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Review Article

Promising Tools for Food Safety and Quality: Artificial Intelligence and Smartphones

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Abstract

The use of artificial intelligence (AI) in the food industry can drastically improve food safety and quality control. The first step in using AI in the food industry would be collecting data from relevant systems, which is typically achieved with the use of various sensors. The data obtained from such sensors can be large and diverse and needs to be processed to extract relevant information. The final goal of using AI based systems for food applications is to create a system that can make independent, localized decisions and take appropriate actions. However, AI based systems can be costly and require expertise for their implementation. Using a smartphone can provide a cost-effective and easy to use solution for the widespread adoption of AI based methods in the food industry since they can be used as controllers, data processors, monitors, and even sensors. The data processing and AI algorithms can be performed trough mobile phone APPS. This review explores the latest research on the field of food safety and quality control using smartphones in combination with AI.

Keywords: Smartphones, artificial intelligence, machine learning, artificial neural networks, food safety, food quality

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Introduction

Since the term artificial intelligence (AI) was first introduced in 1956 by John McCarthy, driven by the focus and perspective of researchers, its definition evolved significantly. In a wide perspective AI is defined as "the ability of machines or computer systems to perform tasks that typically require human intelligence". Game playing such as chess, natural language processing to understand and generate human language, expert systems to mimic the decision-making abilities of human experts and robotics to perform tasks such as manufacturing, assembly, and transportation are among the early applications that made use of AI. Today, AI applications extended to many sectors including transportation, home/service robots, healthcare, education, public safety and security, employment, entertainment (1). In the food industry, the use of AI can greatly improve food safety and quality control. The first step for employing AI in these applications would be the collection of data from the relevant systems. In the food sector this data is usually generated via a wide variety of sensors. This data is large and diverse, characteristically heterogenic, unstructured, noisy, and contain high redundancy. Raw data need to be curated and stored then processed to extract relevant information. The goal is to eventually construct a system capable of autonomously making independent, localized decisions and take appropriate actions (2).

The literature reviewed for this article was collected from Google Scholar in the period 2018-2023. The following sets of keywords were used; Set-1: "food safety" and "artificial intelligence" and "smartphone"; Set-2: "food quality" and "artificial intelligence" and "smartphone". The search yielded a total of 2,250 and 1,310 papers, respectively. This review is limited to papers that include the use of both smartphone and AI.

Types of AI

When data is fed into artificial intelligence (AI), it can use either pre-set knowledge-based rules or identify underlying patterns and rules through machine learning. The former is known as rule-based or expert systems and the latter as machine learning (ML). In the rule-based systems, knowledge-based rules can be defined by physical principles or expert knowledge that is based on experience. Here, sensors or devices continuously monitor the system or process and collected data is analysed using pre-defined rules. Such systems are most beneficial in scenarios where real-time control is needed. However, the food materials' complexity and heterogeneity limits the use of rule-based systems in the food industry (2). In ML the AI learns from data rather than being explicitly programmed using pre-defined rules. Large amounts of unstructured data are input into ML algorithms, which after analysing it can identify patterns and relationships within the data. ML algorithms can be used to perform tasks such as generating an alert, taking action or predictive modelling (3). The three types of ML are; supervised, unsupervised, and semi-supervised ML. In supervised ML, the training data is labeled with the desired output, whereas in unsupervised ML it is not labelled. In semi-supervised ML combination of both type of data is used. ML models can be more precise and accurate than traditional statistical models, particularly when working with datasets that are large and have many variables (4). ML algorithms have tremendous potential in food safety applications. For instance, it was found that ML techniques like AdaBoost can be more successful at predicting the populations of indicator microoroganism E. coli image processing weather data compared to count-based regression models like Poisson and negative binomial(5). Artificial Neural Networks (ANNs) are a type of artificial intelligence (AI) that is based on the structure and function of biological neural networks that are commonly used in machine learning algorithms. They have the ability to learn from data, adapt to new inputs, and make decisions based on the information they have processed. They have gained significant attention in the food science field due to their ability to produce successful results in sensory analysis, pattern recognition, classification, prediction of microbial activity, and optimization of food processes (6).

Applications of AI in for food safety and quality control

AI has been applied in the food industry to classify and sort products based on size and shape, as well as to detect defects and the presence of microorganisms. Robotics, image processing technologies, and sensing technologies, have been used in combination with AI to achieve these goals. The use of AI in the food industry for tasks such as sorting, classifying, and predicting various parameters, quality control and food safety are constantly increasing. Extensively used techniques include expert systems, artificial neural networks, fuzzy logic, adaptive neuro-fuzzy inference systems, and ML. AI can also be near infrared (NIR) spectroscopy, combined with electronic nose, electronic tongue, and computer vision system (CVS), greatly enhancing the capabilities of these technologies. The question remains which AI technique in combination with sensor will yield the best results for a specific task. In a recent review, Mavani et al. provided a detailed guideline on how to choose the most appropriate AI method (7). The guideline is summarised here and readers can refer to the review article for more details. First step in choosing the most suitable AI would be to define the objective of using AI for a given application such as classification, quality control, prediction, detection and so on. Then the sensor that will be used to collect the data needs to be chosen. The most appropriate algorithm based on the data and objective should be decided after which the available data and the algorithm of choice would be integrated. Finally, the performance of the model should be tested and validated based on R^2 and MSE values. If the model is not successfully validated a new algorithm should be chosen and the following steps should be repeated (7).

Combination of smartphones with AI for food safety and quality control

Smartphones are becoming popular tools for on-site sensing applications because they can function as controllers, data processors, monitors, and even sensors with have built-in function modules that can be used independently or in combination with other accessories in various sensing systems (8). The camera of most smartphones can capture images with high resolution and can actually perform as an optical sensor from which raw data is collected. The wired and wireless connectivity of smartphones also provides a point for the integration of external sensors that can be used in combination with the smartphone without compromising the portability of the system (Figure 1). For instance, Hamamatsu Photonics developed an ultra-compact, lightweight, and low-cost micro-spectrophotometer that is small enough to fit on the tip of a finger. It is able to measure in the visible wavelength range and can be used for colour sensing and point-of-care testing with smartphones. Smartphones have been used in optical biosensing systems that utilize techniques such as colorimetry (9), fluorescence (10), and surface plasmon resonance (11) where they act as an image capturer and processer. The processing power of the smartphone provides a platform for programming and/or deploying applications (APPs) empowered with AI for analysing the image. With the use of miniaturised external potentiostats, a smartphone can be used as an electrochemical sensor (12). Biosensors are another type of sensor that can be integrated to smartphones and provide data for food safety and quality control applications. A biosensor is a device that combines a biological component with a physicochemical detector to detect specific components based on the principle that certain biomolecules have the ability to selectively recognize other components. Enzymes, hormones, tissues, cells, or organelles are typically used as sensing elements. They can be used to quickly detect various aspects of food safety, such as microbial burden, additives, and contaminants offering several advantages such as affordability, ease of use, rapid response, high sensitivity, specific detection, and the ability to multiplexing. Hence the combination of biosensors and smartphones can be very useful in portable field detection (6).

The most straightforward technique for combining smartphones with AI is the adaptation of computer vision system (CVS), which analyse various parameters such as the size, colour, shape, and texture from a digital image. A smartphone camera has been proven to be an effective and low-cost tool for the implementation of CVS. In fact, “Smartphone-based Image Processing" has found use in imaging-based quality control applications (13). Such image processing for food quality and safety assessment is becoming more popular due to its advantages over traditional techniques such as; being non-destructive, eco-friendly and user-friendly, safe to use, energy-efficient, fast, low-cost, not requiring highly-skilled personnel, reducing human error and having high precision (14). Besides these, as being naturally portable, a smartphone-based system allow on-site analysis without additional investment costs for information technologies.

Image processing applications typically involve three steps; image capturing, pre-processing, and feature extraction. In the image capturing step a camera module is used to take pictures of the test samples. The most commonly used strategy is to capture RGB (Red, Green, Blue) colour images. RGB images can also be converted to the CIELAB (device-independent colour space; L*, a*, b*, C*ab, and Hab) or HSV (Hue, Saturation, Value) colour space. IR and hyperspectral images can also be used. The pre-processing step consists of removing noise from the input image and separating the region of interest (ROI) from the background. In the feature extraction step, features that are based on colour, texture, morphology and/or the geometry are extracted using image processing techniques. Furthermore, ML can be employed for the quality-based classification of food items. Alternative to feature extraction-based approaches, Convolutional Neural Networks (CNNs) can also be used but such models generally require a large number of images (tens of thousands) as input data (14). A machine vision-based smartphone app was developed to accurately predict the tenderness of beef samples. The app used an image processing algorithm to extract texture features from the images of beef. These features were then correlated with instrumental data obtained through texture analysis using an ANN model (15). Models based on ANNs and colour measurement to predict the fermentation index of fine cocoa beans have been developed and tested using RGB values obtained from a smartphone camera as an inexpensive and easy method for predicting the fermentation index in cocoa beans (16). Nasiri et al. developed a deep Convolutional Neural Network (CNN) for classifying healthy and defective date fruit, and predicting how ripe healthy dates were. The training and testing of the model was performed on a dataset of images of four different classes of date fruit that was collected using a smartphone camera. Their model achieved a classification accuracy of 96.98% outperforming traditional classification methods that were based on feature engineering (14). A sensor system that accurately identify organic and conventional apples has been developed by Song et al. using a diffraction grating sheet and a smartphone. The system was tested on 150 apples and analysed using computer vision techniques and ML algorithms. The employed algorithms were able to accurately classify the samples, even with low-quality images, with accuracies ranging from 93% to 100%. The proposed system was the low-cost and non-invasive (17). In another study, Song et al. developed a sensor where a sequence of light of different colours is generated using a smartphone and the record a video of the reflected light from a food sample to perform authentication. The video was transformed into sensor data using computer vision techniques which was then analysed using pattern recognition techniques. The accuracy of the sensor system tested on olive oil and milk was reported to be 96.2% and 100%, respectively (18).

Turco et al. used Multi Imaging Analysis (MIA) of digital images obtained from a smartphone camera and NIR spectra of geopropolis. They aimed to create Partial Least Square (PLS) regression models to foresee of the total flavonoid content and antioxidant capacity of geopropolis' ethanolic extracts. When models were compared it was observed that Color-based PLS models had better precision while the predictive capacity of the two models was similar. Both the digital photos and NIR spectra combined with PLS models were shown to have a potential for predicting the TFC and AC of geopropolis with acceptable accuracy, offering a fast and low cost method for controlling the quality of geopropolis extracts (19).

Traditional methods for assessing the quality of beverages such as high-performance liquid chromatography, gas chromatography, UV-visible and NIR spectrometers, colorimeters and viscometers etc. can be time-consuming, costly, involve expensive equipment and require trained personnel. Sensory evaluation practices require a fixed panel of trained experts which is costly and time-consuming (20). Some industries rely on a single person to assess the sensory quality which is not objective or reliable. Hence ML coupled smartphone empowered CV methods can also be used for this purpose. For example, Li et al. proposed a novel method for evaluating the quality of Keemun black tea. For this purpose, smartphone imaging, micro-NIR spectrometry, and ML techniques were used. The method involved obtaining colour, texture, and spectral data from the tea samples. An ML was used to classify the quality grades of the tea. The proposed method was reported to be more accurate than evaluating the colour, texture, or spectral data separately (21). De Lima et al. used digital images obtained from a smartphone camera for the classification of red wines based on colour histograms and supervised pattern recognition techniques. They were able to correctly differentiate the wines produced in the São Francisco Valley region from the wines from other regions. Furthermore, their method correctly classified wines based on winemaker and grape variety, with a high degree of accuracy (22).

Gunda et al. developed a mobile application platform for water quality monitoring, and specifically for bacterial contamination. The platform incorporated a low-cost rapid test kit (Mobile Water Kit) to detect indicator bacteria (Escherichia coli) in water samples within an hour. The detection was based on the appearance of pinkish red colour on the surface of the sensing area with its intensity representing the level of bacteria in the water samples. The mobile APP used an image of the sensing area to classify it into E. coli present or absent using deep learning techniques with Google Tensorflow. Approximately 99% accuracy has been achieved in classification (23).

The use of AI incorporated smartphone technologies can be used to detect food adulteration. For example, Costa et al. described a fast, low-cost, and portable colorimetric method for detecting milk adulterants using a smartphone camera and lab-made apps based on the histograms of the RGB images and partial least squares regression. The method was based on reactions that result in colour change such as detect hydrogen peroxide, starch, and sodium hypochlorite (24). Tripathy et al. realized the development of a paper-based pH sensor for detecting milk adulteration using smartphone cameras and ML algorithms to classify the sensing platform's colour transitions into different pH ranges. A high accuracy of the classification using support vector machines was achieved (average accuracy of 99.71%) the freshness of milk and the quality of pasteurization could also be determined (25). Iymen et al. developed a method using AI and transverse sound vibrations to verify the authenticity of food products identifying whether they are organic as claimed by the manufacturer. The method involved neural networks with mel-frequency cepstral coefficient (MFCC) feature extraction techniques. They used a selection of butter and cheese samples with the aim of not only differentiating butter from cheese, but also differentiating between dairy products with and without non-dairy additives. They demonstrated a concept that could be used to create a smartphone app that allows consumers to check the quality of their food (26). A smartphone APP has been developed by Gong et al. for real-time monitoring of food freshness using a colorimetric indicator made of cellulose paper with synthesized gelatin methacryloyl (GleMA) that changes colour based on the freshness of meat. A convolutional neural network (CNN) model trained on labeled images of the indicator has been integrated to the APP resulting in a prediction accuracy of 96.2%. The APP has been proposed to be used by consumers to quickly determine the freshness of meat within 30 seconds (27). More sophisticated yet low-cost apparatus can be combined with smartphones and AI. For instance, Coronel-Reyes et al. developed a method for predicting the storage time of eggs at room temperature using a low-cost smartphone-connected near-infrared reflectance spectrometer and an ML algorithm. According to the researchers their technique has potential in both industrial and consumer use (28). Such systems have the potential to be easily used by the end-users if they can be produced at a low cost (29). Food Sniffer is such an example. It is a handheld device that connects to a smartphone through an app with the ability to assess the freshness of raw meat, poultry, and fish. The device measures the gas levels of the raw meat to determine the freshness and safety of the meat for consumption (30).

Conclusion

AI is defined as the ability of machines or computer systems to perform tasks that typically require human intelligence. The use of AI in the food industry can dramatically improve food safety and quality control. Despite the huge promise it holds, the adoption and use of technologies generating data to support AI in the food and agriculture industry is currently limited to developed countries. Farmers and small producers in less developed parts of the world lack the resources to utilize or implement such tools. Smartphone based systems can contribute to overcome such limitations due to their ease-of-use and cost-effectiveness along with other actions such as education, financial and governmental support for implementation. The first step in using AI in conjugation with smartphones in the food industry is collecting data from relevant systems, which is typically done through the use of sensors. These sensors can either be the camera of a smartphone or an external sensor that can be connected to the smartphone. The data collected can be large and diverse and needs to be processed to extract relevant information which can ideally be performed trough mobile phone APPS. The goal is to create a potable, low-cost and easy to use system that can make independent, localized decisions and take appropriate actions for food safety and quality assessment.

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Figures:

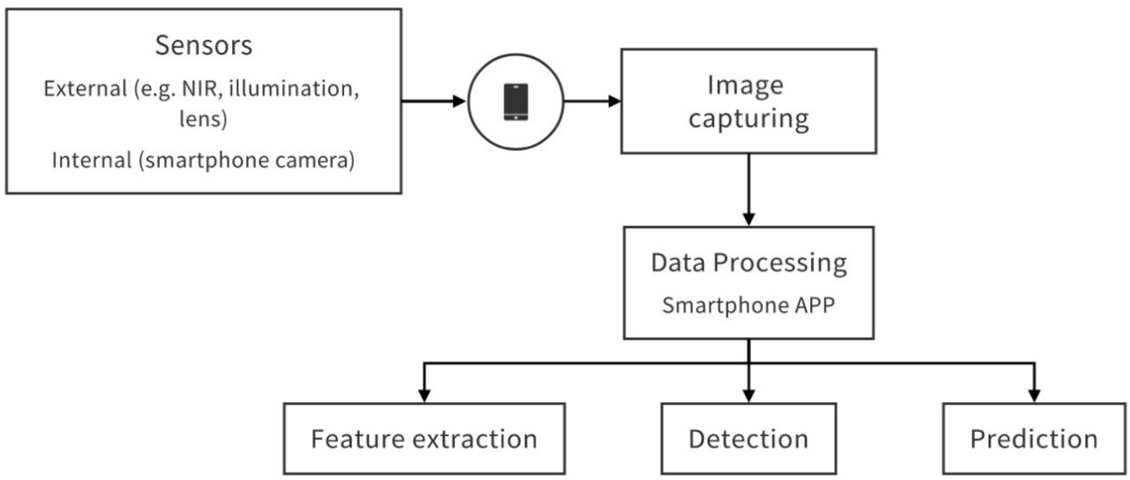

Figure 1. Schematic illustration of the use of smartphones in conjugation with AI basde mobile APPs.