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# Smartphones as tools for equitable food quality assessment

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ABSTRACT

*Background:* The ubiquity of smartphones equipped with an array of sophisticated sensors, ample processing power, network connectivity and a convenient interface makes them a promising tool for non-invasive, portable food quality assessment. Combined with the recent developments in the areas of IoT, deep learning algorithms and cloud computing, they present an opportunity for advancing wide-spread, equitable and sustainable food analytical methods that could be used at each stage of food production and distribution.
*Scope and approach:* This review focuses on the use of smartphone-based methods in food quality assessment and monitoring, with particular emphasis on the ones in which smartphones are used as detectors, either on their own or in conjunction with more elaborate analytical procedures. The role of these methods in common and equitable access to information on food quality is discussed, together with a consideration of the sustainability and greenness of the smartphone-based methods and a perspective on the methodology and validation. Additionally, recent developments and future research trends are also outlined.
*Key findings and conclusions:* Despite the persisting limitations resulting from technical difficulties and the complexity of the food sample matrix, smartphones will play an increasingly important role in popularizing the access to food analytical techniques for on-site analysis as a readily available and convenient integrated interface, connectivity and remote sensing platforms.

## 1. Introduction

The proliferation of smartphones equipped with relatively high-quality cameras has, in recent years, created entirely new possibilities for the wide-spread introduction of easily accessible tools for rapid quality assessment and quality assurance of food products ‘from farm to fork’ (see Fig. 1). In particular, the integration within the Internet of Things coupled with machine learning-based data processing and analysis tools might make tentative food quality tests truly and widely accessible to end-users, provided certain methodological difficulties are overcome. Such developments would be in line with the stipulations of green and equitable analytical chemistry (Chemat, Garrigues, & de la Guardia, 2019; Marcinkowska, Namieśnik, & Tobiszewski, 2019) which focus not only on reducing the environmental footprint of the analytical procedures but also on their widespread availability in terms of low price and applicability.

However, in many cases the implicit promise of using the smartphone’s camera for remote sensing is in reality far from being true. They are often used as convenient tools for data acquisition and processing and as a means of providing a graphic user interface in lieu of personal computers, while still requiring the use of peripherals for the actual analysis. In other scenarios, the analytical procedure required to obtain a meaningful result is relatively elaborate and involves the use of instruments typically only found in laboratories. In particular, time-consuming and multi-stage sample preparation procedures might discourage potential end-users. Moreover, such complexity severely limits the practicality of the proposed solutions, especially in field conditions, and negates the main advantages of using smartphone-based techniques in the first place.

While it is important to account for the issues associated with the use of smartphone cameras themselves, such as white balance functions optimized by default for photography in bright ambient light and the inter-model transferability of colour readouts, it is crucial to also consider and validate the proposed procedures from the analytical and food chemistry perspective. The usability of smartphones for food quality assessment, not unlike any other analytical procedure, is contingent on the repeatability, selectivity and limit of detection (LOD) of the proposed methods (Nelis, Tsagkaris, Dillon, Hajslova, & Elliott, 2020). These issues are particularly important when considering matrices as complex as food. In order to develop practical solutions, it is

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necessary to rigorously validate the smartphone-based approaches, considering the matrix effect, sampling conditions, and not relying heavily on model or heavily spiked samples. This review is concerned with assessing the current status of the approaches to food quality assessment using smartphones and to clearly identify the current limitations and future trends and likely developments. A focus is placed on developments in which smartphones are used as detectors, either on their own or combined with more elaborate instrumental and sample preparation procedures. The role of smartphones in common and equitable access to information on food quality is discussed.

## 2. Equitable and sustainable analytical chemistry

When assessing smartphone-based food evaluation methods, it is important to consider whether the solution in question is in line with the stipulations of sustainable analytical chemistry (de la Guardia & Garrigues, 2011; Keith, Gron, & Young, 2007). The development of novel analytical tools necessarily entails the validation and optimization of the procedure (improving specificity, accuracy, LOD, etc.), as well as the economic aspects of the analysis. However, it is perhaps equally important to consider the sometimes overlooked social and environmental aspects during the decision making and process development, which is the main idea behind the concept of sustainable chemistry (Marcinkowska et al., 2019). This social dimension is reflected by fair, common and equitable possibilities in obtaining information on purchased or stored food products quality. This ease of getting information can be assured with the development of analytical methodologies based on everyday devices, such as desktop scanners or more importantly smartphones.

It might be expected that the proliferation of smartphone-based personal food testing solutions involving e.g. the use of bioassays for quality assessment of food products might initially be limited to the developed countries. However, this likely will not be the case with food production. According to experts at FAO, family farms and small farms are responsible for over 80% of World's food production, and are estimated to constitute over 80% of World's farms overall (Lowder, Sánchez, & Bertini, 2019). The afore-referenced report calls for dedicating more attention to this category of farms and increasing their output as means for eradication of poverty, and indicates that technological progress is the determining factor in improving their

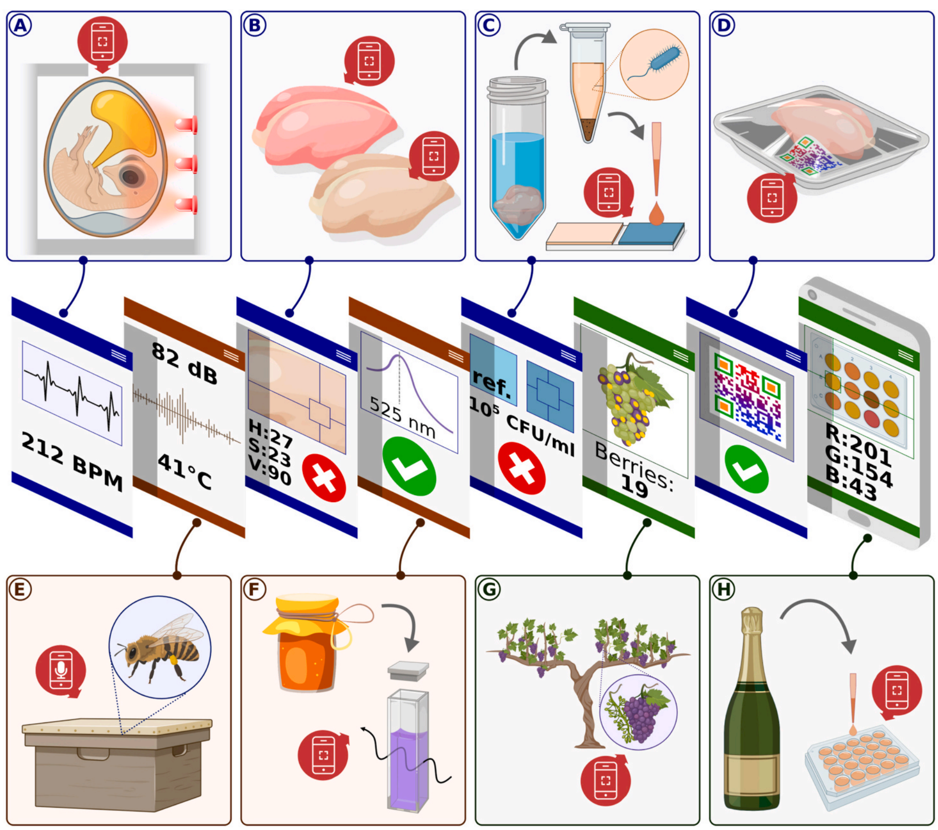


**Fig. 1.** Farm-to-fork use of smartphone-based food quality assessment tools.

- The viability and development of chicken embryos during artificial incubation may be measured in a non-invasive way by monitoring their heart rates using smartphones' video recording capabilities and an external red light source for photoplethysmography (A) (Phuphanin, Sampanporn, & Sutapun, 2019). During processing, the quality of the raw poultry meat, e.g. concerning the pale poultry syndrome, can be assessed by analysing its colour based on the analysis of pictures captured with the smartphone camera (B) (Barbin et al., 2016; You, Liu, Zhang, Xv, & He, 2020). The consumer's safety can be then assured prior to distribution, e.g. by testing for *salmonella* in chicken meat using magnetic particle immunoseparation-based biosensors in resource-scarce settings or as portable kits, with smartphones used for image analysis (C) (Guo et al., 2019), or during distribution and by the consumers themselves by scanning the colourimetric sensors imbedded in packaged poultry meat to detect the onset of spoilage (D) (Chen et al., 2017; Lee, Baek, Kim, & Seo, 2019; Rukchon, Nopwinyuwong, Trevanich, Jinkarn, & Suppakul, 2014).
- The beekeeper might monitor the hive microclimate and the thermal comfort of honeybees by detecting changes in the sound intensity level using the smartphone's built-in microphone (E) (Lima et al., 2019), while an opto-sensing accessory mounted on a smartphone and utilizing aptamer-conjugated gold nanoparticles for point-of-need safety inspection can be used to examine the concentration of streptomycin in honey (F) (Liu et al., 2017).
- Similarly, smartphone-based food quality assessment methods find application in wine production from the pre-harvest grapes inspection in the vineyard (G) (Ang, Seng, Oczkowski, Deloire, & Schmidtke, 2018; Aquino, Barrio, Diago, Millan, & Tardaguila, 2018) to detecting the deterioration of wine's organoleptic properties during ageing and storage by monitoring the browning process (H) (Pérez-Bernal, Villar-Navarro, Morales, Ubeda, & Callejón, 2017).

productivity. Since only approx. 2% of the farms are located in high-income countries (according to the World Bank (World Bank, 2017)), the effort to improve food production through technological innovation ought to be focused on developing countries. This seems to be the perfect use case for smartphone based food quality assessment, especially at the production and distribution stages, as their implementation could drastically improve the otherwise limited access to instrumental methods. For instance, while the machine learning-based methods for crop yield estimation might not be on par with industrial solutions used in extensive farming, they would be of great use in family farms in which the alternative would be to perform the assessment manually, or to dispense of it altogether. While the smartphone ownership in certain developing countries remains relatively low (e.g. 36% in Kenya and 32% in India (Schumacher & Kent, 2020)), it is increasing at a rapid pace, alongside with mobile network connectivity and bandwidth (*Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2017–2022*, 2019).

The environmental impact of the implementation of an analytical method is often indirectly considered during the evaluation of its economic aspects, since certain decisions, such as e.g. reducing the amount of used reagents or increasing the sample throughput might both reduce the operating costs and minimize the environmental footprint (de la Guardia & Armenta, 2011). The issue of the environmental impact can, however, be tackled more directly and purposefully by implementing the stipulations of green analytical chemistry, notably its 12 principles (Gałuszka, Migaszewski, & Namieśnik, 2013). In the context of food analysis, this could entail for instance the monitoring of various production processes in order to evaluate whether unwanted and/or hazardous by-products are formed and by favouring analytical methodologies which do not adversely affect the analyst's health or the environment.

While the 'greenness' of analytical methods is increasingly being considered during their development (Aparecida de Marco, Saú Rechelo, Gandolpho Tótoli, Carolina Kogawa, & Regina Nunes Salgado, 2018; Gilbert-López, Mendiola, & Ibáñez, 2017; Pena-Pereira, Wojnowski, & Tobiszewski, 2020; Płotka-Wasylka, 2018), their social dimension is often overlooked. One of the main tasks of analytical chemistry is to provide analytical information according to the requirements of end-users (Koel, 2016), which is particularly important in the context of food safety and quality control, where ideally the product should be tested by manufacturers, distributors and consumers to assure the latter's well-being. For this reason, analytical devices and the possibility of their use as well as the results of the measurements, should be accessible to everyone who may need them. In other words, emphasis should be put on the development of analytical methodologies that can be applied by non-trained users, preferably with the use of low-cost, readily available equipment. The ubiquity of smartphones, with their integrated and portable suite of features such as optical and other sensors, network connectivity, processing capabilities and, perhaps most importantly, familiar and accessible interface makes them the obvious choice when aiming at increasing the accessibility of food analytical methods (Grudpan, Kolev, Lapanantnopakhun, McKelvie, & Wongwilai, 2015; Roda et al., 2016).

## 3. Smartphones: self-contained, mobile spectrometers

Perhaps the most intuitive application of smartphones in food quality assessment and monitoring would be to use them as mobile spectrometers, since nearly all currently marketed devices are equipped with complementary metal-oxide-semiconductor (CMOS) camera which could act as a detector, coupled with an integrated user interface and image processor. However, there are several factors to which one can attribute the lack of general-purpose smartphone-based spectrometers (Scheeline, 2016). Smartphones are not specifically designed as optical measuring instruments and their image sensors register polychromatic light which decreases the certainty of measurement and resolution (Capitán-Vallvey, López-Ruiz, Martínez-Olmos, Erenas, & Palma, 2015). While on paper the sophisticated smartphone camera sensors with their >40-megapixel resolution (in some recent models up to 100-megapixel) seem more than sufficient for photometry, their performance is limited by the small pixel size and 8-bit digitization, which degrade the S/N ratio and precision. The latter will, however, be greatly improved, since smartphone models with 10-bit encoding are being introduced at the time of writing, effectively increasing the colour palette from $256^3$ to $1024^3$ colours (Tonelli et al., 2019), albeit at the cost of increased file size and computational effort. Still, the capabilities of most smartphone camera sensors are adequate for screening tests and field use (Scheeline, 2016), as evidenced by the number of reported possible applications (Aguirre, Long, Canals, & Cunningham, 2019; de Oliveira Krambeck Franco, Suarez, & Santos, 2017; Jung, Kim, Kim, & Bae, 2017; McGonigle et al., 2018; Patange, Mukundan, & Kumar, 2005; Rico-Yuste et al., 2016; Salinas et al., 2014; Scheeline, 2016; Song, Jiang, Wang, & Vincent, 2020; Ulrici, Foca, Ielo, Volpelli, & Lo Fiego, 2012). Another possible future improvement is broadening the sensor's response range. This could be achieved simply by removing the existing bandpass filters which limit the response only to the visible spectrum or by introducing additional ones, widening the range to between ~310 nm and ~900 nm (Wilkes et al., 2016). This would limit the camera's usefulness for conventional photography, but the manufacturers seem willing to equip the smartphones with as many as 5 or more rear-facing cameras, each with its sensor (Gartenberg, 2019), and so such development does not seem entirely unlikely. It would be particularly useful for non-invasive food content measurement – an application in which NIR spectrometry is already commonly used (Porep, Kammerer, & Carle, 2015). Alternatively, the analytically useful spectrum of radiation could be extended by using external UV light (Intaravanne, Sumriddetchkajorn, & Nukeaw, 2012), also for excitation in fluorescence-based tests (Feng et al., 2013).

Another factor limiting the proliferation of direct smartphone camera-based spectrometry in particular, and smartphone-based imaging in general, is the rapid pace of the development of new image sensors, which presents challenges for standardization (Ozcan, 2014). While most new smartphones now offer access to raw image format (RAW) files, and so to the signal from individual pixels, it should be remembered that proper colour calibration and white balancing is a challenge for professional photographers, and requires at a minimum the use of calibration cards or another reference. In the mid-2010s the reader would point to the possible solving of this issue through the imminent development of modular smartphones with the then ongoing projects such as Ara, Phoneblocks or RePhone (Hankammer, Jiang, Kleer, & Schymanietz, 2016, 2018). The latter could be even equipped with modules geared towards remote sensing, such as a UV sensor or a micro electro mechanical system (MEMS) gas sensor ("RePhone Introduction - Seeed Wiki," n.d.). The implementation of an array of metal–oxide–semiconductor field-effect transistor gas sensors in a replaceable module which could operate as an electronic nose, would have been a particularly useful development. This is because their use in smartphones, despite the small size and low power consumption, is limited by issues with long-term durability and signal stability (Wojnowski, Kalinowska, Majchrzak, Płotka-Wasylka, & Namieśnik, 2019). However, some five years later these concepts have not gained sufficient traction to disrupt the industry. The issue of sensor readout equivalence will perhaps only be compounded by the manufacturers increasingly relying on computational photography for improving image quality, making them even more reluctant to open the access to back-end image processing protocols, and so the researchers instead turn to machine learning to tackle this problem (Abdalla, Cen, Abdel-Rahman, Wan, & He, 2019; Solmaz et al., 2018).

Apart from the camera, smartphones are also equipped with other sensors which could potentially find application in food quality assessment. A good example is the use of the built-in microphone to monitor the thermal comfort of honeybees. The intensity of the sound produced by the insects and registered using a smartphone was linked to the hive microclimate which impacts the honey production and, more importantly concerning agricultural output, the foraging activity of the bees, leading to the pollination of crops (Lima et al., 2019). The device's microphone, in combination with its speaker, could also be used for ultrasonic sensing (Wang et al., 2019) which could be particularly useful for characterization and control of processes such as drying, emulsification, fermentation or crystallization (Mohd Khairi, Ibrahim, Md Yunus, & Faramarzi, 2015).

The current technical difficulties with realizing the smartphone-as-spectrometer concept in food analysis have led some to believe that the future trend will be to combine smartphones with inexpensive attachments with optics (Scheeline, 2016). Others, however, work on increasing the accessibility of food analytical chemistry through the integration of the already-existing methodologies with smartphone-based detector systems, as described in the following section.

## 4. Smartphone-based biosensors

The integration of the already-existing methodologies for food analysis with smartphone-based detector systems is an interesting example of efforts to make food analytical chemistry more accessible. For instance, the coupling of various immunoassays and smartphones is gaining popularity in multiple fields of science. Methods in which the formation of a complex between the analyte and an antibody are used in order to achieve the detection, i.e. immunoassays, have gained vast popularity due to the simplicity of their use (Dixit & Twyman, 2019). Since the results can be expressed through the appearance of one or two coloured lines (control line indicating correct functioning of the assay and, possibly, the test line indicating the presence of the analyte in question), they can be easily read even by a non-trained individual in a way not unlike the interpretation of pregnancy test results. While in some use cases the test's results can be evaluated using the naked eye, this approach is usually not sufficient in situations in which the results obtained using immunoassays are quantitative. This is where the coupling with smartphone-based detection systems facilitates the quantitation of the results, since the intensity of the test line's colour usually depends on the concentration of the analyte. Owing to the advances in smartphone imaging, it is possible to discriminate between colour intensities which would otherwise be indistinguishable to the human eye, especially after converting the colour space from red, green, blue (RGB) model to e.g. hue, saturation, intensity (HSI) colour model, where the intensity component can be easily isolated (see Figs. 1 and 2). For example, in the study of Li et al., latex microsphere immunochromatography was integrated with a smartphone-based device in order to perform a quantitative detection of zearalenone, mycotoxin often present in cereals and feed (Li et al., 2019). With the use of test strip, smartphone, a 3D-printed device with two lenses and *camera obscura* they obtained results highly consistent with the results obtained with both commercial kits and LC-MS/MS.

While paper-based reaction strips are seen as easy to use, even in the field or by untrained personnel, the same cannot be said about glass capillaries which are often used e.g. for the detection of contaminants. However, their fragility limits their usability in field applications. For instance, a smartphone attachment for *E. coli* detection in liquid samples based on quantum dot-based sandwich assays requires a rather

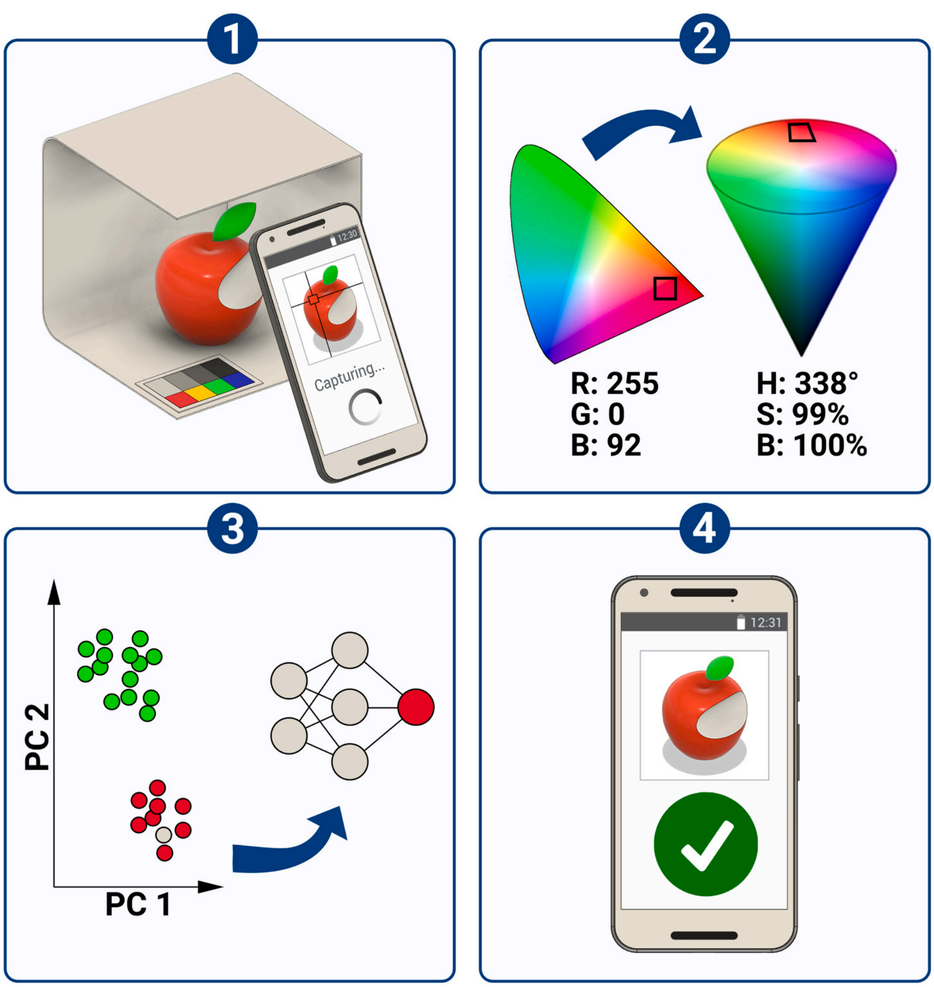


**Fig. 2.** A schematic representation of the approach to food quality assessment based on remote sensing with a smartphone camera: (1) capturing an image in a controlled environment, with reference colour values for calibration; (2) image processing: white balance, calibration, RAW conversion, colour space translation, etc.; (3) extraction and standardization of variables, followed by application of a machine learning model; (4) result expressed in a way convenient to the end-user. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

complicated sample preparation stage to perform the analysis (Zhu, Sikora, & Ozcan, 2012). The use of similar methods in the home setting is further complicated by the need to use equipment that is relatively difficult to obtain and might be too burdensome for someone with no laboratory experience. Since the capillary tubes used for the analysis can be secured within the device, they are far more useful in resource-limited environments compared to traditional capillary-based analytical methods, if not yet ready for home-use.

The ease of use is, however, of utmost importance in the various methodologies developed for the detection of allergens in food products in response to the emerging need, such as the smartphone-based quantum dots ratiometric fluorescence-sensing system for monitoring fluoroquinolone antibiotics in food samples (Ye et al., 2020), or the pocket-sized system utilizing a magneto-chemical sensor for the detection of antigens (Lin et al., 2017), shown in Fig. 3. The system consists of a pocket-sized detector, electrode and extraction kit that may be disposed of after use. Antigens are extracted from food as well as concentrated with the use of the kit and subsequently quantified using a keychain-sized reader in under 10 min. Since the cost of a single analysis is estimated by the authors to be lower than 4 $, it represents a tangible step towards implementing the stipulations of equitable chemistry. The prototype system was tested for only five model antigens, and further research should be performed in order to assess the impact of various food processing techniques and matrix composition could have on extraction and detection of the analytes. However, it showcases the potential of placing smartphone-based biosensors in the hands of involved consumers.

In a similar approach, a smartphone-mounted tube reader was developed for use in tandem with allergy test kits by measuring the absorption of colourimetric assays (Coskun et al., 2013). This application showcases the advantages of utilizing the intuitive and interactive smartphone GUI, guiding the untrained user through the steps required to perform the analysis using a user-friendly interface. This, combined with the possibility of uploading the test results to a dedicated server to build allergen maps, thus leveraging the inherent connectivity of smartphones, indicates the possibility of overcoming the difficulties outlined in Sections 3 and 6. Focusing on utilizing the numerous advantages of smartphones as platforms in which detection and communication capabilities are integrated with a convenient interface might bridge the gap in analytical capabilities between developed and developing countries. Solutions which, when implemented, could facilitate performing routine analyses in resource-scarce environments also include the smartphone-integrated rapid diagnostic tests (RDTs), like the ones used in medical diagnostics (Mudanyali et al., 2012). While these were not developed specifically for food safety assurance, they could be relatively easily geared towards detecting e.g. *E. coli* instead of *M. tuberculosis*. Some methods based on the use of smartphone biosensors, like the one developed for the determination of the phenol index using emulsification microextraction (Shahvar, Saraji, & Shamsaei, 2020) involve sample preparation stages, which might be either too complicated to be performed by untrained staff, or at least not practical in field conditions, as is the case with the method for allergen determination illustrated in Fig. 4. Nonetheless, they could nonetheless greatly improve the accessibility of food analytical methods.

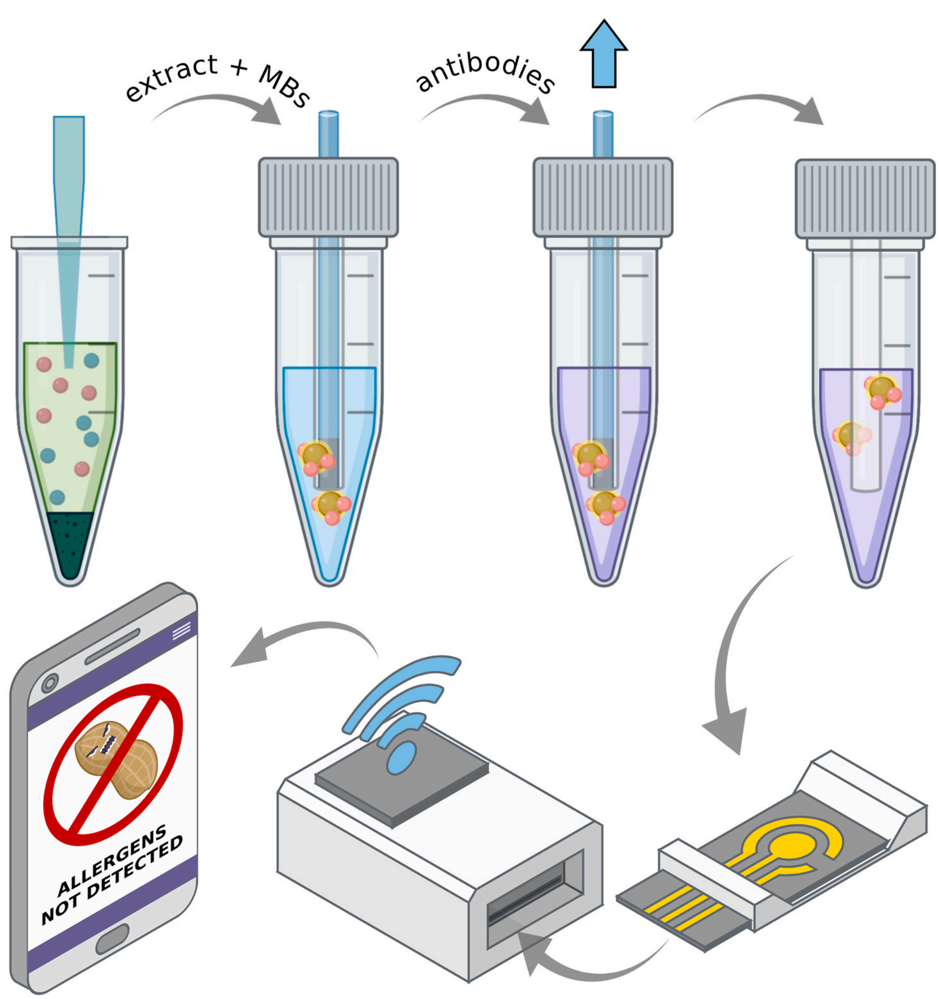


**Fig. 3.** A pocket-size system for antigen detection. Antigens are captured on magnetic beads (MBs) which are held in place during the extraction stage using a sheathed magnetic bar and subsequently labelled with antibodies conjugated with oxidizing agents. The MBs are then mixed with electron mediators and applied on an electrode which is then inserted into a reader which in turn transmits the data to a smartphone, allowing for data registration and system control. Adapted with permission from (Lin et al., 2017). Copyright 2017 American Chemical Society.

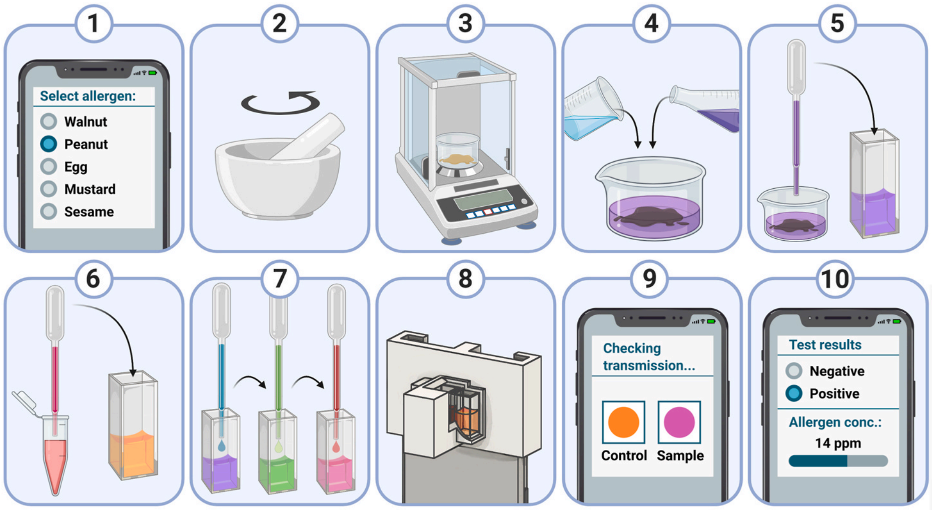


**Fig. 4.** Procedure for determination of allergens in food samples using a smartphone attachment and colourimetric assays: (1) the allergen of interest is selected in the application; (2) a food sample is finely ground; (3) approx. 5 g of the ground sample is transferred to a vessel; (4) the sample is mixed with water at 60 °C and with extraction solvent; (5) 3 drops of the sample solution is added to the first tube; (6) 3 drops of the control solution are added to the second tube which will act as reference; (7) following a 10 min incubation period, both the test and the control tubes are sequentially rinsed with a conjugate, substrate, and a stop solution, with a wash buffer used in between the rinses; (8, 9) absorbance of both solutions is measured using a dedicated smartphone attachment; (10) the test provides qualitative and quantitative information. Own rendering based on (Coskun et al., 2013).

## 5. Pattern recognition and machine learning

Apart from calibration in photometry- and colourimetry-based approaches to the quantification of colour images obtained using smartphone cameras, pattern recognition and image analysis finds application in food manufacturing and quality assessment based on images and videos captured using smartphone cameras. These include crop monitoring, e.g. through evaluating the number of grapevine berries in a grape (Aquino et al., 2018; Font et al., 2014), fruit sorting and grading (Álvarez-Bermejo, Morales-Santos, Castillo-Morales, Parrilla, & López-Ramos, 2019; Giraudo et al., 2018; Mizushima & Lu, 2013), identification of defects and assessing the fat content in meat products (Cruz-Fernández, Luque-Cobija, Cervera, Morales-Rubio, & de la Guardia, 2017; Ulrici et al., 2012). Such approach is to a lesser extent impacted by the device-dependent colour space representation (although it remains a problem, especially in light-dependent scenarios (Álvarez-Bermejo et al., 2019), since the classification and regression models might not be sufficiently robust to accommodate data collected under different conditions). The issues related to colour measurement and colour space conversion in the context of food quality control have been discussed by (Wu & Sun, 2013). Despite the recent developments in this area (Nixon & Aguado, 2020), extracting the features from images of food for the subsequent pattern recognition and machine learning remains a major issue (Zheng, Sun, & Zheng, 2006).

Other difficulties with the use of machine learning algorithms apply to both the pattern recognition and spectrometric applications of smartphone cameras. The more general the application, the greater the effort required to build a data library sufficiently large to train a robust machine learning model without the risk of overfitting. Such libraries, containing hundreds of thousands of reliably labelled objects, could likely only be built in collaboration with major stakeholders, i.e. big food manufacturers, who have at their disposal the necessary resources, infrastructure and procedures. The main incentive here could be the detection of adulterations (Song et al., 2020). On the other hand, the integration of smartphones with other sensor-equipped devices and communication networks within the IoT could, to some extent, democratize the process of data collection with the aim of building vast and robust machine learning libraries, on top of its other uses in food safety (Bouzembrak, Klüche, Gavai, & Marvin, 2019). While this would require some sort of incentive for e.g. manual classification of images, the necessary infrastructure is, on the most part, already in place, with ample processing power of the personal devices and 4G (soon to be 5G) network connectivity, with the notable exception of data storage which is likely to remain the bottleneck for the foreseeable future – an issue which would only be compounded by the increasing imaging capabilities of smartphone cameras in the context of multi-sensor readouts, hyperspectral imaging and large image resolution.

## 6. The use of the smartphone camera instead of a detector – current issues and future perspectives

The accessibility and popularity of smartphones may significantly improve the applicability of biosensors since with their coupling it is possible to facilitate the monitoring of food quality throughout the entire production process. Most smartphone-based analytical methods can be used by both specialized personnel and non-trained consumers and thus, they could be routinely applied to monitor food quality at points of distinctive vulnerability, during all stages of production and distribution and, finally, at-home (Lu, Shi, & Liu, 2019). However, even though significant advances have been made in the area of portable and user-friendly analytical methodologies, a substantial amount of work is to be done before the ubiquitous use of the solutions proposed by researchers could be even considered. This is particularly true with regard to food quality assessment where extensive validation of the potential methodologies is of vital importance.

Numerous smartphone-based analytical solutions are evaluated with the use of model samples. While with this approach it is possible to estimate whether the concept behind the proposed methodology is not misguided, caution should be exercised when ascertaining whether the methodology in question can be applied in the analysis of real samples. This is particularly important with regards to food analysis – both because in case of food quality evaluation or e.g. allergens detection uttermost precautions are required and due to the food itself being a very complex matrix. While the use of model samples is helpful during the method's development, it is difficult to assess the applicability of smartphone-based methodologies, be it at-home water quality analysis or the establishment of wells based on the sand samples evaluation, when they were tested solely on model samples (Iqbal & Bjorklund, 2011b). Moreover, even in the case where model solutions are made by adding the analyte to the commercially available product or otherwise prepared to maintain the similarity to the real samples, it still cannot be said that the conditions are identical to real-life analysis (as discussed in Section 3). As a result, the effectiveness of e.g. a smartphone-based method of coloured additives detection in real-life applications cannot be accurately evaluated since the aim of the preliminary research was to differentiate between samples of transparent soft drink to which ethyl red, reactive blue 2 or bromocresol green was added (Iqbal & Bjorklund, 2011a) which is only a rough approximation of the analysis of artificially coloured drinks that can be performed by the potential consumer. A similar case could be made with regard to e.g. the detection of artificial sweeteners – while the subject is interesting and the proposed methodology may in future find its application in at-home food analysis, its relatively difficult to accurately assess its potential when it is used to detect sweeteners in blank tea solutions prepared in the laboratory and not in a commercially available soft drink which usually has a much longer ingredient list and is thus a far more complicated matrix (Musto, Lim, & Suslick, 2009). A similar problem may arise when pathogens' detection methods are assessed. While it is quite understandable, since obtaining commercially available food contaminated with pathogens might prove to be difficult, there is still room for improvement in the subject of the overall evaluation of these methodologies. Is the proposed approach specific for only one type of bacteria and does the presence of other species distort the obtained results? Is the recovery sufficient in different batches of the product? Does procuring foodstuff from various distributors impact the results? How does the method's limit of detection compare with reference methods? These are all important questions from the point of view of both researchers and industry representative who may be interested in the future implementation of these methods. While much consideration is given to these issues when novel smartphone-based methodologies are reported (de Oliveira Krambeck Franco et al., 2017; Silva & Rocha, 2020; Zeinhom et al., 2018; Zhu et al., 2012), the validation of new approaches has to become as thorough and commonplace as in other branches of food analysis for the smartphone-based techniques to reach maturity.

Several applications reviewed in this work featured components 3d-printed using the widely accessible fused deposition modeling (FDM) technology. This is further facilitated by the availability of freeware parametric design software allowing for easy tailoring of the CAD model to a particular smartphone. The possibility to couple the ease of on-site manufacturing of dedicated interfaces between the sample and the ubiquitous and increasingly powerful detector, i.e. the smartphone, will greatly increase the accessibility of basic food QA/QC methods.

This coupling between 3d-printing and smartphone detection could however be taken a step further. For some years now researchers have used stereolithography (STL) to produce intricate microfluidic devices - by all means miniaturised and sophisticated instruments for sample preparation and analysis (Cocovi-Solberg, Worsfold, & Miró, 2018). Until recently, there were no consumer-grade STL printers available at a price range which would make them a viable option for low-cost applications. However, this is no longer the case, and so it is likely that in the near future we shall see the development of applications involving parametrically customizable STL-printed microfluidic devices with smartphones used as detectors, especially in areas where the sample matrices are relatively complex, i.e. in food analysis and medical diagnostics.

## 7. Conclusions

This review covers the current trends in using smartphones for food quality assessment and how they might impact the accessibility of food analytical methods and their sustainability. The utility of using smartphones as an all-in-one data processing and user interface platform for food quality assessment is undeniable, especially with regard to lowering the cost of instrumental analytical methods and increasing the accessibility to food control procedures in the developing countries. This is even more true when considering making use of smartphones' integrated sensors as detectors, either on their own or in conjunction with straightforward sample treatment procedures. Here the recent developments are focused on using the increasingly sophisticated smartphone cameras at each stage of food production and distribution, from screening the raw materials to assessing the freshness of the product on the shelf. Providing the farmers and consumers alike with ubiquitous access to quality assessment tools literally in their pockets would greatly improve the public confidence in food safety. However, there remain unresolved technical difficulties with utilizing the smartphone camera as a mobile spectrometer without any accessories, stemming mostly from difficulties with limiting the number of variables during measurement and lack of solutions for assuring the equivalence of measurements conducted using different device models and in different conditions. These difficulties are compounded by the fact that food is a particularly complex sample matrix, which is likely why the smartphone-based solutions for food quality assessment that might see widespread practical use in the nearest future involve the use of biosensors. Here the researchers can capitalize on the substantial advances in the fields of microfluidics and bioassays, such as the use of nanoparticles or quantum dots, to deliver targeted solutions (Cocovi-Solberg et al., 2018; Yang, Liu, & Jiang, 2019). This drastically increases the accessibility of analytical methods which would otherwise require costly equipment and infrastructure, thus promoting equitable analytical chemistry. Furthermore, it necessarily translates, through the miniaturization and reduction of the number of analytical steps in a procedure, to reduced consumption of samples and reagents, leading to the development of more green and sustainable analytical techniques.

While smartphone-based methods can be used in numerous areas of food evaluation, including quality assurance and assessment of authenticity, a majority of the reviewed solutions focuses on food safety monitoring and consumer-oriented detection platforms (Kalyani, Goel, & Jaiswal, 2020; Lu et al., 2019). Food safety and quality is a major concern for the consumers, who represent a sufficiently large group of stakeholders to possibly incite electronics manufacturers to consider their needs during hardware development, e.g. through increasing the remote sensing capabilities of the arrays of smartphone cameras. The ubiquity of such remote sensing capabilities could, combined with the integration of big data mining, cloud computing and deep learning made possible through the smartphones' inherent connectivity and developments in wireless networks and IoT, produce more generalized solutions for analysing a vast number of foodstuffs. This, however, presents a chicken-and-egg problem, and so it makes the widespread use of smartphone cameras as mobile spectrometers for food safety monitoring unlikely in the near future. However, it is clear that smartphones will play an increasingly important role in popularizing the access to food analytical techniques for on-site analysis as a readily available and convenient integrated interface, connectivity and remote sensing platforms.

## Declaration of competing interest

The authors declare that there is no conflict of interest.

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