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REVIEW ARTICLE

Food Adulteration Detection using Artificial Intelligence: A Systematic Review

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Abstract
Food Adulteration is a deceptive act of misleading food buyers for economic gain. It has been a major concern due to its risk to public health, reduction of food quality or nutritional value. It is a food fraud that has incensed the food industry and has attracted the attention of the community since the last century. To ensure consumer protection against fraudulent activities, authentication of food and the detection of adulterants in various food items should be taken into consideration. Artificial Intelligence has been proved to be an advanced technology in food science and engineering. In this paper, we intend to proclaim the role of artificial intelligence in food adulteration detection in a systematic way. The potential for machine learning and deep learning in food quality has been analyzed through its applications. Various data sources that are available online to detect food quality have been discussed in this review. The different techniques used to detect food adulteration and the parameters considered while evaluating the food quality have been highlighted. The various comparisons have been done among the state-of-the-art methods along with their datasets sets and results. This study will assist the researchers in analyzing the best method available to detect food quality. It will help them in finding the food products that are studied by different researchers along with relevant future research directions.

1 Introduction

Food acts as a prime source of energy for the living organisms that help them to grow and survive on earth. Quality consumption of food plays a crucial role in the absorption of necessary nutrients for complete growth and development of the body. It has become mandatory to inspect the quality of food and ensure the safety of consumers all over the world. Food adulteration or food fraud is the economically inspired means to harm public health. It is the despicable and facile method of collecting huge fortunes that are a great threat to the lives of people. To quench the thirst of greed, people add adulterants to the food products to get the maximum monetary funds by selling the low-valued products at higher prices. Hence, food adulteration has become a profitable business nowadays. The shopkeepers, vendors and other dealers are playing with the lives of common people just for their illegitimate profits. Almost all food being reported is subject to food adulteration including dairy products, grains, seafood, oils, alcoholic drinks, honey, etc. Also, the fruits and vegetables being sold in the market are not as pure as they are injected with harmful chemicals and pesticides. There are multiple ways of impairing the quality of the food. The food is considered to be adulterated if the valuable constituents of the food are removed or if the poor quality of food products are concealed with an actual food product. Sometimes even the alternative food product is replaced by the actual food item. The food quality deteriorates if some unidentified substance is added to the food or its container is made up of any toxic material. Sometimes even an unsafe pesticide or some other chemical substance is contained in it. Food adulteration is not the only means of debasing the food quality. Contamination of food may happen as a natural consequence of a process. For example, microorganisms may deteriorate the fruits and vegetables. Even the spoilage of dairy products, perishable beverages and other food items can be considered as food contamination.

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It seems that traditional food safety methods are not enough to control the issue. Therefore, innovative and advanced ways have to be developed that may be used by the common public or less trained people in this field to keep a check on the quality. The methods should be user-friendly and affordable tools should be designed to evaluate the food quality and achieve the desired aim.

1.1 Different Types of Adulterants Added in Food

It is quite obvious that food adulteration is done in such a way that it is not easy to identify the adulterant by the techniques that are available in public laboratories.

1.1.1 Colour as Food Additives

The colour of food is believed to influence the approach to detect food quality. Therefore, scientific research has been redirected to preserving food colour [1]. For the same reason, prohibited colouring agents are common food adulterants even though they cause many types of health hazards. Also, the permissible food dyes are used in large quantities to attract customers [2, 3]. There are other colouring agents like Metanil Yellow and Rhodamine B etc. that are widely used in confectionery products, dried fruits, wines, bitter sodas, juices, sauces, pastes, and spices. Food Dyes including Allura red and sunset yellow are used in Strawberry jelly and wine [4].

1.1.2 Preservatives as Food Additives

Every civilized society is using food preservatives but such practice can pose a threat to public health [5]. Secure and effective preservative production for perishable food products is a subject of intense study. For example, a suitable mixture of potassium lactate and sodium diacetate is observed as an acceptable preservative under refrigeration conditions [6]. Salt is found to be an effective meat preservative but it can cause hypertension [7]. Safety and efficiency of preservatives are the fundamental criteria that have to be considered for long-term food preservation. However, malpractice like the addition of harmful preservatives to food is often reported. One should have provision to control the addition of harmful food preservatives but in the modern world, it's not possible to ban safe and effective food preservatives. Therefore, appropriate methodologies have to be set up for the proper screening of food preservatives and food quality.

1.2 Need for Artificial Intelligence for Food Adulteration Detection

Artificial Intelligence (AI) can be used as an opportunity in the food industry. It has a major role to support our food system as it can help in precision farming and many other applications in food production and food consumption. It can also be used as a quality control measure in the food sector. AI is changing the way one thinks about food production, quality, delivery etc. and the era of intelligent mobile apps has a big contribution to this transition. The artificial brains can be used efficiently to create food databases and analyze them. It has the potential to create a healthier and more affordable food industry for workers as well as consumers.

The methods used in industries to detect food adulteration are quite expensive and complex. The specialized infrastructure is required for quality evaluation methods. These methods demand intensive manual labour and are sometimes quite tedious and inefficient. Hence, AI can be used as a platform to develop a low-cost automated system that could be used by the end-user to detect adulteration in fruits, vegetables and dairy products.

The different modern methods in this area like electronic tongues, electronic noses [8], computer vision [9], spectroscopy and spectral imaging [10], and so on, have been widely used to detect food quality. These techniques can acquire a large amount of digital data related to food composition and its properties but it is highly important to analyze this data and extract useful information out of it. But it's a challenging task to bring these methods into real world applications.

AI based techniques shall be used to evaluate the quality and analyze the data. There are many such methods to deal with a large amount of data such as partial least squares [11], artificial neural network (ANN), support vector machine (SVM) [12], random forest [13], k-nearest neighbour (KNN) [14], and so on. For feature extraction, principal component analysis (PCA) [15], wavelet transform (WT) [16], independent component correlation algorithm (ICA) [17], scale-invariant feature transform [18], histogram of oriented gradient [19], and so on. These methods are highly useful in dealing with this type of data. Thus analyzing the current scenario of degradation in food quality has encouraged the researchers to explore the research in this area.

1.3 Motivation for Research

Some of the key points that inspired us to carry out the analysis are as follow.

- Food adulteration is a global issue. In recent times, the cases of food quality degradation by various unfair means are rising exponentially. Some sort of awareness in this context may prevent life-threatening diseases and save the lives of innocent people who become the victim of this menace.
- We were keen to know about the data sources and the datasets available for food quality detection.

- We observed the necessity to gather information about various techniques to detect food adulteration.
- We discerned to figure out the factors considered to evaluate the food quality and various food products that have been studied to detect adulteration.
- We wished to explore different deep learning and machine learning applications in the food domain.
- We desired to study the various existing systems to detect food adulteration and to evaluate food quality.
- We recognized the need for a systematic review after observing the ongoing research in this area of food adulteration detection. Consequently, the available research is summarized in this study based on extensive and methodical research.

1.4 Our Contributions

Our contribution to carry out this review is summarized as follows.

- The relevant research articles have been studied by following a systematic review technique. The papers on food quality detection methods have been classified year wise as well as these were categorized based upon their source of extraction such as conference and journal papers.
- A detailed analysis to study various methods for the detection of food adulteration has been conducted.
- The online available datasets for different food categories are discussed for research in this field.
- This survey discusses the various machine learning as well as deep learning applications in the food domain.
- The existing system is studied that is used to detect food adulteration and to evaluate food quality.
- The research work done on different food products by researchers is also presented.
- The last section discusses future research guidelines in the area of food adulteration detection.

1.5 Related Surveys

The surveys conducted earlier have been productive but they cover a different aspect of food adulteration detection. They have not worked on the survey presenting the machine learning and deep learning techniques to detect food adulteration and also the guidelines to conduct a systematic survey are not followed. Bansal et al. [20] have discussed different types of food adulteration done in various food items, health risks imposed by the adulterants and detection methods available for them. They have studied molecular methods to detect biological adulterants in food [20]. Banerjee et al. [21] have aimed to review the available methods of detection of food fraud to focus on the detection of common adulterants and recent advances [21]. Bhargava et al. (2018) have presented a detailed overview of various methods that address the evaluation of the quality of the fruits and vegetables based on their colour, texture, size, shape and defects. These methods include pre-processing, segmentation, feature extraction, and classification. A critical comparison has been carried out based on different algorithms proposed by the researchers to inspect the quality of fruits and vegetables [22]. Zhou et al. [23] have discussed the use of deep learning in the food domain that includes food recognition, calories estimation, quality detection of fruits, vegetables, meat and aquatic products, food supply chain, and food contamination [23]. The popular architectures of deep neural networks are discussed and it has been found that deep learning can be used as a data analysis tool to solve the challenges and problems of the food category.

1.6 Article Organization

The paper in the following sections is structured as follows. Section 2 covers the review methodology used to conduct the survey. The extraction outcomes in the form of resources of publications are discussed in Sect. 3. The preliminaries of food quality detection are discussed in Sect. 4. Section 5 gives a brief description of the techniques to detect food adulteration. Section 6 provides machine learning and deep learning applications in the food domain. Section 7 deals with the findings identified in the survey and the conclusion of the paper and future directions of research are presented in Sect. 8.

2 Review Methodology Followed

The review of food adulteration detection using machine learning and deep learning methods has been conducted using the following steps.

2.1 Development of Review Protocol

A review methodology is followed to conduct a systematic review. Known electronic databases and the topmost conferences related to the research areas have been consulted for conducting the review. After this, the count of selected studies has been narrowed down by the following the inclusion and exclusion principle. Then the research questions have been framed to select the final research studies and the results are collated after following a thorough analysis.

3 Research Questions

The systematic literature review described in this paper relies on a detailed literature survey that has been conducted to study the various approaches followed by researchers to detect food adulteration. For the effective conduct of the systematic review, the following questions have been framed as listed in Table 1

3.1 Sources of Information

A suitable collection of electronic databases was considered before starting the search process to discern only the relevant research papers. The databases like Google Scholar (www.scholar.google.co.in/), Science Direct (www.sciencedirect.com), IEEE Xplore (www.ieeexplore.ieee.org) and Taylor & Francis (https://www.tandfonline.com/) have been selected to analyze the research studies. Most of the papers have been presented in top food safety and machine learning conferences, and virtually all papers are also covered by Google Scholar. Before the final selection of research articles, the redundant articles on Science Direct and IEEE Xplore have been eliminated.

3.2 Inclusion and Exclusion Criteria

A systematic keyword-based search was carried out to retrieve the pertinent research studies from the electronic databases as presented in Table 2.

This study involves both quantitative and qualitative research articles from the last decade to make sure that the analysis is complete as an effort to work on food adulteration detection. The keywords "food adulteration" and "food quality" led to a large number of results when these were used to find the research articles because this field is explored in different aspects. The abstracts and the titles of the articles have been searched using the search string "Food adulteration/quality detection [with, using, by] [Technique_used]."

The different research studies use multiple ways of writing the same title. Hence, all these options have been considered while searching the related studies so that all of the research articles can be included. The research studies from different journals, conferences, PhD and Masters Thesis have been considered by following an exclusion principle at various stages as shown in Fig. 1.

Our search came out with 300 research studies as depicted in Fig. 1. which were then filtered based upon their titles and reduced to 210. These studies were further sorted based on their abstract and came down to 150.This number went down to 112 based on full-text. After that, these 112 research articles were studied thoroughly to select a final list of research articles.

4 Extraction Outcomes

The main objective of this review is to identify the available research on food adulteration detection using artificial intelligence and is stated in the form of research questions in Table 1. To address the research question **RQ1**, the yearly status of research studies about food adulteration detection methods using artificial intelligence has been shown in Fig. 2a. The origin of sources of their publications is depicted in Fig. 2b.Currently, the field of food quality detection is a hot and challenging research area. Hence, the yearwise status of publications from the last decade is presented in Fig. 2a. It is quite evident from the graph that research in this area is continuously growing from the last couple of years. During the thorough analysis, it has also been seen that most of the research articles on food adulteration detection are published in different kinds of conference proceedings and journals. The conferences cover approximately 21%

Table 1 Research questions for systematic literature review

Research Questions	Motivation
RQ1: What is the status of publications year wise and which are the data sources of research articles for detecting food adulteration?	Find out the time frame and publication sources in which a large number of relevant research studies are conducted
RQ2: Which annotated datasets are available online for food quality detection?	The online available annotated datasets, in the form of images and textual data are to be identified to perform food quality detection
RQ3: Which different techniques are followed to detect food adulteration?	To figure out the methods based upon sensors and images, spectroscopy etc. that can be used to detect adulteration in different food products
RQ4: Which are different deep learning and machine learning applications in food?	Find out the various utilities of machine learning and deep learning in the food domain
RQ5: Which food products have been mostly explored until now to detect the adulteration?	Explore the food products for which most of the research work has been conducted
RQ6: What are the different factors considered while evaluating the food quality?	Identify the factors such as freshness, taste etc. for which analysis of food is performed
RQ7. Whether any system exists to detect food adulteration and to evaluate the food quality?	Follow the literature thoroughly to find out the existing similar experiments done by the researchers to evaluate the food quality
RQ8: What are the future research potentials from the literature review?	Recognize the relevant research areas that have not been explored

Table 2 Keyword based advanced search from the year (2009–2019)

Source	Keyword	Publication	Number of results
Google Scholar	Food adulteration detection [with, using, by] [Technique_used]	C/J/M	110
	Food quality [with, using, by] [Technique_used]		
	Food Safety [with, using, by] [Technique_used]		
	The freshness of fruits and vegetables [with, using, by] [Technique_used]		
Science Direct	Abstract, Title, Keywords: Food adulteration detection [with, using, by] [Technique_used]	J	67
	Abstract, Title, Keywords: Food quality [with, using, by] [Technique_used]		
	Abstract:Food Safety [with, using, by] [Technique_used]		
IEEE Xplore	Abstract: Food adulteration detection [with, using, by] [Technique_used]	C	45
	Abstract:Food quality [with, using, by] [Technique_used]		
	Abstract:Food Safety [with, using, by] [Technique_used]		
Taylor &Francis	Abstract, Title, Keywords: Food adulteration detection [with, using, by] [Technique_used]	J	40
	Abstract, Title, Keywords: Food quality [with, using, by] [Technique_used]		
	Abstract, Title, Keywords: Food Safety [with, using, by] [Technique_used]		

Technique_used: [IoT, Machine Learning, E-Nose, E-Tongue], C: Conferences, J: Journals

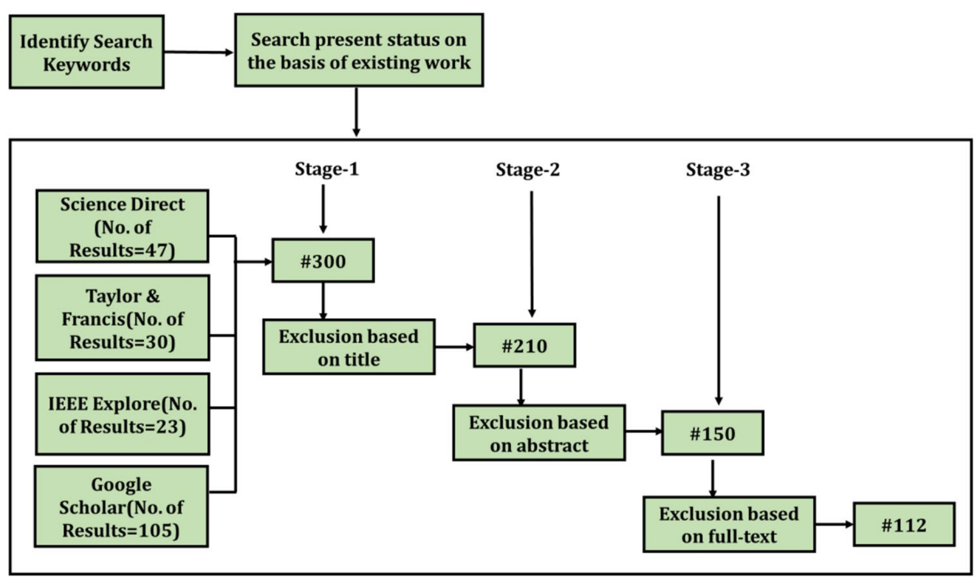
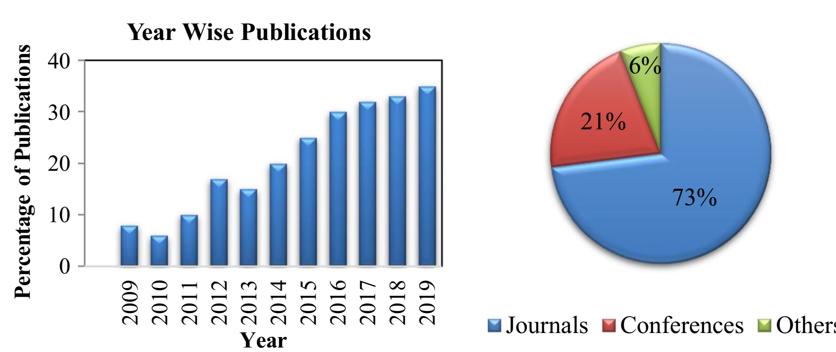


Fig. 1 Review Technique followed



(a). Year-wise publications on food adulteration detection methods

(b). Status of publications from different sources

Fig. 2 **a** Year-wise publications on food adulteration detection methods. **b** Status of publications from different sources of the research articles, journals cover 73% and the remaining 6% are included in thesis and online reports as shown in Fig. 2b. The maximum percentage of research publications have been taken from journals, followed by conferences.

5 Preliminaries for Food Quality Detection

5.1 Dataset

The first phase to perform food adulteration detection is the dataset collection. Mostly the researchers have created their customized datasets based upon their requirements and the parameters to be focused upon to evaluate the food quality. Some of the annotated datasets of images of fruits, vegetable datasets and other few datasets of food of other countries

Table 3 Summary of annotated datasets for food quality detection

Dataset	Dataset details	Model and references	Link
Food-101	101 food categories, with 1000 images per category	Author defined [24] CNN-FOOD [25] Multitask (H. Wu, Merler, Uceda-Sosa, & Smith, 2016) [26] FoodNet [27] DeepFood [28] Inception Module [29, 105] ResNet [30] ResNet-50 [31] Inception V3 [32] Inception V3 [33] wide-slice residual networks (WISeR) [34]	https://www.kaggle.com/dansbecker/food-101/home
UECFood-256	256 Japanese food image Categories	DeepFood [28] Author defined [24] Inception Module (C. [29, 105] DeepFoodCam [35] CNN-FOOD [25] ResNet [30] ResNet-50 [31] Inception V3 [33] Inception-v3 + FP-CNN [32] WISeR [34]	http://foodcam.mobi/dataset256.html
UEC Food-100	Images of 100 kinds of Japanese food with at least 100 images per category	DeepFoodCam [35] DeepFood (Liu et al. 2016a) [28] Inception Module (C. [29, 105] CNN-FOOD [25] ResNet [30] Inception V3 [33] MultiTaskCNN [36] Inception-v3 + FP-CNN [32] WISeR [34]	http://foodcam.mobi/dataset100.html
Fruit-360	90,483 images of 131 categories of fruits and vegetables	CNN EfficientNet [37] CNN (Sakib et al., 2019) [38]	https://www.kaggle.com/moltean/fruits
FIDS30	971 diverse images of 30 fruit categories with around 32 images in every class	CNN (Hussain et al., 2018) [39] CNN LeNet (Sun et al. 2019) [40]	https://www.vicos.si/Downloads/FIDS30
Food 5 K	The dataset containing 2500 food and 2500 non-food images	Jia et al. [11] McAllister, Zheng, Bond, and Moorhead [41]	grebvm2.epfl.ch/lin/food/Food-5K.zip
Food-11	The dataset contained 16,643 images grouped in 11 food categories (Bread, Dairy product, Dessert, Egg, Fried food, Meat, Noodles Pasta, Rice, Seafood, Soup,Vegetable, Fruit	Abdulkadir SENGÜR et al. [42]	grebvm2.epfl.ch/lin/food/Food-11.zip

are available online as given in table Table 3. These datasets include pictures of different fruits, vegetables and some dishes. As the majority of the research work has been done for food recognition and classification, therefore these datasets are available for such purposes. The information given in Table 3 helps in attaining the answer to the research question **RQ2**. This table provides a summary of the online available annotated datasets for different food items.

6 Techniques to Detect Food Adulteration

The food adulteration detection techniques vary from simple visual methods to complex systems. Quality control tests for fruits, vegetables and dairy products are considerable aspects to assure adulterant free products for consumption.

To address the research question **RQ3**, it has been analysed that food adulteration detection techniques can be broadly classified into two categories as shown in Fig. 3. These are Conventional methods to detect food adulteration and Automated food adulteration detection techniques. These techniques have been discussed in detail in the following subsections.

6.1 Conventional Methods to Detect Food Adulteration

The traditional methods used to detect food adulteration include simple chemical tests, check the freshness of food based on smell, various electronic devices or some other manual and observation-based methods. Some of the techniques followed to detect food adulteration are discussed below.

- *Electronic devices to identify food adulteration*: It has been observed that various digital devices that are used to identify the adulteration of the food like lactometer test that measures the specific density of the milk, freezing point determination of the milk or lactoscan device which is used to perform digital analysis of the milk etc.
- *Laboratory tests using chemical substances*: The various laboratory tests that are conducted to check the adulteration of the substance. For example, various pH indicators are used that change the colour of the food if an adulterant ingredient is present in the product. Various chemicals are used to find if the food item is adulterated or not. For example, tincture iodine is used to detect the presence of starch in milk and milk products [43]. Hydrochloric acid (HCl) is used to identify washing soda in jaggery. These lab tests are conducted in the presence of the experts with high domain knowledge and who know about the chemical properties of the food products.
- *Manual inspection of food products*: This method involves the human intervention to manually perform checking of the food products to detect adulteration. Human experts are needed to independently check each adulterant and outline their properties. The manual inspection is done based upon the physical appearance of the food products, their smell, texture and other such parameters. In some instances, even these experts would have trouble making appropriate predictions.
- *Observation-based methods to detect common food adulteration*: There are different methods based on observa-

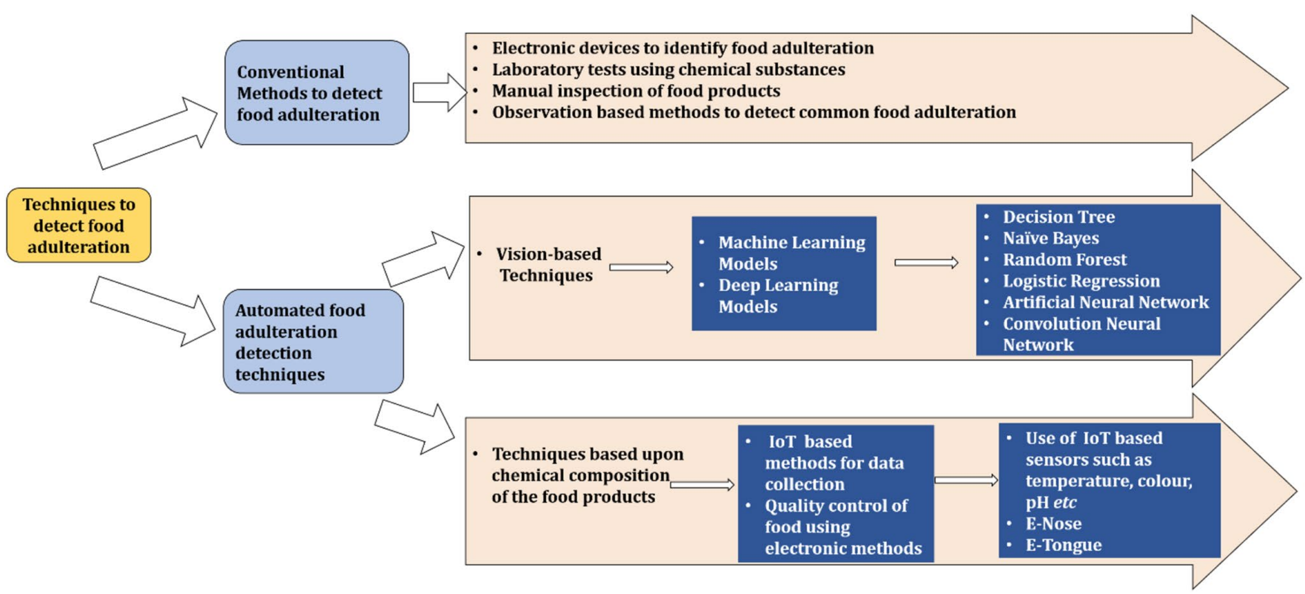


Fig. 3 Methods to detect food adulteration

tion which are used at home and other small scale levels to identify the adulterants in food products such as to detect the water in milk put a drop of milk on the polished slanting surface and if the milk flows leaving the trail behind the milk is pure and in case of adulterated milk, it flows immediately without leaving any mark. Similarly, to detect other oils in coconut oil, refrigerate the oil in transparent glass and the coconut oil solidifies and other oils are deposited as a separate layer in the glass. There are many other methods like heating and dissolving the samples in water etc. are followed which detect the adulterants in different food products.

6.1.1 Challenges of Conventional Methods of Food Adulteration

Researchers have analysed that an automated system sometimes identifies food quality better than humans do. Automated systems can play an important tool in evaluating the quality of different food products. These traditional methods are quite complex and require a lot of manual work and hence there are chances of delay as discussed above. Also, the specialized infrastructure is required for accurate analysis. Not only this but also various agencies are needed for the verification and validation of the results. These methods demand a long time and are quite tedious and inefficient. The current methods of detecting potential adulterants tend to be a burden on domain experts, who do not have the resources and capabilities. Hence to improve these methods and to increase their accuracy; AI comes into a picture that employs different techniques to detect the food adulteration.

6.2 Automated Food Adulteration Detection Techniques

AI has been playing a predominant role in the world of food safety and quality assurance. The food industry has been leveraging the advantages of the latest advancements in AI. Product inspection in the food industry is in high demand, including quality inspection of the food products, classification and grading of fruits and vegetables.

To build an AI system to detect food adulteration, the data required for analysis can be in two forms. The first type of data is used to develop a vision-based model where the main focus is to inspect the quality of food items based upon the parameters like colour, texture, size, shape, defects, morphological features etc. The classification is done based upon the physical appearance of the fruits, vegetables and dairy products by the training of the data using ML models. The second data type consists of parameters such as moisture, pH, temperature, pressure, humidity, viscosity and other related parameters which aim to examine the chemical composition of the food products. For this purpose, the Internet of Things (IoT) can be used to collect the data from different sensors and the decision of adulteration detection is done based upon the contents of the food products. There are other modern types of equipment like electronic tongue and electronic nose that acquire such data and perform analysis to evaluate the food quality.

6.2.1 Vision Based Methods

The visual aspect is one of the most significant parameters to assess the quality of food. Vision based model is a method in which images of the food products can be used to detect adulteration by training the visual dataset on the ML and deep learning (DL) models as depicted in Fig. 4. These models are also used to evaluate the food quality based upon the textual data. The computer vision system is used for automatic and precise classification of food products based on the adulteration level. Food quality evaluation can be done by acquiring the data through a digital camera and then ML models can be used for prediction purposes. The Artificial Neural Networks (ANN) has been highly popular for research works in recent years due to their ability to learn about the features with minimal prior knowledge of the data and independent feature selection. These networks are inspired by the working of the actual neural system of the human body that works like a black box and adjusts the weights as per training rule. The neural network is used in those cases in which the exact model is not known. The ingredients of the food products are used to train the neural network using images to extract textural, shape and morphological properties. The successful implementation of ANN

Fig. 4 Automated Methods to detect Food Adulteration [44]

classifiers can be done to inspect the quality of food products and for grading purposes.

Convolution Neural Network architecture can be proposed that is capable to extract features to detect the food adulteration. The approach based upon a vision system is considered as eco- friendly as it does not involve the usage of chemical reagents. There are several other advantages of this method such as quick and efficient results, low cost and can be widely used in the food industry for classification and grading purposes. To answer the research question **RQ3** the details of the vision based methods used by researchers have been described in Table 4.

Few researchers have used these machine learning methods to access the food quality for textual data. The dataset consists of different parameters related to the food product. Most of the researchers have used ANN to perform the detection of food adulteration. The details of the methods used in the literature survey are summarized in Table 5.

6.2.2 IoT Based Food Adulteration Detection Methods

The AI along with the Internet of Things (IoT) has been a powerful platform for food security and safety. IoT technology can be used to make the system of adulteration detection as a smart device. To enhance the quality of food, it could be a part of the food supply chain by tracking food conditions and live sharing the data with the consumers. As shown in Fig. 5, the system works in three phases: (i) Sense (ii) Analyze (iii) Predict.

In phase one, the data is collected using different sensors. The different sensors can be used to record the data and a Raspberry Pi can be used to control the entire working of the system as shown in step 1 and step 2 in Fig. 5. Next, in phase two the design and implementation of an AI system which may use the data collected from sensors. The food quality system can be designed to keep a watch on various environmental factors such as temperature, humidity, alcohol content and exposure to light that may decay the food as shown in step 3 and step 4 as per the figure. Finally, in phase three the smart decisions for the food adulteration detection system are suggested and predict the output if the food product is pure or adulterated as seen in step 5 and step 6 in the figure. The quality of the food can be detected which can be used as a platform for the food adulteration monitoring system. The related work done by researchers using IoT to perform food quality evaluation is summarized in Table 6.

6.2.3 Quality Control of food using Electronic Methods

The electronic nose (E-Nose) and Electronic Tongue (E-Tongue) are devices that work the same as human nose and taste organs and are composed of an array of sensors. These systems have broad applications in the food adulteration detection system as the complex data sets from E-Nose and E-Tongue signals coupled with multivariate statistics constitute fast and effective instruments for classifying discriminating, recognizing and identifying samples, as well as predicting the concentrations level of various compounds.

An electric nose is used to detect the smell even better than the human's sense of smell. It obtains the data on the nature of the compounds under consideration by using the chemical detection principle; it is a smart sensing tool that utilizes the array of gas sensors that overlap with the pattern of reorganization component. The detection system of the e-nose consisting of sensors when comes in contact with the volatile compounds experience a change in electrical properties. A specific response recorded by the electronic surface transforms the signals into digital values [78]. Computation is done based on the statistical models on the recorded data. It is widely used in the research fields as it detects the hazardous gas present in the adulterated food that is not possible for a human nose.

E-Tongue is a multichannel taste sensor that is used to recognize, classify and quantify the components of liquid samples. The data about the samples are collected from sensors that work the same as gustatory cells present in taste buds of the tongue. The set of specific sensors is used to obtain the digital fingerprint of the sample and the information related to taste generating substances is transmitted into electrical signals which serve as a profile input for the data recognition system. Figure 6 presents the working schema of the E-Nose and E-Tongue where it is observed that the food products can be accessed in three forms solid phase (fruits, vegetables etc.), liquid phase (milk, juices etc.) and gaseous phase (volatile compounds emitted from the products). The solid compounds are analyzed through their texture, shape, colour, thermal and optical properties whereas in case of liquids the taste of the food item is analyzed and for gases, the compounds are judged based upon their odour and volatile compounds emitted from the substances. These electronic devices mimic the olfactory system of the nose to study the gaseous elements and gustatory receptors of the tongue to look over liquid compounds.

The sensory devices such as a spectrophotometer, thermometer etc. are used to examine the solid products. Further, ML and DL models can be applied for classification and pattern recognition based upon which the prediction is done about the presence of adulterants in food. Also, the other parameters such as odour, taste, the flavour of the food, aroma appearance and texture of the food can be analyzed from the predictions of the model. The research work related to these electronic methods is described in Table 7.

Thus, to build a computer-based food adulteration detection system, one needs to use IoT devices to sense the data and ML models for predictions based on the collected data.

Table 4 Summarized review of Food Adulteration Detection System using vision based methods

Author	Proposed Methodology	Techniques and Dataset	Conclusion
Pourreza et al. [45]	The grayscale images of wheat seeds were studied to extract 131 textural features. LDA classifier was employed for classification using top selected features	LDA and Textural Feature Extraction Matrices (GLCM, GLRM, LBP, LSP, LSN) were used. Dataset consisted of 1080 grayscale images of 9 wheat seeds qualities (120 images of each variety)	accuracy: 98.15% Best Results were given by LSP, LSN, LBP
Neelamegam et al. [46]	Image processing was used to differentiate basmati rice from other inferior qualities of rice	Feature extraction using Neural networks and digital imaging. Filters such as grayscale, median smoothening, adaptive thresholding, canny edge detection, Sobel edge detection, morphological operations using computer vision library of functions to pre-process the images	The results obtained improved crop recognition and reduced the time of operations to a great extent
Nandi et al. [47]	Computer Vision based automatic mango grading system is proposed	The automated system collects video image from the CCD camera placed on the top of a conveyer belt carrying mangoes, then it processes the images to collect several relevant features which are sensitive to the maturity level and quality. Finally, a fuzzy rule-based algorithm is used to sort the fruits into four grades	Classification performed well
Carolina et al. [48]	The classification was done based on the degree of maturity of oranges using their physical characteristics	Image Processing	The oranges were classified based upon the maturity level
Ropodi et al. (2014)	Detection of minced beef intentionally adulterated with pork and vice versa using multispectral imaging	Dataset included images in 18 different wavelengths of 220 meat samples in total from four independent experiments (55 samples per experiment). The nine different proportions were prepared by mixing beef and pork-minced meat was mixed. PLS-DA and LDA were used to discriminate among all adulteration classes, as well as among adulterated, pure beef and pure pork samples	Classification Accuracy: 98.48%
Khosa et al. [50]	ANN classifier was used and for quality evaluation 6 texture properties and 16 features were extracted using GLCM at angles of 0, 45, 90 and 135 and PCA was used for discrimination among features	ANN and PCA are used with a dataset consisting of images	The parameters like accuracy, sensitivity and specificity were calculated for extracted features
Kamruzzaman et al. [51]	Adulteration of minced beef with chicken was detected by hyperspectral imaging at three different profiles	Partial least squares regression (PLSR)	(R^2) = 0.97, 0.97, and 0.96 and RMSEP of 2.62, 2.45, and 3.18%
Ali et al. [52]	Detection of fraudulent labelling of rice samples using computer vision and fuzzy knowledge was performed	Neural network	Precision: 90% high accuracy
Lim et al. [53]	mass spectroscopy combined with supervised ML algorithms were used to detect adulterated mixtures of white rice	RF, SVM, DT, ANN and KNN were used and the dataset consisted of 330 samples of white rice mixed in seven different ratios	RF and SVM outperformed other classification techniques

Table 4 (continued)

Author	Proposed Methodology	Techniques and Dataset	Conclusion
Kobek et al. [54]	The images of the milk samples skimmed with bromothymol blue (pH indicator) were captured. The neural network was trained and the image was classified using colour parameters red (R), green (G), blue (B), luminosity	ANN, PLSR and principal component regression analysis (PCR) model	The model proposed was used to identify the milk adulteration
Fayyazi et al. [55]	Image processing and MLP Neural Network were used to identify and classify three varieties of rice where 17 morphological and 41 textural features were extracted from the pictures of the seeds	PCA for feature ranking andMLP for classification was used and 666 images of seeds of rice were considered with 222 images of each type	classification accuracy Type 1: 55.93%, Type 2: 84.62% Type 382.86% In the testing phase, the accuracy was calculated using two varieties of rice at a time
Rong et al. [56]	Detection of the surface defects in the oranges in grey-level images. to segment the various defects	Techniques like window local segmentation algorithm and the image processing were used and dataset comprised of 1191 sample images of orange	The defects of the oranges were identified using the image processing and window local segmentation algorithm
S. Anami et al. [57]	The 7 different samples of paddy are prepared by using a mixture of high-quality paddy with the identical low quality and different adulteration ratios (10%, 15%, 20%, 25%, and 30%)	Classification methods like BPNN, SVM and k-NN and feature selection methods like PCA and Sequential Forward Floating Selection (SFFS) methods were used	An Automated method was successfully implemented to recognize and classify the adulteration levels from the samples of grains of paddy
Tripathy et al. [58]	Paper-based method to detect the milk adulteration using sensors that demonstrate three different colour ranges corresponding to pure (pH lying in range 6.6–6.9), acidic ($pH < 6.6$), and basic ($pH > 6.9$) milk samples. The changes in colour strips were captured using a smartphone camera and classified into one of the three pH ranges using a classifier	pH based sensors and SVM	The pH strips are made and are used to detection of milk adulteration
Al Sarayreh et al. [59]	SVM model was used to detect the adulteration in red meat products and investigate the handcrafted spectral and spatial features and CNN for self-extraction spectral and spatial features	Techniques like Hyperspectral imaging using CNN and SVM Model were used and dataset images of lamb, beef, or pork muscles were collected	CNN model accuracy: 4.4%
Neto et al. [60]	CNN architecture has been proposed to recognize FTIR data collected from infrared spectroscopy to use deep and ensemble learning methods to identify the adulteration of milk	Infrared spectroscopy and ML algorithms such as deep and ensemble DT learners	classification accuracy: 98.76%
Izquierdo et al. [61]	Deep learning was used to classify the five varieties of rice	CNN	Accuracy = 93.4%

Table 5 Summarized review of Food Adulteration Detection System using machine learning

Author	Proposed methodology	Techniques and dataset	Conclusion
Li et al. [62]	Sour skin of onions was detected using SVM and gas sensor array. PCA method was used to show the distinct clusters formed by healthy and infected onions. Hypothesis testing was done using MANOVA to check the p values	SVM and PCA for classification. MANOVA for hypothesis testing	Accuracy: 85% for validation and 81% during training. p-value < 0.0001 concluded that two types of onions were considerably different
Debska et al. [63]	ANN method was used to classify beer samples into two classes (good quality and an unsatisfactory quality) based on 12 features	ANN was used and the dataset consisted of 70 beer samples and 12 features were extracted for analysis	Classification Accuracy: almost 100%
Meire et al. [64]	Authentication of samples of wine was done by collecting from 6 different origins using ML Techniques	SVM, RF, Multilayer Perceptron, k-NN, and Naive Bayes were used. The dataset comprised of 42 samples of grapes	Best accuracy: Random Forest
Bandyopadhyaya et al. [65]	To check the ripeness of tomato and ladyfinger by a touch-sensitive robotic system using machine learning	SVM, KNN	Tomato classification: SVM: 64.23% KNN: 92.86% Lady Finger classification: SVM: 60% KNN: 80%
Dan Peng et al. [66]	Gas chromatography along with multivariate data analysis was used to identify the adulteration of sesame oil with vegetable oils	SVM and Partial Least Square Method (PLSM) were used and a mixture of five types of vegetable oils was used on 746 samples	RMSEP value ranged from 19% to 4.29%
Mu et al. [67]	A partial least square model was built to predict the adulteration concentration with the errors lower than 2%. Then, ANN and SVM were used to classify pure and mixed oils	Multivariate Analysis using laser-induced fluorescence (LIF), ANN and SVM were used where dataset comprised of 280 sets classified into four groups (including olive, rapeseed, peanut, and blend oils)	Pure oils differentiated from a mixed oil well
Rashvand et al. [68]	Adulteration detection using dielectric technique and data mining from the samples of olive oil, sunflower oil and canola oil mixed in different ratios	(LDA) in combination with the dielectric based system was used with a dataset consisting of 15 samples	Highest error rate 60% olive oil and 40% canola oil. Specificity: 98%, Sensitivity: 99% accuracy: 72%
Yu et al. [69]	Identification of wine from grape varieties using NIR spectroscopy combined with RBFNN and (LS-SVMs) based on PCA	NIR spectroscopy combined RBFNN and LS-SVM based on PCA	The accuracy of RBFNN varied from 90.16 to 98.36% RBF LS-SVM, identification rates were in range 91.80—98.36%
Zhang et al. [70]	Use of machine learning to predict the quality risks of dairy products	Methods ELM and K-ELM were used to construct a waring model to evaluate the quality risk of dairy products	K-ELM performed the best in food safety prediction in terms of accuracy and the training time
Santana et al. [71]	Adulteration Detection from primrose oils and ground nutmeg using the random forest in combination with infrared spectroscopy	The primrose oil was adulterated with soybean, corn and sunflower oils. The ground nutmeg was adulterated with cumin, commercial monosodium glutamate, soil, roasted coffee husks and wood sawdust	For the primrose oil, the proposed method presented superior performance than PLS-DA and similar to SIMCA and for the ground nutmeg, the random forest was superior to PLS-DA and SIMCA
Naskar et al. [72]	Detection of grapefruit juice adulterated with sugar solution and water	PCA, Box Plot and LDA	Separability Index (SI) identified adulteration like sugar solution and water in pure grape juice

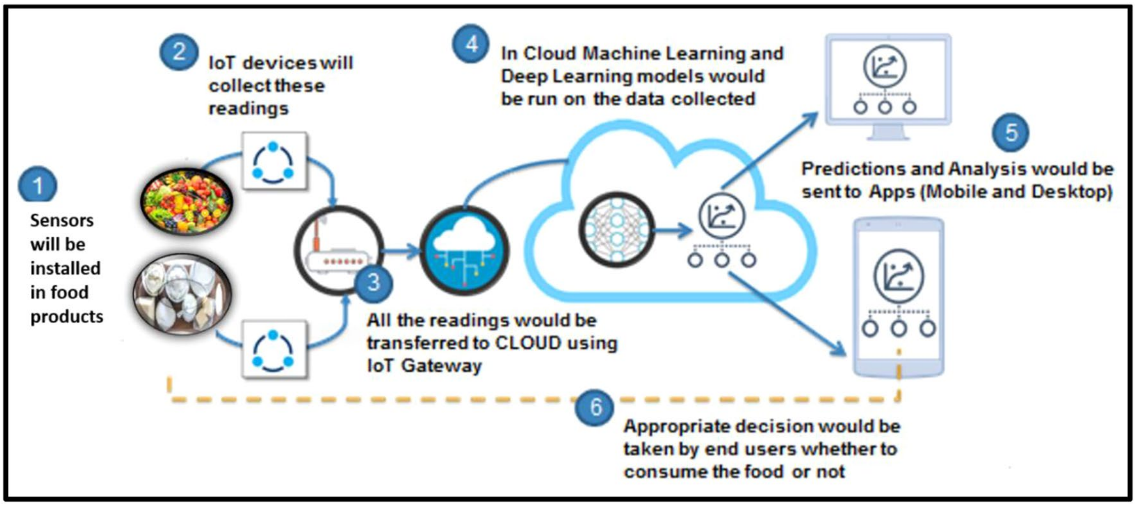


Fig. 5 Working of IoT System

7 Machine Learning and Deep Learning Applications in Food

Machine learning is a subfield of artificial intelligence that makes computers learn without being explicitly programmed. It is constructing the algorithms that can learn from data and make predictions on the related data. ML is categorized into two classes namely supervised and unsupervised machine learning. In supervised ML, there is a predetermined set of classes into which the food items are classified and training data is available for each class. The system uses any of the classification algorithms such as Naive Bayes (NB), Support Vector Machines (SVM), Decision Tree (DT), k-Nearest Neighbour (k-NN) and trains a model from the given data. This trained model is then used for making predictions and assigning the food products into different categories. In the case of the unsupervised approach of ML, no labelled data is provided to models. Deep Learning is a part of machine learning that can be considered as a representation learning method that is inspired by the human brain. It has turned out to be a powerful medium of pattern recognition in the last few years. It uses a deep neural network composed of multiple layers of neurons. It has an advantage of self-feature engineering and good accuracy that makes it work efficiently for even highly complex problems. Deep Learning models are good for classification and regression tasks provided a sufficient amount of data. Deep Learning signifies the number of layers that contain the neural network. The primary neural network is composed of three layers input, hidden and output layer. The number of intermediate layers increases as the complexity of the problems arise.

The inclination towards machine vision in the food domain is quite trending from the last few years. It has experienced a huge expansion in both theory and implementation. It has various applications such as medical diagnostics, automated manufacturing, aerial surveillance, remote sensing and now grading of food and agricultural products. Object detection is one of the classical applications of computer vision that is involved in developing an automated food sorting system. In this, the objective is to identify what and where i.e. to recognize the objects in the given image and where the objects are located in the given image. The task of object detection is a bit complex as compared to object classification as it just recognizes the objects but not their location in the image and also classification fails in images having more than one object. Convolution Neural Network is also used for object detection. It is a deep learning concept in which an image is given as the input, features are extracted from the same and based upon these features, the input image is differentiated from the other images. The answer to **RQ4** is discussed in the following sections that tell about the applications of machine learning and deep learning in the food domain.

7.1 Food Recognition and Classification

Eating habits and daily diets can highly affect the health of people. Food Recognition and classification is a major task that helps human being to record their daily diets. It is mandatory for diabetic and allergic patients to strictly monitor and control their dietary behaviour. The information about the food products is characterized in their images. Image acquisition is an easy and cost-friendly medium for procuring information for food recognition and classification. This task becomes challenging for natural products that vary in size, shape, volume, texture, colour and composition. Various background and layout of foodstuffs also introduce variations for food recognition and classification. At present,

Table 6 Summarized review of food adulteration detection system using IoT

Author	Proposed Methodology	Techniques and Dataset	Conclusion
Jia et al. [73]	A method is proposed to construct a quality supervision platform for food production with the use of IoT. It also presented the use of RFID tags and 1-D code, building methods of food quality model by a theory of ontology-based context modelling, and the combination and presentation methods of service functions for the different users	IoT and RFID Tags	Food quality supervision system is set up
Eom et al. [74]	The freshness of vegetables was evaluated by proposing an oxygen and carbon dioxide concentration monitoring system that used radio RFID	Oxygen and Carbon dioxide sensors were used along with RFID tags	The concentrations of these gases were monitored
Chanthini.B et al. [75]	The concept of IoT was used to monitor the quality of perishable food from a remote location. The use of Raspberry pie as a sensor node and a gateway node to provide data collected from different sensors like temperature, humidity and moisture	IoT	System to monitor food quality using IoT was developed
Gupta et al. [76]	The poor quality of the food was detected using different sensors that were used to record the data and Raspberry Pi to control the entire working of the system	Internet of Things	A food adulteration monitoring system was developed
Kang et al. [77]	Real-time Fruit Detection and Segmentation for Apple Harvesting Using Visual Sensor in Orchards using ResNet 101	The developed detection and segmentation network utilizes the atrous spatial pyramid pooling and the gate feature pyramid network to enhance feature extraction ability of the network	ResNet-101 backbone outperformed on the detection and segmentation tasks with F1 score of 0.832 on the detection of apples and 87.6% and 77.2% on the semantic segmentation of apples

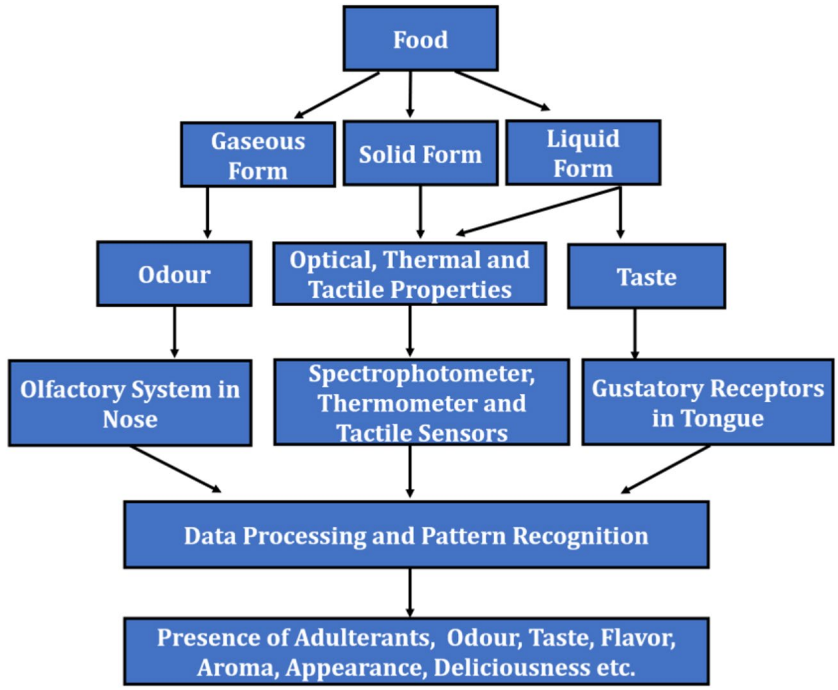


Fig. 6 The architecture of E-Nose and E-Tongue [79]

due to the common use of CNN, image analysis has been the most commonly used pattern in food recognition and classification.

There are various popular machine learning and deep learning methods for this purpose. But, CNN architectures work better for image identification. These structures include AlexNet [89] [90], a network using repetitive units called visual geometry group network (VGG) [90], GoogLeNet [91] that includes parallel data channels, and residual neural network (ResNet (He et al. 2016) constructed by residual blocks [91–93]. Furthermore, these mentioned network architectures can be downloaded from the model zoo with pre-trained weights. That is, the models have already been trained by some image datasets like ImageNet [93] so that these pretraining models have already learned the ability to extract image features (such as colours, texture information, high-level abstract representations, and so on) [94]. Researches can use their specific image datasets to implement transfer learning based on the pre-trained model, which means that we can use our dataset to retrain the weights of a fully connected structure for final classification while keeping the weights of convolution layer unchanged, or slightly adjusting the weights of the whole network. The researchers who have worked upon food recognition and classification are listed in Table 8.

7.2 Food Calorie Estimation

With improved living standards, dietary management is gaining more and more attention. Nowadays, technology can support users to keep track of their food consumption in a more user-friendly way allowing for a more comprehensive daily dietary monitoring. People are more cautious about keeping track of their daily diet to help them control nutrition intake, lose weight, manage their diabetes or food allergies, and improve dietary habits to stay healthy. The food calorie is one of the most concerned indexes. Many mobile APPs have been designed for recording everyday meals including not only food names but also food calorie [101, 102] [103, 104]. The task of food calorie estimation is more challenging than food classification because it's not sufficient to estimate the food calorie just from its texture and colour. The weight or volume of food, cooking directions and ingredients directly affect the calorie content of the food. It is not easy to build a large dataset containing food images, ingredients, cooking methods, and weights (or volumes) labelled with calorie content, which restricts the use of deep learning technology to achieve calorie estimation. Few authors have worked on the image classification part but it just roughly estimates the calorie content of the food. The research work in this area is presented in Table 9.

7.3 Food Supply Chain

The food supply chain is a complex system consisting of multiple economic stakeholders from primary producers to consumers (including farmers, production factories, distributors, retailers, and consumers) [103] [105]. It is hard for regulators, such as governments, to obtain reliable food information due to the unreliable information from the

Table 7 Summarized review of food adulteration detection system using E-Nose and E- Tongue

Author	Proposed methodology	Techniques and dataset	Conclusion
Markom et al. [80]	The samples of odour were taken on the site of plant and the system was capable of distinguishing between the healthy and infected palm tree using different odour parameters such as the odour of the surrounding tree, the odour of bored trunk and odour of soil	Cyranose 320	The classification has been performed well
Kundu et al. [81]	The unknown water samples were classified using ML algorithms and E-Tongue was used for data acquisition	PCA and partial least squares (PLS), E-Tongue are used Dataset consisted of 6 classes of samples with 4402 features	The water samples were classified into 6 classes
Subari et al. [82]	The testing was done on 10 different brands of certified pure honey and samples were created using different adulteration concentrations (20%, 40%, 60% and 80%) of two types of sugar solutions (cane sugar and beet)	LDA and PCA were used Data Collection using E-Nose and FTIR	Accuracy of FTIR based data is 88% and for E-Nose data was 76.5%
Teye et al. [83]	Identification of Cocoa beans was done using E-Tongue and pattern recognition methods	Pattern Recognition methods Fisher's discriminant analysis (FDA), PCA, KNN and SVM were used and data was collected using E-Tongue	The best results were achieved by SVM
Tian et al. [84]	Detection of mutton in minced pork using E-Nose	An Enose of metal oxide sensors were used for the collection of volatiles presented in the samples. Partial least square analysis (PLS), Multiple Linear Regression (MLR) and Backpropagation neural network (BPNN) were used to build a predictive model for the pork content in minced mutton	BPNN outperformed all
Heidarbeigi et al. [85]	E-Nose was used to find the different types of adulterants in the saffron samples. The aroma fingerprints of saffron, saffron with yellow styles, safflower, and dyed corn stigma were detected by an E-Nose system	Backpropagation and ANN were used for classification and the PCA method was used for feature reduction	Accuracy: 86.87%
Bougrini et al. [86]	The samples of honey were classified and analyzed using three-pattern recognition techniques. For adulterant detection, these adulterants were with authentic honey with the ratios 2, 5, 10, and 20% by weight, respectively	E-Tongue for data collection and pattern recognition techniques: PCA, SVMs, and hierarchical cluster analysis (HCA) were used. Dataset consisted of 18 and 7 varieties of honey based on geographical and botanical origins respectively	Excellent classification results were achieved
Ordukaya et al. [87]	Quality control of olive oil using ML and E-Nose with two methods. In the first technique, 32 inputs were applied to the classifiers and in the second method, PCA was used to minimize the 32 to 8 input	Naive Bayesian, *k*-NN, LDA, DT, ANN, and SVM	The second method produced better as compared to the first one with the best accuracy achieved in the case of Naive Bayes classifier as 70.83%

Table 7 (continued)

Author	Proposed methodology	Techniques and dataset	Conclusion
Ayari et al. [88]	Cow ghee was analyzed to identify adulteration using an E-Nose to identify sunflower oil and cow body fat mixed with pure cow ghee in different ratios	PCA and ANN	PCA Accuracy: sunflower oil: 96% Cow body fat:97% ANN accuracy: sunflower oil: 91.3% Cow body fat: 82.5%
Tian et al. [89]	A combination of E-Nose and E-Tongue was used to detect the adulteration of minced mutton mixed with pork	For Normalization, LDA and PCA were used. For regression, MLR, PLS and BPNN were used	$R^2=0.97$ for BPNN

supply chain, which can easily lead to food fraud and food safety problems. Mao et al. [103] presented a credit evaluation system based on blockchain for the food supply chain using a deep learning network named LSTM. The evaluation task was carried out by analyzation of credit evaluation texts. Text data like "The fruit does not look very fresh" were labelled as "negative," and the sentence such as "the quality is good" has a "positive" label. Sentence feature extraction was performed by LSTM and these features act as the input of DNN based classifier. The proposed method showed approximately 90% classification accuracy on a Chinese text dataset, which was beyond the reach of traditional methods such as SVM and naive Bayes. The research in [103] solved a problem that how to transform a large number of credit evaluation text data into some simple evaluation indicators [105]. Similarly, another article [104] [106] introduced a sentence classification method using deep learning, which can be tested using the dataset mentioned in Mao et al. [103] for comparison. Such research relies heavily on big data, so much work (such as dataset in the type of audio, text, and so on, for food domain should be collected, for example) remains to be done in the future.

7.4 Quality Detection of Fruits and Vegetables

Fruits and vegetables being an essential part of a healthy diet are explored a lot and their quality detection has been a trending research area. It provides the necessary nutrients for human beings. Deep Learning and machine learning along with image processing has become an efficient tool for fruit and vegetable quality detection in the last few years. The various research studies on the quality detection of fruits and vegetables are presented in Table 10.

8 Findings of Systematic Survey

This section summarizes the established findings as the comprehensive survey has been conducted and efforts have been made to answer all the research questions given in Table 1. From the literature survey, it is concluded that the researchers have used machine learning and deep learning techniques followed by sensor-based approaches as shown in Fig. 7. PCA has been commonly used for dimensionality reduction. There is too much potential in AI-based methods, beyond some of the labour intensive tasks for food adulteration detection. Most of the research experiments (i.e. approx. 75%) have therefore opted for machine learning as well as deep learning in parallel to detect food adulteration. Nevertheless, researchers are being attracted in recent times to experiment with deep learning due to improved accuracy regardless of the time constraint needed to train the data. Researchers have also used sensor based methods

Table 8 Summarized review of food recognition and classification

Author	Model	Dataset	Result
Rocha et al. [95]	Automatic fruit and vegetable classification using a combination of features	Supermarket Produce Dataset available online	High classification results with SVM
Bossard et al. [98]	Machine Learning Methods	Food-101 database	Accuracy: 50.76%
Yanai et al. [25]	fine-tuned AlexNet	Food-101 database	Top-1% Accuracy: 70.41%
Heravi et al. [24]	The modified version of AlexNet	dataset included 1316 images in 13 food categories	Accuracy: 95%
Ragusa et al. [97]	Fine-tuned AlexNet in combination with a binary SVM classifier	The dataset comprised of 8005 non-food images and 3583 food images from Flickr and 3583 food from UNICT-FD889	Accuracy: 94.86%
Shimoda et al. [99]	CNN VGG -16	UECFOOD-100	High classification accuracy
Tatsuma et al. [100]	covariances of features of trained CNN	Food-101 database	Accuracy: 58.65%
Herruzo et al. [102]	GoogLeNet	FoodCAT was presented based on Catalan food. Food-101	Food Identification Accuracy: Top-1%:68.07% Top-5%: 89.53% Food categories Recognition Accuracy: Top-1%:72.29% Top-5%:97.07%)
Liu et al. [28]	Deep Food Network	Food-101 database	Accuracy Top-1%: 77.40% Top-5%: 93.70%
Fu, Chen, and Li [30]	fine-tuned deep 50-layer ResNet	Food-101 database	Accuracy Top-1%: 78.5% Top-5%: 94.1%
Mezgec and Seljak [101]	The modified AlexNet model was used to develop a system named NutriNet	training dataset: 225,953 images of food and drink items Testing images: 130,517	Classification accuracy: Training: 86.72% Testing: 94.47%
Fu et al. [30]	ResNet architecture	ChinFood1000 database	Accuracy Top-1%: 44.10% Top-5%: 68.40%
Pandey et al. [27]	multilayered CNN that used AlexNet architecture	Food-101 dataset and Indian food database that consisted of 50 categories with 100 images of each	Accuracy for Food-101 Top-1%: 72.12% Top-5%: 91.61% Top-10%: 95.95% Accuracy for Indian Food Dataset Top-1%: 73.5% Top-5%: 94.4% Top-10%: 97.6%
Ciocca et al. [31]	ResNet-50 model	Food-527, Food-475, Food-50, and VIREO	High classification accuracy
McAllister et al. [41]	ANN, SVM, Random Forest and Naive Bayes, ResNet-1522 model	Food-5 K Food-11 and RawFooT-DB Food-101	Accuracy for Food-5 K SVM: 99.4% ANN: 98.8% Accuracy for Food-11 ANN: 91.34% Accuracy for RawFooT-DB ANN: 99.28% Accuracy for Food-101 SVM: 64.98%
Martinel et al. [34]	CNN structure called WISeR was proposed in which they first designed a slice convolution unit for extracting common vertical characteristics of food and then added deep residual blocks to make a combination to calculate the classification score	Food-101, UECFood-256 and UEC-Food-100	Accuracy for Food-101 Top-1%: 90.27% Top-5%: 98.71% Accuracy for UECFood-256 Top-1%: 83.15% Top-5%: 95.45% Accuracy for UECFood-100 Top-1%: 89.58% Top-5%: 99.23%

Table 8 (continued)

Author	Model	Dataset	Result
Jia et al. [11]	GoogLeNet model for Binary Classification	Food-5 K database	Accuracy: 99.2%
McAllister et al. [41]	Radial Basis Function (RBF) kernel-based SVM with ResNet-152	Food-5 K database	Accuracy: 99.4% for validation dataset and 98.8% for evaluation dataset)
Khaing et al. [96]	CNN	The dataset consisted of 971 images	Accuracy: 94%

Table 9 Summarized review of food calorie estimation

Author	Model	Attributes and dataset	Result
Myers et al. [103]	GoogLeNet CNN model	Identification of food items, their volume, and calorie density	A mobile app named Im2Calories was designed for food calorie estimation from images
Ege and Yanai [104]	Multitask with 16-layer VGG network CNN	The attributes like food calories, categories, ingredients, and cooking directions are considered Japanese and American datasets were used for training purposes	Multitask CNN achieved 27.4% for related error, Absolute error: 91.2 kcal for absolute and correlation: 0.817

and primarily focused on ANN and CNN for the development of a food adulteration detection system. The response to question **RQ3** has been obtained through Fig. 7 which summarizes the AI-based techniques for food adulteration detection.

It has been observed that the food products that have been focused by the researchers are dairy products mainly milk, cheese and ghee. In the category of fruits, the experiments have been conducted on apples, mangos, oranges, bananas, grapes and plums etc.

The vegetables for which adulteration detection and quality evaluation have been performed are the carrot, tomato, onions, cucumber, spinach etc. Also, the researchers have worked to detect adulteration in other food products like honey, olive oil, saffron etc. Figure 8. depicts the commonly adulterated food products. The response to research question **RQ5** is stated in Table 11 which describes the major food items that have been explored by researchers to study about food quality detection system.

8.1 Features used for Food Quality Detection System

The research articles have been studied thoroughly and the answer to the research question **RQ6** has been reported in Table 12. As discussed before that the food item is evaluated based upon vision parameters that include colour, morphological and texture features.

8.1.1 Colour Features

Colour features are the ones that influence the buyer to accept/ reject the foodstuff as it characterizes the freshness and quality. Images of the food products are acquired by widely used RGB colour models based on red (R), green (G), blue (B) primitive colours. This colour model separates an object into red, green and blue planes. In an image, various RGB devices produce different RGB values for the same pixel, multiple transformations techniques are used to standardize these values. As RGB is not linear with the human visual inspection, the sensory properties of food products cannot be analyzed. HSI is proposed and developed to resolve such problems. It is a leading method for evolving colour based image processing algorithms that are easily visualized by humans. However, HSI and RGB are similar and do not respond to minute colour variations. Therefore, it is not advised to evaluate the transformation of product colour during processing. CIELAB colour space identifies all the colours to the human eye and was designed to be used as a device dependent model as to where 'L' is the measure of lightness, 'a' and 'b' adjusts the red/green and green/blue balance respectively. It can be perceptually related in such a way that colour differences in CIE-LAB space that a person recognizes are the same as Euclidean distances. Since the colour measured by computer vision can be compared easily with colour obtained from CIELAB colour space, it provides a feasible way to assess the quality of object colour measurement. Table 13. summarizes the quality analysis of fruits and vegetables based upon different parameters and colour space model employed by numerous researchers.

8.1.2 Morphological Features

The morphological features that depict the shape and size are generally used to classify fruits and vegetables. Grading of these food items is performed based upon their size. The

Table 10 Summarized review of food quality detection of fruits and vegetables

Author	Proposed Methodology	Techniques and Dataset	Conclusion
Li et al. [62]	Sour skin of onions was detected using SVM and gas sensor array. PCA method was used to show the distinct clusters formed by healthy and infected onions. Later hypothesis testing was done using MANOVA to check the p values	SVM and PCA MANOVA for hypothesis testing	Accuracy: 85% for validation and 81% during training p-value < 0.0001 concluded that two types of onions were considerably different
Mustafa et al. [108]	Sorting of fruits using 17 features using morphological and colour characteristics of fruits (apple, banana, mango, orange and carrot)	DIP, ANN and Probabilistic Neural Network (PNN)	Accuracy: 90%
Jhuria et al. [109]	ANN was used to detect the diseases apples (Appli Scab and Rot) and grapes (Black Rot and Powdery Mildew)	Image processing and ANN	Accuracy: 90%
Moallem et al. [110]	computer vision-based algorithm for golden delicious apple grading is proposed based upon surface features	SVM, MLP, KNN for classification and dataset included 120 images	SVM classifier works as the best one with a recognition rate of 92.5% and 89.2% for two categories (healthy and defected) and three quality categories (first rank, second rank and rejected ones
Tan et al. [114]	AI-based alerting system for pests and diseases of apple	CNN	Accuracy: 97.5%
Sahu et al. [111]	Development of an automated tool using the concept of computer vision to find the defect and detect if the mango is mature based on its features like shape, size and colour	Digital Image Analysis	The mangos were separated based upon defects and maturity levels
Azizah et al. [113]	Detection of defected surfaces of mangosteen using 120 RGB images. The manual labels were obtained and then cropped and resized to 512 × 512 pixels as the dataset for modeling and evaluation	CNN coupled with fourfold cross-validation	Accuracy: 97.5%
Mithun et al. [115]	Screening out the artificially ripened banana by hyperspectral sensing and RGB imaging using 120 RGB images from each class (artificially/normally ripened, for training and 30 images for testing) were used to train and evaluate the model	AlexNet Model	Accuracy: 90%
Sun et al. [116]	Detection of diseased peaches using hyperspectral imaging on 420 channels and 54 image features	PCA and deep belief network	Peaches were classified well
Rodriguez et al. [112]	Discrimination of plum varieties based upon their maturity level	AlexNet Architecture	Accuracy: 91% to 97% for different datasets
Z. Liu et al. [107]	Cucumber defect detection based on hyperspectral imaging	Stacked autoencoder in combination with CNN	Accuracy: 91.1%

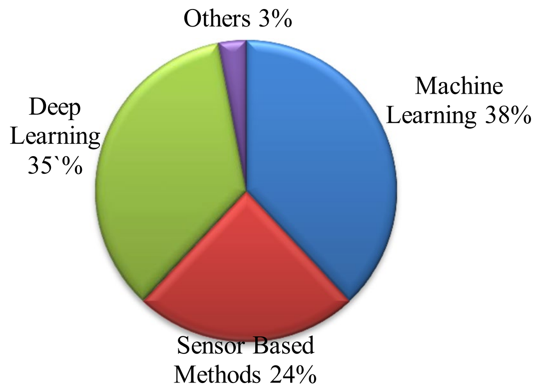


Fig. 7 Percentage of research work using food adulteration detection methods

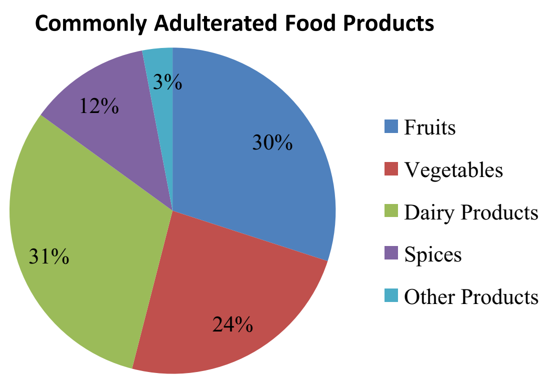


Fig. 8 Percentage of food products commonly used for adulteration

size of the food item is measured using features like projected area, perimeter, length, width, major and minor axis. Such features are commonly used in industries for automated sorting purposes. The area (a scalar quantity) measures the actual number of pixels in the region. Pixels of the area are used to calculate the projected area. Feature extraction is done using the gap of two neighbouring pixels. Perimeter is determined by the distance between the boundaries of the region. These features are efficient enough once the object is segmented, irrespective of shape and size. Length and width are used to measure the size of fruits and vegetables. As the shape of food products typically changes during processing, it is necessary to restore the orientation at which length and width are measured. The major axis is the longest line across the object, obtained by the length of each of two boundary pixels.

The shortest line perpendicular to the major axis is the minor axis. The shape is a crucial visual attribute for image content description that cannot be defined precisely because it is not an easy task to measure the similarity between shapes.

The two shape descriptor categories are region-based (based on integral object area) and contour-based (boundary segmented by local features). Roundness, aspect ratio and compactness are used to characterize the shape of the food item. In the food industry for quality analysis convexity, roundness, compactness, length, width, elongation, boundary encoding, length/width ratio, Fourier descriptor and invariant moments are the most common

Table 11 Commonly used food products for food adulteration detection

Types of food products	Authors
Milk/cheese/ghee	Kobek et al. [54]; Tripathy et al. [58]; Neto et al. [60]; Ayari et al. [88]; Lukinac et al. (2018) [117]
Cocoa Beans	Teye et al. [83]
Honey	Bougrini et al. [86]; Subari et al. [82]
Apple	Jhuria et al. [109]; Mustafa et al. [108]; Moallem et al. [110]; Ali and Thai [118] Tan et al. [114]
Mango	Sahu et al. [111]; Mustafa et al. [108]; Nandi et al. [119]; Ali and Thai [118]
Oranges	Mustafa et al. [108]; Li et al. [120]; Carolina et al. [48]; Rong et al. [56]
Plum	Rodriguez et al. [112]
Peach	Sun et al. [116]
Water	Kundu et al. [81]
Banana	Mustafa et al. [108]; Hu et al. [121]; Mithun et al. [115]
Grapes	Jhuria et al. [109]; Meire et al. [64], Naskar et al. [72]
Onion	Li et al. [62]
Tomato	Bandyopadhyaya et al. [65], Arakeria [122]; Mehra et al. [123]
Cucumber	Liu et al. [107]
Rice Seeds/ Wheat Seeds	Fayyazi et al. [55]; Pourreza et al. [45]; Ali et al. [52]; Lim et al. [53]; Anami et al. [57]
Olive Oil/Sesame Oil	Rashvand et al. [68]; Ordukaya et al. [87]; Mu et al. [67]
Chicken/Beef/Pork/Meat	Kamruzzaman et al. [51]; Al-Sarayreh et al. [59]; Tian et al. [84]
Wine/Beer	Debska et al. [63]; Meire et al. [64]; Yu et al. [69]
Saffron	Heidarbeigi et al. [85]

shape features used. Table 14 illustrates the quality analysis of fruits and vegetables based upon different morphological features employed by different researchers.

8.1.3 Texture Features

The texture is suitable for a wide range of objects that understand and interpret human visual systems. Texture measured from a group of pixels depicts the distribution of elements and appearance of the surface and is useful in machine

Table 12 Different parameters studied for food adulteration detection

Features	Parameters
Colour Features	RGB, HSI values and CIE-lab colour space for maturity evaluation and colour rating
Morphological features	Shape grading and size parameters like Fourier descriptors, length, width, the difference of diameters (max, min) and roundness etc
Texture features	Roughness, contrast, entropy, orientation, regularity and correlation, energy etc
Composition Features	Temperature, moisture, pH, volatile gases like carbon dioxide, oxygen, odour, pressure, viscosity etc

Table 13 Comparison of different colour features for quality analysis of fruits and vegetables

Author	Types of fruits and vegetables	Parameters	Colour space	Accuracy
Blasco et al. [124]	Pomegranate	Grading by colour	Grading by colour	90.00%
Liming and Yanchao [125]	Strawberry	Grading by external quality	CIE Lab	88.80%
Dorj et al. [126]	Citrus	Grading by colour	RGB	$R^2=.93$
Vidal et al. [127]		Colour evaluation		$R^2=.92$
Wang et al. [128]	Banana	Quality evaluation	RGB	–
Prabha and Kumar [129]		Maturity evaluation		99.1%
Kalsom et al. [130]	Mango	Maturity detection	RGB	–
Zou et al. [131]	Apple	Grading by colour	RGB& HIS	–
Garrido-Novell et al. [132]		Maturity discrimination	RGB	95.83%
Singh Chauhan and Pratap Singh [133]		Colour classification	HIS	98%
Suresha et al. [134]		Colour classification	RGB	99%
Stefany et al. [135]		Maturity detection	CIELab	98.6%
Esehaghbeygi et al. [136]	Peach	Colour and Size	HIS	90%
Pereira et al. [137]	Papaya	Grading by colour	RGB	94.3%

Table 14 Comparison of different morphological features for quality analysis of fruits and vegetables

Author	Types of Fruits and Vegetables	Parameters	Morphological Features	Accuracy
Zhang et al. [138]	Apple	Shape grading	Fourier descriptors	95.24%
Ashok and Vinod [139]				88.33%
Zhang and Wu [140]	Pear	Physical properties	Depends on size	88.20%
Kondo [141]		Grading by external quality	Deformability, Complexity, Roundness	–
Ohali [142]	Date	Grading by external quality	Fourier descriptors	80%
Yimyam and Clark [143]	Mango	Physical properties	Length and width	–
Khoje and Bodhe [144]			Fourier descriptors	89.83%
ElMasry et al. [145]	Potato	Sorting of irregular potatoes	Roundness, extent, and Fourier descriptors	99%
Dimatira [146]		Size-Shape	Fuzzy Logic	–
Zhang et al. [147–150]		Irregularity evaluation	Fourier descriptors	98.10%

vision which predicts the surface in form of roughness, contrast, entropy, orientation, etc.

The texture is consistent with maturity and sugar content (internal quality of fruits and vegetables). It is also used by extracting intensity values between pixels to isolate different patterns in images. Quantitative and qualitative analysis can be used to study the texture. As per the quantitative analysis, six textural characteristics i.e. contrast, coarseness, line-likeness, directionality, roughness and regularity whereas four features i.e. contrast, correlation, entropy and energy are according to qualitative analysis. Statistical texture, model-based texture, structural texture and transform based texture are various types of texture characteristics. Statistical texture, extract matrix which is dependent on intensity values of pixels. The different model-based texture is a fractal model, random field model and autoregressive model. Structure texture comprises of lines, edges that are constructed by pixels intensity. Spatial domain images can be derived from transform based texture. The statistical texture is widely used due to low computational cost and high accuracy. Table 15 illustrates the quality analysis of fruits and vegetables based upon different morphological features employed by different researchers.

Features based upon chemical composition can also be used to detect adulteration in the food as they aim to know about the content of the food product. The quality and adulteration content of the food item can be predicted by using sensors that measure temperature, moisture, pH, volatile gases like carbon dioxide, oxygen, odour, pressure, viscosity etc. There is a particular range of temperature which is to be maintained to increase the shelflife of the foodstuff. The acidic level of the item can be measured using a pH sensor and also the concentrations of these gases change for the fresh and the spoiled food. The values of these parameters vary once the food is spoiled or the quality has been degraded.

8.2 Work in Progress

The research in this field of food quality is going on worldwide. The answer to RQ.7 is addressed below that discusses some existing studies.

- *pH Sensing Using Electrospun Halochromic Nanofibres*: The researchers at IIT Hyderabad have been working on a project to develop a smartphone-based system that is equipped with sensors to detect the amount of adulteration in milk [58]. Initially, they have developed a system to measure the acidity of milk through an indicator paper that changes colour based on the level of adulteration. Besides this, they have also developed algorithms that can be incorporated on a mobile phone to detect the colour change accurately.
- *Paper Strip-Based Tests*: An innovative kit has been developed to detect the adulteration of milk by the National Dairy Research Institute (NDRI), Karnal [165]. The paper strip-based tests have been developed which can rapidly detect adulteration of milk containing neutralizers, urea, glucose, hydrogen peroxide, sucrose and maltodextrin. The test involves dipping a strip in the milk

Table 15 Comparison of different texture features for quality analysis of fruits and vegetables

Author	Types of Fruits and vegetables	Parameters	Accuracy
Zhang et al. [149]	Apple	Stem end/Calyx	95.24%
Li et al. [151]		Shape, Texture	
Jana et al. [152]		Colour, Texture	
Pan et al. [153]		Texture	95.83%
Moallem et al. [110]		Statistical, texture and geometric features	92.50%
Deepa and Geethalakshmi [154]	Mix	Shape, Texture	Texture96.00% Shape 100%
Savakar [155]		Colour, Texture	Chickoo 94.00% Apple, Lemon 93.00%
Khoje et al. [156, 157]		Texture	Guava, Lemon 96.00%
Nozari et al. [158]	Date	Length, Width, Thickness	93.50%
Alavi [159]		Size	86.00%
Pourjafar et al. [160]		Length, Width, Thickness	90%
Liming and Yanchao [125]	Strawberry	Colour, Size	Colour: 88.80%, Size: 90.00%
Khojastehnazhand et al. [161]	Lemon	Colour, Size	94.04%
Razak et al. [162]	Mango	Size, colour and skin	80.00%
Sahu and Potdar [163]		Global features	–
Naik and Patel [164]		Colour and texture	91%

sample for a short duration followed by immediate visualization of the colour of the strip.

- *Food Sniffer*: A smart portable kitchen gadget has been developed to check the freshness of raw meat, poultry or fish. It's a wireless device designed by Swiss Scientists that detects these non-veg products if they are fresh, spoiled or in the stage of getting spoiled and the results are displayed on the smartphone [167]. It contains a sensor that collects the gases emitted by meat to examine its freshness and helps to avoid food wastage and of course takes care of food safety.
- *Paper Sensor to detect Milk Freshness*: The researchers at IIT Guwahati have developed a paper kit that can test the freshness of milk and tell how well the milk has been pasteurized [168].They have used a filter paper to design a detector that can react with a milk enzyme, Alkaline Phosphatase (ALP). This compound is removed from milk once it is pasteurized. Hence, ALP acts as an indicator to milk quality because it reacts with the sensor probe to generate precipitate and indicates the presence of microbes in the milk. The colour of the paper on dipping in milk changes and these colour changes are captured using a smartphone camera to get the corresponding RGB values. These values are compared with the standard threshold values to measure the amount of ALP present in the milk sample and the quality of the milk can be predicted based upon the analysis.
- *Fruit Sorting at Amazon*: There has been a practical application of machine learning at Amazon that uses these algorithms to predict the quality of groceries. It grades different types of products and prevents the wastage of fruits and vegetables by providing consistent results. It predicts if the fruit quality is good or bad. The different fruits stored in the warehouse are scanned through a set of cameras and sensors to inspect their quality.

The research question **RQ8** is replied in Sect. 7. The key results of the research questions mentioned in Table 1 from this systematic survey can be summarized as follows.

- The research work in the field of food adulteration detection is being done for a long time but we have studied the research work of the last decade to gather information about the current trends followed to evaluate the food quality.
- The annotated datasets are available for different food categories like fruits, Italian and Japanese food items. Researchers can easily use these resources as a description along with online availability is provided in this systematic review.
- Different food adulteration detection methods such as machine learning, deep learning and IoT based detection systems are briefly described in this research study. However, due to better accuracy achieved by these techniques, the researchers are also enticed by deep learning techniques
- This survey brings out major machine learning and deep learning applications in the food domain.
- This systematic review comes up with the information about the food items that have been explored by researchers to work upon to detect the adulteration and to evaluate their quality.
- From this systematic survey, it can be said that researchers have tried to work upon colour, texture, defects, and morphological features etc. Also, they have focused upon features that try to extract the components of the food products.
- It has been noticed that there are few existing similar works going on who are working to develop a food adulteration detection system.
- This research survey concludes that researchers have performed mostly on food adulteration detection for the presence or absence of adulterant.

It has also been seen that an extensive amount of research work has been carried out for food adulteration detection using various approaches and techniques. Therefore, these studies can also be implemented to develop a low cost, user-friendly food adulteration detection system. To perform the food adulteration detection system for the Indian market, one can generate his dataset and can develop a model using the available features and models. Also, the best performing ML technique used by researchers for food adulteration detection can be applied to the Indian context dataset.

9 Conclusion and Future Work

We were inspired to conduct this systematic survey by the growth of research work in the area of food adulteration detection. The extensive research has been done to keep a quality control check on food but still, the Indian market is facing major challenges due to less technical development in the field of food adulteration detection. Certain challenges are witnessed while building an AI and Sensor-based system to detect food adulteration.

Few research studies are available that cover a thorough analysis of the machine learning techniques to detect food adulteration. We realized the need for a systematic literature survey after reviewing the groundbreaking research in the field of detection of food adulteration. This paper is, therefore, an important contribution to the literature on the detection of food adulteration using artificial intelligence. This survey includes 112 research studies published on food adulteration detection using machine learning from the last decade to include the relevant work only. The 112 research studies taken into account in this systematic survey have been determined by developing a review protocol that includes the research questions, sources of information, inclusion and exclusion criteria. The different results of this survey have been examined to get the answers to the targeted research questions drafted in this article.

The overview of the food adulteration detection approaches, major food products to be worked upon, and important parameters are given in this paper. From this review, it has been observed that most of the research work in this field has been published in conferences followed by journals. It has also been analyzed that mainly ML and DL (i.e. 75%) approaches have been used by the researchers have in comparison to other sensor based and hybrid approaches. This paper also gives about the different types of experiments followed by researchers to detect food adulteration. The different food categories and major parameters that can be referred to are mentioned in the paper.

There is a lot of work to be done to improve the accuracy of the detection system for food adulteration. It has been observed that the datasets are not readily available online because the researchers do not provide any links to the same. As there is a lack of annotated datasets and the creation of labelled datasets for different foodstuffs is a time-consuming task. In the future, these resources can be provided to utilize these by other researchers so that they can focus only on enhancing the efficiency of the system by developing new food adulteration detection methods. It has also been analyzed that deep learning approaches for food adulteration detection are in demand. Hence, researchers can experiment with these approaches to achieve improved results. And, also there is a need to build online systems which can perform food adulteration detection. The research can be done to develop a low-cost smartphone-system to detect food adulteration which can serve as an aid to end-users for their quality satisfaction. This field needs to be integrated with a real-time system for food adulteration detection. Thus, this survey can help the researchers in building the effective food adulteration detection system by using the different methods and techniques used by other researchers which can help in the benefits of society.

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