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Emerging trends in the detection of adulteration in pulses: from phenotypic traits to imaging and molecular tools – a systematic review

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Pulses (dals) are valued worldwide due to their high nutritional content and eco-sustainability, making them an essential component of human diets. However, adulteration increasingly compromises their quality and safety by reducing their nutritional value and posing serious health risks, thereby undermining consumer trust and public health. This review provides an overview of traditional adulteration detection methods, including visual inspection and chemical tests, which are often limited by subjectivity and labor-intensive procedures. These limitations have driven the development of modern, non-destructive analytical and advanced technologies, including NIRS, FTIR spectroscopy, TLC, DNA barcoding, electrophoresis, hyperspectral imaging, image processing, computer vision, and X-ray imaging, which offer improved accuracy, efficiency, and reliability. The significance of both qualitative and quantitative approaches is explored, with a particular emphasis on measurable traits such as size, shape, color, and texture, which can be effectively analyzed using image processing and machine learning techniques for more accurate assessments. Furthermore, the role of regulatory frameworks, including FSSAI, UK-FSA, EFSA, and US-FDA standards, in establishing safe limits for contaminants is highlighted. A combined application of low-cost tools and advanced technologies is recommended to improve adulteration detection strategies and ensure public confidence in the quality and safety of pulses.

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Sustainability spotlight

This review advances sustainable food safety and quality assurance by showcasing non-destructive, efficient, and environmentally conscious approaches for detecting adulteration in pulses. By minimizing food wastage and reducing the use of harmful chemicals, these modern imaging and molecular tools strengthen food integrity while safeguarding consumer health. The study highlights how affordable, data-driven technologies can bridge the gap between laboratory innovation and practical, large-scale applications in the food industry. By promoting resource efficiency, waste reduction, and responsible production practices, this work contributes to SDG 2 (Zero Hunger) through the protection of nutritious and safe food, SDG 9 (Industry, Innovation, and Infrastructure) by encouraging innovation in sustainable detection technologies, and SDG 12 (Responsible Consumption and Production) by fostering environmentally responsible food systems.

1 Introduction

Pulses are dried edible seeds of plants belonging to the Fabaceae (Leguminosae) family and represent one of the most important food groups worldwide. Commonly consumed pulses include chickpeas, lentils, peas, pigeon peas, mung beans, urad beans, rajma, and khesari, which are consumed in whole, dehulled, split, flour, and sprouted forms.¹ The term “pulse” originates from the Latin word “puls”, meaning thick soup or porridge, reflecting its long-standing role in human diets.² Pulses are cultivated across diverse agro-climatic regions and play a crucial role in ensuring food and nutritional security, particularly in developing countries.

Pulses are recognized as a major source of plant-based proteins, dietary fibers, complex carbohydrates, vitamins, and essential minerals. According to Mudryj *et al.* (2014), pulses offer a balanced nutritional profile per 100 g, contributing significantly to daily protein requirements while being low in fat and rich in micronutrients,³ as summarized in Table 1. In addition to their nutritional value, pulses support sustainable agriculture through biological nitrogen fixation, reducing dependence on synthetic fertilizers and improving soil health.^{4,5} Global pulse production reached approximately 95.9 million tonnes in 2022, with India accounting for nearly 28% of global production and covering around 38% of the world's pulse-growing area. India is also the largest consumer and importer of pulses, while Canada, Nigeria, Brazil, and the European Union remain major producers.⁵ Despite their importance, per capita pulse consumption varies widely, ranging from 2.97 kg in

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Europe to 11.46 kg in Africa, with a global average of 7.77 kg per year.

With increasing demand and market competition, pulse authenticity has become a growing global concern. Adulteration in pulses refers to the intentional or unintentional compromise of food quality through the addition, substitution, or removal of components, often driven by economic incentives.⁶ Traders may adulterate pulses to reduce costs, increase profit margins, or enhance visual appeal, making pulses particularly vulnerable to food fraud.⁷ Common adulterants include extraneous materials such as stones, marble chips, plastic beads, chalk powder, soapstone, and industrial starch.⁸ In addition, synthetic dyes such as metanil yellow and lead chromate are deliberately added to improve color and marketability, despite their toxic nature and adverse effects on human health.⁹ Nutritional adulteration is also prevalent, involving the removal of seed coats or substitution with cheaper materials such as khesari or maize flour, especially in processed pulse products like besan.¹⁰

Adulteration may also arise from poor post-harvest handling, storage, and transportation conditions, leading to contamination with pesticide residues, heavy metals (such as lead and arsenic), and rodent excreta, insect infestation, and microbial growth.¹¹ Natural adulteration can occur when toxic pulse species such as *Lathyrus sativus* unintentionally enter the food chain, resulting in neurological disorders like neurolethyrism.¹² The U.S. Food Fraud Database identifies lentils as a high-risk food commodity, underscoring the economic motivation behind pulse adulteration. These practices generally fall into three categories: replacement (substitution with inferior pulses), addition (blending with harmful or illegal substances), and removal (extraction of nutrient-rich components), all of which compromise consumer safety and product integrity.¹³

The consequences of pulse adulteration are severe and multifaceted. The consumption of adulterated pulses can cause acute health effects such as nausea, vomiting, diarrhea, and abdominal pain, as well as long-term complications including cancer, reproductive disorders, neurological damage, and organ



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Table 1 Key nutritional compositions of pulses per 100 grams

| Nutrient | White beans | Lentils | Chickpeas | Broad beans | Pigeon pea |
|-----------------------------|-------------|---------|-----------|-------------|------------|
| Energy (kcal) | 286 | 297 | 320 | 245 | 343 |
| Protein (g) | 21.4 | 24.3 | 21.3 | 26.1 | 21.7 |
| Fat (g) | 1.6 | 1.9 | 5.4 | 2.1 | 1.6 |
| Carbohydrate (g) | 49.7 | 48.8 | 49.6 | 32.5 | 62.8 |
| Fibre (g) | 17 | 8.9 | 10.7 | 27.6 | 15.0 |
| Iron (mg) | 6.7 | 11.1 | 5.5 | 5.5 | 3.9 |
| Calcium (mg) | 180 | 71 | 160 | 100 | 120.8 |
| Potassium (mg) | 1160 | 940 | 1000 | 1090 | 1392 |
| Zinc (mg) | 2.8 | 3.9 | 3.0 | 3.1 | 2.3 |
| Vitamin B ₆ (mg) | 0.56 | 0.93 | 0.53 | 0.37 | 0.28 |
| Thiamin (mg) | 0.45 | 0.41 | 0.39 | 0.50 | 0.64 |

toxicity.¹⁴ Vulnerable populations, particularly children, pregnant women, and the elderly, are at heightened risk.¹⁵ Beyond health impacts, adulteration leads to economic losses, erosion of consumer trust, and reputational damage to farmers and food businesses. Companies may face product recalls, litigation, regulatory penalties, and loss of market share, while regulatory authorities struggle with enforcement challenges and limited monitoring capacity.^{8,16} Notably, food security alone does not ensure nutritional security when food quality is compromised.¹⁷

To address these challenges, a range of traditional and advanced methods have been developed for detecting adulteration in pulses. Conventional techniques such as visual inspection and chemical tests are widely used but are often limited by subjectivity, labor intensity, and low sensitivity. Consequently, modern analytical and non-destructive techniques including near-infrared (NIR) spectroscopy, Fourier-transform infrared (FTIR) spectroscopy, thin-layer chromatography (TLC), DNA barcoding, electrophoresis, hyperspectral imaging, image processing, computer vision, X-ray imaging, long-read DNA sequencing, and laser-based methods have gained prominence due to their improved accuracy, speed, and reliability. These methods enable both qualitative and quantitative assessment of adulteration and support regulatory compliance.

Therefore, this review critically examines the nature and extent of adulteration in pulses, associated health and economic risks, and existing detection strategies. Particular emphasis is placed on emerging image processing and machine learning approaches as rapid, non-destructive, and cost-effective tools for ensuring pulse authenticity, thereby contributing to safer and more resilient food systems.

2 Qualitative and quantitative analysis methods

The detection of adulteration in pulses has primarily relied on qualitative and quantitative approaches, each serving distinct roles in evaluating the integrity and safety of the product (Fig. 1). Qualitative analysis focuses on identifying the presence of adulterants and their types without determining their exact concentrations and often relies on simple field-level techniques,

whereas the quantitative assessment focuses on measuring the exact concentration of the adulterant percentage.^{18,19}

2.1 Qualitative analysis methods

Qualitative methods primarily rely on visual inspection, judgment and simple laboratory techniques. Methods such as visual inspection, colorimetric tests, chemical tests, sensory evaluation, and flotation tests are a few methods for qualitatively analyzing adulterants in pulses (Fig. 2). The phenotypic trait-based methods such as visual examination using magnifying glasses and forceps are widely used methods to detect inorganic impurities like small stones or marble chips, rodent hair and animal excreta,²⁰ while toxic seeds such as datura seeds, chakunda beans and argemone can also be identified visually based on their distinct morphological features.¹⁰ Adulteration with khesari dal (*Lathyrus sativus*) can be visually detected by spreading the sample and identifying its characteristic, wedge-shaped, light grey or yellow seeds, which are most likely to be square in appearance compared to other pulses.²¹ Furthermore, Bengal gram adulterated with substances like tapioca flour or yellow dye can be visually identified due to its unnaturally

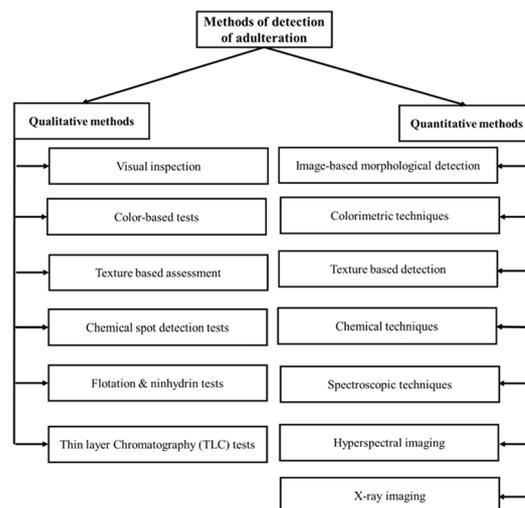


Fig. 1 Classification of qualitative and quantitative methods for pulse adulteration detection.



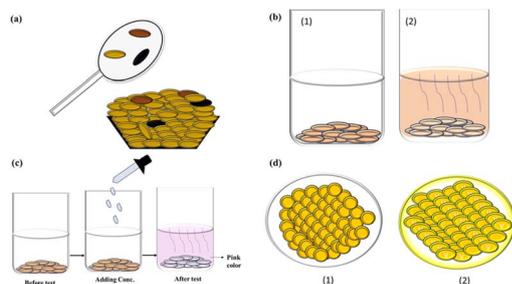


Fig. 2 Qualitative detection techniques: (a) detection of unwanted grains by visual inspection using a magnifying glass; (b) soaking of pulses in pure water for detecting artificial colors: (1) pure and (2) adulterated; (c) soaking of pulses in Conc. HCl for detecting metanil yellow adulteration; and (d) effect of chalk powder adulteration on the visual appearance of pulses: (1) pure pulses with a coarse texture and (2) pulses adulterated with chalk powder with a smooth, slippery texture.

smooth and bright appearance, which is distinctly different from the dull, matte surface of pure Bengal gram.

Rhodamine B adulteration in finger millet (*ragi*) can be detected using solvent extraction followed by acid treatment, where the appearance of a pink or reddish coloration confirms the presence of the synthetic dye. Chalk powder adulteration in pulses is used to enhance whiteness and visual appeal, making inferior-quality or aged pulses appear fresh. However, it poses health risks, as chalk powder is non-edible and can cause digestive discomfort, indicating poor hygiene and unethical processing practices. Turmeric adulteration in sella rice is commonly identified by adding dilute hydrochloric acid or rubbing the grains on moist filter paper, which produces a yellow stain or color leaching indicative of curcumin-based coloring agents. Excess wheat bran adulteration in wheat flour is qualitatively detected by visual inspection, sedimentation tests, or iodine reaction, where bran particles remain suspended or exhibit distinct color changes due to higher fiber content.²² Although visual inspection offers quick and low-cost screening, it is subjective and lacks accuracy for reliable detection of adulteration.

Colorimetric testing is one of the important qualitative analysis methods widely used for detecting synthetic dyes and chemical adulterants in food products.²³ For instance, a rapid screening method involves soaking-colored pulses, such as green peas or lentils, in water to detect the presence of artificial colors. If the sample is adulterated, the synthetic dye tends to leach out, causing visible discoloration of the water, indicating the presence of chemical adulterants. In contrast, pure samples retain their natural appearance and do not release any color into the water. Although color-based tests provide rapid visual clues of adulteration, they may yield false positives and are affected by surrounding environmental conditions.

Chemical-based colorimetric tests also play a key role in qualitative analysis for identifying synthetic dyes in adulterated pulses. Basic chemicals such as hydrochloric acid, lead chromate, and potassium iodide are commonly used for detecting adulterants in pulses. One such method involves soaking the

pulse sample in water by the addition of concentrated hydrochloric acid; the solution turns pink in color. The color change indicates that the sample is adulterated with metanil yellow.²⁴ Similarly, to detect lead chromate, the sample is treated with diluted nitric acid, which turns the solution yellow. Upon adding potassium iodide, a yellow precipitate forms, indicating the presence of adulteration.²⁵ Therefore, simple chemical tests provide immediate detection but suffer from poor specificity and lower sensitivity at trace levels.

Texture-based qualitative methods offer an alternative approach for detecting adulteration by assessing the physical feel and surface characteristics of pulses. Adulterants such as chalk powder or soapstone can often be identified by their unusually smooth, slippery, or powdery texture, which contrasts with the natural coarse surface of unadulterated pulses.¹⁰ Texture-based evaluation enables quick sensory differentiation; however, it remains highly subjective and unreliable without instrumental support, particularly when adulterants are present in small quantities.

Evaluating the physical feel and surface characteristics of pulses provides another useful approach for qualitative analysis, particularly for detecting adulterants through texture-based methods. Adulterants like chalk powder or soapstone can often be detected by their unnaturally smooth or powdery texture, which clearly differs from the natural coarse feel of unadulterated pulses.¹⁰

In addition to texture-based evaluation, several other qualitative methods including flotation tests, ninhydrin-based paper tests, thin-layer chromatography (TLC), and hydrocyanic acid detection are commonly employed. Flotation tests are useful for detecting fungal contamination such as ergot, where infected grains float in a saline solution while healthy grains sink, enabling rapid visual identification.¹⁰ The ninhydrin paper test is used to identify hidden insect infestations by crushing grains on ninhydrin-treated filter paper; the appearance of bluish-purple spots indicates internal insect damage that is not visible externally.²⁴ TLC is widely applied for qualitative detection of adulterants in pulse-based products and is particularly useful for identifying the neurotoxin β -*N*-oxalyl-L- α , β -diaminopropionic acid (BOAA) in khesari dal. The presence of BOAA is confirmed by the appearance of a purple spot on the TLC plate after spraying with a ninhydrin reagent.^{26,27} Additionally, the detection of hydrocyanic acid in beans involves autolysis followed by steam distillation and titration to identify toxic compounds that pose health risks, as described by the Association of Official Analytical Chemists.²⁸ Although these methods are simple, cost-effective, and suitable for field-level screening, they are limited by low sensitivity and a lack of quantitative precision.

2.2 Quantitative analysis methods

Quantitative analysis techniques focus on determining the levels of adulterants present in pulses. As it involves a range of instrumental methods such as Hunter Lab, colorimeter, spectrophotometer, and texture analyser, along with analytical techniques like TLC and gas chromatography-mass



spectrometry (GC-MS), as well as imaging approaches including image processing and computer vision techniques, all of which provide numerical or measurable outputs.

Similarly, the image processing and computer vision techniques combined with machine learning techniques offer a powerful approach for quantitative analysis to extract morphological parameters such as area, perimeter, roundness and aspect ratio for detecting inconsistencies in shape and size geometries, as well as in color intensity and textural patterns between pure and adulterated pulses, which helps in distinguishing samples with improved accuracy.^{29,30} Certainly, image processing enables the fast, objective, and reproducible measurement of grain size, shape, and structure.

For color-based quantification, the color serves as a measurable parameter where any slight variations in hue, intensity, or brightness can indicate the presence of adulterants. To capture these differences accurately, instruments such as colorimeters, spectrophotometers and Hunter Lab meters are employed, which measure absorbance or reflectance at specific wavelengths, helping to identify synthetic dyes like metanil yellow.³¹ Therefore, quantitative color analysis yields precise data for colorant adulterants, but requires standardized lighting and calibration for consistency.

Texture, when expressed in numerical terms, plays a crucial role in quantifying surface characteristics, such as roughness or smoothness, to differentiate between pure and adulterated samples. This analysis is carried out using instruments such as texture analyzers and image-based algorithms, including the gray-level co-occurrence matrix (GLCM), gray-level run-length matrix (GLRLM), local binary patterns (LBP), and neighbourhood gray-tone difference matrix (NGTDM). These algorithms extract statistical and spatial patterns from grayscale images by analyzing pixel relationships, repetitive structures and tonal variations. The key features extracted from these algorithms include contrast (intensity variation difference), homogeneity (gray level uniformity), energy (pattern repetition strength), entropy (texture randomness measure) and correlation (gray level dependency), among others, all of which provide numerical evidence of surface irregularities caused by adulteration.³² Certainly, texture analysis using both instrumental methods and statistical descriptors, such as GLCM and GLRLM, provides consistent and quantitative insights into surface patterns and signs of adulteration.

Quantitative detection of adulterants at the molecular level relies on advanced chemical techniques that separate, identify and measure specific components in a sample. Methods such as high-performance liquid chromatography (HPLC), gas chromatography-mass spectrometry (GC-MS) and TLC are applied to detect BOAA toxin in *Lathyrus sativus*, as well as in chickpea and red gram, and to detect non-permitted dyes with clear retention times and coefficient of determination (R^2) values.²⁷ Nevertheless, chemical techniques offer highly accurate and specific quantification of even trace amounts of adulterants.

Spectroscopic methods offer non-destructive and rapid quantification by analyzing how materials interact with specific wavelengths of light. Techniques such as near-infrared (NIR) spectroscopy and Fourier-transform infrared (FTIR) spectroscopy, often coupled with chemometric models like partial least squares regression (PLSR), are highly accurate, as evidenced by

glyphosate detection in pulses with R^2 values ranging from 0.91 to 0.96,³³ indicating robust model performance. Similarly, Bala *et al.* (2022) achieved an exceptionally high R^2 value of 0.999 for detecting maize flour adulteration in chickpea flour using modified partial least squares regression (MPLSR), underscoring the model's precision and reliability in quantitative analysis.³⁴ Therefore, the methods offer rapid, non-destructive detection with high sensitivity and chemical specificity.

Similarly, hyperspectral imaging is an advanced analytical technique that captures detailed spectral information across hundreds of wavelengths for each pixel in an image. Unlike traditional RGB imaging, which captures only three-color bands, HSI records reflectance or absorbance data over a wide spectral range, typically from 400 to 2500 nm.³⁵ In quantitative analysis, HSI is highly useful because it enables the detection and measurement of minute chemical variations within a sample. When this was combined with one convolutional neural network (1D-CNN), it achieved an R^2 value of 0.992 for metanil yellow detection, indicating a strong correlation between predicted and actual concentrations.³⁶ While FoodExpert devices integrating NIR, image processing, and machine learning attained up to 96% for pulse quality detection and 94% detection accuracy in field samples, the model was successfully deployed on a Raspberry Pi-based hardware prototype and mobile application, demonstrating its practical applicability in real-time field conditions.⁹ Additionally, fungal contamination was identified *via* NIR hyperspectral imaging coupled with linear discriminant analysis (LDA) using two-way models, achieving classification accuracies of 98–100%, which is more significant than those achieved with quadratic discriminant analysis (QDA).³⁷ Undoubtedly, this method helps clearly identify adulteration by utilizing multiple wavelengths, providing both image and chemical details simultaneously.

Additionally, X-ray imaging is a non-destructive technique that utilizes high-energy electromagnetic waves to visualize the internal composition and structure of materials based on their density differences. In the context of food and pulse adulteration detection, it helps quantitatively identify foreign particles or denser adulterants that are not visible to the naked eye. X-ray imaging methods identify insect infestations with over 92% accuracy,³⁸ and GAN-augmented X-ray imaging yielded a 94% detection accuracy in green gram.³⁹ Certainly, X-ray imaging provides a fast and non-destructive method for detecting internal differences in grains and identifying adulteration.

These quantitative methods provide accurate and reliable estimates of adulterant levels using measurable parameters under controlled laboratory conditions. Moreover, exploring easily measurable phenotypic characteristics such as size, shape, color, and texture provides a practical and visually intuitive approach that complements advanced analytical techniques, making the detection of adulteration more accessible at both laboratory and market levels.

3 Phenotypic parameters

Phenotypic parameters including morphological, color, and textural characteristics represent the most fundamental and



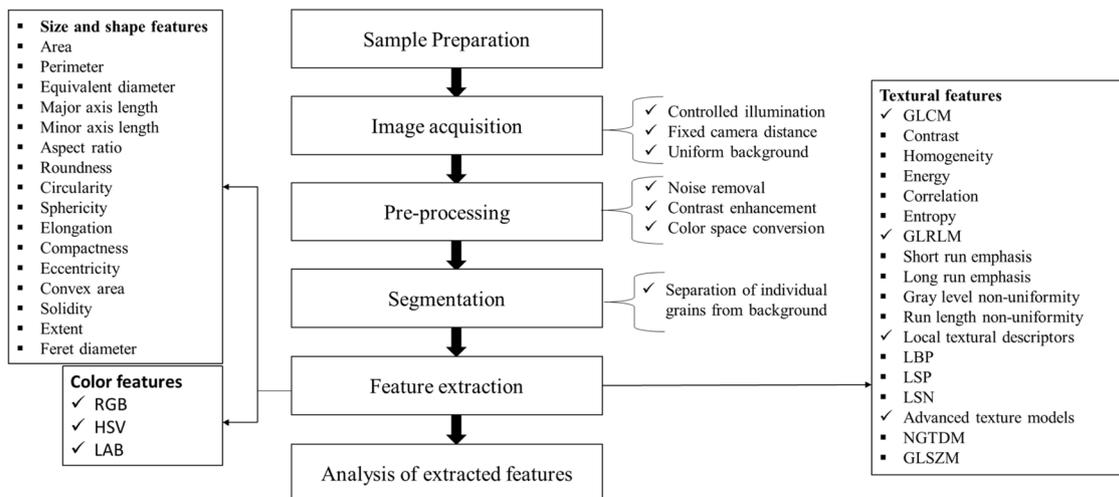


Fig. 3 Image-based workflow for phenotypic parameter extraction.

accessible indicators for assessing pulse quality, identifying varieties, and detecting adulteration. The image-based workflow for phenotypic parameter extraction is illustrated in Fig. 3. Therefore, the following are a few phenotypic parameters that primarily focus on size, shape, color, and texture, which directly influence product uniformity, processing efficiency, market value, and consumer acceptance.

3.1 Size

Size is one of the most critical phenotypic characteristics for identifying adulterants in grains and pulses. Impurities such as stones, pebbles, broken grains, or foreign materials often exhibit distinct size differences. Traditionally, the grain size has been measured by mechanical sieving through vibrating stacks of sieves, each with decreasing aperture sizes. Particles larger or smaller than the desired grain size can be successfully identified. For instance, smaller particles including broken pulses or husk fragments are separated, while larger unwanted items such as stones or other foreign materials can also be identified.⁴⁰ Irregularly shaped grains such as chickpeas often exhibit inconsistent sieving behavior, which contributes to misclassification. LeMasurier *et al.* (2014) reported misclassification rates of up to 10% when sieving lentils, and the data collected are limited due to these sieve size constraints.^{41,42}

Size-based morphological analysis provides an additional layer of validation for distinguishing authentic grains from adulterants using image analysis, while the algorithms like image segmentation and object measurement techniques accurately quantify parameters such as area, equivalent diameter, perimeter and volume, enabling precise, non-destructive assessment and improved classification accuracy.^{29,40,43} Furthermore, differences in thousand-seed weight, bulk density, and hydration indices have been used to detect foreign or damaged grains in cereals, millets and pulses.^{44–46}

3.2 Shape

Shape attributes are equally significant for quality assessment and impurity detection. While authentic grains typically exhibit

uniform, consistent, type- or variety-specific geometric profiles, adulterants often have irregular or atypical forms that deviate from these profiles. For instance, synthetic materials, insect-damaged kernels or chemically treated granules tend to show unique contours that deviate from natural grain profiles. The key descriptors include roundness, circularity, aspect ratio, elongation and sphericity derived from image-based analysis.^{30,47}

Several studies have validated the importance of shape descriptors in adulteration detection. Dutta *et al.*⁴⁴ and Mohsenin (1970)⁴⁸ highlighted the use of roundness derived from comparing a grain's projected area to the smallest enclosing circle as a key indicator of surface smoothness or angularity. Koklu and Ozkan (2020) demonstrated that variations in aspect ratio in dried beans can signal the presence of broken, shrivelled or foreign grains.³⁰ Salam *et al.* (2022) utilized shape descriptors including circularity, elongation, and sphericity to detect adulterants in chickpeas using machine vision techniques.⁴⁹ Kaur *et al.* (2021) applied image analysis to identify physical grain damage and impurity levels based on geometric features such as major-/minor-axis lengths and eccentricity.⁵⁰ Similarly, Kumar *et al.* 2013 classified pulse varieties by analyzing shape metrics including contour features and perimeter-based measures.⁵¹ Such digital imaging approaches also provide high accuracy in detecting broken or shrivelled grains and identifying varietal differences.⁴⁰ Collectively, these studies confirm that shape-based parameters extracted through image processing provide a reliable, non-destructive approach for quality control and the detection of adulteration.

3.3 Color

Color is another critical trait influencing consumer perception and market grading. It reflects the grain's freshness, varietal purity and potential chemical or environmental damage. Uniform and bright-colored grains are generally preferred, whereas discolored or unevenly colored grains can indicate aging, poor storage, or adulteration. The color assessment



initially heavily relied on visual grading by human perception, which is subjective and prone to inconsistency. However, later it was evaluated using visual charts like the system, which described the hue, chroma and brightness.⁵² The development of methods involving instruments such as colorimeters and spectrophotometers has enabled an objective methodology for precise color measurement using systems like CIELAB.^{23,53} In this system, L^* represents lightness, a^* the red-green axis and b^* the yellow-blue axis.⁵⁴ Moreover,⁵⁵ quantified grain and meal color in hard white spring wheat using the HunterLab colorimeter, finding that NaOH treatment reduced L -values (from 40.9–50.4 to 22.7–38.1), slightly increased a -values (7.0–8.3 to 7.7–9.7), and decreased b -values (13.6–19.1 to 9.2–17.9), thereby enhancing genotype differentiation. The higher b -values were associated with decreased kernel hardness. Additionally, they used a Hunter Lab Color Difference Meter to quantify color deviations (ΔE) from standard colors, confirming that NaOH treatment is a useful method for distinguishing among hard red, hard white, and soft white wheat genotypes. A previous study³¹ assessed the red colour intensity in milled red lentil flour using both the HunterLab and Nix Spectro 2 instruments, reporting that a^* and b^* values obtained from Nix were strongly correlated with HunterLab values ($r^2 = 0.90$ – 0.95), while L^* values showed moderate correlation ($r^2 = 0.58$ – 0.61), probably due to the differences in instrument lighting. Both instruments successfully distinguished and ranked lentil genotypes by red colour intensity, validating the Nix device as a reliable, low-sample alternative for assessing lentil flour colour. A previous study⁵⁶ evaluated color measurement in flour, barley, and lentils using a visible-NIR spectrophotometer (400–2500 nm), comparing two techniques: one using calibration models developed from HunterLab colorimeter values and another applying ASTM E308-95, based on the CIE system, to calculate Lab^* directly from visible spectra. Their findings showed that

the E308-based method provided the most accurate and efficient results, allowing reliable color prediction without requiring product-specific calibration equations or duplicate instrumentation. Singh *et al.* (2010) used many features (color, texture, and morphological), mainly involving RGB color values, hue, saturation, brightness and shape/texture metrics for classifying wheat kernels. Combining these with NIR features improved classification using QDA, achieving up to 96.3% accuracy for healthy kernels and 91.0–100.0% accuracy for insect-damaged kernels, although kernels damaged by *Tribolium castaneum* were more challenging to detect accurately.⁵⁷ Additionally, color features, when integrated with imaging systems and statistical models, support high-throughput screening and precise grain classification.

3.4 Texture

Texture analysis offers valuable insights into grain physical integrity and structural characteristics of food grains and pulses. Over the past decades, the mechanical texture analysis has been widely utilized for evaluating the physical properties of food materials such as hardness, cohesiveness and brittleness to assess quality, processing behavior and consumer acceptability, and especially⁵⁸ applied Texture Profile Analysis (TPA) on chickpea seeds using an Instron Universal Testing Machine to measure the compressive properties of soaked and cooked chickpea seeds. With the technological advancements, the image-based texture analysis has become prominent. Based on advancements, an earlier study⁵⁹ used machine vision to classify nine Iranian wheat varieties extracting features from GLCM (such as energy, correlation, entropy, homogeneity and contrast) and GLRLM (short/long-run emphasis), whereas LBP, local similarity pattern (LSP) and local similarity number (LSN) offered detailed local texture patterns and similarity-based

Table 2 Methodologies followed for analysing various phenotypic traits of pulses

| Parameter | Method | References |
|------------------|---|---------------------------|
| Size | Digital micrometre | 61 |
| | Vernier calliper | 62 |
| | Image analysis | 29, 30, 42, 43, 63 and 64 |
| Shape | Geometric measurements | 65 |
| | Roundness | 66 and 67 |
| | Aspect ratio | 30, 68 and 69 |
| | Image analysis | 29, 30, 42, 49, 50 and 70 |
| 1000 seed weight | Weighing 100 grains and multiplying by 10 | 44 and 46 |
| Color | Visual inspection: Munsell color chart | 52 |
| | Colorimeter | 23 |
| | Hunter lab color difference meter | 55 and 71 |
| | Spectrophotometer | 31 |
| | NIR spectroscopy | 56 |
| | Image analysis | 32, 57, 63 and 70 |
| Texture | Texture analyser | 58 |
| | GLCM | 32, 70, 72 and 73 |
| | GLRLM | 60, 74 and 75 |
| | NGTDM | 60 and 75 |
| | LBP | 59 and 76 |
| | LSN | 59 and 77 |
| | LSP | 59 and 77 |



Table 3 Phenotypic traits and classification approaches for pulses and grains

| Crop | Variety or sample | Parameters | Trait(s) | Classification and method summary | References |
|---------------------|---|---|-----------------------------------|--|------------|
| Lentils | Red, green, and red-green crossed | Seed diameter, area, volume, plumpness and roundness index | Size and shape | Predicted seed size index, mass; high correlation using image analysis in MATLAB | 42 |
| Beans | White and yellow-green | Damaged color % and pixel classification | Color and shape/size | 90.6% overall efficiency using image processing and ANN in MATLAB | 78 |
| Soybean | — | Mean, standard deviation, coefficient of variance, skewness and kurtosis | Size and shape | Size uniformity classification >84% using discriminant functions and ANN | 40 |
| Wheat seed | 9 Iranian varieties | LBP, LSP, LSN texture features | Texture | 98.15% accuracy using machine vision and image processing | 59 |
| Lentil and rice | — | GLCM texture, color, scanning electron microscopy and surface features | Color and texture | Textural properties linked to hardness; classified freeze-dried vs. cooked samples | 32 |
| Lentils | Red and green | Equivalent diameter, perimeter, circularity | Shape | Volume and surface area estimated with image analysis (LUCIA system) | 47 |
| Legumes | Beans and lentils | Projected area, diameter and thickness | Size and shape | Volume and surface <i>via</i> pycnometer and digital imaging | 29 |
| Grains | Wheat | Area, axis lengths and perimeter | Size/shape, color and texture | Classified quality using image processing and neural networks | 79 |
| Lentils | Red, green and yellow | Area, perimeter, axis lengths and eccentricity | Color and size/shape | Classified varieties and sizes with 97.08% accuracy using ANN | 63 |
| Pulses | Bengal, black, green and red grams | Hue, saturation and chromaticity | Color | Identified boiled grains at different temperatures using image processing | 80 |
| Pulses | Pigeon pea | RGB color and surface smoothness/roughness | Size/shape, color and texture | Classified texture and size metrics using MATLAB | 70 |
| Grains | Multiple cereal and millets | Area, axis lengths, aspect ratio and RGB color | Morphological and color | 85% accuracy using image processing and neural networks | 81 |
| Cereal grains | Canada western red spring, Canada western amber durum, barley, rye and oats | Morphological, color and textural features | Size/shape, color and texture | 99% + accuracy using image processing in MATLAB | 82 |
| Cereal grains | Wheat, barley, rye and oats | Contour length, area and shape moments | Size and shape | Kernel-based classification; accuracies up to 100% | 83 |
| Wheat grains | Multiple wheat varieties | Length, width and shape index | Size and shape | Classified with 90–100% accuracy using progressive analysis | 84 |
| Cereal grains | Barley, oat, rye and wheat | Aspect ratio, diameter and roundness | Morphological and color | High accuracy (98–100%) using digital imaging | 85 |
| Dry beans | 7 Turkish varieties | Area, perimeter, convex area and solidity | Color and size/shape | Classified by ML (SVM, DT, and kNN) in MATLAB | 30 |
| Cereals and pulses | Rice and foxtail millet | Size, shape, color, texture and moisture | Size/shape, color and texture | Graded into 3 classes; storage suitability assessed | 86 |
| Cereals | Wheat, maize and jowar | Leaf color and texture symptoms | Color and texture | Disease detection with 68–91% accuracy (ANN and SVM) | 87 |
| Chickpea | BG1105, MNK-1 | Seed recovery % and germination rates | Size and shape | Max seed recovery and germination using sieving | 88 |
| Grains | Maize, rye and pearl millet | Germination indices | Size | mAP: 94–97% using CNN | 89 |
| Cereals and millets | Pearl millet and maize | Grading parameters <i>via</i> images | Size/shape, color and texture | Detected quality grades using YOLO v5 and MCSCQT | 90 |
| Millets | Jowar, bajra and ragi | Size, shape and textural parameters | Size and shape and texture | 92% accuracy using image processing and ML | 91 |
| Cowpea | — | Area, length, width and aspect ratios | Morphological, color, and texture | Identified variety, insects, and foreign matter using MATLAB | 92 |
| Rice | 5 rice varieties | Size, shape, color, texture <i>via</i> logistic regression, decision tree and random forest | Size/shape, color and texture | Features classified using MATLAB and Raspberry pi | 93 |



structural traits, including histogram groups and statistical descriptors (such as mean, standard deviation and entropy) achieving 98.15% accuracy using stepwise discrimination and LDA, highlighting the utility of LSP, LSN and LBP features. Later, a study³² evaluated the grain surface texture using GLCM features as mentioned above, which offers a non-destructive assessment of hardness and processing effects. Furthermore,⁶⁰ combined multiple texture models including GLCM, GLRLM, LBP, NGTDM, and Gray Level Size Zone Matrix (GLSZM) were used with a Back Propagation Neural Network to classify five rice varieties, achieving 99.40% accuracy with GLSZM and minimal misclassifications with GLRLM.

These phenotypic traits not only define the physical and visual identities of pulses and grains but also serve as reliable indicators of authenticity, purity, and overall market readiness. Beyond their traditional roles in grading and sorting, they now serve as critical checkpoints for food safety and traceability in a global supply chain increasingly focused on transparency and quality assurance. Integrating these morphological and physical features with advanced analytical tools sets the foundation for next-generation smart grain quality monitoring systems. Further, following this detailed discussion, the methodologies employed for assessing these traits, as well as specific applications across various crops and studies, are summarized in Tables 2 and 3.

While phenotypic traits and classification models are highly effective in detecting visible and structural adulterations in pulses, they do not address the growing concerns around chemical adulterants, including synthetic dyes, pesticide residues and other toxic contaminants. These pose significant health hazards and are often undetectable through visual or spectral assessment alone. Thus, a comprehensive understanding of the regulatory limitations on such adulterants is essential for ensuring food safety.

4 Limitations on the application of pesticides as adulterants in pulses

The FSSAI 2011 regulations prohibit the direct use of pesticides on food products.⁹⁴ However, fumigants that have been formally registered and approved for use on food by the Registration Committee, established under the Insecticides Act of 1968, are exempt from this regulation. Furthermore, the allowed dosage of each insecticide for specific foods, including pulses, cannot exceed the tolerance levels listed in Table 4. Beyond these thresholds, the use of pesticides in pulses is strictly prohibited and considered adulteration.

Key foreign regulatory bodies, such as those in the UK, the USA, and the European Union, play a crucial role in defining, monitoring, and controlling adulteration-related practices (Table 5), which are discussed below:

4.1 UK Food Standards Agency (FSA)

The UK Food Standards Agency (FSA) plays a pivotal role in maintaining food safety, authenticity, and compliance throughout the food supply chain. In the UK, intentional

adulteration and fraudulent substitution fall under food crime – a serious category of offences involving dishonesty in production and distribution. Adulteration is explicitly recognized as a form of food crime, and the National Food Crime Unit (NFCU), operating under the FSA, investigates and prevents such fraudulent behaviours to safeguard consumer trust and public health.⁹⁵ The FSA also publishes guidance for businesses on identifying and mitigating risks related to food fraud, encompassing acts such as adulteration, misrepresentation, and substitution in food products.⁹⁶

4.2 US food and drug administration (FDA)

In the United States, the FDA addresses adulteration through the concept of economically motivated adulteration (EMA), also known as food fraud, which is defined as the intentional omission, substitution, or addition of substances for economic benefit that may mislead consumers or compromise product integrity. The FDA actively tracks such adulteration through compliance and enforcement programs, highlighting the health risks posed by fraudulent practices, such as the presence of allergens or toxic adulterants (*e.g.*, melamine in milk).⁹⁷

4.3 European food safety authority (EFSA) and EU food law

While EFSA does not directly enforce laws, it provides the scientific foundation for EU food safety legislation, including requirements that food placed on the EU market is safe, accurately labeled, and traceable. The foundational EU Food Safety Regulation no 178/2002 establishes general principles of food law covering safety, consumer interests, and traceability obligations throughout the food chain. EFSA's scientific risk assessments also inform how novel or adulterated foods are evaluated and regulated within the EU framework.⁹⁸

Pulses are not only crucial for maintaining food quality but also vital for protecting public health, as adulteration can lead to food poisoning, allergic reactions, and long-term health issues. It may also erode consumer trust and tarnish the reputation of food producers, ultimately impacting the market value. Therefore, adopting effective, rapid detection strategies is fundamental for maintaining food integrity and safety.

As discussed above, phenotypic traits such as size, shape, color, and texture play a crucial role in distinguishing physical impurities and serve as an essential basis for the initial stage of quality evaluation. When combined with complementary analytical methods, phenotypic evaluations enhance the overall detection capability by supporting the identification of non-visible adulterants, such as synthetic dyes, pesticide residues, and chemical contaminants, as outlined in relevant Tables 5 and 6 under FSSAI regulations and foreign food safety standards including those of the UK Food Standards Agency (FSA), the US Food and Drug Administration (FDA), and the European Union food law framework. These integrated approaches collectively strengthen food authenticity assessment and regulatory compliance at both national and international levels.



Table 4 Insecticide usage restrictions and permissible limits in pulses for food safety under FSSAI 2011 regulations

| Name of insecticides | Sample | Tolerance limit (mg/kg ppm) |
|--|-----------------------------------|-----------------------------|
| Aldrin and dieldrin (the specified limits apply to aldrin and dieldrin individually or combined, measured as dieldrin) | Food grains | 0.01 |
| | Processed food grains | Nil |
| Carbaryl | Food grains | 1.5 |
| | Processed food grains | Nil |
| Chlordane | Food grains | 0.02 |
| | Processed food grains | Nil |
| Diazinon | Food grains | 0.05 |
| | Processed food grains | Nil |
| Dichlorvos | Food grains | 1.0 |
| | Processed food grains | 0.25 |
| Endosulfan | Bengal gram | 0.20 |
| | Pigeon pea | 0.10 |
| Heptachlor | Food grains | 0.01 |
| | Processed food grains | 0.002 |
| Fenitrothion | Food grains | 0.02 |
| | Processed food grains | 0.005 |
| Hydrogen cyanide | Food grains | 37.5 |
| | Processed food grains | 3.0 |
| Hydrogen phosphide | Food grains | Nil |
| | Processed food grains | Nil |
| Decamethrin/deltamethrin | Food grains | 0.50 |
| | Processed food grains | 0.20 |
| Cypermethrin (total isomers) (fat-soluble residue) | Whole wheat kernels | 0.05 |
| | Milled wheat grains | 0.01 |
| Captan carbofuran | Food grains | 0.10 |
| | Processed food grains | 0.03 |
| Benomyl | Food grains | 0.50 |
| | Processed food grains | 0.12 |
| Carbendazim | Food grains | 0.50 |
| | Processed food grains | 0.12 |
| Thiometon | Food grains | 0.025 |
| | Processed food grains | 0.006 |
| Trichlorfon | Food grains | 0.05 |
| | Processed food grains | 0.0125 |
| Praquat dichloride | Food grains | 0.1 |
| | Processed food grains | 0.025 |
| Monocrotophos | Food grains | 0.025 |
| | Processed food grains | 0.006 |
| Ethion | Food grains | 0.025 |
| | Processed food grains | 0.006 |
| 2, 4D | Food grains | 0.01 |
| | Processed food grains | 0.003 |
| Chlorpyrifos | Food grains | 0.05 |
| | Processed food grains | 0.01 |
| Pyrethrins | Food grains | Nil |
| | Processed food grains | Nil |
| Chlorienvinphos | Food grains | 0.025 |
| | Processed food grains | 0.006 |
| Phosphamidon residues | Food grains | 0.05 |
| | Processed food grains | Nil |
| Malathion | Food grains | 4.0 |
| | Processed food grains | 1.0 |
| Fenthion | Beans and food grains | 0.10 |
| | Food grains | 0.20 |
| Dithiocarbamates | Food grains | 0.20 |
| | Processed food grains | 0.05 |
| Phenthoate | Food grains | 0.05 |
| | Processed food grains | 0.01 |
| Phorate | Food grains | 0.05 |
| | Processed food grains | 0.01 |
| Pirimiphos-methyl | Food grains except rice | 5.00 |
| | Processed food grains except rice | 1.00 |



Table 4 (Contd.)

| Name of insecticides | Sample | Tolerance limit (mg/kg ppm) |
|----------------------|-----------------------|-----------------------------|
| Oxydemeton methyl | Food-grains | 0.02 |
| Quinalphos | Pigeon pea | 0.01 |
| Linuron | Pea | 0.05 |
| Triadimefon | Pea | 0.1 |
| Inorganic bromide | Food grains | 25.0 |
| | Processed food grains | 25.0 |

5 Health implications of adulterants and contaminants in pulses

Various adulterants and contaminants are commonly found in grains and pulses, ranging from physical impurities like stones and dirt to toxic substances such as pesticide residues, fungal toxins and non-permitted colors. These can lead to serious health effects including digestive injuries, cancer, neurotoxicity and even fatal conditions like lathyrism and hemorrhagic fever.^{24,105} An inventory of grain pollutants and their effects on well-being is given in Table 7. Therefore, biological and

molecular techniques such as DNA barcoding provide powerful tools for the precise identification of pulse adulteration. Their advanced sensitivity and accuracy contribute significantly to ensuring food safety and quality assurance.

6 Techniques for detecting adulterants in pulses

Sometimes pulses are mixed with other substances either fully or partially. When only a small amount is added, it becomes more difficult to detect because we first need to determine what was mixed in and whether it occurred intentionally or by

Table 5 Permissible contaminant limits according to foreign regulatory frameworks for pulses and legumes

| Name of contaminant | Food article | Regulatory authority | Maximum limit (mg kg ⁻¹ or ppm) | Notes/source |
|----------------------------------|-------------------------------------|-------------------------------|--|---|
| Lead (Pb) | Cereals, legumes, pulses | EU (Reg 2023/915) | ~0.1–0.2 mg kg ⁻¹ typical | Maximum levels set for heavy metals in food; specific category varies by food type (legumes included). ⁹⁹ |
| Cadmium (Cd) | Cereals, legumes, pulses | EU (Reg 2023/915) | ~0.10–0.20 mg kg ⁻¹ typical | Maximum levels for cadmium also apply to pulses and similar foods. ¹⁰⁰ |
| Aflatoxins (total) | Nuts/cereals/pulses (general scope) | EU | Food group-specific; examples vary (2–12 µg kg ⁻¹ for cereals/dried fruits) | EU sets MLs for multiple mycotoxins; pulses fall under similar cereal/legume categories. ^{99,101} |
| Aflatoxin B1 | Cereals, legumes, pulses | EU | ~2–12 µg kg ⁻¹ (some categories) | The EU has established several contaminant limits, including those for aflatoxins. ¹⁰² |
| Aflatoxins (FDA action level) | All human foods | US FDA | 20 ppb (µg kg ⁻¹) | The FDA action level for aflatoxin contamination in foods. ¹⁰³ |
| Defect and foreign matter limits | Any food, including pulses | US FDA (defect action levels) | Variable by commodity | FDA “defect action levels” for extraneous matter (insects, filth) apply generically; if exceeded, the product is deemed adulterated. ¹⁰⁴ |
| Pesticide residues | Pulses/Legumes | UK and EU (MRLs) | Varies by pesticide | The UK and EU enforce maximum residue levels for pesticides under the EU and UK regimes. ⁹⁸ |



Table 6 Maximum permissible levels of contaminants, toxins and residues in food under FSSAI 2011 regulations

| Name of contaminants | Food article | Maximum limit (ppm) |
|--|---|---------------------|
| Lead | Canned green beans and canned wax beans | 1.0 |
| | Canned green peas | 1.0 |
| Arsenic | Synthetic food color-preparation and mixtures | 3.0 |
| Methyl mercury (calculated as the element) | All foods | 0.25 |
| Total aflatoxins | Pulses | 0.015 |
| Aflatoxin B1 | Pulses | 0.010 |
| Metanil yellow | Pulses | 100 |
| Hydrocyanic acid | Beans | 5 |
| Khesari dal | Pulses | 20000 |

mistake. This is crucial for protecting people's health and ensuring that industries comply with food safety laws. However, over the years, several methods for detecting adulteration have been developed, ranging from traditional approaches, such as examining physical features, taste, and simple chemical tests, to modern techniques, including analytical, spectroscopic, and molecular methods (Fig. 4). More recently, advanced tools like machine learning and image processing are being used for quick and accurate adulteration detection.

6.1 Traditional methods

Traditional methods for detecting adulteration in cereals and pulses rely on physical, sensory, and simple chemical principles, and have been employed for preliminary screening for a long time. Physical methods involve visual inspection, manual sorting, and assessment of grain size, shape, colour, surface texture, and the presence of foreign matter, allowing the identification of visibly abnormal or extraneous materials. Sensory approaches such as tactile and olfactory evaluation assess

hardness, smoothness, or unusual odours that may indicate contamination or spoilage. Chemical-based tests utilize basic reagents or reactions that produce colour changes, precipitates, or characteristic odours to enable the qualitative detection of certain adulterants. These traditional methods are valued for their low cost, ease of application, and minimal instrumentation, making them suitable for field-level and routine quality assessment. The procedures about traditional methods have been discussed earlier in Section 2.1 under Qualitative Analysis Methods.

However, they are generally limited to detecting gross or visually apparent adulterants, rely heavily on human judgment, and lack the sensitivity required to identify low-level, concealed, or chemically complex adulteration. Consequently, these approaches remain largely qualitative and operator-dependent, and do not provide quantitative precision. Due to these limitations, traditional methods are being increasingly complemented or replaced by advanced analytical, imaging, and molecular techniques that offer higher sensitivity, objectivity,

Table 7 Inventory of grain pollutants and their effects on well-being

| Food product | Adulterants/contaminants | Diseases or health effects | References |
|--|--|--|------------|
| Grains and pulses Khesari dal | Sand, marble chips, stones and dirt | Digestive tract injury | 24 and 105 |
| | <i>Lathyrus sativus</i> | Lathyrism (crippling spastic paraplegia) | 24 and 105 |
| Whole and split dal | Pebble, straw, weed seeds, damaged grain, weevil-led grain, hidden insects, rodent hair and excreta, kernel bunt, clay, gravels and webs | Toxic, incurable paralysis, tumor and cancer, anaemia, epilepsy, neurotoxicity | 105 |
| Pulses | Non-permitted food color | Mental impairment, cancer and other toxic effects | 24 and 105 |
| Grains | Mercury treated with grains | Brain damage, paralysis and fatal outcomes | 24 |
| | <i>Fusarium sporotrichiella</i> toxins are typically found in moist grains | Urov disease (Kaschin-Beck disease) | |
| | Sterigmatocystin from <i>Aspergillus versicolor</i> , <i>Aspergillus nidulans</i> and <i>Aspergillus bipolaris</i> | Hepatitis | |
| | Machupo virus is contaminated by rodent urine | Bolivian hemorrhagic fever | |
| Polished rice, pulses, processed foods | Asbestos (present in talc, kaolin or anti-caking agents) | Cancer risk due to particulate absorption | 24 |
| Food products | Pesticide residues | Acute or chronic poisoning affecting nerves, liver, kidneys etc. | 24 |



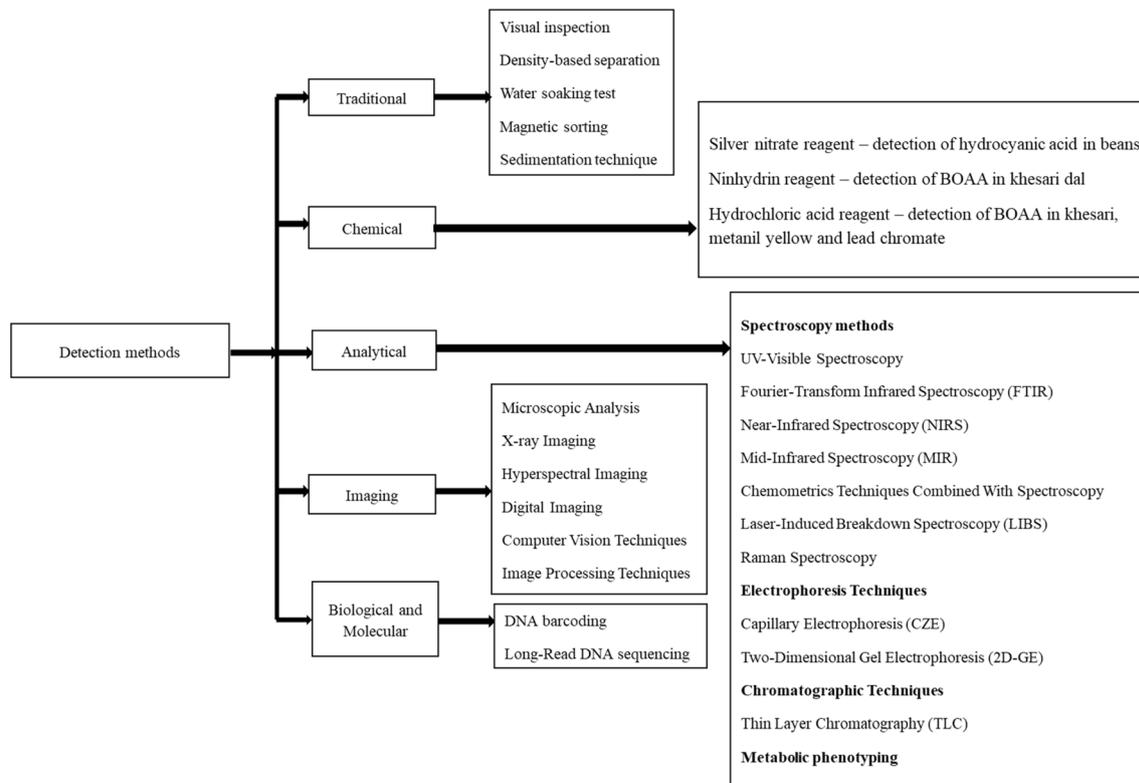


Fig. 4 Domain-wise categorization of adulteration detection techniques in pulses.

and reproducibility, thereby enabling the accurate identification and quantification of adulterants, as discussed in subsequent sections (Table 8).

6.2 Chemical methods

Due to their ease of use, affordability, and speed, chemical procedures are the most widely utilized approaches for identifying adulterants in pulses. These techniques rely on specific reagents such as silver nitrate, ninhydrin reagent, and hydrochloric acid. These are commonly used to react with certain adulterants, such as hydrocyanic acid in beans, BOAA in khesari dal, metanil yellow, and lead chromate, producing noticeable color changes for the detection of these dyes. These methods require minimal instrumentation and are ideal for preliminary screening before applying advanced analytical techniques.

Hydrocyanic acid, which is present in beans, can be detected by a method involving grinding the sample and allowing it to undergo autolysis in water.²⁸ The mixture is then subjected to steam distillation, and the distillate is treated with specific reagents. Titration with silver nitrate is performed, and the appearance of a faint, permanent turbidity at the endpoint confirms the presence of hydrocyanic acid and allows its approximate quantification in the sample.

Khesari dal adulteration can be detected using the method recommended by FSSAI and the Indian Standard Institution.^{28,106} A portion of the powdered pulse is extracted using ethyl alcohol with occasional shaking and left to stand overnight. After filtration and drying, the extract is dissolved in

isopropanol and applied to chromatographic paper.¹⁰⁷ The chromatographic paper was placed in a chamber containing a phenol–water mixture, which facilitated the separation of the compounds. Once dried, the paper is sprayed with ninhydrin reagent and gently heated. The appearance of a bluish-purple spot or bluish violet color at retention factor (R_f) values of 0.58 and 0.1 confirms the presence of BOAA, a toxic amino acid naturally found in khesari dal.

A chemical method for visually detecting khesari dal adulteration in pulses, such as yellow lentils and besan powder, has been proposed.^{21,99} In this procedure, the sample is first heated in simmering water for approximately 15 minutes. Afterward, diluted hydrochloric acid is added, and if the solution turns pink, it indicates the presence of khesari dal.^{108,109} Therefore, the detection of khesari dal adulteration in pulses can be achieved through visual colorimetric chemical methods targeting the adulterant itself, while the confirmatory identification of its neurotoxic compound, BOAA, is accomplished *via* chromatographic separation and ninhydrin-based visualization.

Moreover, for the detection of metanil yellow and lead chromate in pulses, previous studies^{25,110} proposed a simple chemical method using hydrochloric acid. In this test, a small amount of the pulse sample is mixed with water, followed by the addition of a few drops of strong acid. The development of a pink color indicates the presence of metanil yellow, a toxic synthetic dye. Similarly, the same color change may also indicate lead chromate, while both are used to enhance visual appearance but pose serious health risks such as anaemia, nerve damage and reproductive disorders.



Table 8 Typical food impurities in pulses and simple and chemical detection methods

| Adulteration | Detection test | Test | References |
|--|------------------------------|---|----------------|
| Inorganic matter (small stones/ marble chips) | Magnifying glass and forceps | → Spread pulses on white paper → examine with magnifying glass and forceps → spot foreign particles | 10 and 20 |
| Rodent hair/animal excreta | Visual inspection | → Observe under magnifying glass → detect hair or droppings | |
| Khesari dal (BOAA neurotoxin) | Visual inspection | → Spread pulses → identify wedge- shaped, flat, light grey/yellow seeds | 20 and 21 |
| | TLC | → Extract with ethanol → dry → redissolve in isopropanol → run paper chromatography (phenol- water) → spray with ninhydrin → purple spot at R_f 0.1 indicates presence | 28 and 106 |
| Ergot (a fungus that produces poison) | Chemical test | → Take dal → add diluted HCl → heat gently in water bath for few minutes → pink color indicates BOAA | 21, 24 and 106 |
| | Flotation test | → Place grains in salt water → ergot float → pure grains sink | 10 |
| Dhatura seeds | Visual observation | → Identify flat edges and dark brown color → remove by inspection | 10 |
| Chakunda beans | Visual inspection | → Spread pulses on glass plate → spot chakunda beans → remove carefully | 10 |
| Artificial color in green peas | Water soaking test | → Place peas in water → stir and rest → color leaching indicates dye | 20 |
| Metanil yellow (dye) | Chemical test | → Take dal in water → add concentrated HCl → pink color indicates metanil yellow | 10, 24 and 25 |
| Synthetic colours | Water soaking test | → Add pulses to water → stir → colored water indicates dyes → pure pulses will not release color | 10 |
| Lead chromate | Chemical test | → Mix lentils with water → add few drops HCl → pink shade shows lead chromate | 10, 24 and 25 |
| Hydrocyanic acid (beans) | Chemical test | → Grind the sample → add water → autolyze → steam distillation → treat distillate with NH_4OH and KI → titrate with 0.02 M AgNO_3 → turbidity indicates presence | 28 |
| Hidden insect infestation | Chemical test | → Take filter paper with 1% alcohol ninhydrin → place grain → fold and crush → bluish-purple spots indicate infestation | 24 |

Chemical techniques provide a quick and easy way to detect typical adulterants in pulses; however, they may lack the sensitivity and specificity of more advanced instrumental methods. Hence, they are best suited for preliminary screening and should be complemented with more precise analytical techniques for a thorough evaluation of food safety.

6.3 Advanced analytical techniques

When it comes to identifying adulterants in pulses, even at trace levels, advanced analytical techniques offer excellent sensitivity, specificity, and precision. Methods such as ultraviolet-visible (UV-Vis) spectroscopy, FTIR spectroscopy, NIRS spectroscopy, chromatography and electrophoresis allow for accurate

quantitative analysis and the identification of complex adulterants. Unlike simple chemical tests, these techniques are capable of detecting heavy metals, synthetic chemicals and toxic dyes that may not produce visible changes, thereby ensuring better compliance with food safety regulations.

6.3.1 Spectroscopic techniques. Spectroscopic techniques analyze the interaction of light with matter to identify and quantify adulterants in food based on their unique spectral signatures. Near-infrared spectroscopy (NIRS) and mid-infrared (MIR) spectroscopy offer non-destructive, rapid, and accurate tools for analyzing molecular interactions and detecting adulteration in food products. NIRS operating between 750 and 2500 nm and MIR between 2500 and 25000 nm have been applied across various commodities, as highlighted in



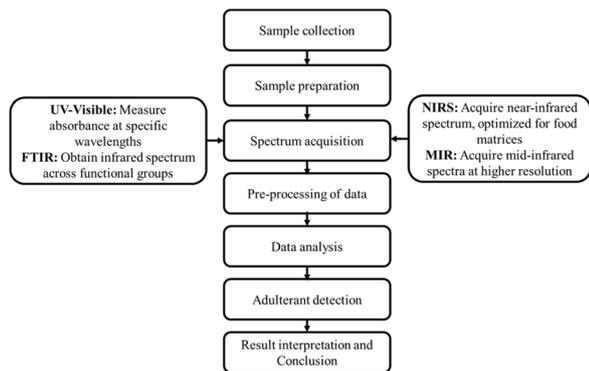


Fig. 5 Flow chart of spectroscopy-based methods.

a previous work.¹¹¹ Though NIRS requires commodity-specific calibration and involves high equipment cost, it has also been effectively used to identify adulterants in foods such as pistachios,¹¹² turmeric,¹¹³ saffron¹¹⁴ and wheat flour.¹¹⁵ A general process flowsheet for spectroscopy-based methods is given in Fig. 5.

The study focused on characterizing chickpea flour composition using NIRS and chemometrics, reporting strong calibration ($R^2 > 0.95$) for parameters like moisture, protein, and starch.¹¹⁶ They collected NIR spectra of chickpea flour samples across 1100–2500 nm and applied partial least squares regression (PLSR) to correlate spectral data with reference chemical analyses, enabling a rapid and non-destructive assessment of flour composition. Font *et al.* (2021) applied NIR-visible spectroscopy with MPLS regression to estimate neutral and acid detergent fibers in chickpea with R^2 values of 0.89 and 0.91.¹¹⁷ The study involved scanning chickpea samples using a NIR-Vis spectrometer, preprocessing the spectra to reduce noise, and constructing MPLS models to predict fiber content. Rathore *et al.* (2021) used NIRS (up to 2500 nm) to assess the nutritional quality of chickpea, reporting ~19.78% protein and ~58.4% carbohydrate, emphasizing its health benefits and rapid analytical potential.¹¹⁸ They measured the spectra of multiple chickpea genotypes, applied chemometric models for calibration, and validated the predicted nutrient content against standard proximate analysis results.

Later, the adulteration of besan with maize flour is considered a form of food fraud, as consumers pay a higher price for a product that lacks the expected nutritional quality. Besan is naturally rich in protein, whereas maize flour contains only about 8–9% protein, leading to inferior taste, texture, and reduced nutritional value in processed foods. Bala *et al.* (2022) applied NIRS combined with modified partial least squares regression (MPLSR) for detection, achieving an R^2 value of 0.999 for maize flour in chickpea flour.³⁴ They prepared adulterated samples with known maize flour concentrations, recorded NIR spectra, and developed MPLSR calibration models to quantify adulteration levels with high precision.

Advanced applications that integrate spectroscopy with chemometrics have further enhanced detection capabilities. Sindhu *et al.* (2023) employed FTIR spectroscopy with principal

component analysis (PCA) and partial least squares (PLS) to detect glyphosate in six pulse varieties.³³ Pulses were spiked with glyphosate at different concentrations (0–20 mg kg⁻¹), spectra were recorded using FTIR spectroscopy, and PCA-PLS models were applied to distinguish and predict the contamination levels accurately.

Menevseoglu *et al.* (2021) used portable FTIR and UV-Visible spectroscopy with soft independent modelling of class analogy (SIMCA) and PLSR to classify adulterants such as green peas in pistachio down to 5% levels (validation $R^2 > 0.93$).¹¹⁹ Samples were scanned using handheld FTIR/UV-Vis devices, and spectral preprocessing was performed. SIMCA and PLSR models were then developed for the rapid classification and quantification of low-level adulterants.

Laser-induced breakdown spectroscopy (LIBS) and Raman spectroscopy have been widely applied in food authenticity studies, although research on specific pulse adulteration is currently limited.

LIBS for food authentication technique has been widely applied to authenticate various food materials and differentiate complex powdered products, which is conceptually similar to detecting adulterants in pulse flours. A study utilized commercial handheld LIBS to authenticate various high-value agricultural commodities including cheese, coffee beans, spices, and vanilla extracts. This work demonstrated that LIBS, coupled with chemometric analysis, can differentiate between pure and adulterated products based on elemental emission spectra with high accuracy, thereby showcasing the method's potential for authenticating complex solid and powdered food matrices.¹²⁰ In relation to pulses, LIBS has a future scope to generate elemental fingerprints of pulse powders and detect adulteration that alters the elemental composition. At the same time, Raman spectroscopy has been widely reviewed as a powerful non-destructive method for assessing food authenticity by capturing unique molecular vibrational fingerprints, enabling the detection of adulterants such as dyes, fillers, and compounds through chemometric analysis.¹²¹ This spectroscopic method has been used to assess the composition of green beans, demonstrating its applicability to legumes.

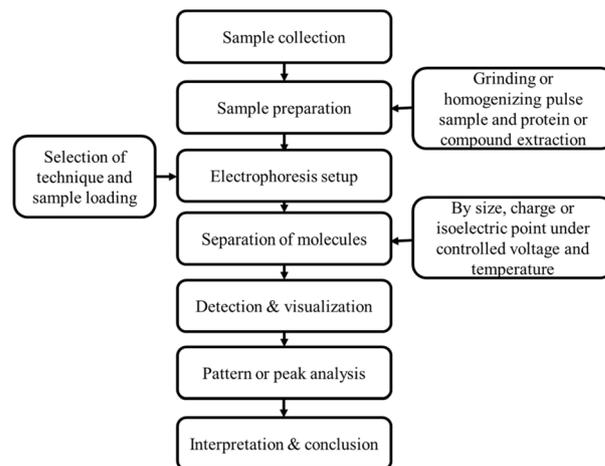


Fig. 6 Electrophoresis technique for pulse adulteration detection.



Although this work focused on quality and phytic acid detection, it shows Raman's capability to probe molecular features in beans, which could be extended to adulteration detection.¹²² Studies have developed Raman hyperspectral imaging systems to detect dyes and chemical adulterants in powdered foods, such as paprika or wheat flour, showing a high correlation between the concentration of added adulterants and spectral responses, with strong chemometric quantification.¹²³ Moreover, combined LIBS-Raman systems enhance detection reliability by integrating molecular and elemental fingerprints.¹²⁴

Collectively, these studies assure the reliability of spectroscopy, especially when integrated with chemometric models, for precise, efficient, and non-invasive food quality assessment.

6.3.2 Electrophoresis techniques. Electrophoresis is a laboratory technique used to separate charged molecules, such as DNA, RNA, and proteins, based on their size and charge by applying an electric field. The main types of electrophoresis include gel electrophoresis, capillary zone electrophoresis (CZE), and isoelectric and two-dimensional gel electrophoresis (2D-GE).¹²⁵ Therefore, studies have reported the use of CZE and 2D-GE as electrophoretic techniques specifically applied for detecting adulteration in pulses. The method for adulteration detection using electrophoresis techniques is given in Fig. 6.

An advanced protein separation method, 2D-GE, first separates proteins based on their isoelectric point and molecular weight, allowing detailed protein profiling for quality assessment. The effectiveness of this method in detecting adulteration was demonstrated by Amane and Anantharayan (2019).¹²⁶ They extracted proteins from pure and adulterated black gram samples, ran the extracts through 2D gel electrophoresis (2D-GE), and visualized the protein spots using staining. The 2D-GE analysis revealed clear differences in protein profiles between pure and adulterated samples: pure black gram exhibited characteristic protein spots, whereas adulterated samples displayed additional spots from foreign proteins and a reduction in the intensity or absence of some native spots. These distinct patterns enabled the unambiguous differentiation and even semi-quantitative assessment of adulteration,

confirming the method's sensitivity and reliability in detecting low levels of adulteration.

Additionally, CZE is a high-resolution, rapid separation technique that operates within narrow capillaries under an electric field, enabling the differentiation of molecules based on their charge-to-size ratio. It is especially valuable for detecting low levels of adulterants or toxic compounds in food samples due to its sensitivity and minimal sample requirement. Zhao *et al.* (1999) developed a CZE method to analyze β -N-oxalyl-L- α , β -diaminopropionic acid (β -ODAP) and homoarginine in *Lathyrus sativus* seeds.¹²⁷ The samples were prepared by extracting the target compounds, the extracts were injected into a narrow capillary, and separation was performed using a phosphate buffer at pH 9.0 at an applied voltage of 20 kV at 25 °C. Detection was achieved using UV absorbance at 214 nm. This approach provided a rapid, sensitive, and precise quantification of neurotoxic β -ODAP, highlighting its importance for food safety and monitoring the adulteration of pulses.

6.3.3 Chromatographic techniques. Chromatographic methods are used to separate, identify and quantify components in a mixture based on their differential movement through a stationary and a mobile phase. Several studies have employed chromatographic methods for detecting food adulteration. The chromatography techniques were used for the detection of adulterants in saffron using TLC and high-performance thin-layer chromatography (HPTLC) with image analysis,^{128,129} synthetic food colors using paper chromatography and a spectrophotometer¹³⁰ and milk fat using chromatography and chemometrics.¹³¹ The methodology followed for adulteration detection using the chromatographic technique is given in Fig. 7.

Despite such developments, only limited work has been carried out on pulses using chromatographic techniques. One such method is thin-layer chromatography (TLC), a simple, fast, and economical technique for separating compounds. Using TLC, Paradkar *et al.* (2003) demonstrated its use in detecting khesari dal adulteration in red gram and chickpea products.²⁷ In their procedure, pulse flour samples were first extracted using an appropriate solvent to obtain the target compounds. The extracts were then spotted onto silica gel TLC plates and developed in a suitable mobile phase. After development, the plates were visualized under UV light, and the adulterant was identified by its distinct R_f value of 0.54, which clearly differentiated it from the pure pulse components. This study confirmed TLC's reliability, affordability, and effectiveness in ensuring the purity of pulse-based products.

6.3.4 Metabolic phenotyping. Metabolic phenotyping, also known as metabolomics, is an advanced analytical approach that is increasingly applied in food authenticity studies to detect adulteration through the comprehensive profiling of low-molecular-weight metabolites.

Several studies have applied metabolomics to the investigation of legumes and pulses, highlighting its promise for quality control and authentication. For example, untargeted LC-MS-based metabolomic fingerprinting has been used to profile the chemical composition of common legumes such as chickpeas, lentils, and white beans, identifying discriminative

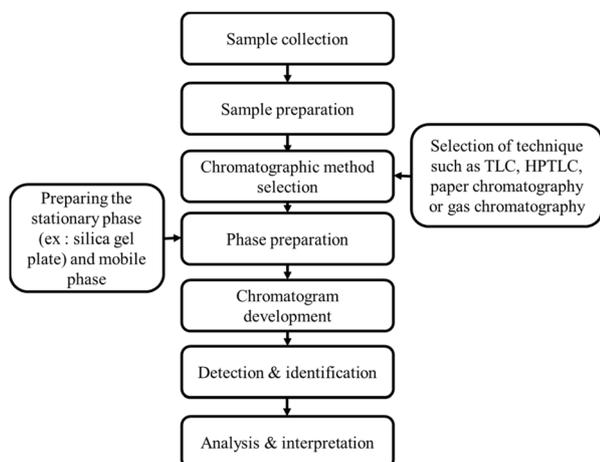


Fig. 7 Chromatographic techniques for pulse adulteration detection.



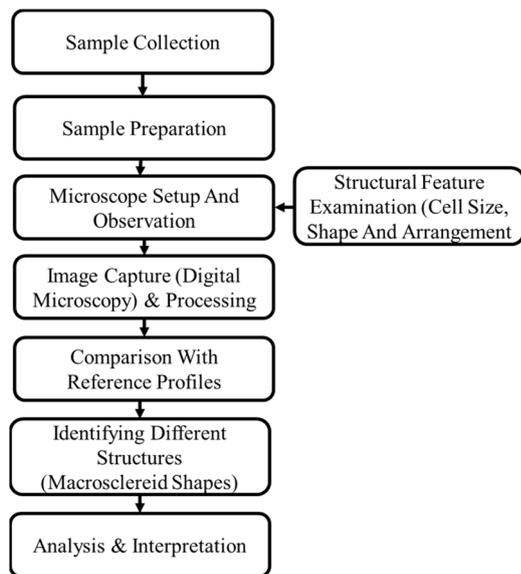


Fig. 8 Microscopic analysis technique for pulse adulteration detection.

metabolite features that differentiate between these pulse types based on their phenolic, lipid, and organic compound profiles. Such metabolite differences reflect inherent biochemical distinctions between pulses and suggest that metabolomics can serve as a basis for authenticity and quality control assessments in legumes.¹³²

Although most metabolomics work in pulses has focused on compositional profiling rather than explicit adulteration models, the principles are directly relevant to the detection of adulteration. Untargeted metabolomic approaches capture wide panels of metabolites that can reveal deviations from expected profiles when inferior legumes, fillers, or synthetic adulterants are present. This untargeted strategy is thus well-suited to discovering biomarkers of authenticity or unexpected adulterants in complex legume mixtures when coupled with multivariate analysis.¹³³

In the context of food science, metabolomics applications have successfully differentiated authentic from adulterated products using small molecular signatures and chemometrics, demonstrating that metabolomic fingerprinting and biomarker discovery are effective for food authentication and the detection of adulteration across diverse matrices. These findings support the potential feasibility of similar approaches for pulses as metabolomics platforms and data analytics continue to advance.¹³⁴

The analytical techniques provide a scientific edge in detecting hidden contaminants, ensuring the nutritional and safety standards of pulses by detecting even trace levels of adulterants.

6.4 Imaging techniques

Adulteration in pulses has traditionally been detected using physical and chemical methods. However, these techniques are often time-consuming, labor-intensive and destructive in nature.¹³⁵ To overcome these limitations, recent researchers

have explored the use of image processing, aiming to enhance the speed and efficiency for pulse quality assessment and adulteration detection.^{136,137} These digital and imaging-based technologies are emerging as valuable supplements to conventional methods, offering non-destructive, real-time, and automated detection through tools such as computer vision, machine learning, hyperspectral imaging, and X-ray imaging.

6.4.1 Microscopic image analysis. One method for detecting adulteration is microscopic examination, which involves examining the structural features of pulses under a microscope. This method differentiates pure and adulterated samples based on variations in cell size, shape and arrangement. Therefore, several researchers have increasingly utilized microscopic imaging techniques for detecting different adulterations in various foods, such as fishmeal, using deep learning-based image analysis,¹³⁸ food structure evaluation using light microscopy,¹³⁹ and the detection of cane sugar in honey.¹⁴⁰ The microscopic analysis technique for pulse adulteration detection is given in Fig. 8.

Moreover, multiple pulse adulteration scenarios have been effectively explored using microscopic imaging techniques. This technique has been used to detect adulteration in Bengal gram flour by examining macrosclereid characteristics, based on distinct structural differences. Rajan *et al.* (2018) prepared pure and adulterated Bengal gram flour samples, observed them under light microscopy, and captured the images of the macrosclereid cells. Pure Bengal gram showed elongated and bent macrosclereids, while adulterants exhibited flat-ended shapes, allowing for clear differentiation.¹⁴¹ The study confirmed that microscopic imaging can effectively reveal structural differences caused by adulteration.

In further studies, Dattatreya *et al.* (2011) focused on the accurate identification of adulterants, such as peas and *Lathyrus*, in Bengal gram flour.¹⁴² Flour samples were prepared with controlled adulteration, captured microscopic images, and analyzed cell morphology. Although no differences were found in cell length or general structure, variations in cell shape enabled

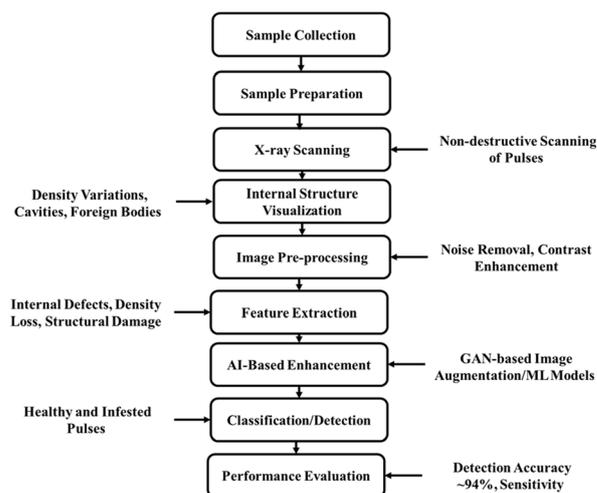


Fig. 9 X-ray imaging technique for pulse adulteration detection.



the detection of adulterants, highlighting the sensitivity of microscopic imaging for subtle microstructural changes.

Thus, microscopic imaging becomes a powerful image analysis technique when coupled with digital capture and image processing, enabling the precise characterization of microstructural features of pulses and their products for the detection of adulteration.

6.4.2 X-ray imaging. X-ray imaging is a highly effective, non-destructive technique that enables the identification of internal insect damage without altering the grain's physical properties. Several researchers investigated and studied how X-ray imaging techniques are used for detecting food adulteration and internal defects, such as for detecting foreign contaminants and structural defects in various food products,¹⁴³ insect damage and hidden defects in agricultural produce,¹⁴⁴ detection of foreign elements in food items¹⁴⁵ and lead chromate adulteration in turmeric.¹⁴⁶ The procedure for X-ray imaging technique is given in Fig. 9.

In the context of pulse adulteration, the detection of *Callosobruchus maculatus* infestation in chickpeas, pigeon peas, and mung beans was performed using X-ray imaging, NIR spectroscopy, and visual inspection.³⁸ Pulse samples were scanned using X-ray imaging to capture internal structural information, while NIR spectroscopy and visual inspection provided complementary assessments of external and spectral features. X-ray imaging proved the most effective method, detecting over 92% of infested grains by revealing internal insect damage. Infested pulses exhibited 12–18% weight loss and 22–30% contamination from insect waste, highlighting the impact of infestation on both quality and quantity. Additionally, phosphine fumigation reduced infestation by 85%, and controlled atmosphere storage achieved a 75% reduction, emphasizing the importance of early detection combined with effective control measures.

Further, Divyanth *et al.* (2022)³⁹ enhanced pulse adulteration detection in green gram by integrating X-ray imaging with generative adversarial networks (GANs) for image augmentation. Original X-ray images of infested and healthy pulses were captured, and GANs were used to expand the dataset synthetically, highlighting subtle density loss and internal structural changes. While X-ray imaging alone detected 89% of infested grains, the GAN-enhanced approach increased detection accuracy to 94%, demonstrating that integrating machine learning

significantly improves reliability and efficiency in identifying internal defects.

Collectively, these studies confirm that X-ray imaging, especially when combined with AI-based image augmentation, provides a rapid, non-destructive, and highly accurate tool for detecting both biological and structural adulteration in pulses, ensuring improved safety and quality in pulse processing.

6.4.3 Line-scan near-infrared hyperspectral imaging (NIR-HSI). Line-scan hyperspectral imaging is an advanced imaging technique that combines spectroscopy and imaging. It captures both spatial and spectral information by scanning the sample line by line. Researchers have employed related technologies to identify diverse adulterants across various food categories, such as the detection of adulteration in butter using line-scan Raman spectroscopy¹⁴⁷ and the identification of contaminants and assurance of product quality through line-scan hyperspectral imaging.¹⁴⁸

Focusing specifically on pulses, Saha *et al.* (2023) conducted a study to detect metanil yellow adulteration in chickpea flour using line-scan near-infrared hyperspectral imaging (NIR-HSI).³⁶ Chickpea flour samples were spiked with 0.1–2% metanil yellow and scanned across the 900–1700 nm wavelength range, capturing both spatial and spectral information. The hyperspectral images were pre-processed to remove noise and correct background variations, and spectral data from the adulterated regions were extracted for analysis. The data were then modeled using partial least squares regression (PLSR) and a one-dimensional convolutional neural network (1D-CNN) to predict the levels of adulterants. The PLSR model achieved an R^2 value of 0.978, while the 1D-CNN model performed even better with an R^2 value of 0.992, demonstrating extremely high accuracy in detecting and quantifying low levels of metanil yellow. This study highlights line-scan NIR-HSI as a rapid, non-destructive, and highly reliable technique for accurately detecting adulteration in pulses, thereby ensuring both food safety and consumer protection.

6.4.4 Digital imaging with hyperspectral analysis. Hyperspectral imaging is a non-destructive technique that captures spectral information from food products, enabling precise identification of fungal contamination. Various forms of food adulteration detection have been explored across a wide range of commodities using hyperspectral imaging and its variants. It has been utilized to identify adulteration in honey,¹⁴⁹ powdered foods using a Raman hyperspectral imaging system,¹⁵⁰ red chilli powder¹⁵¹ and detection of chicken meat adulteration in minced beef using visible-NIR hyperspectral imaging system with machine learning.¹⁵² This confirms the applicability in detecting slight chemical and structural changes in food matrices. The hyperspectral imaging technique is illustrated in Fig. 10.

Despite such advancements in various food matrices, limited research has been conducted specifically on pulses. Karupiah *et al.* (2016) focused on detecting fungal infections in five different types of pulses, namely chickpeas, pigeon peas, mung beans, lentils, and black grams, using NIR-HIS.³⁷ They scanned pure and contaminated pulse samples across the 1000–1700 nm wavelength range, extracted spectral features, and applied

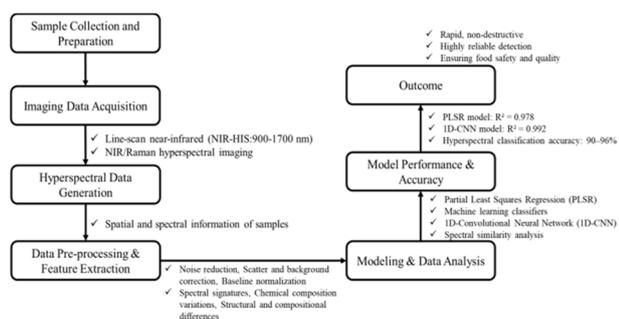


Fig. 10 Hyperspectral imaging technique for pulse adulteration detection.



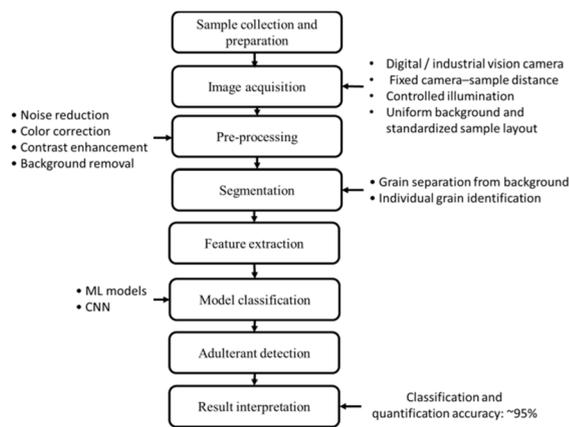


Fig. 11 Computer vision technique for pulse adulteration detection.

classification models to differentiate between pure and contaminated samples. The results showed 90–96% accuracy in identifying fungal contamination, demonstrating that hyperspectral imaging is a rapid, non-invasive, and reliable tool for ensuring pulse safety.

In cereals, Lohumi *et al.* (2019) expanded their earlier work by using Raman hyperspectral imaging combined with spectral similarity analysis to detect multiple adulterants in wheat flour. They collected hyperspectral Raman images of pure and adulterated wheat flour samples, processed the spectral data to remove noise, and applied spectral similarity analysis to identify and quantify adulterants. Their results confirmed that Raman hyperspectral imaging can accurately detect and estimate multiple adulterants in complex food powders, demonstrating its strength in multi-adulterant detection.¹⁵³

Together, these studies reinforce the effectiveness of hyperspectral imaging, particularly NIR and Raman-based systems, in detecting food adulteration across a wide range of commodities.

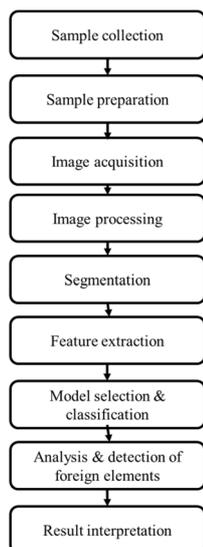


Fig. 12 Image processing technique for pulse adulteration detection.

6.4.5 Computer vision techniques. Computer vision is a field of artificial intelligence that enables machines to interpret and analyze visual data from the real world. It simulates human vision capabilities through algorithms that extract meaningful information from images using image-based feature extraction techniques, such as color, shape, and texture analysis. In pulse authenticity assessment, CV involves image acquisition, pre-processing, segmentation, and feature extraction to capture relevant visual characteristics such as grain size, shape, surface texture, color distribution, and spatial arrangement. These extracted features serve as quantitative inputs for ML models, facilitating automated and objective adulteration detection.¹⁵⁴ The recent advancements have shown the wide applicability of computer vision in identifying adulteration across various food commodities such as saffron using imaging and electronic nose systems,^{155,156} grape syrup adulteration,¹⁵⁷ identifying different rice varieties,¹⁵⁸ turmeric adulterants using visual color analysis¹⁵⁹ and ghee adulteration.¹⁶⁰ The procedure for computer vision technique is illustrated in Fig. 11.

For computer vision-based adulteration detection in pulses, image acquisition is a critical step that directly influences feature extraction and classification accuracy. Images are typically captured using a digital camera or an industrial vision camera mounted at a fixed distance above the sample under controlled illumination conditions to minimize shadows and reflections. A uniform background and standardized sample arrangement are used to ensure repeatability. Camera parameters such as resolution, focal length, exposure time, aperture, and white balance are kept constant across all samples to maintain consistency and reduce variability caused by imaging conditions. This standardized image acquisition protocol ensures that variations observed in color, shape, and texture are attributable to adulteration rather than differences in imaging setup.¹⁶¹

Despite the increasing adoption of computer vision in food quality evaluation, there is a limited body of literature specifically focused on its application for detecting adulteration in pulses. Lidiya and Mohanapriya (2025) explored the use of computer vision and CNN models to identify adulteration in thoor dal with khesari dal based on features like shape, color and texture.¹⁶² Their model not only classified pure and adulterated grains with high accuracy but also quantified adulteration levels (with an accuracy of 0.95%), offering a user-friendly and efficient alternative to traditional, labor-intensive methods.

6.4.6 Image processing techniques. Image processing techniques, integrated with machine learning and sensor-based tools, are increasingly used for detecting adulterants and quality defects in pulses (Fig. 12). Machine learning (ML) is a branch of artificial intelligence that enables computational models to automatically learn patterns and relationships from data for classification, regression, and prediction tasks without explicit rule-based programming. In pulse adulteration detection, ML algorithms analyze multidimensional data derived from imaging and spectroscopic techniques, including morphological, color, textural, and spectral features, to distinguish pure samples from adulterated ones and to quantify adulterant levels. ML-based approaches support supervised and



Table 9 Comparative evaluation of adulteration detection techniques^a

| Detection method | Advantages | Limitations | Operational Cost | Eco-friendly | Throughput/suitability | References |
|---|--|---|------------------|--------------|------------------------|--|
| Visual inspection (traditional) | Simple, rapid, no instrumentation required | Subjective; low sensitivity; ineffective for low-level adulteration | ↓ | ⊙⊙⊙ | ✓ | Preliminary field-level screening 10 |
| Density-based separation | Low cost; easy to implement | Poor specificity when density differences are small | ↓ | ⊙⊙⊙ | ✓ | Routine but limited accuracy 20 |
| Water soaking test | Inexpensive; simple field test | Time-consuming; qualitative; variety dependent | ↓ | ⊙⊙⊙ | ✓ | Small-scale screening 10 |
| Magnetic sorting | Rapid; non-destructive | Limited to magnetic/coated adulterants only | → | ⊙⊙ | ✓ | High throughput; narrow applicability 20 |
| Sedimentation technique | Simple; minimal equipment | Low reproducibility; poor discrimination | ↓ | ⊙⊙⊙ | ✓ | Preliminary assessment 20 |
| Chemical tests (AgNO ₃ , ninhydrin, HCl) | Sensitive and specific to target adulterants | Destructive; reagent handling; chemical waste | → | ⊙⊙ | ✗ | Laboratory-based screening 107 |
| UV-Visible spectroscopy | Rapid; minimal sample preparation | Low selectivity; spectral overlap | → | ⊙⊙ | ✓ | Routine laboratory analysis 117 |
| FTIR spectroscopy | Non-destructive; molecular fingerprinting | High instrument cost; skilled interpretation | ↑ | ⊙⊙ | ✓ | Confirmatory analysis 119 |
| NIR spectroscopy (NIRS) | Fast; suitable for bulk and online analysis | Requires calibration models; lower trace sensitivity | ↑ | ⊙⊙ | ✓ | Industrial high-throughput use 34 |
| Mid-IR spectroscopy (MIR) | High chemical specificity | Sample preparation often required | ↑ | ⊙⊙ | ✓ | Research and validation studies 111 |
| Spectroscopy + Chemometrics | Quantitative and highly accurate | Model-dependent; large datasets needed | ↑ | ⊙ | ✓ | Advanced analytical applications 116 |
| Microscopic analysis | Direct visualization of structural features | Labor-intensive; subjective interpretation | → | ⊙⊙ | ✓ | Low-throughput laboratory analysis 139 |
| X-ray imaging | Non-destructive internal structure assessment | Very high cost; safety concerns | ↑ | ⊙ | ✓ | Specialized applications 38 |
| Hyperspectral imaging | Combines spatial and spectral data; high accuracy | Expensive; complex data processing | ↑ | ⊙ | ✓ | Advanced research and industry 37 |
| Digital imaging | Low cost; rapid acquisition | Limited chemical sensitivity | ↓ | ⊙⊙⊙ | ✓ | High-throughput screening 151 |
| Computer vision techniques | Automated; objective; scalable | Dependent on image quality and algorithms | → | ⊙⊙ | ✓ | Industrial and research use 162 |
| Image processing techniques | Enhances visual features; non-destructive | Indirect detection; needs validation | → | ⊙⊙ | ✓ | Routine screening 9 |
| Capillary electrophoresis (CZE) | High resolution; high sensitivity | Expensive; skilled operation required | ↑ | ⊙ | ✗ | Confirmatory analysis 127 |
| 2D-gel electrophoresis | High separation efficiency | Time-consuming; poor routine applicability | ↑ | ⊙ | ✗ | Research-oriented 126 |
| Thin-layer chromatography (TLC) | Simple; relatively low cost | Semi-quantitative; lower sensitivity | → | ⊙⊙ | ✗ | Screening and confirmation 27 |
| DNA barcoding | Very high specificity; species authentication | High cost; ineffective for processed samples | ↑ | ⊙ | ✗ | Regulatory and forensic analysis 170 |
| Metabolic phenotyping of pulses | Comprehensive biochemical profiling; high discrimination | Expensive instrumentation; complex data analysis | ↑ | ⊙ | ✓ | Advanced research applications 132 |
| Long-read DNA sequencing | High accuracy; resolves complex genomic regions | Very high cost; high computational demand | ↑ | ⊙ | ✗ | Regulatory and advanced research 171 |
| Laser-based methods (LBIS, Raman spectroscopy) | Rapid, non-destructive, minimal sample preparation | High instrument cost; fluorescence interference | ↑ | ⊙⊙ | ✓ | Rapid screening and confirmation ^{120, 121} |

^a ↓: Low cost; →: medium cost, ↑: high cost; ✓: eco-friendly, ✗: not eco-friendly; ⊙: easy operation, ⊙⊙: moderate operation, ⊙⊙⊙: complex operation.



unsupervised learning frameworks, allowing model training using labeled reference samples as well as pattern discovery in unknown datasets.¹⁶³ Compared with conventional chemical and manual methods, ML provides higher analytical accuracy, improved reproducibility, and scalability while enabling rapid, non-destructive, and high-throughput authenticity monitoring suitable for real-time quality control applications (Table 9).¹⁶⁴

Several studies have demonstrated the effectiveness of image-based and sensor-integrated techniques in detecting adulteration in various food commodities, such as roasted coffee powders using digital image processing,¹⁶⁵ raw meat products using multispectral image analysis,¹⁶⁶ milk using a smartphone-based colorimetric test,¹⁶⁷ milk powder using Raman chemical imaging.¹⁴⁸ Coffee adulteration was detected by digital imaging.¹⁶⁸

Recent advancements have introduced image processing, machine learning, and sensor-based systems as effective tools for detecting pulse adulterants. A Raspberry Pi-based hardware prototype, FoodExpert, was developed to combine NIR spectroscopy, image processing, and machine learning for rapid screening of pulses, specifically targeting metanil yellow

contamination. The system captured images of pulse samples, extracted visual and spectral features, and classified them using a trained machine learning model. It achieved 94% accuracy on the dataset and 87% accuracy on real-world images, demonstrating potential as a portable, low-cost tool for real-time adulteration detection.⁹

Souto *et al.* (2015) provided a comprehensive overview of image acquisition techniques for assessing the quality of legumes. They employed digital imaging setups to capture images of pulses and analyzed parameters such as color, texture, and surface defects using image processing software.¹⁶⁹ Their study confirmed that automated image-based tools can reliably detect physical quality deviations, ensuring pulse safety and quality.

In a related application, visual and imaging techniques were employed to detect biological adulteration in pulses caused by the pulse beetle (*Callosobruchus maculatus*) during storage and transportation. The study observed external damage and contamination, with infested samples showing up to 30% increased impurity levels. Control strategies such as fumigation and the use of biological agents helped reduce infestation by

Table 10 Overview of pulse adulteration studies highlighting advanced detection techniques and major outcomes

| Product | Adulterant | Detection technique | Major findings | References |
|--|--|---|---|------------|
| Yellow pea, chickpea, large green lentil, red lentil, black beluga and French green lentil | Glyphosate residues | FTIR spectroscopy | PLSR model, $R^2 = 0.93, 0.92, 0.96, 0.91, 0.96, \text{ and } 0.92$, respectively | 33 |
| Pulses | Metanil yellow | Food expert device (NIRS, Image processing and ML) | $R^2 = 0.096$ 87% accuracy on real real-world dataset 94% accuracy on test set | 9 |
| Black gram | Pea (<i>Pisum sativum</i>) and <i>Lathyrus</i> | Microscopic analysis | Bengal gram macrosclereids-155.6 microns, bent; pea-61.8 microns, flat and <i>Lathyrus</i> -72 microns, flat | 142 |
| Thoor dal | <i>Lathyrus sativus</i> | Computer vision technique with CNN | 95% accuracy | 162 |
| Chickpea and red gram | <i>Lathyrus sativus</i> | TLC | $R^2 = 0.54$ | 27 |
| Legumes (Bengal gram and green gram) | Black gram | 2D-GE | Adulteration ($\geq 5\%$), observed 250+ protein spots, molecular weight (10–100 kDa), with distinct protein profile variations | 126 |
| Chickpeas, pigeon peas, mung beans | Pulse beetle (<i>Callosobruchus maculatus</i>) | Visual inspection, X-ray imaging, NIR spectroscopy and gravimetric analysis | Fumigation reduced infestation by 85%, while controlled atmosphere storage achieved a 75% reduction. X-ray imaging detected over 92% of infested pulses | 38 |
| Green gram (<i>Vigna radiata</i>) | Pulse beetle (<i>Callosobruchus maculatus</i>) | X-ray imaging, GAN-based image augmentation | GAN-augmented X-ray | 39 |
| Chickpeas, pigeon peas, mung beans, lentils, and black grams | Fungal species | NIR-HSI (1000–1700 nm) | LDA and QDA models | 37 |
| Chickpea flour | Maize flour | NIR (400–2948 nm) | MPLSR model, $R^2 = 0.999$ | 34 |
| Chickpea flour | Metanil yellow | NIR-HSI (900–1700 nm) | PLSR model, $R^2 = 0.978$ | 36 |
| Black gram products | Wheat flour (maida) and white pea flour | DNA barcoding loci: rbcL, trnH-psbA, ITS | 1D-CNN model, $R^2 = 0.992$ PCR, accuracy = 100% | 170 |



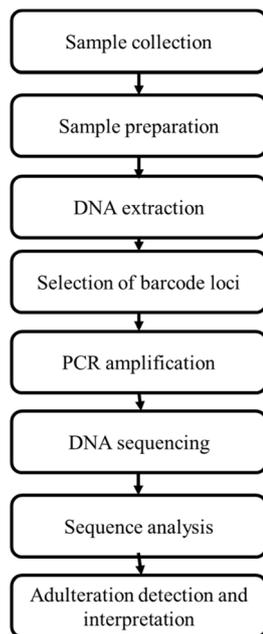


Fig. 13 Biological and molecular techniques for pulse adulteration detection.

75–85%, contributing to improved pulse safety and quality.³⁸ Therefore, these studies showcase the effectiveness of image processing techniques in detecting both chemical and biological adulterants.

Overall, imaging techniques have emerged as powerful, non-destructive tools for detecting pulse adulteration, offering rapid, accurate, and real-time analysis. Their ability to capture subtle visual and spectral variations enables the precise identification of adulterants and the verification of authenticity. With growing advancements in imaging and AI integration, these methods hold great promise for ensuring pulse quality and consumer safety.

6.5 Biological and molecular techniques

Biological and molecular techniques provide highly sensitive and specific tools for detecting adulterants in pulse-based food products. These methods work at the genetic and biochemical level, enabling the identification of adulterants that are difficult to detect visually or chemically. DNA barcoding is a molecular identification method that utilizes short, standardized gene regions to detect, verify, and confirm the species of plants or animals in food products. It is particularly effective in processed or powdered forms, where morphological identification is impossible. Modern approaches to food adulteration detection are increasingly relying on molecular and advanced imaging techniques (Table 10) to enhance the sensitivity, speed, and accuracy (Fig. 13). Various molecular and imaging-based methods, such as PCR and CNN-integrated thermography, have demonstrated strong potential for the accurate and real-time detection of food adulteration.^{172,173}

Building on these technological advances, molecular methods have also been extended to detect adulteration in

pulses. Amane and Anantharayan (2019) used DNA barcoding to authenticate black gram-based products. They tested three barcoding loci: *rbcL* (600 bp), *trnH-psbA* (380 bp), and *ITS* (680 bp), on samples adulterated with 5% refined wheat flour and white pea flour. PCR amplification and sequencing were performed for each locus, followed by comparison with reference sequences to identify adulterants.¹⁷⁰ The loci *rbcL* and *trnH-psbA* showed higher suitability for detecting refined wheat flour in black gram flour. Analysis of 11 market samples confirmed adulteration in one sample, demonstrating the capability of DNA barcoding to detect low-level adulteration in processed pulse products.

Long-read DNA sequencing, a third-generation sequencing technology exemplified by platforms such as Oxford Nanopore Technologies and Pacific Biosciences (PacBio SMRT), generates much longer continuous DNA sequence reads compared to earlier next-generation sequencing platforms. Long reads can exceed tens of kilobases and provide greater context for genomic assembly, structural variant detection, and accurate species discrimination. These extended reads enable improved resolution of taxonomically informative regions, overcoming limitations of short reads in distinguishing closely related species or in resolving complex genomic mixtures.¹⁷⁴

In the context of pulse adulteration, long-read sequencing allows comprehensive analysis of total genomic DNA extracted from pulse flours, lentil/bean mixtures, or processed legume products. Rather than targeting a single barcode region, untargeted long-read sequencing can capture whole-genome fragments from all species present in a sample. By comparing these sequences against extensive reference databases, researchers can detect undeclared or substituted legume species, identify adulterants even at low proportions, and assess mixed-species compositions without prior assumptions about which adulterants may be present. Although such workflows have not yet been widely published specifically for pulses, similar strategies have been successfully demonstrated for other high-protein food matrices. For example, deep sequencing of total genomic DNA from complex protein powders accurately identified expected and unexpected plant and animal species, emphasizing the method's ability to detect contaminants and authenticate ingredients in a single assay.¹⁷¹

Beyond species identification, long-read sequencing can facilitate untargeted authentication, meaning that it does not require predetermined PCR primers or specific target loci. Instead, it sequences all the DNA present, allowing for the detection of unexpected or novel adulterants. Bioinformatic pipelines map long reads to reference genomes, enabling both the qualitative detection of species and the quantitative estimation of their proportions in mixed samples capabilities that are especially valuable in food fraud investigations, where the identity and concentration of adulterants are both critical. Emerging collaborations between sequencing technology providers and food analysis companies are now developing portable nanopore-based authenticity tests that aim to provide industry-validated tools for rapid, on-site detection of food fraud using long-read sequencing.¹⁷⁵



7 Challenges

Food adulteration in pulses is a significant concern for public health, consumer trust and economic stability. The key challenges include low consumer awareness of adulteration and strong economic incentives to the sellers when cheaper, unsafe materials replace pure products to enhance visual appeal.¹⁷⁶ While most existing facilities are confined to research-oriented setups that have shown successful results, as discussed in this review, the transition of recent advances from laboratory scale to large-scale application is underway.¹⁷⁷ However, their high cost and need for skilled operators limit their use. Moreover, weak enforcement and the complexity of modern supply chains create further opportunities for adulteration at multiple stages.¹⁷⁸

Multiple strategies are necessary to address these issues, which include investing in accessible and reasonably priced detection technologies, strengthening regulatory frameworks to ensure stricter enforcement, increasing consumer education to raise awareness about food adulteration, and improving the supply chain system to identify and eliminate adulteration practices effectively.

8 Future prospects

Focusing on adulteration in pulses, even at trace levels, the accuracy of detection can be improved by combining deep learning algorithms with hyperspectral photography. FoodExpert and other portable equipment also show promise for application at the field level. In processed and powdered items, further investigation into molecular techniques, such as DNA barcoding, can yield conclusive identification. Additionally, electrophoresis-based techniques, such as gel electrophoresis and isoelectric focusing, need to regain attention for detecting adulteration. In contrast, computer vision systems have seen only limited research on adulteration in pulses. Therefore, expanding these technologies and accelerating their transition from laboratory setups to large-scale market applications is necessary. By combining artificial intelligence, machine learning, and spectroscopic technologies, the field of pulse adulteration detection is poised for significant innovation in the future. Despite technological advancements, this approach requires specific hardware setups and calibration procedures, which can limit its portability and flexibility. The development of affordable, non-invasive, and real-time mobile detection methods is essential as adulteration becomes increasingly complex. It is also crucial to raise public awareness, implement blockchain-based traceability mechanisms, and enhance regulatory enforcement through the use of digital monitoring tools. The possibility of international cooperation to create centralized databases for adulteration, standardize detection procedures, and ensure uniform food safety standards needs to be explored. Therefore, future efforts should focus on expanding sample diversity and validating these advanced models in field environments to ensure their applicability and consistency in real-world monitoring.

9 Conclusions

The issue of adulteration in pulses continues to pose a serious risk to people's well-being, consumer confidence, and safe food handling practices. Additionally, the range of adulterants, from biological pollutants to hazardous synthetic colors, necessitates reliable detection systems. While traditional methods alone are often insufficient, recent technological advances in spectroscopy, machine vision, electrophoresis, and molecular diagnostics have enabled more sensitive and accurate detection of adulteration. However, in environments with limited resources, cost-effectiveness with easy access remains an obstacle. It is crucial to take a multidisciplinary approach that includes fair supply chain practices, public education, regulatory alertness and scientific innovation. Protecting pulse purity not only upholds nutritional integrity but also strengthens consumer confidence and supports broader goals of sustainable food systems.

Author contributions

Dharni Asritha: data curation, writing – original draft, writing – review and editing, and visualization. Sandhya Singh: conceptualization, methodology, data curation, writing – review and editing, supervision, and project administration. Manpreet Kaur Saini: supervision and project administration. Vimal Challana: data curation, writing – review and editing, and visualization.

Conflicts of interest

There are no conflicts to declare.

Abbreviation

| | |
|--------|--|
| 1D-CNN | One-dimensional convolutional neural network |
| 2D-GE | Two-dimensional gel electrophoresis |
| BOAA | β -N-oxalyl-L- α , β -diaminopropionic acid |
| CIELAB | Commission internationale de l'éclairage Lab* color space |
| CZE | Capillary zone electrophoresis |
| DNA | Deoxyribonucleic acid |
| FAO | Food and agriculture organization |
| FSSAI | Food safety and standards authority of india |
| FSA | Food standards agency |
| EFSA | European food safety authority |
| FDA | Food and drug administration |
| FTIR | Fourier-transform infrared |
| GAN | Generative adversarial network |
| GC-MS | Gas chromatography-mass spectrometry |
| GLCM | Gray-level co-occurrence matrix |
| GLRLM | Gray-level run-length matrix |
| GLSZM | Gray-level size zone matrix |
| HCl | Hydrochloric acid |
| HPLC | High-performance liquid chromatography |
| HPTLC | High-performance thin-layer chromatography |
| HSI | Hyperspectral imaging |
| IS | Indian standards |
| LBP | Local binary patterns |



| | |
|-------|---|
| LDA | Linear discriminant analysis |
| LSP | Local structure pattern |
| LSN | Least squares normalization |
| MIR | Mid-infrared |
| ML | Machine learning |
| MPLS | Modified partial least squares |
| MPLSR | Modified partial least squares regression |
| NGTDM | Neighbourhood gray-tone difference matrix |
| NIR | Near infrared |
| NIRS | Near-infrared spectroscopy |
| PCA | Principal component analysis |
| PCR | Polymerase chain reaction |
| PLS | Partial least squares |
| PLSR | Partial least squares regression |
| QDA | Quadratic discriminant analysis |
| RF | Retention factor |
| RGB | Red, green, blue |
| TLC | Thin-layer chromatography |
| TPA | Texture profile analysis |
| UV | Ultraviolet |
| LIBS | Laser-induced breakdown spectroscopy |

Data availability

No primary research results, software or code have been included and no new data were generated or analysed as part of this review.

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References

- 1 N. Singh, Pulses: an overview, *J. Food Sci. Technol.*, 2017, **54**, 853–857.
- 2 V. Kumar and I. Dutt, Time series change in pulse scenario in India with special reference to Haryana, *Legume Res.*, 2019, **42**, 228–232.
- 3 A. N. Mudryj, N. Yu and H. M. Aukema, Nutritional and health benefits of pulses, *Appl. Physiol., Nutr., Metab.*, 2014, **39**, 1197–1204.
- 4 V. Rawal and D. K. Navarro, *The Global Economy Of Pulses*, 2019.
- 5 FAO, *A Guide to World Pulses Day 2025*, 2025.
- 6 G. B. Patil, S. P. Wani, P. S. Bafna, V. S. Bagul, M. G. Kalaskar and R. E. Mutha, Milk adulteration: From detection to health impact, *Food Human.*, 2024, **3**, 100339.
- 7 Z. Mansuri, *Study of Adulterants in Foods*, Delhi, India, 2011.
- 8 A. Choudhary, N. Gupta, F. Hameed and S. Choton, An overview of food adulteration: Concept, sources, impact, challenges and detection, *Int. J. Chem. Stud.*, 2020, **8**, 2564–2573.
- 9 H. Pandey, S. Arya, D. Das and V. Udutalapally, FoodExpert: Portable Intelligent Device for Rapid Screening of Pulse Quality and Adulteration, *IEEE Trans. AgriFood Electron.*, 2024, **2**, 2–11.
- 10 A. Verma, *Ensuring Safety of Pulses & Besan*, 2018.
- 11 A. Ayza and Z. Yilma, Patterns of milk and milk products adulteration in Boditti town and its surrounding, South Ethiopia, *J. Agric. Sci.*, 2014, **4**, 512–516.
- 12 D. Narayan, Food Adulteration: Types, worldwide laws and futures, *Health Care*, 2014, **1**, 2–8.
- 13 M. Banti, Food adulteration and some methods of detection, review, *Int. J. Nutr. Food Sci.*, 2020, **9**, 86–94.
- 14 A. Asrat, Y. Zelalem and N. Ajebu, Quality of fresh whole milk produced in and around Boditti, Wolaita, South Ethiopia, *S. Afr. J. Anim. Sci.*, 2012, **7**, 95–99.
- 15 G. Anita and S. Neetu, Hazards of new technology in promoting food adulteration, *IOSR J. Environ. Sci. Toxicol. Food Technol.*, 2013, **5**, 8–10.
- 16 S. Kandpal, A. Srivastava and K. Negi, Estimation of quality of raw milk (open & branded) by milk adulteration testing kit, *Indian J. Community Health*, 2012, **24**, 188–192.
- 17 T. Tripathy, Magic of Dals or Pulses in Homoeopathy, *Saudi Med. J.*, 2023, **8**, 500–504.
- 18 T. Azad and S. Ahmed, Common milk adulteration and their detection techniques, *Int. J. Food Contam.*, 2016, **3**, 22.
- 19 Y. He, X. Bai, Q. Xiao, F. Liu, L. Zhou and C. Zhang, Detection of adulteration in food based on nondestructive analysis techniques: a review, *Crit. Rev. Food Sci. Nutr.*, 2021, **61**, 2351–2371.
- 20 IS, *Quick methods for detection of adulterants/contaminants in common food products*, 2006.
- 21 FSSAI, *Quick Test for Some Adulterants in Food-Instruction manual- part I (common methods for detection at households)*, 2012.
- 22 F. DartBook, *Common Quick Tests for Detection of Some Food Adulterants at Household.*, Ministry of health and family, Government of India., 2017.
- 23 M. R. A. Avaro, Z. Pan, T. Yoshida and Y. Wada, Two alternative methods to predict amylose content of rice grain by using tristimulus CIE lab values and developing a specific color board of starch-iodine complex solution, *Plant Prod. Sci.*, 2011, **14**, 164–168.
- 24 D. Attrej, in *Food Safety in the 21st Century*, Elsevier, 2017, pp. 129–143.
- 25 S. Awasthi, K. Jain, A. Das, R. Alam, G. Surti and N. Kishan, Analysis of food quality and food adulterants from different departmental & local grocery stores by qualitative analysis for food safety, *IOSR J. Environ. Sci. Toxicol. Food Technol.*, 2014, **8**, 22–26.
- 26 B. Ghosh, J. Mitra, S. Chakraborty, J. Bhattacharyya, A. Chakraborty, S. K. Sen and M. Neerathilingam, Simple detection methods for antinutritive factor β -ODAP present in *Lathyrus sativus* L. by high pressure liquid chromatography and thin layer chromatography, *PLoS One*, 2015, **10**, e0140649.
- 27 M. M. Paradkar, R. S. Singhal and P. R. Kulkarni, Detection of *Lathyrus sativus* in processed chickpea- and red gram-



- based products by thin layer chromatography, *J. Sci. Food Agric.*, 2003, **83**, 727–730.
- 28 FSSAI, *Manual of Methods of Analysis of Foods for Cereals and Pulses Products*, 2016.
- 29 E. Firatlıgil-Durmuş, E. Šárka, Z. Bubník, M. Schejbal and P. Kadlec, Size properties of legume seeds of different varieties using image analysis, *J. Food Eng.*, 2010, **99**, 445–451.
- 30 M. Koklu and I. A. Ozkan, Multiclass classification of dry beans using computer vision and machine learning techniques, *Comput. Electron. Agric.*, 2020, **174**, 105507.
- 31 S. Viscarra, A. Vargas, L. Jardine, M. Tulbek and K. Bett, Detecting color differences in lentil flour samples using an inexpensive, hand-held colorimeter, *bioRxiv*, preprint, 2024, DOI: [10.48550/2022.590631](https://doi.org/10.48550/2022.590631).
- 32 F. Pieniazek, A. Sancho and V. Messina, Texture and Color Analysis of Lentils and Rice for Instant Meal Using Image Processing Techniques, *J. Food Process. Preserv.*, 2016, **40**, 969–978.
- 33 S. Sindhu, S. Sharma and A. Manickavasagan, Evaluating chemometric techniques for non-destructive detection of glyphosate residues in single pulse grains by using FTIR spectroscopy, *J. Consum. Prot. Food Saf.*, 2023, **18**, 309–326.
- 34 M. Bala, S. Sethi, S. Sharma, D. Mridula and G. Kaur, Prediction of maize flour adulteration in chickpea flour (besan) using near infrared spectroscopy, *J. Food Sci. Technol.*, 2022, **59**, 3130–3138.
- 35 L. Ravikanth, D. S. Jayas, N. D. G. White, P. G. Fields and D.-W. Sun, Extraction of Spectral Information from Hyperspectral Data and Application of Hyperspectral Imaging for Food and Agricultural Products, *Food Bioprocess Technol.*, 2017, **10**, 1–33.
- 36 D. Saha, T. Senthilkumar, C. B. Singh and A. Manickavasagan, Quantitative detection of metanil yellow adulteration in chickpea flour using line-scan near-infrared hyperspectral imaging with partial least square regression and one-dimensional convolutional neural network, *J. Food Compos. Anal.*, 2023, **120**, 105290.
- 37 K. Karuppiyah, T. Senthilkumar, D. S. Jayas and N. D. G. White, Detection of fungal infection in five different pulses using near-infrared hyperspectral imaging, *J. Stored Prod. Res.*, 2016, **65**, 13–18.
- 38 S. Kumar and K. Gupta, Detection, Identification and Management of Pulse Beetle (*Callosobruchus maculatus*) during Quarantine Processing, *Krishi Udyan Darpan*, 2022, 127.
- 39 L. G. Divyanth, V. Chelladurai, M. Loganathan, D. S. Jayas and P. Soni, Identification of Green Gram (*Vigna radiata*) Grains Infested by *Callosobruchus maculatus* Through X-ray Imaging and GAN-Based Image Augmentation, *Iran. J. Biosyst. Eng.*, 2022, **47**, 302–317.
- 40 M. A. Shahin, S. J. Symons and V. W. Poysa, Determining Soya Bean Seed Size Uniformity with Image Analysis, *Biosyst. Eng.*, 2006, **94**, 191–198.
- 41 L. McDonald and J. Panozzo, A review of the opportunities for spectral-based technologies in post-harvest testing of pulse grains, *Ligure Sci.*, 2023, **5**, e175.
- 42 L. S. LeMasurier, J. F. Panozzo and C. K. Walker, A digital image analysis method for assessment of lentil size traits, *J. Food Eng.*, 2014, **128**, 72–78.
- 43 A. Khoshroo, A. Arefi, A. Masoumiasl and G.-h. Jowkar, *Classification of wheat cultivars using image processing and artificial neural networks*, 2014.
- 44 S. K. Dutta, V. K. Nema and R. K. Bhardwaj, Physical properties of gram, *J. Agric. Eng. Res.*, 1988, **39**, 259–268.
- 45 M. Kaur, A. Masih and B. Singh, Engineering Properties of Major Legumes, *J. - Am. Water Works Assoc.*, 2004, **44**, 1–31.
- 46 M. Mathur, A. Kumari and R. Grewal, Physical and functional properties of different cereals, pulses, millet and oil seeds: physical and functional properties of major foods and oil seeds, *Agrosearch A J. Agric. Food Dev.*, 2020, **7**, 97–103.
- 47 E. Firatlıgil-Durmuş, E. Šárka and Z. BuBNík, Image vision technology for the characterisation of shape and geometrical properties of two varieties of lentil grown in Turkey, *Czech J. Food Sci.*, 2008, **26**, 109–116.
- 48 N. N. Mohsenin, in *Structure, Physical Characteristics and Mechanical Properties*, 1970, vol. 1, ch. 3, pp. 79–127.
- 49 S. Salam, K. Kheiralipour and F. Jian, Detection of Unripe Kernels and Foreign Materials in Chickpea Mixtures Using Image Processing, *Agriculture*, 2022, **12**, 995.
- 50 R. Kaur, S. Shekhar, P. Kumar and K. Prasad, Image analysis as a non-destructive approach in selective characterization of promising Indian chickpea cultivars, *Biology and Life Sciences Forum*, 2021.
- 51 M. Kumar, G. Bora and D. Lin, Image processing technique to estimate geometric parameters and volume of selected dry beans, *J. Food Meas. Char.*, 2013, **7**, 81–89.
- 52 A. Munsell, *A Color Notation*, George H Ellis Co, Boston, MA, 1905.
- 53 J. Rodgers, D. Thibobeaux, X. Cui, V. Martin, M. Watson and J. Knowlton, *Instrumental and operational impacts on spectrophotometer color measurements*, 2008.
- 54 A. P. Whan, A. B. Smith, C. R. Cavanagh, J.-P. F. Ral, L. M. Shaw, C. A. Howitt and L. Bischof, GrainScan: a low cost, fast method for grain size and colour measurements, *Plant Methods*, 2014, **10**, 23.
- 55 M. Matus-Cádiz, P. Hucl, C. Perron and R. Tyler, Genotype × environment interaction for grain color in hard white spring wheat, *Crop Sci.*, 2003, **43**, 219–226.
- 56 C. Black and J. Panozzo, Accurate technique for measuring color values of grain and grain products using a visible-NIR instrument, *Cereal Chem.*, 2004, **81**, 469–474.
- 57 C. B. Singh, D. S. Jayas, J. Paliwal and N. D. G. White, Identification of insect-damaged wheat kernels using short-wave near-infrared hyperspectral and digital colour imaging, *Comput. Electron. Agric.*, 2010, **73**, 118–125.
- 58 M. Kaur, N. Singh and N. S. Sodhi, Physicochemical, cooking, textural and roasting characteristics of chickpea (*Cicer arietinum* L.) cultivars, *J. Food Eng.*, 2005, **69**, 511–517.
- 59 A. Pourreza, H. Pourreza, M.-H. Abbaspour-Fard and H. Sadriana, Identification of nine Iranian wheat seed



- varieties by textural analysis with image processing, *Comput. Electron. Agric.*, 2012, **83**, 102–108.
- 60 K. R. Singh, S. Chaudhury, S. Datta and S. Deb, Gray level size zone matrix for rice grain classification using back propagation neural network: a comparative study, *Int. J. Syst. Assur. Eng. Manag.*, 2022, **13**, 2683–2697.
- 61 M. Berman, D. Coward, L. Whitbourn and B. Osborne, Measurement of wheat grain thickness using profilometry, *Cereal Chem.*, 2007, **84**, 282.
- 62 M. V. Santos, R. P. O. Cuevas, N. Sreenivasulu and L. Molina, in *Rice Grain Quality: Methods and Protocols*, ed. N. Sreenivasulu, Springer New York, New York, NY, 2019, pp. 99–108, DOI: [10.1007/978-1-4939-8914-0_6](https://doi.org/10.1007/978-1-4939-8914-0_6).
- 63 V. Narendra and M. Abdorrazzagli, An intelligent system for identification of Indian Lentil types using Artificial Neural Network (BPNN), *IOSR J. Comput. Eng.*, 2013, **15**, 54–60.
- 64 M. Shahin and S. Symons, Lentil type identification using machine vision, *Can. Biosyst. Eng.*, 2003, **45**, 3.5.
- 65 M. R. Cox and M. Budhu, A practical approach to grain shape quantification, *Eng. Geol.*, 2008, **96**, 1–16.
- 66 F. Jian and D. S. Jayas, *Grains: Engineering Fundamentals of Drying and Storage*, CRC Press, 2021.
- 67 P. K. Sundaram, A. K. Singh and S. Kumar, Studies on some engineering properties of faba bean seeds, *Agrosearch A J. Agric. Food Dev.*, 2014, **1**.
- 68 E. Karababa and Y. Coşkuner, Physical properties of carob bean (*Ceratonia siliqua* L.): An industrial gum yielding crop, *Ind. Crops Prod.*, 2013, **42**, 440–446.
- 69 V. Sharma, L. Das, R. C. Pradhan, S. N. Naik, N. Bhatnagar and R. S. Kureel, Physical properties of tung seed: An industrial oil yielding crop, *Ind. Crops Prod.*, 2011, **33**, 440–444.
- 70 M. Suma and M. I. Gandhi, *Feature Detection and Analysis of Pigeon Peas Using Image Processing*, 2017.
- 71 R. Ranawaka and M. Wansapala, *Development of micronutrient enriched composite flour with selected grains, pulses, and herbs*, 2024.
- 72 E. Komyshev, M. Genaev and D. Afonnikov, Analysis of color and texture characteristics of cereals on digital images, *Vavilovskij Ž. Genet. Sel.*, 2020, **24**, 340.
- 73 S. Majumdar and D. S. Jayas, Classification of cereal grains using machine vision: III. Texture models, *Trans. ASAE*, 2000, **43**, 1681–1687.
- 74 T. Hayit, A. Endes and F. Hayit, KNN-based approach for the classification of fusarium wilt disease in chickpea based on color and texture features, *Eur. J. Plant Pathol.*, 2024, **168**, 665–681.
- 75 K. Robert Singh and S. Chaudhury, Comparative analysis of texture feature extraction techniques for rice grain classification, *IET Image Process.*, 2020, **14**, 2532–2540.
- 76 S. S. Ribeiro, Classification of grain based on the morphology, color and texture information extracted from digital images, *Int. J. Comput. Appl. Eng. Technol. Sci.*, 2016, **5**, 359–366.
- 77 M.-H. Abbaspour-Fard, A. Pourreza, H. R. Pourreza and H. Sadrnia, Wheat Class Identification Using LBP, LSP and LSN Textural Features and Monochrome Images, *12th International Conference in Agricultural Engineering*, Chonburi, Thailand, 2011.
- 78 K. Kiliç, İ. H. Boyacı, H. Köksel and İ. Küsmenoğlu, A classification system for beans using computer vision system and artificial neural networks, *J. Food Eng.*, 2007, **78**, 897–904.
- 79 D. Sharma and S. D. Sawant, Grain quality detection by using image processing for public distribution, *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2017.
- 80 B. S. Anami and V. C. Burkpalli, Color based recognition and estimation of temperature levels of images of boiled food grains, *Int. J. Comput. Appl.*, 2010, **1**, 98–103.
- 81 N. Sidnal, U. V. Patil and P. Patil, Grading and quality testing of food grains using neural network, *Int. J. Innov. Res. Sci. Eng. Technol.*, 2013, **2**, 545–549.
- 82 R. Choudhary, J. Paliwal and D. Jayas, Classification of cereal grains using wavelet, morphological, colour, and textural features of non-touching kernel images, *Biosyst. Eng.*, 2008, **99**, 330–337.
- 83 H. D. Sapirstein, M. Neuman, E. H. Wright, E. Shweddyk and W. Bushuk, An instrumental system for cereal grain classification using digital image analysis, *J. Cereal. Sci.*, 1987, **6**, 3–14.
- 84 P. Zapotoczny, Discrimination of wheat grain varieties using image analysis: morphological features, *Eur. Food Res. Technol.*, 2011, **233**, 769–779.
- 85 H. K. Mebatsion, J. Paliwal and D. S. Jayas, Automatic classification of non-touching cereal grains in digital images using limited morphological and color features, *Comput. Electron. Agric.*, 2013, **90**, 99–105.
- 86 T. Malini, M. Narmatha, M. Nandhini, T. Megha and A. Nandha Kumar, Testing the quality of cereals and pulses using LabVIEW, *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, Coimbatore, India, 2021.
- 87 J. D. Pujari, R. Yakkundimath and A. S. Byadgi, Classification of fungal disease symptoms affected on cereals using color texture features, *Int. J. Signal Process.*, 2013, **6**, 321–330.
- 88 P. Shinde and R. Hunje, Influence of size grading on seed quality of Kabuli chickpea (*Cicer arietinum* L.) varieties, *J. Pharmacogn. Phytochem.*, 2018, **7**, 1024–1029.
- 89 N. Genze, R. Bharti, M. Grieb, S. J. Schultheiss and D. G. Grimm, Accurate machine learning-based germination detection, prediction and quality assessment of three grain crops, *Plant Methods*, 2020, **16**, 157.
- 90 N. Kundu, G. Rani and V. S. Dhaka, Seeds classification and quality testing using deep learning and YOLO v5, *Proceedings of the International Conference on Data Science, Machine Learning and Artificial Intelligence*, New York, 2021.
- 91 S. Shilaskar, S. Bhatlawande, P. Duddalwar, S. Jaiswal, D. Kadam and K. Chavan, *Image based identification of millets using fusion of Hu moments and LBP*, 2024.
- 92 N. Aviara, A. Adesanya, I. Iyilade, E. Olorunsola and S. Oyeniyi, Application of image analysis in food grain



- quality inspection and evaluation during bulk storage, *Arid Zone J. Eng. Technol. Environ.*, 2022, **18**, 693–706.
- 93 C. Kurade, M. Meenu, S. Kalra, A. Miglani, B. C. Neelapu, Y. Yu and H. S. Ramaswamy, An automated image processing module for quality evaluation of milled rice, *Foods*, 2023, **12**, 1273.
- 94 FSSAI, *Food Safety and Standards (Contaminants, Toxins and Residues) Regulations*, 2011, 2020.
- 95 L. M. Nollet, in *Global Regulations of Medicinal, Pharmaceutical, and Food Products*, CRC Press, 2024, pp. 302–309.
- 96 A. Fearne and M. G. Martinez, Opportunities for the coregulation of food safety: insights from the United Kingdom, *Choices*, 2005, **20**, 109–116.
- 97 N. D. Fortin, The United States FDA food safety modernization act: The key new requirements, *Eur. Food & Feed L. Rev.*, 2011, 260–268.
- 98 A. Smith, S. Terry and D. Detken, 10 years of the European Food Safety Authority (EFSA) and the EU food safety system, *Eur. Food & Feed L. Rev.*, 2012, **7**, 111–116.
- 99 E. C. Regulation, *Commission Regulation (EU) 2023/915 on Maximum Levels for Certain Contaminants in Food and Repealing Regulation (EC) No 1881/2006*, Journal, 2023.
- 100 P. Gomez-Ramirez, R. Shore, N. Van Den Brink, B. Van Hattum, J. O. Bustnes, G. Duke, C. Fritsch, A. García-Fernández, B. Helander and V. Jaspers, An overview of existing raptor contaminant monitoring activities in Europe, *Environ. Int.*, 2014, **67**, 12–21.
- 101 A. A. Dib, N. Louka, J. C. Assaf, S. El Khatib, A. El Khoury and E. Debs, A Methodological Review of Strategies for Artificial Contamination of Solid Food With *Aspergillus flavus* and Aflatoxin B1: Insights Into Growth Dynamics, AFB1 Production, and Spiking Techniques for Cereals, Nuts, and Seeds, *eFood*, 2025, **6**, e70082.
- 102 J. Ramesh, G. Sarathchandra and V. Sureshkumar, Survey of market samples of food grains and grain flour for Aflatoxin B1 contamination, *Int. J. Curr. Microbiol. Appl. Sci.*, 2013, **2**, 184–188.
- 103 N. J. Mitchell, E. Bowers, C. Hurburgh and F. Wu, Potential economic losses to the US corn industry from aflatoxin contamination, *Food Addit. Contam.*, 2016, **33**, 540–550.
- 104 D. A. Fairfield, *NGFA Guidance on FDA Regulations Applicable to the Grain, Feed and Processing Industry*, 2024.
- 105 S. Pardeshi, Food adulteration: Injurious adulterants and contaminants in foods and their health effects and its safety measures in India, *Int. J. Sci. Res.*, 2019, **4**, 231–232.
- 106 ISI, *IS 10768: Method of test for quality characteristics of pulses*, 1984.
- 107 I. Chakraborti and R. Salhan, Khesari Dal: A Food or a Dreadful Poison and Its Prevention and Detection by Chromatographic Method, *Asian J. Chem.*, 2002, **14**, 555.
- 108 R. Kumar, Methods for detection of common adulterants in food, <https://agriculture.vikaspedia.in/viewcontent/health/health-campaigns/beware-of-adulteration/methods-for-detection-of-common-adulterants-in-food?lgn=en>, accessed 09 September, 2025.
- 109 S. Sharma, N. Goel and P. Paliwal, Evaluation of Adulterants in Food by Different Physico-Chemical Method, *Int. J. Sci. Res. Dev.*, 2017, **4**, 0613–2321.
- 110 S. Dixit, *Food Adulteration Testing Manual*, 2019.
- 111 I. Parmar, P. Gehlot, V. Modi and D. Patel, Recent Development in Food Adulteration Analytical Techniques, *Int. J. Pharm. Sci. Res.*, 2021, **13**, 2001–2012.
- 112 D. P. Aykas and A. Menevseoglu, A rapid method to detect green pea and peanut adulteration in pistachio by using portable FT-MIR and FT-NIR spectroscopy combined with chemometrics, *Food Control*, 2021, **121**, 107670.
- 113 S. Kar, B. Tudu, A. Jana and R. Bandyopadhyay, FT-NIR spectroscopy coupled with multivariate analysis for detection of starch adulteration in turmeric powder, *Food Addit. Contam.*, 2019, **36**, 863–875.
- 114 A. Amirvaresi, N. Nikounezhad, M. Amirahmadi, B. Daraei and H. Parastar, Comparison of near-infrared (NIR) and mid-infrared (MIR) spectroscopy based on chemometrics for saffron authentication and adulteration detection, *Food Chem.*, 2021, **344**, 128647.
- 115 M. Cocchi, C. Durante, G. Foca, A. Marchetti, L. Tassi and A. Ulrici, Durum wheat adulteration detection by NIR spectroscopy multivariate calibration, *Talanta*, 2006, **68**, 1505–1511.
- 116 U. Kamboj, P. Guha and S. Mishra, Characterization of Chickpea Flour by Near Infrared Spectroscopy and Chemometrics, *Anal. Lett.*, 2017, **50**, 1754–1766.
- 117 R. Font, M. del Río-Celestino, D. Luna, J. Gil and A. de Haro-Bailón, Rapid and Cost-Effective Assessment of the Neutral and Acid Detergent Fiber Fractions of Chickpea (*Cicer arietinum* L.) by Combining Modified PLS and Visible with Near-Infrared Spectroscopy, *Agronomy*, 2021, **11**, 666.
- 118 M. Rathore, H. Prakash and S. Bala, Evaluation of the Nutritional quality and health benefits of chickpea (*Cicer arietinum* L.) by using new technology in agriculture (Near Infra-red spectroscopy-2500), *Asian J. Dairy Food Res.*, 2021, **40**, 123–126.
- 119 A. Menevseoglu, D. P. Aykas and E. Adal, Non-targeted approach to detect green pea and peanut adulteration in pistachio by using portable FT-IR, and UV-Vis spectroscopy, *J. Food Meas. Char.*, 2021, **15**, 1075–1082.
- 120 X. Wu, S. Shin, C. Gondhalekar, V. Patsekin, E. Bae, J. P. Robinson and B. Rajwa, Rapid Food Authentication Using a Portable Laser-Induced Breakdown Spectroscopy System, *Foods*, 2023, **12**, 402.
- 121 M. Petersen, Z. Yu and X. Lu, Application of Raman Spectroscopic Methods in Food Safety: A Review, *Biosensors*, 2021, **11**.
- 122 T. S. Manyatsi and Y.-T. Jou, Evaluation of Raman Spectroscopy as a detection Tool for Phytic Acid in Common beans (*Phaseolus vulgaris*), *Int. Comp. Corp. Law J.*, 2021, **16**, 1–22.
- 123 B. Chang, Z. Li, K. Ji, Y. Ruan and R. Liu, Rapid Quantitative Determination of Adulteration of Camellia Oil Using Portable Raman Spectroscopy and Chemometrics, *Processes*, 2025, **13**, 456.



- 124 S. Shin, I.-J. Doh, K. Okeyo, E. Bae, J. P. Robinson and B. Rajwa, Hybrid Raman and Laser-Induced Breakdown Spectroscopy for Food Authentication Applications, *Molecules*, 2023, **28**, 6087.
- 125 S. Bansal, A. Singh, M. Mangal, A. K. Mangal and S. Kumar, Food adulteration: Sources, health risks, and detection methods, *Crit. Rev. Food Sci. Nutr.*, 2017, **57**, 1174–1189.
- 126 D. Amane and L. Ananthanarayan, Application of two-dimensional gel electrophoresis technique for protein profiling of Indian black gram varieties and detection of adulteration in black gram-based food products using comparative proteomics, *Food Chem. X*, 2019, **3**, 100051.
- 127 J. Zhao, T. Hooker and J. W. Jorgenson, Synchronous cyclic capillary electrophoresis using conventional capillaries: System design and preliminary results, *J. Microcolumn Sep.*, 1999, **11**, 431–437.
- 128 A. Amirvaresi, M. Rashidi, M. Kamyar, M. Amirahmadi, B. Daraei and H. Parastar, Combining multivariate image analysis with high-performance thin-layer chromatography for development of a reliable tool for saffron authentication and adulteration detection, *J. Chromatogr. A*, 2020, **1628**, 461461.
- 129 H. Sereshti, Z. Poursorkh, G. Aliakbarzadeh and S. Zarre, Quality control of saffron and evaluation of potential adulteration by means of thin layer chromatography-image analysis and chemometrics methods, *Food Control*, 2018, **90**, 48–57.
- 130 N. Bachalla, Identification of synthetic food colors adulteration by paper chromatography and spectrophotometric methods, *Int. Arch. Integr. Med.*, 2016, **3**, 182–191.
- 131 D. Trbović, R. Petronijević and V. Đorđević, Chromatography methods and chemometrics for determination of milk fat adulterants, *IOP Conference Series: Earth and Environmental Science*, Zlatibor, Serbia, 2017.
- 132 R. Llorach, C. Favari, D. Alonso, M. Garcia-Aloy, C. Andres-Lacueva and M. Urpi-Sarda, Comparative metabolite fingerprinting of legumes using LC-MS-based untargeted metabolomics, *Food Res. Int.*, 2019, **126**, 108666.
- 133 J. Selamat, N. A. A. Rozani and S. Murugesu, Application of the metabolomics approach in food authentication, *Molecules*, 2021, **26**, 7565.
- 134 Y. Gao, L. Hou, J. Gao, D. Li, Z. Tian, B. Fan, F. Wang and S. Li, Metabolomics Approaches for the Comprehensive Evaluation of Fermented Foods: A Review, *Foods*, 2021, **10**, 2294.
- 135 S. J. Bhonsle and S. Krishnan, Grain quality evaluation and organoleptic analysis of aromatic rice varieties of Goa, India, *J. Agric. Sci.*, 2010, **2**, 99.
- 136 M. Chakraborty and K. Biswas, Limit of detection for five common adulterants in milk: A study with different fat percent, *IEEE Sens. J.*, 2018, **18**, 2395–2403.
- 137 S. Nag, D. Das, H. Naskar, B. Tudu, R. Bandyopadhyay and R. B. Roy, Detection of Metanil Yellow Adulteration in Turmeric Powder Using Nano Nickel Cobalt Oxide Modified Graphite Electrode, *IEEE Sens. J.*, 2022, **22**, 12515–12521.
- 138 J. Geng, J. Liu, X. Kong, B. Shen and Z. Niu, The fishmeal adulteration identification based on microscopic image and deep learning, *Comput. Electron. Agric.*, 2022, **198**, 106974.
- 139 M. Kaláb, P. Allan-Wojtas and S. S. Miller, Microscopy and other imaging techniques in food structure analysis, *Trends Food Sci. Technol.*, 1995, **6**, 177–186.
- 140 J. Kerkvliet, M. Shrestha, K. Tuladhar and H. Manandhar, Microscopic detection of adulteration of honey with cane sugar and cane sugar products, *Apidologie*, 1995, **26**, 131–139.
- 141 P. Rajan and K. S. Nagabhushana, *Detection of Adulteration in Besan (Cicer Arietinum) Using Microscopic Technique*, 2011.
- 142 A. M. Dattatreya, D. K. Nanjegowda and P. Viswanath, Microscopic detection of adulteration of Bengal gram (Cicer arietinum) flour with other legume flour based on the seed testa macrosclereids, *J. Food Sci. Technol.*, 2011, **48**, 114–119.
- 143 R. P. Haff and N. Toyofuku, X-ray detection of defects and contaminants in the food industry, *Sens. & Instrumen. Food Qual.*, 2008, **2**, 262–273.
- 144 N. Kotwaliwale, K. Singh, A. Kalne, S. N. Jha, N. Seth and A. Kar, X-ray imaging methods for internal quality evaluation of agricultural produce, *J. Food Sci. Technol.*, 2014, **51**, 1–15.
- 145 D.-H. Lee, E.-S. Kim, J.-S. Cho, J.-H. Ryu and B.-S. Min, A two-stage automatic labeling method for detecting abnormal food items in X-ray images, *J. Food Meas. Char.*, 2022, **16**, 2999–3009.
- 146 R. Paranthaman, J. A. Moses and C. Anandharamakrishnan, Development of a method for qualitative detection of lead chromate adulteration in turmeric powder using X-ray powder diffraction, *Food Control*, 2021, **126**, 107992.
- 147 S. Lohumi, H. Lee, M. S. Kim, J. Qin and B.-K. Cho, Through-packaging analysis of butter adulteration using line-scan spatially offset Raman spectroscopy, *Anal. Bioanal. Chem.*, 2018, **410**, 5663–5673.
- 148 J. Qin, M. S. Kim, K. Chao, D. E. Chan, S. R. Delwiche and B.-K. Cho, Line-Scan Hyperspectral Imaging Techniques for Food Safety and Quality Applications, *Appl. Sci.*, 2017, **7**, 125.
- 149 S. Shafiee, G. Polder, S. Minaei, N. Moghadam-Charkari, S. van Ruth and P. M. Kuś, Detection of Honey Adulteration using Hyperspectral Imaging, *IFAC-PapersOnLine*, 2016, **49**, 311–314.
- 150 S. Lohumi, H. Lee, M. S. Kim, J. Qin, L. M. Kandpal, H. Bae, A. Rahman and B.-K. Cho, Calibration and testing of a Raman hyperspectral imaging system to reveal powdered food adulteration, *PLoS One*, 2018, **13**, e0195253.
- 151 M. H. Khan, Z. Saleem, M. Ahmad, A. Sohaib, H. Ayaz and M. Mazzara, Hyperspectral imaging for color adulteration detection in red chili, *Appl. Sci.*, 2020, **10**, 5955.
- 152 M. Kamruzzaman, Y. Makino and S. Oshita, Rapid and non-destructive detection of chicken adulteration in minced



- beef using visible near-infrared hyperspectral imaging and machine learning, *J. Food Eng.*, 2016, **170**, 8–15.
- 153 S. Lohumi, H. Lee, M. S. Kim, J. Qin and B.-K. Cho, Raman hyperspectral imaging and spectral similarity analysis for quantitative detection of multiple adulterants in wheat flour, *Biosyst. Eng.*, 2019, **181**, 103–113.
- 154 D. S. Brar, A. K. Aggarwal, V. Nanda, S. Saxena and S. Gautam, AI and CV based 2D-CNN algorithm: botanical authentication of Indian honey, *Sustainable Food Technology*, 2024, **2**, 373–385.
- 155 B. Akbari-Adergani, M. Mohammadzade Moghadam, M. Karimi Noghabi, M. Mohammadpour and M. Khalilian-Movahhed, Application of computer vision on non-destructive detection of the authentic and adulterated saffron, *Saffron Agron. Technol.*, 2021, **9**, 409–429.
- 156 S. Kiani, S. Minaei and M. Ghasemi-Varnamkhasti, Integration of computer vision and electronic nose as non-destructive systems for saffron adulteration detection, *Comput. Electron. Agric.*, 2017, **141**, 46–53.
- 157 A. Taheri-Garavand and M. Yousefian, Application of computer vision on non-destructive detection of grape syrup adulteration, *Innov. Food Technol.*, 2020, **7**, 479–495.
- 158 T. Ali, Z. Jhandhir, A. Ahmad, M. Khan, A. A. Khan and G. S. Choi, Detecting fraudulent labeling of rice samples using computer vision and fuzzy knowledge, *Multim. Tools Appl.*, 2017, **76**, 24675–24704.
- 159 D. Mandal, *Application of computer vision techniques to detect principal adulterants in turmeric powder* 2024.
- 160 A. Upadhyay and N. Chaudhary, in *Recent Trends in Intensive Computing*, IOS Press, 2021, pp. 355–362.
- 161 E. Beta, A. S. Parikh, M. Street and J. R. Duncan, Capture and analysis of data from image-guided procedures, *J. Vasc. Interv. Radiol.*, 2009, **20**, 769–781.
- 162 D. A. Lidiya and M. Mohanapriya, Detection Of Adulteration In Food Using Python, *Int. J. Emerg. Technol. Innov. Res.*, 2025, **12**.
- 163 T. Chung, I. Y. S. Tam, N. Y. Y. Lam, Y. Yang, B. Liu, B. He, W. Li, J. Xu, Z. Yang and L. Zhang, Non-targeted detection of food adulteration using an ensemble machine-learning model, *Sci. Rep.*, 2022, **12**, 20956.
- 164 R. Goyal, P. Singha and S. K. Singh, Spectroscopic food adulteration detection using machine learning: Current challenges and future prospects, *Trends Food Sci. Technol.*, 2024, **146**, 104377.
- 165 E. E. Sano, E. D. Assad, S. A. R. Cunha, T. B. S. Correa and H. R. Rodrigues, Quantifying Adulteration In Roast Coffee Powders By Digital Image Processing, *J. Food Qual.*, 2003, **26**, 123–134.
- 166 A. I. Ropodi, D. E. Pavlidis, F. Mohareb, E. Z. Panagou and G. J. E. Nychas, Multispectral image analysis approach to detect adulteration of beef and pork in raw meats, *Food Res. Int.*, 2015, **67**, 12–18.
- 167 R. A. Costa, C. L. Morais, T. R. Rosa, P. R. Filgueiras, M. S. Mendonça, I. E. Pereira, B. V. Vittorazzi, M. B. Lyra, K. M. Lima and W. Romão, Quantification of milk adulterants (starch, H₂O₂, and NaClO) using colorimetric assays coupled to smartphone image analysis, *Microchem. J.*, 2020, **156**, 104968.
- 168 U. T. C. P. Souto, M. F. Barbosa, H. V. Dantas, A. S. de Pontes, W. d. S. Lyra, P. H. G. D. Diniz, M. C. U. de Araújo and E. C. da Silva, Screening for Coffee Adulteration Using Digital Images and SPA-LDA, *Food Anal. Methods*, 2015, **8**, 1515–1521.
- 169 S. Mahajan, A. Das and H. K. Sardana, Image acquisition techniques for assessment of legume quality, *Trends Food Sci. Technol.*, 2015, **42**, 116–133.
- 170 D. Amane and L. Ananthanarayan, Detection of adulteration in black gram-based food products using DNA barcoding, *Food Control*, 2019, **104**, 193–200.
- 171 N. Haiminen, S. Edlund, D. Chambliss, M. Kunitomi, B. C. Weimer, B. Ganesan, R. Baker, P. Markwell, M. Davis and B. C. Huang, Food authentication from shotgun sequencing reads with an application on high protein powders, *npj Sci. Food*, 2019, **3**, 24.
- 172 E. Habza-Kowalska, M. Grela, M. Gryzińska and P. Listos, *Molecular techniques for detecting food adulteration*, 2019.
- 173 M. Izquierdo, M. Lastra-Mejías, E. González-Flores, J. C. Cancilla, M. Pérez and J. S. Torrecilla, Convolutional decoding of thermographic images to locate and quantify honey adulterations, *Talanta*, 2020, **209**, 120500.
- 174 A. K. Das, A. Ansary, S. S. Das, K. N. Dutta, S. Lamichhane, J. Pandey and D. Hazarika, in *Novel Food Analysis: Techniques and Applications*, ed. T. Sarkar, Springer US, New York, NY, 2026, pp. 159–179, DOI: [10.1007/978-1-0716-4787-5_8](https://doi.org/10.1007/978-1-0716-4787-5_8).
- 175 P. Chen, Z. Sun, J. Wang, X. Liu, Y. Bai, J. Chen, A. Liu, F. Qiao, Y. Chen and C. Yuan, Portable nanopore-sequencing technology: Trends in development and applications, *Front. Microbiol.*, 2023, **14**, 1043967.
- 176 K. Everstine, J. Spink and S. Kennedy, Economically Motivated Adulteration (EMA) of Food: Common Characteristics of EMA Incidents, *J. Food Prot.*, 2013, **76**, 723–735.
- 177 R. R. P. Prathusha G, L. V. Vijaya and D. K. Uma, Assessment of Student Awareness and Impact of Intervention Regarding Food Adulteration, *Int. J. Adulteration*, 2025, **18**.
- 178 J. C. Moore, J. Spink and M. Lipp, Development and Application of a Database of Food Ingredient Fraud and Economically Motivated Adulteration from 1980 to 2010, *J. Food Sci.*, 2012, **77**, R118–R126.

