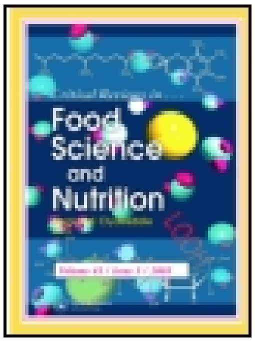

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REVIEW

Current progress in the utilization of smartphone-based imaging for quality assessment of food products: a review

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ABSTRACT
The cell phone has been merely used for image acquisition and transmission in the last decades. Owing to the recent technological progress, its new generation, i.e., the smartphone, draws remarkable attention to food quality assessment with versatile applications. Smartphones possess high-resolution cameras, enabling them to be used instead of digital cameras in the computer vision system. Furthermore, their programmability and portability have recently encouraged researchers to introduce smartphone-based image processing in food analytical studies. This promising approach has advantages such as high sensing capability, being user friendly, and cost-effective over the conventional method, and therefore might be considered an emerging nondestructive technique for quality control purposes. However, there is a great effort to tackle implementation, calibration, as well as industrialization issues. In this context, this review aims to highlight the most recent studies of smartphone-based imaging systems in various food systems such as dairy, meat, fruit, and vegetables. Besides, the existing challenges and future trends for applying smartphones in food quality control are discussed. Although moving the computer vision systems toward a portable tool like a smartphone improves its versatility, more research works are needed to resolve its set-up weakness and limitations.

KEYWORDS
Smartphone; computer vision; image processing; food products

Introduction

With the increasing demand for high-quality food products, the need for accurate and rapid quality assessment is growing. Various quality parameters of food are correlated to the appearance criteria such as size, shape, form, color, which can be monitored/inspected using visual assessment and/or image processing (Wu and Sun 2013; Kays 1991). The Computer vision system (CVS) is a powerful tool, which allows analyzing various appearance parameters (e.g., size, color, shape, and texture) from a digitalized image (Kandpal et al. 2019). This method has numerous advantages in speed, cost-effectiveness, and flexibility over conventional destructive methods (Sonka, Hlavac, and Boyle 2014; Sun et al. 2008). This superiority has made this method a useful non-invasive technique for various food analyses such as classification (Majumdar and Jayas 2000; Neethirajan et al. 2006; Du and Sun 2004), risk assessment of μ-hemolysin, paralytic shellfish poisoning toxins, saxitoxins, mycotoxins, and cholera toxin (Ye, Guo, and Sun 2019; McCracken and Yoon 2016), shelf-life studies (Grillo et al. 2014; Kamani et al. 2017) as well as adulterations assessments (Rafiq et al. 2013; Xiong et al. 2017; Mao and Huang2012). The CVS has thus far been introduced for quality assessment of a wide range of food categories, including in fish and meat (Storbeck and Daan 2001; Jackman and Sun 2012; Amani et al. 2015), fruits, and vegetables (Ding, Zhang, and Kan 2015; Vibhute and Bodhe 2012; Brosnan and Sun 2004), bakery and confectionery (Grillo et al. 2014; Kaur 2012; Abdullah, Aziz, and Mohamed 2000), and dairy products (Baiano 2017; Kucheryavskiy, Melenteva, and Bogomolov 2014; Agrawal and Goyal 2017).

Image processing is the core of CVS, which has different processing (low, intermediate, and high levels)(Sun 2012). This system is mainly composed of an image acquisition part, including a light source, camera, software, and hardware components (Hosseininia, Kamani, and Rani 2017). As the capturing device, the camera is an essential part of this system (Amani et al. 2015). The capturing device can be the form of a digital camera and webcam or scanner, which is externally connected to a computer, where image information is processed. A camera used for CVS can be characterized by white balance, aperture, ISO sensitivity, and exposure compensation. These parameters are briefly defined as below (Lin and Jerabek 2008; Blommaert et al. 2003):

- **Aperture** is specified as the f-value, the lens's opening part, where light passes through it. The range of this value may vary depending on the type of camera or lens. A lower number, such as f/1.8, indicates a wider aperture, and a higher number, such as f/22, denotes a

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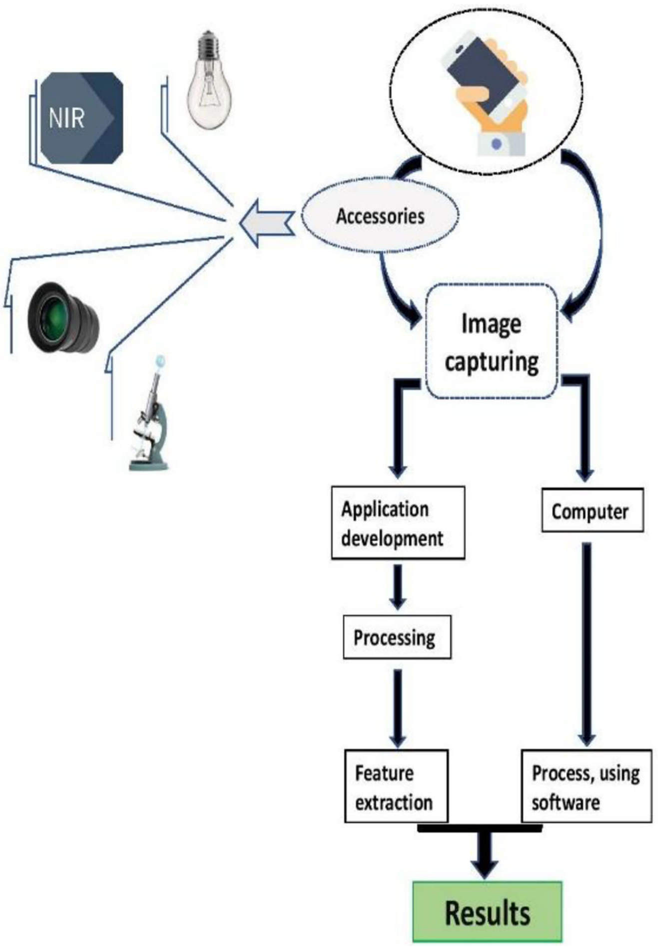

Figure 1. Flowchart of the general procedure of smartphone-based computer vision.

smaller aperture. When a lens is zoomed out to the widest position, the aperture value is f/1.8, which provides a shallow depth of field, and less of the photo appears in focus. On the contrary, when the lens is zoomed in, it can only have an aperture as wide as f/22 and provides a more in-depth focus but in less light.

- **ISO** is the digital equivalent (or approximation) of film speed, which determines how sensitive a camera is to incoming light. The faster ISO speeds indicate more sensitivity to light. Low ISO has the advantage of high accuracy of represented light in an exposure. Although high ISOs are costly, they can be useful for selecting more details in a dark photograph without decreasing the shutter speed or widening the aperture. However, with increasing ISO in the camera setting, image noise will dramatically increase.
- **Exposure** specifies the lightness/darkness condition(s) of a captured image. Exposure compensation helps to add or subtract light from an image. If the image is dark, it can be adjusted by exposure compensation. Exposure can be controlled by shutter speed, aperture, and ISO.
- **White balance** is related to the sensor, which works with the light's color instead of brightness. When the white balance is not accurate, color seems unnatural and fake.
- **Shutter speed** can control camera sensors' opening and closing to determine incoming light from the camera sensor. Also, it refers to how long this light is allowed to enter the camera. Many cameras have a mechanical shutter, whereas others use a digital shutter to allow light to reach the sensor. Shutter speed can be used to manipulate the optical effects of the final image. Slow shutter speed may cause blur in the subject.

With increasing advances in technology, the replacement of regular digital cameras by new smartphones has been initiated for two reasons: (i) appropriate resolution of a smartphone camera and (ii) its programmability. The smartphone camera can portably capture an image with high resolution, whereas its programmability enables users to accurately analyze the captured image via developing an app(s) (Jeanmonod, Keisuke, and Suzuki 2018). In this context, the food researchers have taken these advantages as a reference point and recently introduced the "*Smartphone-based Image Processing*" as a novel technique for imaging-based quality control of foods (Ye, Guo, and Sun 2019; Roda et al. 2016; Capitán-Vallvey et al. 2015; Bueno, Muñoz, and Marty 2016).

Apart from the mentioned advantages, smartphone-based image processing exhibits further benefits. This method enables users to implement a wide range of app software for different operating systems, including IOS, mobile, Windows, and Android, without requiring other analyzer factors (Lane et al. 2010). They can also design and develop their personalized app(s) based on intended data processing (Kwon and Park 2017). Moreover, in smartphones with built-in cameras, there is an option to easily set the camera setting (Zhu et al. 2013; Li et al. 2016). Furthermore, this method may not require an external computer, which is beneficial in terms of cost-effectiveness.

The smartphone-based computer vision technique is becoming a promising analytical quality assessment method for a wide range of food products (Consolvo et al. 2008; Miluzzo et al. 2008; Majdinasab, Mitsubayashi, and Marty 2019). In this perspective, this paper aimed to provide an overview of smartphone-based imaging systems' principal concept by explaining the current studies in different food aspects, including meat and fish, fruit and vegetables, milk and dairy products, water and drinks. Besides, it addresses the latest advances and current challenges of smartphone-based imaging techniques in the quality inspection of food products. Figure 1 shows the general procedure of smartphone-based computer vision.

Application of smartphone-based computer vision system in food products

Application of smartphone-based computer vision system in meat products

Meat products are one of the most popular food categories. In recent years, various quality aspects of meat products have been assessed by smartphone-based image processing methods. In this context, a machine vision-based smartphone app was recently developed by Hosseinpour, Ilkhchi, and Aghbashlo (2019) to predict the beef sample's tenderness. For this purpose, an image processing algorithm, namely rotation-, scale-, illumination- and translation-invariant, were employed to extract invariant texture features from fresh beef images. This algorithm could eliminate the effects of uncontrolled conditions during imaging and ensure the final results' accuracy. In addition to image analysis, the fresh meat samples were also subjected to texture analysis, i.e., the Warner-Bratzler shear force test. The correlation between this instrumental data and processed image features were assessed using an artificial neural network model. Their results indicated that the processed image textural features were well correlated with the instrumental data. The Android app could promisingly predict the tenderness in unseen meat samples with a high determination coefficient (0.98). Their findings ultimately suggested that the developed app had great potential to predict beef tenderness from its processed images (Hosseinpour, Ilkhchi, and Aghbashlo 2019).

In a recent study by Kartakoullis et al. (2019), a smartphone-based spectrometer's predictive ability was compared with a benchtop NIR spectrometer for estimating the protein, moisture, and fat contents in salted meat. Both spectrometers were used to acquire 1312 spectra from meat samples stored at different temperatures (ranging from −14°C to 25 °C). Different predictive models (global models, random forest, and partial least squares methods) were built to predict the targeted composition. The final output demonstrated that the constructed global model could successfully predict moisture and fat contents using the smartphone-based spectrometer. This predictive model showed acceptable accuracy for a wide range of temperatures that can be useful for quality control purposes (Kartakoullis et al. 2019).

In another attempt, Cruz-Fernández et al. (2017) developed a method for the determination of fat content in different cold meat products (cured ham, salami, chorizo, and Salchichón) using the processing of their images by a mobile phone. For this aim, image capturing of the samples was carried out by a smartphone camera and then followed by extracting RGB values' mean pixels (red, green, and blue) using MATLAB software. The estimation of fat content was also performed by the standard analytical method (Soxhlet method). The extracted colorimetric pixel information was then used as the input variable to study their correlation with meat samples' fat content using support vector machine and partial least squares methods. The best predictive capability between fat content and measured colorimetric parameters (R, G, and B values) was found for salami and salchichón meats using the support vector machine model. Based on this output, the authors suggested the smartphone-based imaging method as a useful nondestructive technique for predicting the fat content in meat products. However, heterogeneity in the meat sample (even in the same slices) causes high variability in the meat sample's fat content, which is an important obstacle for the accuracy of this proposed smartphone method (Cruz-Fernández et al. 2017).

Another research work focused on developing a portable system to monitor pork meat's pH (Yao et al. 2019). The system consisted of a hyperspectral scanner and a smartphone (as a data receiver) linked together through a wireless network. The system also had two white LED-type lamps to illuminate the sample (with white background) during the image capturing. The obtained images were then subjected to image analysis (generation of the hyperspectral cube and threshold segmentation) to compute the average reflected spectra. The meat samples' pH measurement was also carried out using a pH-meter and the models between the pH values and the image processing data were established using support vector regression (SVR). The overall results indicated the SVR prediction model and average reflectance spectra could quantitatively predict the meat sample's pH values. The prediction accuracy rate and R-square were found to be ∼ 90% and 0.93, respectively, indicating the good potential of the proposed method in real-time testing pH of the pork meat.

In a different approach, Liang, Park, and Yoon (2014) attempted to present a smartphone-based biosensor to quantify microbial spoilage of ground beef without using any common reagents. The developed biosensor system consisted of an iPhone 4S (with a software application and digital camera) and a near-infrared LED (10 mW, 880 nm). The *Xcode* application was programmed on a smartphone (iPhone 4S), which made the smartphone capture images at the four angles of the sample at a fixed distance. In order to simulate the spoilage, serial dilutions of *Escherichia coli* K12 (10^1–10^8 CFU/mL) were added to the ground beef samples, and the smartphone took pictures of *E. coli*-applied samples at varying angles (15°, 30°, 45°, and 60°). The images were analyzed using Image J software to identify the light scattering intensities. All images were circular-cropped, noise eliminated, and converted to grayscale to analyze the median intensity value and Mie scattering. Their finding indicated that the concentrations of *E. coli* could be determined by the pattern of such scatter intensities over the angles. Based on this output, the authors proposed this smartphone-based method as an inexpensive and rapid technique for determining the microbial load of meat products (Liang, Park, and Yoon 2014). However, there was a significant limitation in this proposed method. The method was not capable of pathogenicity assessment or distinguishing similar microbial species (for example, *Salmonella spp.* and *E. coli*) in the same meat sample, which is a significant drawback. Therefore, its application is solely restricted to the preliminary monitoring of meat samples for general microbial contamination.

As indicated above, meat and meat products have been regarded as an interesting specimen for quality assessment by several smartphone-based studies. However, variations in the nature or type of meat might result in various obstacles for image analysis. For instance, there is a high variation in the color/appearance of each type of meat, even if it is obtained from the same source. This variability typically results from the factors like feeding/breeding conditions of animals and/or during pre- and processing steps. These factors may also create heterogeneity in the distribution of principal visible constituents like fat, limiting this method's usability and accuracy. Therefore, to avoid the effect of this variation type, an advanced processing app(s) with sensitive features must be designed to accurately distinguish the existing differences, detect the false data and neutralize the unwanted effects during computation and processing of the image's features.

Application of smartphone-based computer vision system in fruits and vegetables

As the consumer's awareness and expectations increase, the importance of objective measurement for quality assessment of vegetable-based foods is parallelly increasing. Intaravanne, Sumriddetchkajorn, and Nukeaw (2012) utilized a smartphone to assess a 2-D spectral analysis to classify the ripening level in bananas (Intaravanne, Sumriddetchkajorn, and Nukeaw 2012). They examined two-dimensional images of the banana under different illuminations, viz., ultraviolet and white light. Calculated red, green, and blue color planes from these broad-spectral images were used to sort banana into three stages of immature, ripe, and overripe. According to the results, the banana's ripeness level could be successfully classified using this spectral method.

In another research, Aquino et al. (2018) developed a smartphone-based technique to assist berry counting in clusters images. The smartphone application was manually operated for this purpose, called *vitisBerry*. The analysis of the application was based on two devices, which could evaluate 12 varieties of grapevine. After the image acquisition, the RGB images converted to the CIE LAB color space. Morphological processing and maximum light reflection points were identified, and a neural network was applied to discard false positives. Mean and standard deviation of a* and b* in the CIE LAB color space were extracted as color descriptors. The developed application could successfully analyze 144 images of grapevine within only a few seconds. However, variations in the exposition of sunlight in vineyards can be a potential challenge for in-place use of this technique. Hence, future improvement might be needed by creating a broader variated training set of images in different imaging conditions to thoroughly neutralize this effect (Aquino et al. 2018).

A smartphone-based spectrophotometer was designed by Das et al. (2016) for nondestructive monitoring of fruit ripeness. A developed app was also utilized to receive, plot, and analyze the data by different features like controlling integration time and dark subtraction. In this method, each sample's chlorophyll spectra was measured by pointing the spectrometer to the sample's region of interest. The obtained results were compared with typical benchtop spectrometers in order to validate the described method. For this purpose, first, they measured the amount of Ultra-Violet (UV) fluorescence from chlorophyll in different varieties of apples during the ripening process. Afterward, they compared the obtained output with the existing routine laboratory tests. The results of this method showed a significant correlation between ripeness and fluorescence signals. Based on this output, these researchers suggested this nondestructive method as a useful tool for farmers to determine the optimum harvest times of fruits (Das et al. 2016). Since the current methods of testing ripeness in fruits are destructive (i.e., mechanical method), this device's nondestructiveness is advantageous for the farmers. Additionally, this method could also be adapted to screen defects, which might not be captured visually.

Although considerable research has been carried out on fruits and vegetables, more modifications should be implemented to obtain a clear output. For instance, a smartphone can quickly move, and the researcher can use this portability advantage for capturing 3D-images from fruit products. A 3-D structure image may give more in-depth information on the targeted sample condition and might also facilities the quantitative analysis of pixels by the processor app. Moreover, taking advantage of colorful plant components such as chlorophyll, a suitable indicator for photosynthetic activity in smartphone-based spectrometry, will be a smart idea to expand this technique's usability for quality assessments (e.g., ripening, defect, or damage) for various fruits and vegetables.

Application of smartphone-based computer vision system in milk and dairy products

The capability of smartphone-based computer vision, as a viable approach, has also been shown for the inspection and quality assessment of milk and dairy products. For the rapid quantification of alkaline phosphatase activity (ALP) in milk, Yu et al. (2015) developed a lateral flow-through strip using a camera of a smartphone as a convenient portable method (Yu et al. 2015). The strip was comprised of a conjugation pad loaded with phosphotyrosine-coated gold nanoparticles (AuNPs@Cys-Try-p) and a testing line coated with anti-phosphotyrosine antibody (anti-Tyr-p mAb). In this method, ALP's dephosphorylation activity at the testing zone could be quantified by evaluating the smartphone camera's accumulated AuNPs-induced color changes. Their results showed that the proposed method could provide a sensitive analysis of ALP activity for the raw milk sanitation examination. The main advantage of this proposed method is avoiding biohazard reagents, which decreases producing harmful wastes.

In another study, Masawat, Harfield, and Namwong (2015) proposed a portable iPhone-based colorimeter to quantitatively determine the level of tetracycline (TC) in different bovine milk samples (pasteurized, sterilized, and UHT milk) (Masawat, Harfield, and Namwong 2015). In this system, an application (named *ColorConc* App) was also used to measure the concentration of TC in samples using the image matching algorithm. For this purpose, the authors measured the color values including hue (H), brightness (V), Saturation (S), gray (Gr), red (R), green (G), and blue (B) obtained from digital images of standard solutions of tetracycline. In the next step, the color values were compared with the UV-Visible spectrophotometer results to predict TC's quantification. The results revealed that both techniques represented an agreement with no significant difference ($p > 0.05$). This technique also provided a simple, rapid, and high accuracy procedure for detecting any analytes with natural color or analytes having a color complex solution. The advantages of the method mentioned above might be due to the high speed of evaluation and the sufficiency of the application's one-time calibration per day for analyzing all the samples. Price and the size of the smartphone can be other pros when compared to other routine spectrometers. On the contrary, the technique's disadvantage might be the necessity of a steady condition of image capturing during the whole process.

Zeinhom, Wang, Sheng, et al. (2018) presented a sensitive smartphone-based fluorescence device to detect *E. coli* (*Escherichia coli*) in yogurt. The device was constructed of a laser-diode-based photo source, an insert lenses, and a long-pass filter, which provided minimum noise to the background imaging system. The certain concentrations of *E. coli* O157: H7 (10^1–10^6 CFU/mL) were impaled into the experimental samples, and their images were obtained with high resolutions. Data processing was performed using Image J software, and the amount of *E. coli* in real samples and solutions was counted. The analysis was based on converting the fluorescence image into fluorescence intensity that allowed the user to quantify *E. coli* in the samples. Values were compared with the commercial microplate reader in two different wavelengths. The results of the proposed method were in agreement with the microplate method. Hence, the authors introduced this developed device as a new promising platform for detecting food pathogens. However, like most smartphone-based sensing techniques, it has the weakness of afterward image processing. It worth doing further study on this method due to its high detection ability (Zeinhom, Wang, Sheng, et al. 2018).

In another research work, a smartphone-based nano immunosensor was developed to detect *Salmonella Enteritidis* in dairy products (milk and cheese) and water. *S. Enteritidis* in different concentrations were inoculated to cheese, milk, and tap water to examine anti-*S. Enteritidis* streptavidin magnetic beads and biotin-labeled antibody as capture platform and coupled with nanocomposite. Illumination light was arranged to uniformly function as the lightning source from a backlight panel for the microplate reader. A smartphone reader was employed to capture light signals from the microplate, and the imaging parameters like exposure time and ISO were adjusted by a designed application. The measurement of RGB values was carried out using the Image J software, and the absorbances were finally computed. The results were agreed with the ordinary microplate reader in terms of accuracy and sensitivity. This method detects 1.0 CFU/mL and 1.0 CFU/g *S. Enteritidis* in cheese, milk, and water, respectively. The recovery percentages were obtained by spiked cheese, milk, and tap water with different concentration of *Salmonella* (10^2, 10^3, and 10^4 CFU/mL) were 98.6 and 99.5 (for cheese), 98.2, 96.1 and 95.4 (for milk), 94.3 and 95.8, 101.2 and 97.8 (for water) using the described technique. Since the smartphone-based assay exhibited a similar accuracy performance to the microplate method, its possible application was suggested to detect foodborne pathogens in various food products (Zeinhom, Wang, Song, et al. 2018).

Application of smartphone-based computer vision system in water and drinks

There is increasing evidence of using the smartphone-based device as a useful tool for quality detection of water, documented by various research works.

McCracken et al. (2017) proposed a smartphone-based fluorescence sensing method to identify Bisphenol A (BPA) in water samples. For this purpose, a fluorescent probe (HPTS) with suitable specificity to BPA was used, and the detection of BPA was designed based on BPA–HPTS quenching interaction. Two different smartphones (Nexus 5X and iPhone 5s) were used for the smartphone detection systems, and their results were compared to the BPA quantified by the standard fluorescence spectroscopy method. Their results showed a strong HPTS–BPA binding complex and both smartphones exhibited the same response to fluorescence quenching. However, further research works like enhancing smartphone signal processing techniques suggested a more appropriate adaption of this proposed method for general environmental sensing (McCracken et al. 2017). In another study, Wei et al. (2014) presented a smartphone-based platform to determine mercury (II) ions in water samples with the two-color ratiometric technique's help. For digitally measuring the concentration of mercury, an opto-mechanical attachment to the smartphone camera was utilized. Different water sources, including beaches, rivers, and lakes, were measured using the proposed mercury contamination map (Wei et al. 2014). Their results introduced this new smartphone detection platform as a sensitive technique to digitally quantify the water's mercury level.

In another attempt by Levin et al. (2016), a smartphone-based colorimetric analyzer was developed to determine the fluoride concentration in drinking water (Levin et al. 2016). Three different commercial phones, namely Samsung DUOS, Moto G, and Asus Zenfone, were used for this goal. The software was also programmed to analyze the RGB color from the pictures of samples. The calibration of smartphones was also done using a blank solution and different standard samples of fluoride ranging from 0.5 to 2.0 ppm. This system consisted of a smartphone, test chamber, reagent capsules, and distilled water. The chamber was filled with the sample, and the zirconium xylenol orange reagent was located in the opening of the sample chamber. The reagent is dispensed into the test chamber after tightening the lid, and an immediate reaction between the sample's fluoride and reagent leads to produce a colored solution. Five images were captured using a smartphone camera, and then RGB color values were analyzed. Comparing these values with the interpolated color values was made, and the final concentration was calculated based on the resulting average. Results obtained from the smartphone colorimetric analyzer method were compared to the Ion-selective electrode (ISE) method. A positive correlation was also found between the ISE and the smartphone-based methods, with R^2 values between 0.9952 and 1.000, indicating the suitability of this new technique for measuring the fluoride level in water samples. High accuracy and cost-effectiveness are two major pros of this proposed method. However, a measurement limitation (up to 2 ppm) requires dilution before analysis, and the diluted sample may not give accurate results. It is a significant drawback, which should be addressed adequately in their future works.

In order to monitor the browning process in sparkling wine, Pérez-Bernal et al. (2017) proposed a new smartphone-based colorimetric approach. In this method, the smartphone camera (Apple iPhone model 4S, 8-megapixel) was used as the image acquisition device, and the captured images were processed via the image J software with the help of RGB color space. In this color space, each channel, i.e., R, G, and B, was separately extracted from photos and used to monitor the browning procedure. The browning indices of wines were in parallel estimated using two conventional browning methods (i.e., measuring 5-HMF content and absorbance spectroscopy at 420 nm), and their data were compared with the image processing approach. According to the results, red and green channels remained constant, whereas the blue channel exhibited changes, and therefore was deemed a quality determiner. The blue channel was positively correlated with the results of both conventional methods, implicating its potential as a suitable indicator to describe the browning process in wine. These results demonstrated that the blue channel could be used as a new indicator for assessing the wine sample's browning process (Pérez-Bernal et al. 2017).

In another research, Aguirre et al. (2019) recently developed a spectrometric smartphone-based detection system with dispersive liquid-liquid microextraction (DLLME) quantitively determine the ascorbic acid in the aqueous sample. This method was based on the extraction of aqueous-phase methylene blue using the oxidation-reduction reaction between methylene blue and ascorbic acid. The extracted methylene blue was then transferred to an aqueous media, and the developed smartphone system measured the spectrometric absorption of the sample. An illumination fiber was used to direct white light through the sample. The light was also reflected in the sample by a mirror, and the reflected light of the second pass was collected. This proposed applicability was assessed concerning natural orange juice and a vitamin C supplement, and its suitable performance was found in these samples representative compared to the standard laboratory procedures (Aguirre et al. 2019).

The feasibility of a smartphone-based sensor to quantitively measure the fluoride concentration in drinking water was investigated by Hussain, Ahamad, and Nath (2017). The system consisted of a LED flashlight (as the optical source) and an ambient light sensor (ALS) of the smartphone to detect light. A developed android App (called *FSense*) was also used to analyze fluoride in the water samples reliably. The method was designed based on the SPADNS colorimetric method, which includes a reaction between zirconium dye and fluoride and developing a colorless complex anion and the dye. With the increase of fluoride, bleaching of the dye occurs that may lead to a lighter color. The standard fluoride solutions with different concentrations (0–3.0 mg/L) were also used for calibration. Their overall results demonstrated that the proposed system could effectively estimate the concentration of fluoride in water samples (with a resolution of 1.23×10^{-4} mg/L), and its performance was found to be on par compared to its commercial counterparts. Comparing the findings of the method mentioned above with previous conventional methods indicates that the proposed sensor can be used as an alternative, inexpensive, and portable fluoride detection method. However, it would be more practical if these techniques' feasibility is also examined on other elements such as chloride and nitrate contributing to water contamination.

A smartphone-based sensor's efficiency for monitoring the salinity level in water was examined (Hussain, Ahamad, and Nath 2017b). For this purpose, two different sensor modules were presented, and their performances were comparatively assessed. The first technique was based on the Beer-Lambert principle, where attenuating a collimated light beam occurs when it passed through the saline medium. This phenomenon is owing to absorption by the medium, which is accurately detected and analyzed by the smartphone sensor. The second method was designed based on evanescent field absorption from an unclouded U-bent optical fiber. In this method, a smartphone was used to monitor the evanescent field's affected absorption, which results from variation in the salinity concentration of the surrounding medium of the fiber sensing region. In this system, an in-built flash lamp and smartphone ambient light sensor were utilized as source and image detector. To determine water salinity, the researchers used two free android-based apps (*stanXY* and *Light meter*) for salinity data analyses. Their overall output indicated the successful estimation of salinity level in a different range (0–100 ppt) in the water samples, and a good correlation was recorded when compared with the performance of a commercial conductivity meter. Therefore, the introduced smartphone method was proposed as a promising stand-alone device for measuring salinity concentration for various biological and clinical purposes.

Sumriddetchkajorn, Chaitavon, and Intaravanne (2013) introduced a smartphone-based self-referencing colorimetric technique to estimate chlorine concentration in water. A smartphone, reference scene, white light, and a transparent bottle filled with water samples were utilized to construct their system. Their goal was to design a capable system to fit both reference material and small transparent bottles in the field of view of the smartphone camera by using 2-D detection. This feature enabled them to obtain images with two regions, resulting in a self-referencing configuration. Following image acquisition, a specific color ratio from both obtained regions was used to convert the water's color inside the small transparent bottle into its corresponding chlorine level. Their findings revealed that this new system could estimate chlorine levels (in the range of 0.3–1.0 ppm) in the presence of a KI-starch solution and chlorine reaction. This technique had less than 7% errors and was proposed as a new portable platform for market applications (Sumriddetchkajorn, Chaitavon, and Intaravanne 2013).

According to the literature provided in this section, water has received more attention than other food categories to be analyzed by the smartphone-based imaging system, which might be due to the easy-to-assess nature of water compared to other complex foods meat, which has a complex biological matrix. Detection of colorless analytes like fluoride in water seems simpler than those analytes that have visible color. This issue becomes more complicated if the water sample has colored contaminations or turbidity that burden additional pre-processing efforts such as filtration or dilution before image processing.

Other applications of the smartphone-based computer vision system

Apart from the food, as mentioned earlier, a few studies have also investigated the application of the smartphone-based computer vision system in other food categories such as seafood, peanut milk, and beans. For instance, working on the marine toxins, Fang et al. (2016) designed a smartphone-based analytical method to rapidly quantify the marine toxins (saxitoxin and okadaic acid) in shellfish. The system consisted of a portable accessory, homemade strip, and smartphone (iPhone 5S). The smartphone was used as a light detector for image capturing and also for processing of the data. The authors also developed an IOS APP-iStrip to calibrate, measure, and share the data. The first step was noise reduction and filtering and then obtaining the pixel value valley, which is considered the sensor output. Image acquiring of unknown samples and finally calculating linear correlation to calculate the concentration of the sample was done. The results showed that the proposed method measured the ratio of saxitoxin and Okadaic acid marine toxins and proposed a promising platform for further food applications (Fang et al. 2016).

Dutta et al. (2017) described a smartphone-based platform to colorimetrically estimate protein, enzyme, and carbohydrate concentration in test samples (Dutta et al. 2017). In this system, a rear camera (8 megapixels) of an ASUS Zenfone 5 (for imaging) and a developed android App (for the colorimetric estimation of the sample) were used. The system's principle was based on capturing the samples' images, which were treated with the specific reagents, and further processing the image using HSV color space. In this space, V-channel was useful as a detection parameter to estimate the concentration of these biological macromolecules analytes. Comparing the obtained results from the smartphone system with standard spectrophotometry data (conventional laboratory method) showed similar sensitivity performance.

Shrivastava, Lee, and Lee (2018) described a sensitive culture-free method to detect *Staphylococcus aureus* in a minimally processed peanut milk sample using a smartphone-based platform. The proposed method utilized fluorescent magnetic nanoparticles to capture and quantitatively measure *S. aureus* by a smartphone camera. A bacterial cell detection cassette and a magnet holder were built up for accurate imaging of pathogens, and imaging was carried out with a smartphone-fluorescence microscope accessory, light, and a computer for image processing and analyzing the data. According to their findings, the presented method could provide a quantitative detect minimum concentration of 10 CFU/mL *S. aureus* cells by counting individual bacteria cells from a peanut milk sample within 10 minutes (Shrivastava, Lee, and Lee 2018).

For fermentation index prediction of fine cocoa beans, León-Roque et al. (2016) developed different models based on a simple artificial neural network (ANNs) and color measurement (León-Roque et al. 2016). They fermented cocoa; then, ANN models were tested using RGB values, which acquired using a mobile phone, scanner, and even absorption spectrum of extracts. The results demonstrated that this method could be applicable for predicting the fermentation index in cocoa beans as a suitable inexpensive, and easy method.

As compared to other food products, few attempts thus far have been made to assess the quality of grain-based products portably. While such promising techniques have a good research scope, more efforts must be devoted to this regard. Table 1 summarizes the smartphone-based method used for detecting/monitoring the various food samples.

Development of application software (app) for smartphone-based computer vision

As earlier mentioned, there is a growing interest in designing suitable applications, particularly for the android system, to make smartphones a unique optical sensing tool for quality assessment. In some cases, the developed apps have also capturing features, which enable them to take a picture of the sample directly; however, some of the apps do not have this feature, and their usage is limited only to processing the captured images. Various influential factors such as rotation, illumination, translation, scaling, and camera features (e.g., shutter speed, ISO, focus, and light balance) must be considered to develop an app. (Hosseinpour, Ilkhchi, and Aghbashlo 2019). These features must also be designed based on targeted foods' nature (liquid, semi-, or full solid) and intended parameters. For instance, Hosseinpour, Ilkhchi, and Aghbashlo (2019) designed an android app for LG smartphones called "*Beef Quality*" for predicting beef tenderness under uncontrolled conditions. The app was developed using Simulink programming, and modification was done to compile to Java programming language in Android Studio 2.0, 64 bits include Ice-cream sandwich platform, android software development kit, and Java development kit. Moreover, for image processing purposes, the Open CV_2.4.9 was used. This app's proposed algorithm was: Start → Take & read image → Illumination-invariant algorithm → Rotation & scale-invariant algorithm → Feature extraction algorithm → Neural network → Quality estimation and print the results. The *Beef Quality* app could

Table 1. Summary of the smartphone-based sensing researches for quality assessment of food products.

#	Sample	Purpose	Results	Reference
1	Beef	Prediction of tenderness of fresh beef	Developing a new machine vision-based smartphone app which could promisingly predict beef tenderness from fresh beef image captured with R^2 of 0.99.	(Hosseinpour, Ilkhchi, and Aghbashlo 2019)
2	Aqueous sample containing Vitamin C	Detection of ascorbic acid	Successful application of smartphone for quantification of ascorbic acid.	(Aguirre et al. 2019)
3	Berries	Evaluating the number of grapevine berries in vineyard	The new system could precisely detect the berry in clusters at phenological stages between berry-set and cluster-closure using developed app (*vitisBerry*).	(Aquino et al. 2018)
4	Standard solutions containing Ochratoxin A	Detection of Ochratoxin A	A new fluorescence analyzer developed based on smartphone camera, which was comparable with commercial equipment. However, a limit of detection was determined (2 μg/L).	(Bueno, Muñoz, and Marty 2016)
5	Cold meat products (*Salchichón*, *chorizo*, *salami* and cured ham)	Estimation of fat content	The new smart phone system (with the help of Partial Least Squares (PLS) and Support Vector Machine (SVM)) could estimate the fat content successfully in *salchichón* and *salami* sample.	(Cruz-Fernández et al. 2017)
6	Fruit	Determination of ripeness	Developing a wireless smartphone spectrometer with a dedicated app. This new system had comparable performance with existing benchtop spectrometer.	(Das et al. 2016)
7	Sample containing biological macromolecules	Estimating the total concentration of BSA protein, catalase enzyme and carbohydrate (D-glucose) in prepared samples	Developing a new smartphone-based sensing platform, including an android app, which could easily estimate the parameters from taken image. This new method was found to be similar as compared with the standard spectrophotometer method.	(Dutta et al. 2017)
8	Drinking water	Detection of fluoride level	Proposing a portable smartphone fluoride sensor using an ambient light sensor (ALS) and an android application "*FSense*" which could detect and analyze fluoride concentration level.	(Hussain, Ahamad, and Nath 2017)
9	Banana	Estimation of ripeness	Developing a cell phone-based two-dimensional sensor which can specifically classify the whole banana into immature, ripe, and overripe zones	(Intaravanne, Sumriddetchkajorn, and Nukeaw 2012)
10	Ground beef	Detecting microbial contamination (*Escherichia coli* concentration)	Proposing a smartphone-based biosensor (including an internal gyro sensor, developed app) that can monitor bacterial contamination in beef sample.	(Liang, Park, and Yoon 2014)
11	Milk	Detecting tetracycline	Introducing a portable iPhone-based digital image colorimeter with a *ColorConc* app. which could successfully monitor tetracycline in tetracycline solutions based on image matching algorithm Determination range was between 0.5–10 μg m/L.	(Masawat, Harfield, and Namwong 2015)
12	Water	Detection of Bisphenol A	Developing a smartphone-based fluorescence sensing method that successfully detected Bisphenol A in water sample with detection limit of 4.4 μM.	(McCracken et al. 2017)
13	Water	Measuring pH	Developing a handheld smartphone-based pH sensor that successfully measures the water quality. The obtained data were fairly reliable as compare to the results obtained from standard spectrophotometer tool.	(Dutta et al. 2015)
14	Sugar cane spirits (cachaça)	Determination of Methanol	The method could be detected by smartphone camera with regression coefficient (R^2) of 0.998. The developed method was compared with the spectrophotometric method with a confidence level of 95%.	(de Oliveira Krambeck Franco et al. 2017)
15	Cereals and feed	In-line quantitative inspection of zearalenone (ZEN)	Combination of a 3D printed smartphone-based detection with solid phase latex	(X. Li et al. 2019)

(*continued*)

Table 1. Continued.

#	Sample	Purpose	Results	Reference
			microsphere immunochromatography platform could detect ZEN with the coefficient of variation 2.7%-8.9% and 7.8-10.9%.	
16	Milk	Quality assessment of milk adulterated with melamine	A smartphone-based fluorescence spectrometer could successfully detect the amount of melamine in milk, with recoveries of 102.75%–105.64%.	(Hu et al. 2019)

capture photos from the beef specimen by pressing the respective bottom embedded in the app and further processed using the defined algorithm (Hosseinpour, Ilkhchi, and Aghbashlo 2019).

Aquino et al. (2018) recently introduced an android-based smartphone app named "*vitisBerry*." It was designed to assess vineyard features by counting the number of berries per visible cluster in images at a phenological stage between berry-set and cluster-closure. The application was first allowed to take a cluster picture. Then a three-steps algorithm was applied for image analysis, which includes: a) *Image pre-processing step*: It was included extracting the cluster in the image from the background and then converting from the native RGB into CIE L*a*b* space, and finally extraction of the region of interest using color discrimination criteria; b) *Image analysis step*: The extraction of berry candidates were done in this step. It was based on the light reflection pattern (using extended h-maxima transform) on the convex surface of berries, and c) *Image post-processing step*: This step's focus was on analyzing the set of connected components representing berry candidates previously obtained for discarding false positives. A set of berry descriptors was computed and presented as input to a neural network trained with supervised learning for each candidate. After analyzing all candidates, a probability map was created. Finally, the image was binarized by the threshold automatically provided by the Otsu's method and discarded the false positives. According to these results, the *vitisBerry* app constitutes a viticulturists' tool to easily acquire phenotyping information from their vineyards (Aquino et al. 2018).

Das et al. (2016) used an in-house app to develop a smartphone spectrometer for evaluating fruit ripeness used. The app had features such as reference plots, control over integration time, and dark subtraction and was capable of capturing plot and export data. The app first captured the sample's image, and then the region of interest was selected using a cross-polarizer and lighting arrangement on the smartphone. Afterward, the spectrometer was pointed to the region of interest, which was imaged earlier, and UV fluorescence of chlorophyll spectra was obtained at those locations. This data was then saved on the smartphone and used for further comparison with a commercial spectrometer (Das et al. 2016).

Hosu et al. (2019) utilized an android application (was called *ColorLab*®, available in Google Play Store) to develop a smartphone-based multiplexed enzymatic biosensor. The app used to enable the easy and clear display of the sensors' response, indicating remarkable optical feature changes. The images were acquired using a 16-megapixel camera of a smartphone at a fixed distance (60 mm). The *ColorLab*® was then converted to the pixel intensity of acquired images by its image processing algorithm. The algorithm initially determined each color spot's center to calculate the mean pixel intensity of 20 neighboring pixels. This new approach analyzed three analytes (i.e., hydrogen peroxide, glucose, and catechol) (Hosu et al. 2019).

An android application (called "*FSense*") was used by Hussain, Ahamad, and Nath (2017) to develop a smartphone-based sensor to detect the level of fluoride in water. The app was used to detect the intensity reading of the ambient light sensor (ALS) while measuring the fluoride concentrations of samples. The application was developed using MIT app inventor 2: a cloud-based platform where one can design and develop applications according to its requirement. Further, a light sensor extension provided by the Pura Vida app was also used for the detection of the modulated light signal intensity received by the ALS of the smartphone. In this study, the designed sensor was first calibrated with a known range of fluoride concentrations (0–2 mg/L). When the user inserts the fluoride content sample in the set-up's optical path, the smartphone measures the corresponding modulated light intensity in lux units. Using these pre-calibration data, the sensing app can estimate the unknown sample's fluoride level when the user clicks the "*Find Fluoride Concentration*" button in the application. A threshold level was also defined in the app for the fluoride, based on the permissible limit defined by the World Health Organization (WHO) (Hussain, Ahamad, and Nath 2017). The same authors used a similar approach to develop a smartphone-based device for salinity measurement in another effort. Two freely available android applications (*Light meter* and *stanXY*) were used in this study. The *Lightmeter* was applied to measure the light beam's intensity transmitted through the LUX unit sample. This app measures the average value by recording the minimum and the maximum variation of the intensity for a specific period. The digital output was then normalized by dividing with the intensity value when the sample holder contains only distilled water, and the normalized sensor response was computed. *StanXY*, the second app, was used to plot the variation of sensor data with a change in the medium's salinity level. The calibration curve of the absorbance values for standard saline media was obtained by this app, which was later used for estimating the salinity value in the unknown sample (Hussain, Ahamad, and Nath 2017a).

Working on meat products, Liang, Park, and Yoon (2014) focused on programming an application using *Xcode* in order to quantify the microbial contamination (*E. coli*) in

Table 2. The advantages and disadvantages of using smartphone-based computer vision system in food products.

Advantages	Disadvantages
• Being cost-effective and cheaper as compared to analytical method • Portability and nondestructiveness • Rapid analysis which is suitable for real-time monitoring applications • Easy-to-operate compared to the routine analytical method • User-friendly environment	• Limitation of computational power which may cause inaccuracy issue • Difficulty in proof accuracy in the heterogenic food sample like meat • Lesser images resolution compared to CCD camera images • Require developing specific app software for processing the images • Illumination limitation. In many cases additional accessories need to be attached (like diffuser) • Data processing usually must be done in another device

ground beef. The application allows users to take images with a fixed distance at four angles, shown by a built-in gyro sensor. The application further analyzed the pictures by an image processing algorithm. This process was based on estimating the scattering intensity of the surface in the meat sample, which was varied depending on the number of *E. coli* colonies. The results were finally displayed as bacteria concentration on the smartphone screen (Liang, Park, and Yoon 2014).

As mentioned in the above-summarized works, various mobile application software has designed and employed for quality assessment of food samples. However, most of them need specific calibration before use due to significant variation among phone, camera, or food samples.

Current challenges and gaps

Although there are numerous reports of using smartphones in computer vision systems in the literature, these works are mainly concerned with general proof of this concept, and the state of the art of these approaches is far from maturity. One of these significant limitations is maintaining the quality and uniformity of the captured images. The current smartphones have quality optical components in their built-in cameras, but they are not designed to use images for analytical purposes (Al. 2012). An entirely reliable method requires the images to be taken in the same fixed photographic conditions in terms of position, light, distance, pixels, and magnification to prevent non-standardized conditions and unwanted errors. Some optical components like optical fibers, macro lenses, collimators, and filters are not typically available for mobiles and must be produced for each application in case of need. Illumination conditions during image acquisition are also another potential uniformity challenge, which must be duly addressed when a smartphone-based system is designed (Contreras-Naranjo, Wei, and Ozcan 2016). For instance, light scattering from an unknown source may create an unpleasant noise. In this respect, different studies have been highlighted the concern of uniformity issues as a challenge during their analyses (Masawat, Harfield, and Namwong 2015).

The lag of data speed and storage in smartphones could be another limitation, as these data are vital for the performance of statistical and mathematical algorithms during image analysis (Zeinhom, Wang, Sheng, et al. 2018; Zeinhom, Wang, Song, et al. 2018; Cavallo et al. 2019). Besides, the smartphone's function alone might not be as efficient as laboratory instruments, and other supplementary attachment is necessary for its augment and proper performance. Another challenge is the existence of significant differences in smartphones' camera hardware, which results in remarkable variations in color sensing in the output data in different smartphones (Levin et al. 2016). This may oblige the end-user to set and define a specific re-calibration for each phone device. This re-calibration may also be applicable for each application software from mobile to mobile to ensure accuracy in the final result. Table 2 summarizes the significant drawbacks/limitations of smartphone devices' usage in computer vision systems against its advantages/benefits. Given the above gaps and limitations, future research works are suggested to resolve smartphone set-ups' weaknesses and limitations.

Conclusion and future perspectives

The significance of the smartphone, as the core communication device, is drastically increasing in daily life. Apart from communication, smartphones are regarded as a valuable set of sensors and features (e.g., camera, gyroscope, microphone, GPS, and digital compass), making them a portable, user-friendly device with versatile technological functions and applications. The current generation of smartphones is also programmable, equipped with the cheapest, robust embedded sensors, app software, and software development tools. The computational power of smartphones is almost comparable to the personal computers that include multi-core processors and GHz CPU frequency, several GB memories, and the ability to connect cloud computing. All these capabilities make the smartphone devices a promising part of a computer vision system for quality assessment of food products. The literature presented in this review paper revealed smartphone-based image analysis's successful applications in the quality assessment of meat, fruits and vegetables, water and drinks, milk, and dairy products. The reliability, accuracy, and repeatability of this emerging technology are also verified in various studies compared with standard analytical routine methods. Portability, rapidness, programmability, inexpensiveness, easy-to-implement, and operation and user-friendliness have been mentioned as prime superiority points compared to conventional methods. However, various limitations and drawbacks such as lesser image resolution compared to CCD camera or additional accessories requirement for processing data exist that require more efforts to resolve. Thinking about these significant challenges may provide motivations for future innovative trends in this field. Here are examples of these perspectives/trends, which can be considered in future studies to open up new avenues:

- Eliminating the illumination variations of the system using the additional device(s) such as flashlight
- Improving the detection limit using greater sensors and defining a precise threshold and permissible level in the respective app software as per the guidelines recommended by the food regulatory agencies.
- Avoiding re-calibration of the system for the subsequent analysis by defining a single-time calibration system.
- Developing efficient filtering tools to eliminate unwanted noise and false data during accelerated image processing conditions.
- Fully utilize network features of smartphones such as Bluetooth, GPRS, or 4G network as a communication tool for an online/wireless transferring data platform.
- Further research efforts must be devoted to fully convert this newly born concept into a reliable, standardized analytical method.

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Disclosure statement

The authors declare no conflict of interest.

Abbreviations

SDKs	Software development kits
CCD	Charged-coupled device
ALS	Ambient light sensor
ISE	Ion Selective Electrode
S	Saturation
Gr	Gray
H	Hue
V	Brightness (intensity value)
CR	Color ratio
WSN	Wireless sensor network
HSV	Hue, Saturation, and Value color space
CMOS	Complementary Metal-Oxide Semiconductor
CFU	Colony-forming unit
CPU	Central Processing Unit (of computer)
UV	Ultra-Violet
ALP	Alkaline phosphatase
TC	Tetracycline
ISO	International Standards Organization
GPS	Global Positioning System
GPRS	General Packet Radio Services
GSM	Global System for Mobile communication
ANN	Artificial neural network
LOD	Limit of detection
CVS	Computer vision system
IOS	Mobile operating system created by Apple
NIR	Near-Infrared
PLS	Partial Least Squares
SVM	Support Vector Machine
RGB	Red, green and blue colors
WIFI	Wireless fidelity
SVR	Support vector regression
ROI	region of interest
LED	Light-Emitting Diode
FMNPs	Fluorescent magnetic nanoparticles

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