* (2009b). By using simple thresholding and clustering with contrast enlargement via a customized grayscale, background and marbling were removed. Two different segmentation methods automatically derived images and were compared with the manual segmentation method; significant coefficients of correlation (up to R = 1 and R = 0.96) were found in both sets. In addition, Girolami *et al.* (2013) attempted to compare the means of the Minolta CR-400 colorimeter with a computer vision system to evaluate the colorimetric fidelity of the beef image. The study showed that computer vision system outperformed colorimetry, especially in measuring translucent and heterogeneous objects. Besides, a true color map of meat can be generated much similar to the real one by computer vision system.

Up to now, computer vision has made great progress in the quality assessment of beef attributes. Especially, prediction of beef palatability by Jackman *et al.* (2008, 2009a, 2009b, 2009c, 2009d, 2010a, 2010b) has affected the grading of beef by United States Department of Agriculture (Jackman *et al.*, 2011).

3.1.2 Poultry

Poultry meat is popular around the world due to its high nutritional values. Therefore, poultry carcass inspection is one of the most promising issues for computer vision, by which the whole poultry carcass can be inspected including identifying carcass diseases, detecting contaminants, as well as classifying the poultry carcasses. Recently, Chmiel *et al.* (2011a) evaluated the fat content of chicken breast muscles, thigh muscles (R^2=0.74) and turkey thigh muscles (R^2=0.65) by means of a computer vision system. However, it was difficult to distinguish between fat and meat in the images because of low fat content and similarity between the color of meat and fat as well as the existence of connective tissue. On the other hand, Girolami *et al.* (2013) reported that a computer vision system performed better than a Minolta CR-400 colorimeter in evaluating the colorimetric fidelity of the chicken images, on account that a colorimeter requires opaque and homogeneous matrices while computer vision system is much more flexible. More recently, most applications in this area are combined with spectroscopic techniques.

3.1.3 Other meats

The utilization of computer vision in fish, shrimps, and other meats like mutton and pork also holds great potential. Like beef meats, evaluation of pork and lamb meats focus mainly on texture features. For example, a study (Chandraratne *et al.*, 2007) on classification of lamb carcasses showed that models established by artificial neural network were more appropriate than that by discriminant function analysis. In that study, 136 textural features including co-occurrence, run length and gray-level difference histogram were extracted from the acquired images divided in three parts, and the results demonstrated that the classification accuracy of the three parts by using discriminant function analysis were 64.4%, 79.4%, and 84.4%, and those acquired by artificial neural network were 87.5%, 94.4%, and 96.9% (Chandraratne *et al.*, 2007). Also, Chmiel *et al.* (2011b) attempted to discriminate PSE (pale, soft, exudative) pork. In their study, 50 slices of pork *longissimus* muscles from 50 different animals were obtained and three color spaces (RGB, HSV/HSB and HSL) were used to predict the quality of the meat. The results revealed that it was possible to evaluate pork meat quality by using the three color spaces. Also, Girolami *et al.* (2013) reported that a computer vision system was better when compared with a Minolta CR-400 colorimeter in evaluating the colorimetric fidelity of pork. On the other hand, Alçiçek and Balaban (2012) proposed a new method (two-image method) to predict the quality of salmon pieces, squid tubes, as well as peeled raw shrimps. By using special polarized light, all images were acquired. This method was better for detecting semi-transparent materials and overcoming the difficulty in segmenting objects containing colors resembling the background. Later, color change of shrimp during drying under different drying temperatures and drying medium velocity was evaluated and color parameters were determined, including lightness, redness, yellowness, total color difference, chroma, hue angle, and browning index (Hosseinpour *et al.*, 2013).

3.1.4 Hams

Quality classification for hams is dependent on the amount of muscles and brine solution injected (Valous *et al.*, 2010a). High-quality ham can only be one single muscle and must show no injected water when being cut (Jackman *et al.*, 2010c). However, injection of brine solution in hams affects some quality parameters and increases weights, which are difficult to discriminate and classify from those of high quality due to similar appearance (Valous *et al.*, 2010a). Therefore, the introduction of computer vision in ham quality assessments can help to inspect the quality of hams more objectively and accurately (Table 2).

Iberian ham is popular in Spain, which is also a type of essential dish at banquets. Thus, many studies have been performed on Iberian hams. Antequera *et al.* (2007) detected *biceps femoris* and *semimembranosus* muscles in Iberian ham by means of magnetic resonance imaging combined with a fully automated image analysis. Moisture and weight in the product's ripening process were accurately evaluated and the coefficient for weight loss during the ripening process was R^2=0.992. Generally speaking, surface color plays a significant role in the quality of pork hams. Color of ham, one of the principal characteristics, was determined by using computer vision with high accuracy of 99.2% (Valous *et al*., 2009a) and 100% (Jackman *et al*., 2010c) by testing four types of pork hams, respectively. In addition, Ulrici *et al.* (2012) attempted to detect the red skin defect of raw hams by means of extracting the signals (called colorgrams) that codify the color-related information including a RGB (Red–Green–Blue) image. Furthermore,

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Iqbal *et al.* (2010) predicted images of three qualities of pre-sliced pork hams, and analyzed 26 color features and 40 textural features by using Mahalanobis distance and feature inter-correlation analysis. The most accurate correlation coefficient was 0.968 for bitonality. Moreover, correlation properties for pre-sliced cooked pork hams were quantified using detrended fluctuation analysis. The results showed that quality of three types of ham could be characterized and quantified with a global scaling exponent (Valous *et al.*, 2010c). On the other hand, Sánchez *et al.* (2008) conducted some research on controlling the process of ham salting, which is one of the classical processes in the meat industry. Quantifying regions of lean, fat, and connective tissue by using image segmentation and analysis of the relationships of those regions during the salting process were the main purposes in this research. In different regions of ham, the correlation coefficient about salt concentration at the end of salting step was 0.80. Except for traditional statistics and analysis methods, some new measures such as quaternionic singular value decomposition technique were proposed, resulting in high classification rates of 90.3%, 94.4%, and 86.1%, for the training, validation and test set, respectively (Valous *et al.*, 2010b). Valous *et al.* (2009b; 2010d) also used fractal metrics like Fourier analysis dimension and lacunarity to characterize the appearance of pork ham images. Multifractal analysis was also explored for the characterization of fat-connective tissue size distribution in pre-sliced pork hams by Mendoza *et al.* (2009).

In recent years, many studies have employed computer vision for the evaluation of turkey hams

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and chicken hams. In quality evaluation of these hams, color and textural features are the most significant attributes, representing their basic quality. For example, Jackman *et al.* (2010c) prepared turkey hams and evaluated their color and texture features, with a 100% correct classification rate attained for both calibration and validation sets. Iqbal *et al.* (2010) also evaluated color and textural features for turkey hams and achieved classification accuracy higher than 83.3%. Additionally, evaluation for chicken and turkey hams were achieved by computing pore area distributions, and the coefficients (R^2) of the fit equations (the fit equations were a polynomial function and a peak function) for the total pore area of roasted chicken hams and turkey hams were 0.983 and 0.917, respectively (Valous *et al.*, 2009a).

3.2 Fruits and vegetables

For fruits and vegetables, external attributes such as size, shape, colors, as well as defects, are factors affecting consumer preferences; therefore these attributes play an essential role in the quality assessment of fruits and vegetables. Computer vision has been widely used for inspection and classification for fruits and vegetables due to its non-invasive nature. Over the past decade, numerous studies have been conducted and encouraging results have been obtained. Table 3 summarizes applications of computer vision in some main fruits such as apples, oranges, berries, and banana.

3.2.1. Apples

Defect detection for apples is a challenging task, which is complex, difficult, and laborious. A 3-color camera computer-controlled system was established to help identify apple defects, and the apple images were segmented by a multi-threshold method. By using this type of detecting model, the classification error decreased from 15% to 11%, but the shortcoming of this model was its lack of differentiation of various defects (Zou *et al.*, 2010). The quality of bi-colored food products has been evaluated extensively. Multispectral imaging has been employed to evaluate the quality of bi-colored apples (Unay *et al.*, 2011). Textural and geometric features were extracted from segmentation regions and statistical and syntactical classifiers were trained with a recognition rate of up to 93.5%. Another evaluation for bi-color apples was performed by Kang and Sabarez (2009), who utilized a new simple segmentation algorithm to analyze dried apple slices, which was also suitable for measurement of multiple objects. On the other hand, Lunadei *et al.* (2011) established a multispectral imaging system to predict a color-changing process for fresh-cut apple slices, during which the color of the apple slices changed to brown by enzymatic action.

3.2.2. Oranges

Consumers tend to pay more attention to skin defects when they select fruits, especially oranges. The multivariate image analysis approach has been combined with computer vision to detect orange skin defects. For example, a successful coefficient of 100% was obtained to evaluate stem-end injured oranges by Blasco *et al.* (2007b). Later, Blasco *et al.* (2009b) identified eleven types of defects in five spectral areas, and the identification coefficient turned out to be 86%. The most successful result (up to 97%) was obtained by using ultraviolet-induced fluorescence to detect green mould (Blasco *et al.* 2009b). As oranges, after reasonable assortment, can better adapt to the demands of consumers, a computer vision system has already successfully provided some effective detecting methods to classify the oranges. Blasco *et al.* (2007a) applied a region-oriented segmentation algorithm to detect orange peel defects. The proposed algorithm could attain a high correct rate of 95% for detecting defects. Besides, defect detection was conducted on 120 samples of oranges and mandarins from four different cultivars with an accuracy rate of 91.5%. Classification was also conducted on these samples, which achieved a correct rate of 94.2% (López-García *et al.*, 2010). In addition, Wang and Nguang (2007) used computer vision with a low-cost sensor to determine the volume and surface area of limes.

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3.2.3. Berries

Without epicarp protection, berries are highly perishable and easily damaged. During the harvest season, in the transport and handing process, berries are usually bruised more or less due to mechanical forces. Therefore, color (Matiacevich *et al.*, 2011) and water content (Agudelo-Laverde *et al.*, 2010) were evaluated as two main quality attributes of berries. Furthermore, Lu *et al.* (2011) used SVM model based on fractal theory to detect bruises on red bayberries, obtaining an accuracy of 100%; however, by the models on RGB values, they only acquired an accuracy of 85.29%. In addition, a new study for blueberries was conducted by Swain *et al.* (2010) to predict the yield of wild blueberries in the field. The system included a digital color camera, a positioning system receiver and a computer mounted on a motorized farm vehicle. By using this specially designed vehicle, the yield of wild blueberries could be estimated in real-time and the prediction coefficient between the quantified part of blue in images and that of actual fruit yield was R^2=0.97 (Swain *et al.*, 2010).

3.2.4. Bananas and dates

During the ripening process, like most ordinary fruits, bananas are subject to the gradual transformation in color and texture. At a rapid speed of senescence, banana peels degrade from greenish-yellow to dark spotting (Quevedo *et al.*, 2008). As a result, scientific assessment for the over-ripening process is important to improve the quality of bananas and provide consumers with products of superior quality. Quevedo *et al.* (2008) showed that fractal texture analysis based on spectral Fourier analysis was a potential and promising method for evaluating “senescent spotting” of the banana peels. Later, Quevedo *et al.* (2009b) developed a “fractal browning indicator” based on non-homogeneous color information from digital images to evaluate the kinetic enzymatic browning in banana slices. In addition, it is of great significance to determine the ripening stages of bananas (Mendoza et al., 2005). Mendoza and his co-workers applied computer vision system for classification of the ripening of bananas based on color, development of brown spots as well as image textural characteristics. By using the three features of L*,a*,b*bands, brown area percentage, and contrast, they successfully classified 49 banana samples into 7 ripening stages, with an accuracy of 98% (Mendoza & Aguilera, 2004).

A computer vision system has also been used to classify dates. Ohali (2011) developed a date classification system with the help of a back-propagation neural network classifier. The system could successfully separate dates into three different quality grades with a rate of 80% accuracy. On the other hand, Lee *et al.* (2008) established a date maturity evaluation system by using color space conversion and color distribution analysis. This system had a high degree of automation and was suitable for commercial production. In conclusion, the computer vision technique is playing an increasingly role in evaluating the quality of bananas and dates.

3.2.5. Mangoes and pears

Mangoes are very popular in many parts of the world due to their bright color, special taste, and nutritional value (Zheng & Lu, 2012). Kang *et al.* (2008) used a computer vision system to monitor the ripening process of mangoes to ensure fruit quality; the system also provided a possibility for quantitative analysis of color characteristics. In addition, based on fractal analysis and CIELab parameters, Zheng and Lu (2012) employed least-squares SVM to classify mangoes into different grades and the results demonstrated that a classifier based on both fractal analysis and CIELab (with an accuracy of 100%) performed better than that based only on either fractal analysis (88.98%) or CIELab (85.19%). Moreover, computer vision evaluating systems were developed to detect enzymatic browning in pear slices (Quevedo *et al.*, 2009a; Quevedo *et al.*, 2011) and avocado purée (Quevedo *et al.*, 2011). In these studies, color in digital images was transformed into L*a*b* color space by means of a transformation function, and three kinds of pears were detected, and the results were encouraging.

3.2.6. Potatoes and beans

Potatoes are easy to grade due to their different sizes, shapes, and regularities. Therefore, classification for potatoes is very important before peeling. Two different studies based on the detection of size and shape achieved successful classification of potatoes into various grades. ElMasry *et al.* (2012) tried to sort irregular potatoes into different grades by using an automated computer vision system. A database of potato images was first established and then some indispensable physical characteristics were extracted, including perimeter, centroid, moment of inertia, area, length and width. Two tests were completed to corroborate the accuracy of classification and the most successful results showed that the correct classification rate was 96.5% for testing 228 potatoes. Another classification study for potatoes was conducted by Razmjooy *et al.* (2012), who used a real time computer vision system, and the accuracy of the classification was about 95%.

In general, beans are a particularly favorite vegetable due to their high nutritious values, including abundant carbohydrates, proteins, dietary fiber, and significant amount of vitamins and minerals. The essential physical characteristics of beans are the surface area and the volume. Therefore, some studies have been conducted to evaluate the quality of beans. Combining the computer vision system with artificial neural networks, a new classification system for beans was developed by Kılıç *et al.*, (2007), by which it was possible to correctly classify beans automatically, and the total correct classification rate was 90.6%. Besides, Firatligil-Durmus *et al.*, (2010) attempted to predict the sizes for legume seeds by means of image analysis.

3.2.7. Other fruits and vegetables

Computer vision systems can also be used for many other varieties of fruits and vegetables. In recent years, numerous applications have been described for food sorting and classifying, such as raisin sorting (Abbasgholipour *et al.*, 2011) by means of color segmentation. Additionally, a classification technique based on computer vision has made great progress for grading pomegranate arils (Blasco *et al.*, 2009a) and sweet cherries (Wang *et al.*, 2012). Blasco *et al.* (2009a) utilized two different image segmentation methods including thresholding and Bayesian linear discriminant analysis to classify pomegranate arils, and both methods had a successful rate of 90% on the validation set. As for sorting cherries, similar accuracy of 85% was obtained by overcoming two big challenges: the effect of inconsistent ambient light and glaring reflections on cherry skins (Wang *et al.*, 2012). Moreover, Jarimopas and Jaisin (2008) classified sweet tamarinds according to three attributes: shape, size, and defects. Analysis software was tested by changing three controlling factors: belt conveyor speed, pod spacing, and orientation. The results indicated that an accurate rate of 89.8% could be achieved for separating tamarind pods. On the other hand, Pace *et al.* (2011) evaluated the relationship between appearance and browning based on image analysis and chemical traits in fresh-cut nectarines. The chemical quality characteristics, including titratable acidity, browning score, and pH, were detected and quantitatively analyzed. A correlation coefficient of 0.76 was achieved. Finally, Wang and Nguang (2007) calculated the volume and surface area of axi-symmetric agricultural products such as lemons, limes and tamarillos, by using a low-cost image sensor.

3.3 Evaluation for other food products

Computer vision technology has found its way to the quality evaluation or classification of many foods, including nuts, grains, baked food, cheese products, and fried foods. Most of the attempts

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have achieved encouraging results, which should stimulate further research.

3.3.1. Nuts

Nuts are generally rich in nutrients, including significant amounts of proteins, fats, minerals, and vitamins. Defect detection is particularly important for nuts, and the computer vision system has shown some successful examples. Wang *et al.* (2011) applied pattern recognition to distinguish worn eaten chestnuts based on computer vision, and the classification accuracy was 100% for both worn eaten chestnuts and normal chestnuts. Most recently, Donis-González *et al.* (2013) investigated chestnut sorting by evaluating color, texture, and geometric features from computer vision images, and the overall performance accuracy was 89.6%. Moreover, Mathanker *et al.* (2011) employed AdaBoost classifiers to evaluate and classify defects in pecans. With the help of AdaBoost and SVM, a high classification accuracy of 99% was obtained. Besides, computer vision also showed the capability to separate nut meat from shell. Jin *et al.*, (2008) developed a computer vision system for separating black walnut meat from shell. Based on the differences between the characteristics of black walnut meat and its shell in backlit images, the overall separation accuracy rate of 98.2% was achieved by using a supervised self-organizing map and invariant features.

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3.3.2. Cereals

Lei *et al.*, (2007) monitored the change of the amount of rice–glucose–lysine blending with twin-screw extrusion by evaluating color development using computer vision as affected by different extrusion conditions including changing moisture content, screw speed, barrel temperature, and screw geometry, while Igathinathane *et al.* (2009) estimated the major orthogonal dimensions of eight types of cereals based on images. At a computing speed of 254 ± 125 particles/s, an overall accuracy greater than 96.6% was obtained to assess all shapes and particle orientations. In addition, Szczypiński and Zapotoczny (2012) employed a computer vision algorithm to identify barley kernels, in order to estimate orientation, and assess surface structure; an accuracy of 93% was obtained for surface structure.

3.3.3. Eggs

In egg production, cracks in the egg shell affect the quality and safety of eggs and may lead to bacterial contamination. Therefore, effective inspection systems are needed. Li *et al.* (2012) employed a computer vision system to identify micro-cracks in egg shells. In their study, they developed a robust algorithm to extract the crack from the acquired image and the presence of dirt in the egg shell did not affect the results. They achieved an accuracy of 100% by using this system. Wang and Nguang (2007) used a low-cost image sensor and a low-cost programmable microcontroller to automatically analyze the volume and surface area of the egg. Compared with the results obtained by traditional methods, a good accuracy of 95% was obtained.

3.3.4. Baked food

During baking, heat is transferred from the surface to the center, causing baked goods to have a firm dry crust and a softer center. One of the most common baked foods is bread and browning on the surface of bread during baking must be properly controlled as browning affects bread appearance and is an important quality index. Purlis and Salvadori (2007, 2009) used a computer vision system for monitoring weight loss variation and bread browning kinetics during baking. Apart from browning, thickness and other characteristics of the crust also affect the quality of bread. Mohd Jusoh *et al.* (2009) employed a computer vision approach with the L* a* b* color system to determine the thickness of bread crust by differentiating the crust from crumb color regions. Their results showed that thickness and color of crust increased with baking temperature and baking time, and baking temperature affected the crust structure more than baking time. In addition, Paquet-Durand *et al.* (2012) investigated ways to achieve optimal baking temperature and baking time, and their results demonstrated that the optimum baking process could be identified accurately by a computer vision system.

Pizza quality, involving pizza base, sauce spread, and topping, needs to be inspected. However, manual and visual inspection is time-consuming, laborious, costly, inconsistent, as well as subject to human error. Computer vision coupled with SVM has overcome these difficulties. Du & Sun (2008) attempted to perform a multi-classification of pizza base, sauce spread, and

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topping by using image processing and SVM. The encouraging results obtained demonstrated great potential of computer vision for multi-classification of pizza, which can be useful to pizza retailers in the future.

Biscuits are a type of popular snacks, and their visual qualities such as color, crust browning and surface cracking all affect consumer purchase decision. Lara *et al.* (2011) monitored changes in quality parameters of corn biscuits during baking as affected by baking temperatures, by means of a computer vision system continuously or in real time, and results showed that the system was effective.

Apart from evaluating the baking process, computer vision can also be used for real-time inspection of biscuits on a moving conveyor belt. Nashat *et al.* (2011) employed computer vision on the basis of color to classify biscuits into four groups presenting four degrees of baking (under-baked, moderately baked, over-baked, and substantially over-baked) by using SVM and discriminant analysis (DA) classifiers according to the extent of baking. The results showed that the classification rate by means of SVM-R was the highest compared with other methods, with an accuracy of 96.5%. Also, Mery *et al.* (2010) performed quality classification for corn tortillas by utilizing computer vision. They developed a computer vision system to classify corn tortillas into five grades determined by a sensory panel. The classification rate was over 95%. Their study has demonstrated the possibility of replacing manual inspection by computer vision for quality monitoring in tortilla manufacture.

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3.3.5. Cheese products

In recent years, there has been a trend towards developing new types of cheese. Thus, new techniques and approaches are in great demand for controlling cheese production and quality assessment. Jeliński *et al.* (2007) employed a computer vision system to inspect distribution and the amount of ingredients of two types of pasteurized cheese: one combined with garlic and parsley, the other mixed with vegetables including pepper and parsley. After building an image pre-processing algorithm and developing an image feature extraction method, the distribution and amount of each ingredient were estimated, achieving an accuracy of over 88% for estimating ingredient distribution and 71% - 81% for amount of ingredient.

3.3.6. Fried foods

Potato chips are among the most popular fried food products in the world. However, acrylamide has been found to develop during the frying process, which is a kind of chemical substance and can seriously affect the color quality of potato chips with potential harm to health. Image analysis was performed by Gökmen *et al.* (2007) to estimate the content of acrylamide in potato chips and French fries. They classified the pixels of fried potato images into three sets (Set 1, Set 2 and Set 3) and a close correlation between acrylamide concentration and the number of pixels in Set 2 was found.

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3.3.7. Tea

Tea is a significant crop of high nutritional and economic values throughout the world. There have been various instrumental and manual evaluating approaches available. However, computer vision has been proven to be more suitable as it can overcome the shortcomings of time consuming, inaccuracy, and high expenditure that are normally associated with the above traditional methods, and therefore it has been used for tea quality evaluation. For example, color differences were measured by computer vision to distinguish fermenting tea images using histogram method (Borah and Bhuyan, 2003). On the other hand, Wu *et al.* (2008) applied multispectral imaging for sorting different types of green tea based on the textural features of entropy values with 100% accuracy using least squares support vector machine (LS-SVM) combined with radial basis function kernel. In addition, wavelet texture analysis (WTA) method was adopted to discriminate images of eight different degrees of CTC (cutting, tearing, and curling) tea (Borah *et al.*, 2007). The classification rates were 74.67% and 80% by multi-layer perceptron (MLP) network and learning vector quantization (LVQ), respectively.

4. Future trends

Current research shows that computer vision is an effective, rapid, and objective technology for recognition, detection, and classification applicable to many agri-food products. Image acquisition is an essential step in a computer vision system, and a 3-dimensional image will

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reflect the features of samples more accurately and comprehensively. With the help of diverse algorithms, computer vision systems have the potential to combine with other non-destructive imaging systems to provide even better evaluations.

4.1. 3-Dimensional technique

In general, 2D can be competent to handle most cases for grading, classification, defect detection, and quality evaluation. However, 3-dimensional images may provide more information or details to improve quality analysis in many applications.

Uyar and Erdoğdu *et al.* (2009) predicted the size and shape of pears, strawberries, bananas, apples, and eggs by using a 3-dimensional scanner. More complex and irregular-shaped materials can be described with fewer errors and less time. Sun *et al.* (2007) detected the crease in grains and measured the thickness of wheat kernels by means of a 3-dimensional technique. However, its disadvantages may be the complex and abundant data analysis as well as the difficulties in establishing geometrical models.

4.2. Hyperspectral imaging

A computer vision system has the capability to provide superior spatial information for defect detection, classification, and sorting of food products by predicting external attributes such as size, shape, and surface color and texture. However, extra chemical composition information such as moisture, fat, and protein contents cannot be extracted by using computer vision alone. With the help of spectrometry, chemical composition information can be obtained successfully.

In a variety of applications, hyperspectral imaging presents excellent feasibility for defect detection (Kim *et al.*, 2007, Elmasry *et al.*, 2009, Xing *et al.*, 2007; Ariana and Lu, 2008), determination of quality parameters such as firmness and soluble solids content (SSC) in apples (Noh and Lu, 2007; Peng and Lu, 2008; Qin and Peng, 2009), sugar content in peach (Guo *et al.*, 2007), fat, water, and salt prediction in fish (ElMasry and Wold, 2008; Segtnan *et al.*, 2009), quality classification (Mahesh *et al.*, 2008; Choudhary *et al.*, 2009) and quality evaluation (Naganathan *et al.*, 2008; Qiao *et al.*, 2007; Park *et al.*, 2007; ElMasry *et al.*, 2009; Sivertsen *et al.*, 2009).

4.3. Combination of computer vision with sonar or acoustic response

Sonar technique combined with computer vision is a newly developed technology, which can be applied for detecting the content of impurities existing in milk, juice, and other liquid agri-food products as well as measuring viscosity by using different frequency of sound waves. However, it should be noticed that sound waves of high frequencies may probably heat the samples or even cause internal damage to the samples. On the other hand, by means of back-propagation artificial neural network, Pan *et al.* (2011) developed an eggshell crack detection system coupled with computer vision and acoustic response. The accuracy (98%) of the eggshell detection was better than that by either of the two alone.

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5. Conclusions

The development of computer vision is based on the hardware and learning algorithms, and the technique can be used to extract and analyze useful information from agri-food products to perform detection, recognition, and classification. The basic image processing procedure of a computer vision system is mainly composed of image acquisition, pre-processing, segmentation and recognition, among which segmentation is the most important step for extracting the region of interest. Computer vision system plays a vital role in evaluating food products, including inspection of defects, shape, size, color, maturity, and classification according to different quality levels, as well as process control. Products that can be detected by computer vision include meat, fruits, vegetables, nuts, grains and so on. On the other hand, the technology of computer vision can be developed further to combine with other techniques such as spectroscopy (hyperspectral imaging). Such combinations will further enhance the technique, with great potentials for future applications in the food industry.

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Figure captions

Figure 1 Components of a computer vision system.

Figure 2 Principles of a computer vision system.

Figure 3 Different levels in the image processing process containing low level processing, intermediate level processing and high level processing.

Figure 4 Chart depicting the amount of the published articles which were cited from ScienceDirect from 2007 to 2012 involving the studies utilizing computer vision system in the area of agri-food products.

Figure 5 Computer vision for evaluating beef consists of different image processing, such as (a) de-noised image (Du *et al.*, 2008) (b) meat sample image before and after segmentation (Jackman *et al.*, 2009b) (c) LD muscle image (Du *et al.*, 2008) and (d) marbling fat image (Jackman *et al.*, 2008). First row shows the beef in original captured image, and the second row is the tested beef after different image processing.

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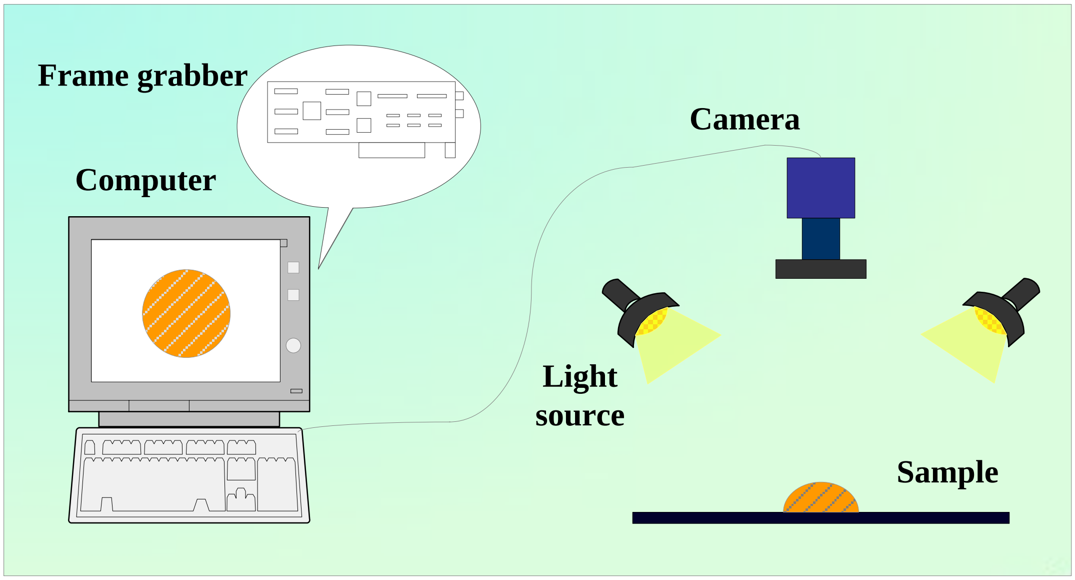


Figure 1. Components of a computer vision system.

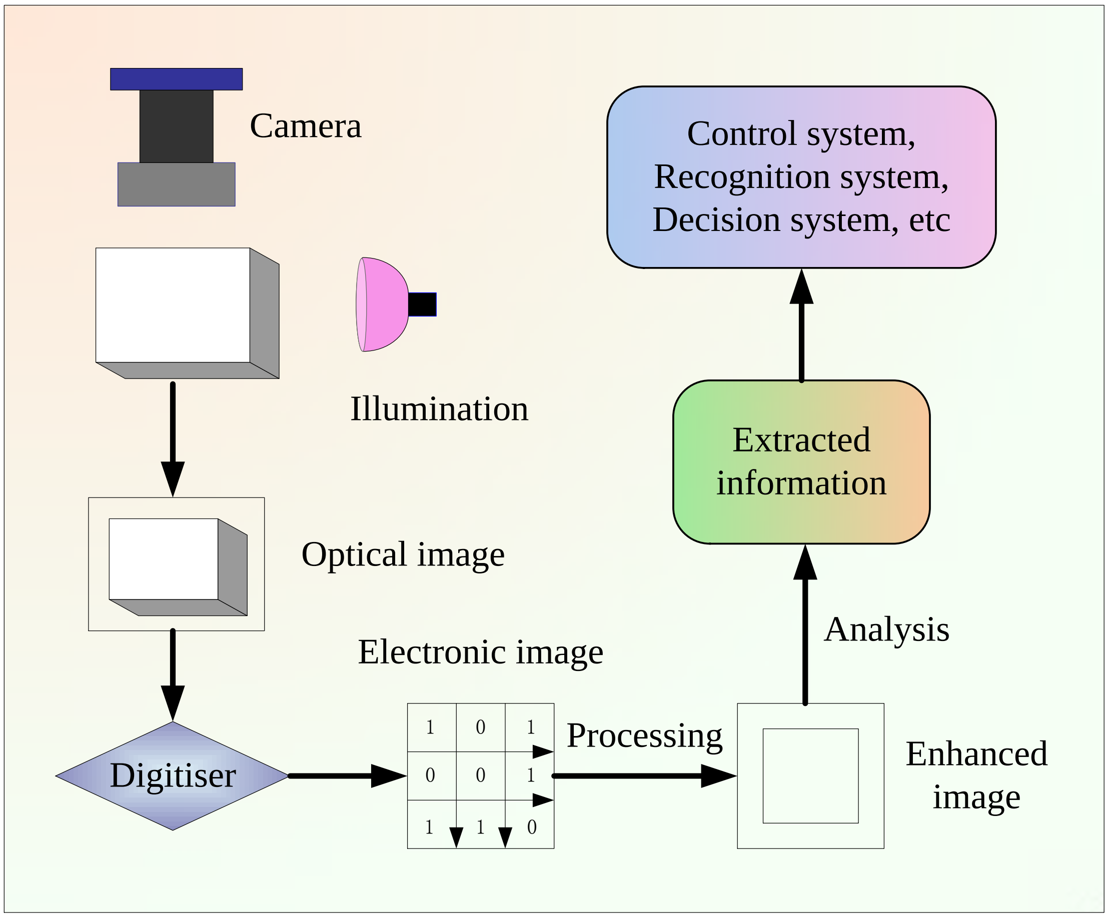


Figure 2. Principles of a computer vision system.

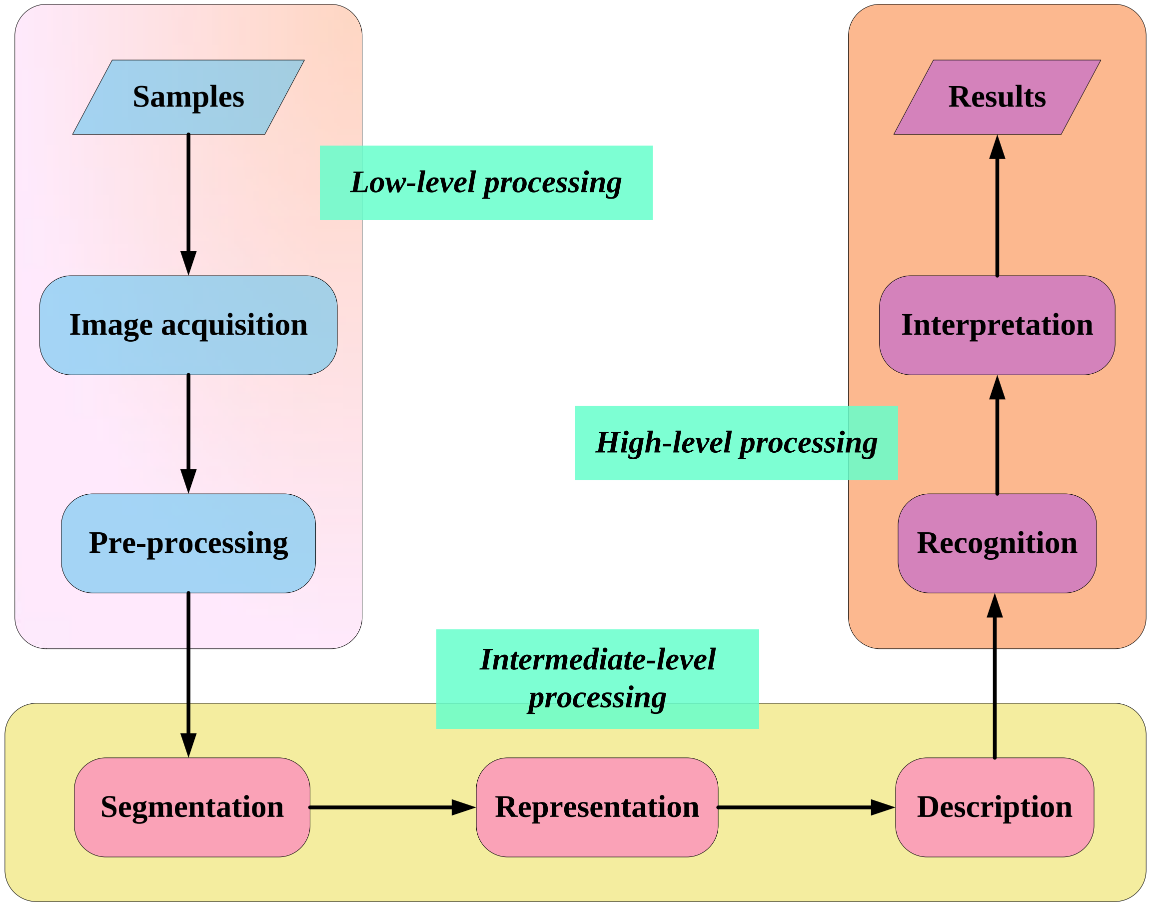
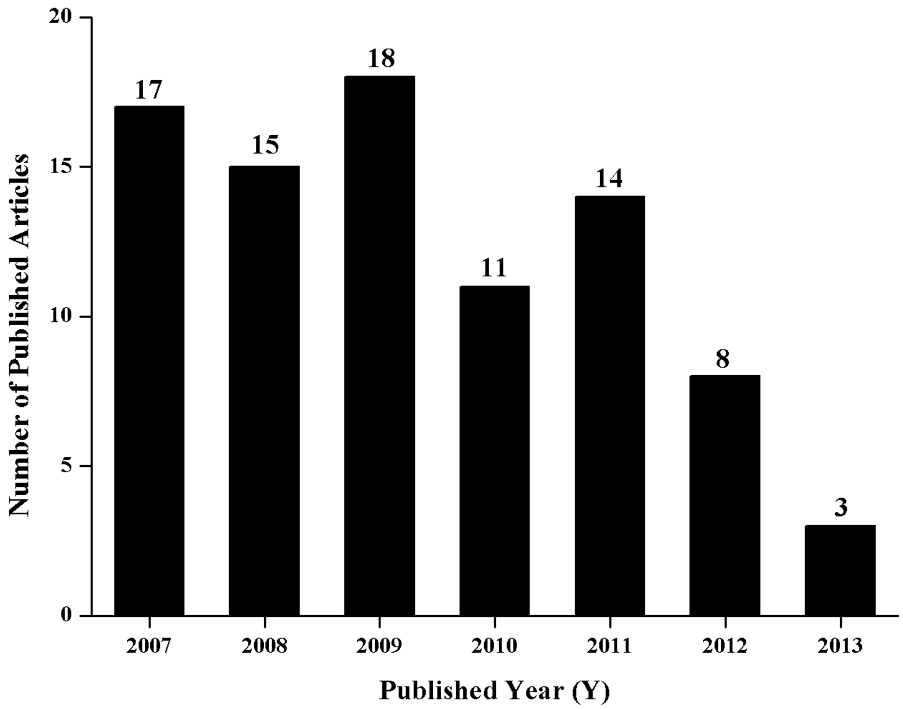


Figure 3. Different levels in the image processing process containing low-level processing, intermediate-level processing and high-level processing (Brosnan and Sun, 2004).



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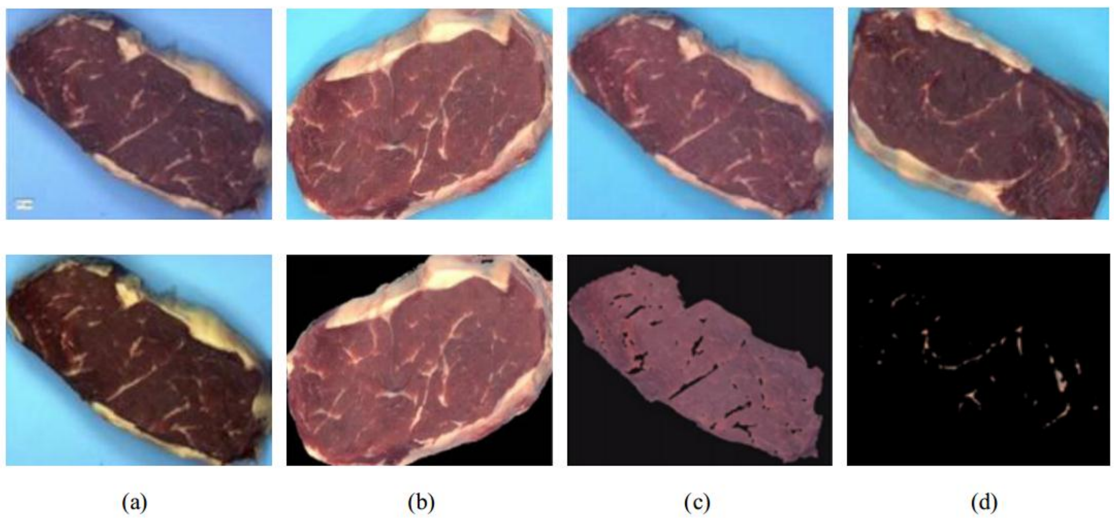

Figure 5. Computer vision for evaluating beef consists of different image processing, such as (a) de-noised image (Du *et al.*, 2008) (b) meat sample image before and after segmentation (Jackman *et al.*, 2009b) (c) LD muscle image (Du *et al.*, 2008) and (d) marbling fat image (Jackman *et al.*, 2008). First row shows the beef in original captured image, and the second row is the tested beef after different image processing.

Table 1. Applications of computer vision in quality assessment of beef sorted by different attributes

Product	Applications	Data analysis	Accuracy	Reference
Beef	Acceptability, tenderness, hardness, juiciness, flavor	PLSR	0.88, 0.78, 0.48, 0.60, 0.65	Jackman *et al.* (2008)
	Acceptability, tenderness, hardness, juiciness, flavor	PLSR, MLR	0.82, 0.72, 0.60, 0.46, 0.78	Jackman *et al.* (2009a)
	Acceptability, tenderness, hardness, juiciness, flavor	PLSR	0.79, 0.64, 0.29, 0.71, 0.82	Jackman *et al.* (2009c)
	Acceptability, tenderness, hardness, juiciness, flavor	PLSR,	0.91, 0.70, 0.56, 0.89, 0.72	Jackman *et al.* (2010a)
	Juiciness, tenderness, flavor	PLSR,	0.69, 0.76, 0.78	Jackman *et al.* (2010b)
	Texture with color and marbling, Texture only	PLSR	0.93, 0.79	Jackman *et al.* (2009d)
	Muscle color, marbling features		1, 0.96	Jackman *et al.* (2009b)
	IMF	KFCM	0.852	Du *et al.* (2008)
	Volume, surface area, major axis		0.684, 0.674 0.745	Zheng *et al.* (2007)
	Classification	SVM	0.974	Chen *et al.* (2010)

IMF= intramuscular fat, KFCM= kernel fuzzy-c-means

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Table 2. Applications of computer vision in quality assessment of hams sorted by different attributes

Product	Applications	Data analysis	Accuracy	Reference
Pork ham	Weight, moisture of biceps femoris and weight, moisture of semimembranosus	Dynamic programming	0.944, 0.944 & 0.681, 0.876	Antequera *et al.* (2007)
	Acceptability, surface color, color uniformity, bitonality, texture,	Mahalanobis distance and feature inter-correlation	0.924, 0.900, 0.902, 0.968, 0.741	Iqbal *et al.* (2010)
	Classification	Genetic algorithm	1	Jackman *et al.* (2010c)
	Classification	Quaternionic singular values	86.1%-94.4%	Valous *et al.* (2010b)
	Salting process	K-nearest-neighbors pattern recognition	0.80	Sánchez *et al.* (2008)
	Total pore area and total fat-connective tissue area	Thresholding	0.905-0.992 and 0.875-0.895	Valous *et al.* (2009a)
Turkey ham	Acceptability, surface color, color uniformity, bitonality, texture,	Mahalanobis distance and feature inter-correlation	0.895, 0.923, 0.936, 0.833, 0.859	Iqbal *et al.* (2010)
	Classification	Genetic algorithm	1	Jackman *et al.* (2010c)
	Total pore area	Thresholding	0.917	Valous *et al.* (2009a)
Chicken ham	Total pore area	Thresholding	0.983	Valous *et al.* (2009a)

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Table 3. Applications of computer vision in quality assessment of some major fruits sorted by different attributes

Product	Applications	Data analysis	Accuracy	Reference
Apple	Grading	SVM	93.5%	Unay *et al.* (2011)
	Defect detection	Multi-threshold	89%	Zou *et al.* (2010)
	Color quality	Thresholding		Kang & Sabarez (2009)
	Enzymatic browning	Thresholding		Lunadei *et al.* (2011)
Orange	Defect detection and classification	MIA	91.5% & 94.2%	López-García *et al.* (2010)
	Defect detection and classification	Thresholding	95%	Blasco *et al.* (2009a)
	Defect detection		95%	Blasco *et al.* (2007b)
	Defect detection	LDA	100%	Blasco *et al.* (2007a)
Berries	Bruise detection	Fractal analysis and SVM	100%	Lu *et al.* (2011)
	Yield		0.97	Swain *et al.* (2010)
	Water content	Thresholding	75%	Agudelo-Laverde *et al.* (2010)
Banana	Senescent spotting	Fractal texture analysis		Quevedo *et al.* (2008)
	Enzymatic browning	Fractal browning indicator		Quevedo *et al.* (2009b)

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