**A assessment of artificial intelligence-based methods for spotting defects and adulterations in the food and agriculture sectors**

In especially for adulteration and deficiency detection in the food and agriculture industry, artificial intelligence (AI) approaches have developed into useful, quick, and efficient tools in combination with detecting devices for quality assessment. In order to identify food fraud and flaws in agricultural products, this paper highlights recent developments in AI approaches and how they can be integrated with different types of sensing equipment. In order to improve categorization, prediction, and understanding of the acquired high-dimensional information, case-specific AI algorithms must be applied to the sensor results. It is clear that the integration of AI technology and sensors has produced promising results in the detection of adulteration and defects in food and agricultural products, with an accuracy range of between 81.2 and 100%. Along with the research guidelines and trends, With the intention of offering references and direction to both academic researchers and commercial stakeholders in the field of food and agricultural quality evaluation, research trends and guidelines are also put forth. The difficulties and potential of AI approaches were also made clear. Furthermore, it's important to seek and validate potential future advancements, new sensors, and innovative algorithms. With the integration of multiple sensors and the use of deep learning algorithms, it is possible to foresee future AI detection of food adulteration and agricultural product flaws. Predictive modelling and real-time monitoring may also get a lot of attention because they can help prevent quality issues from happening in the first place, reduce the danger of fraud and guarantee highly valuable products.

**Keywords**

Artificial intelligence, Food adulteration, Defect detection, Deep learning, Quality Food

**Introduction**

Especially for customers and the government sector, but also for the entire food industry, food quality, safety, and authenticity are major considerations. Since fraud in the food industry has the potential to seriously harm public health, food authenticity has become vital [1]. The estimated annual cost of global food fraud is $US49 billion [2]. The 2008 Chinese milk scandal and the 2013 horse-meat scandal serve as examples of the broad repercussions that a contaminated food supply chain can have globally [3]. With a greater need for alert, prompt, and reliable food tracking to safeguard the food supply chain, these atrocities have refocused efforts on strengthening activities to ensure the reliability of the food supply [4]. Over the past ten years, a number of researchers have made an effort to go beyond traditional procedures by utilising quick techniques.

AI has emerged with big data technologies and high-implementation computation to unlock, quantify, and analyse complex data patterns. Over the past few years, they have grown in prominence and have been used to address challenging technological problems. A variety of food and agricultural systems, from production [[6], [7], [8]] [9] to disease detection [[10], [11], [12], [13], [14], [15]], are progressively utilising AI. Finding weeds [[16, 17], and [18]] Phenomenology (19,20) Production of livestock [[21, 22], and [23]] Aquaculture [25], yield prediction [[26], [27], [28]], harvesting [[29], [30], [31]], processing [[32], [33], [34]], and packing and consumer distribution [[35], [36], [37]] are all examples of integrated crop-livestock systems. Reviews of AI applications in agriculture and the food industry generally are already available [38, 39] as well as farming in general [40, 41]. While others have concentrated only on a few AI algorithms, such as ANN in food processing [38], ANN in drying technologies [42], and CNN in agriculture [43]. The use of AI-based applications in all phases of the agro-food system, from crop and livestock production to food consumption and waste management, has been described by Kutyauripo and colleagues [44]. Furthermore, Kakani and associates have talked about the requirement for AI technology in relation to sustainable food production and agricultural applications such food processing, agriculture-based apps, farming, plant data analysis, smart irrigation, and next-generation farming [45].

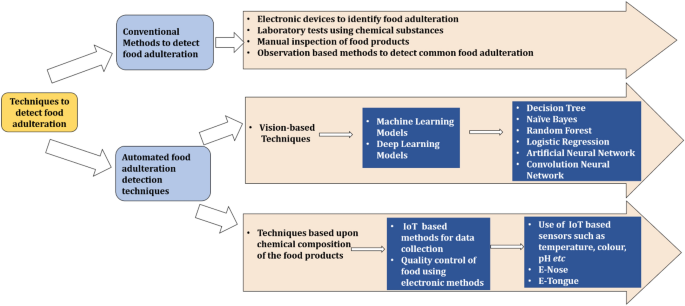
In recent years, the application of AI to combat food adulteration has increased. AI for food adulteration detection includes managing data sets of real and fake products to train algorithms to detect minute compositional variations. These variations are then used to develop models that can accurately assess whether a food product has been tampered with or not by sensing it. This technology has a great deal of promise for non-destructively identifying adulteration that would not be visible to the naked eye or by standard laboratory techniques. Additionally, the use of AI in food adulteration detection can be a cheap and effective approach to check a lot of items for potential adulterants, which is crucial for food manufacturers and merchants that need to verify the quality and safety of their products. Additionally, when AI examines more samples of real and fake goods, its accuracy will eventually increase due to its capacity to learn from new data and adapt. Artificial intelligence (AI) is being used more and more in a variety of food-related products, including meat [[46, [47], [48]], edible oil [[49], [50], [51]], beverages [[52], [53], [54]], and fruit defect detection [[55], [56], [57], [58], [59].

However, to the author's knowledge, there is a dearth of thorough and focused reviews on the use of AI for identifying food adulteration and flaws in agricultural products. Because there is a lot of research in this area, the current review will give an overview of how artificial neural networks (ANN), deep learning (DL), fuzzy logic (FL), support vector machines (SVM), and random forests (RF) are used to quickly assess the attributes of food quality. Although there are additional types of AI that must be used in addition to the five strategies stated above, this analysis solely examines the most well-known AI methods used especially in food adulteration and defect detection. There are many resources for other people.

In this review, the importance of analysing these traits is emphasised, the concepts of these techniques are provided, many application scenarios are described, and the benefits and drawbacks of AI techniques are examined. Additionally, research trends are forecasted, and recommendations are also made with the intention of giving references and guidance to both academic researchers and industrial participants in the subject of food quality evaluation. The introduction is offered in this section, while section 2 presents an overview of the AI techniques utilised in food quality, particularly in adulteration and defect identification. The use of AI for detecting food adulteration was discussed in the third segment, and the application of AI for detecting defects and evaluating the quality of agricultural products was covered in the fourth. The guidelines for selecting AI techniques for food authentication and quality classification were covered in the fifth section. The trends, difficulties, and outlook for AI techniques for food authentication and quality detection were covered in the sixth section. The survey was then concluded in the seventh section.

**Overview of AI strategies for food quality, with a focus on adulteration and defect detection**

Artificial intelligence (AI) is a catch-all phrase for computing technologies including machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision that can carry out tasks that humans can. Barr and Feigenbaum (1981) defined artificial intelligence (AI) as a branch of computer science that focuses on creating intelligent computer systems—that is, systems that display intellectual capacity traits similar to those of humans, such as comprehension, speech, learning, logic, and problem-solving. The use of AI techniques in integrated systems or as a replacement for conventional methods has many advantages. As they can learn from examples, deal with nonlinear equations, and perform high-speed prediction and generalisation after being trained, AI can deal with noisy and missing data [62]. Due to their symbolic reasoning, flexibility, and capacity for explanation, they are becoming established and used in a variety of applications all around the world. They have also been applied to the modelling, control, identification, prediction, and forecasting of complex systems. Fig. 1 presents an overview of AI methods for detecting fruit defects and adulteration in food and beverages. The details on common AI techniques, such as artificial neural networks (ANNs), deep learning (DL), fuzzy logic (FL), support vector machine (SVM), and random forest (RF), are provided below with their benefits and drawbacks. Tables 1 and 2 summarise various AI techniques and their designated applications.



Overview of AI approaches for detecting fruit defects and adulteration in food and beverages.

Table 1. Recent applications of AI techniques for the authentication and adulteration determination in food.

| **Instrument** | **AI technique** | **Product Applied** | **Objective** | **Performance Evaluation** | **References** |
| --- | --- | --- | --- | --- | --- |
| Fourier-transform infrared (FTIR), visible-near-infrared (Vis-NIR) | Artificial neural network (ANN) | Olive oil | Detect olive oil adulteration. | 100% accuracy | [[66](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib66)] |
| NIR spectrometer | Support vector machine (SVM) | Butteroil | Identify adulteration in butteroil. | 90% accuracy | [[116](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib116)] |
| infrared (IR) spectrophotometer | Support vector machine (SVM) | Milk | Identification of adulterated milk with melamine | 99.05% accuracy | [[117](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib117)] |
| Dielectric spectroscopy | Artificial neural network (ANN) | Sesame oil | Classification and quantification of sesame oil adulteration | accuracy of 100% accuracy | [[118](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib118)] |
| near-infrared hyperspectral imaging | Support vector machine (SVM) | Fishmeal | Marine fishmeal adulteration | 99.43% accuracy | [[119](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib119)] |
| hyperspectral | Deep learning (CNN) | Mutton | Adulteration identification | 99.95% accuracy | [[109](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib109)] |
| Imaging system | Deep learning (CNN) | Meat | Mutton adulteration with pork detection | 82.12% accuracy | [[47](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib47)] |
| Fourier Transform-NIR spectrophotometer | Deep learning (CNN) | Coffee | Adulteration detection | R2 > 0.98 | [[120](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib120)] |
| Hyperspectral imaging | Deep learning (CNN) | Marine fishmeal | Adulteration with low-cost processed animal proteins identification | 99.37% accuracy | [[81](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib81)] |
| laser-induced breakdown spectroscopy | Deep learning (CNN) | Milk powder | Milk powder adulteration detection | 97.8% accuracy | [[121](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib121)] |
| optical microscope | Deep learning (CNN) | Extra virgin olive oils | Extra virgin olive oils adulteration with vegetable oils detection | 96% accuracy | [[122](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib122)] |
| MIR spectroscopy | Deep learning (CNN) | Honey | sugar adulteration identification in honey | 97.96% accuracy | [[123](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib123)] |
| hyperspectral imaging | Deep learning (CNN) | Wheat flour | adulteration in wheat flour | 92.45% accuracy | [[124](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib124)] |
| hyperspectral imaging | Support vector machine (SVM) | Honey | honey adulterated with syrup | 92.5% accuracy | [[125](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib125)] |
| Raman spectroscopy | Deep learning (CNN) | Honey | honey adulterated with syrup | 99.76% accuracy | [[126](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib126)] |
| Raman spectroscopy | Deep learning (CNN) | Honey | honey adulterated with syrup | 94.79% accuracy | [[127](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib127)] |
| thermal imaging | Deep learning (CNN) | Minced mutton | minced mutton adulteration with pork | 99.97% accuracy | [[107](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib107)] |
| Camera | Deep learning (CNN) ResNet34 | Rice | rice adulteration detection | 98.8% accuracy | [[128](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib128)] |
| Camera | Deep learning (CNN) ResNet34 | Avocado oil | avocado oil adulterated | 95% accuracy | [[129](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib129)] |
| NIR spectrometer | Deep learning (CNN) | Edible oils | adulteration analysis for edible oils | 97.3% accuracy | [[49](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib49)] |
| Dielectric spectroscopy | Support vector machine (SVM) | Sesame oils | identification of sesame oils adulteration | correlation coefficient (R) of 0.9604 | [[130](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib130)] |
| FTIR | Support vector machine (SVM) | Honey | Adulteration detection | 90.1% accuracy | [[131](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib131)] |
| Hyperspectral imaging | Support vector machine (SVM) | Sea cucumber | Adulteration detection | 97.98% accuracy | [[96](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib96)] |
| Raman spectroscopy | Support vector machine (SVM) | Cassava starch | Detect adulteration in cassava starch | 86.9% accuracy | [[111](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib111)] |
| multispectral imaging | Support vector machine (SVM) | Minced meat | Minced meat adulteration | 97.78% accuracy | [[132](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib132)] |
| Thermographic camera | Deep learning (CNN) | Honey | Adulteration detection | 95% accuracy | [[108](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib108)] |
| excitation-emission matrix fluorescence | Support vector machine (SVM) | Sesame oil | Detection of the authenticity and adulteration of sesame oil | 100% accuracy | [[133](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib133)] |
| ATR-FTIR | Support vector machine (SVM) | Honey | rice syrup adulteration determination in honey | 97.09% accuracy | [[110](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib110)] |
| Spectrophotometry | Artificial neural network (ANN) | Black tea | Detection of carmine in black tea | 100% accuracy | [[53](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib53)] |
| Fluorescence sensors | Artificial neural network (ANN) | Extra virgin olive oil | Monitor storage conditions and locate adulterations | accuracies ranging between 91 and 100% | [[50](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib50)] |
| infrared spectroscopy | Random Forest | Ground nutmeg | adulteration detection in evening primrose oils and ground nutmeg | specificity >99% | [[134](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib134)] |
| hyperspectral imaging | Support vector machine (SVM) | Beef | prediction of beef adulteration with spoiled beef | coefficients of determination (R2) of 0.94 | [[48](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib48)] |
| NIR and FT-MIR | Support vector machine (SVM) | Ginseng | Adulteration detection with lower-grade ginseng | 96.65% accuracy | [[135](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib135)] |
| Laser diode induced | Artificial neural network (ANN) | Extra virgin olive oil (EVOO) | Adulteration detection | mean absolute error (MAE) 1.5% (w/w) | [[136](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib136)] |
| hyperspectral imaging system | Deep learning (CNN) | Peanut | Detection of Aflatoxin in peanut | 96% accuracy | [[137](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib137)] |
| hyperspectral imaging system | Support vector machine (SVM) | Flour | Adulteration detection | 100% accuracy | [[138](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib138)] |
| Electronic nose | Fuzzy wavelet neural networks | Beef | Adulteration detection | 95.71% accuracy | [[46](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib46)] |
| Electronic nose | Support vector machine (SVM) | Saffron | adulteration detection | Color: 89% accuracy aroma: 100% accuracy | [[139](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib139)] |
| near‐mid infrared spectroscopy | Support vector machine (SVM) | Sesame oil | Adulteration detection with corn oil | 100% accuracy | [[140](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib140)] |
| Laser-induced fluorescence (LIF) | artificial neural network (ANN) and support vector machine (SVM) | Extra virgin olive oil (EVOO) | adulteration detection | 100% accuracy | [[141](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib141)] |

Table 2. Recent applications of AI techniques to detect defection and quality assessment in agriculture products.

| **Instrument** | **AI technique** | **Product Applied** | **Objective** | **Performance Evaluation** | **References** |
| --- | --- | --- | --- | --- | --- |
| multispectral | Deep learning (CNN) YOLOv3 | Potato | Detection of potato defect | 90.26% Precision | [[146](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib146)] |
| charge-coupled device (CCD) industrial camera | Deep learning (CNN) YOLOv4 | Pineapple | A surface defect detection | 90.94% accuracy | [[57](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib57)] |
| Vis/NIR | Deep learning (CNN) | Oranges | freezing damage detection in oranges | 91.96% accuracy | [[80](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib80)] |
| camera under incandescent and ultraviolet (UV) light | R–CNN | Strawberry | postharvest strawberry bruise detection | F1 score 0.99 | [[152](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib152)] |
| NIR cameras | Deep learning (CNN) YOLOv4 | Apple | Real-time defects detection for apple sorting | 93.9% accuracy | [[59](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib59)] |
| NIR camera imaging | R–CNN, Yolov3-Tiny and Yolov5s | Apple | Early bruises detection | more than 96% accuracy | [[153](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib153)] |
| X-ray micro-CT imaging | Deep learning (CNN) | Sugar beet fruit | Quality classification | 98.6 accuracy | [[154](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib154)] |
| X-ray CT scans | Deep learning (CNN) U-net | Pear | Internal disorders Detection | 99.4% accuracy | [[155](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib155)] |
| Computer vision | Deep learning (CNN) ResNet50 | Tomatoes | Detection of external defects | precision of 94.6% | [[56](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib56)] |
| 3D scan | Deep learning (CNN) | Apple | Identification of bruised apples | 97.67% accuracy | [[156](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib156)] |
| Imaging system | Deep learning (CNN) | Sour lemon | Quality classification | 100% accuracy | [[157](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib157)] |
| Imaging system | Artificial neural network (ANN) | Mulberry | Quality classification | accuracy of 100%, 98.9%, and 98.3% | [[158](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib158)] |
| laser-induced light backscattering imaging | Deep learning (CNN) | Apple | Detection of apple defect | 92.5% accuracy | [[159](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib159)] |
| near-infrared hyperspectral imaging system | Deep learning (CNN) | Blueberries | Early detection of internal bruises | 81.2% accuracy | [[160](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib160)] |
| Imaging system | Deep learning (CNN) | Dates | Quality classification | 96.98% accuracy | [[161](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib161)] |
| Hyperspectral imaging | Deep learning (CNN) | Strawberry | Bruising detection | 99% accuracy | [[162](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib162)] |
| Hyperspectral imaging | Random Forest (RF) | Apple | Bruising detection | Average accuracy 99.9% | [[163](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib163)] |
| near-infrared hyperspectral imaging | Support vector machine (SVM) | Chili peppers | Quality assessment | 98% accuracy | [[151](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib151)] |
| Vis/NIR hyperspectral | Deep learning (CNN) | Pear | Predicting firmness Korla fragrant pear | 92% accuracy | [[164](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib164)] |
| Color and Thermal imaging | Deep learning (CNN) | Citrus | Immature fruit detection | 95.5% accuracy | [[165](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib165)] |
| Hyrperspectral imaging | Support vector machine (SVM) | Blueberry | Bruising detection | 87.5% accuracy | [[98](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib98)] |
| Hyrperspectral imaging | Deep learning (CNN) | Blueberry | Internal mechanical damage | 88% accuracy | [[166](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib166)] |
| Hyrperspectral imaging | Deep learning (CNN) | Cucumber | Detection of internal defect | 91% accuracy | [[167](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib167)] |
| Hyrperspectral imaging | Random Forest (RF) | Apple | Classification of degree of bruising | 92% accuracy | [[168](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib168)] |
| Hyrperspectral imaging | Random Forest (RF) | Strawberry | Detection of fungal infection | 89% accuracy | [[169](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib169)] |
| Hyperspectral reflectance imaging | Artificial neural network (ANN) & Support vector machine (SVM) | Peaches | Chilling injury classification | accuracies ranging between 92.96% and 97.28% | [[170](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib170)] |
| infrared imaging system | Deep learning (CNN) | Apple | Detection of bruise apples | prediction accuracy up to 97.67% | [[171](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib171)] |
| Digital Camera | Deep learning (CNN) | Mangosteen | Surface defect detection | 97% accuracy | [[172](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib172)] |
| Machine vision | Artificial neural network (ANN) | Cucumber | Quality classification | 97.1% accuracy | [[173](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib173)] |
| Hyrperspectral imaging | Artificial neural network (ANN) | Peaches | Cold injury | Overall accuracy 95.8% | [[69](https://www.sciencedirect.com/science/article/pii/S2666154323000972?ref=pdf_download&fr=RR-2&rr=7e913f608f091796#bib69)] |