Digital Image Analysis (DIA) in Food Technology: An Overview

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ABSTRACT

Digital Image Analysis (DIA) has emerged as a transformative tool in food science, particularly in quality control, safety, and analysis. DIA techniques allow for non-destructive testing, rapid assessments, and remote accessibility, addressing the industry's growing demand for efficiency and accuracy. This technology converts visual data into computer-readable formats, enabling detailed analysis of food characteristics through pixel grids. Various DIA applications include detecting pesticide residues, acrylamide levels, and adulterants in food products such as milk and ethanol-based beverages. Additionally, DIA aids in grading dried figs, predicting moisture content in drying processes, and estimating live animal weights without invasive methods. This paper explores the key components of DIA, such as image acquisition, feature extraction, and processing, alongside their practical applications in food quality control, illustrating the potential for DIA to enhance food safety and efficiency across the food industry.

Keywords: Digital image analysis, Pesticide, Acrylamide, Ascorbic Acid, Nitrite, Ethanol, Milk, Moisture, Texture, RGB image analysis, Machine Learning.

INTRODUCTION

Digital Image Analysis (DIA) is a scientific and artistic approach that utilizes computer algorithms to enhance and interpret digital images, revealing insights and improving their visual appeal. A digital image is a representation of real-world objects, composed of pixels that store information in binary format (Gonzalez & Woods, 2018). In recent years, DIA has emerged as a powerful tool in food technology, revolutionizing traditional methods of quality assessment and process optimization. By utilizing advanced imaging techniques and sophisticated algorithms, this technology offers a non-invasive, accurate, and efficient means of evaluating various properties of food products. From detecting surface defects in fruits and vegetables to assessing color, texture, and composition, DIA enhances precision in quality control. It also plays a significant role in food safety by identifying contaminants and ensuring compliance with regulatory standards. Furthermore, its applications extend to innovative areas such as authenticity verification, shelf-life prediction, and process automation, leveraging machine learning and artificial intelligence to analyze complex datasets. As the food industry increasingly integrates smart technologies, DIA not only improves operational efficiency but also aligns with consumer demands for transparency and high-quality products. This intersection of imaging technology and food science marks a transformative step toward smarter, safer, and more sustainable food systems (Meenu *et al.,* 2021).

Key Components of DIA:

Image Acquisition

This is the initial step where images are captured using sensors (Figure 1). In the food industry, Centralized Charge Transfer (CCD) sensors are preferred for quality checks due to their high image quality, low noise, and better performance in low light conditions compared to Complementary Metal Oxide Semiconductor (CMOS) sensors, which tend to have more noise and a rolling shutter effect as shown in Figure (2) (Decker & Beekman, 2007).

Pre-Processing

This phase involves noise elimination and segmentation of the region of interest (Figure 3). Techniques such as intensity thresholding and connected component analysis are commonly used. The Commission Internationale de l'Éclairage (CIE) colour space is often employed for its device-independent and perceptually uniform characteristics as colors are different from one device to another (Gonzalez & Woods, 2018).

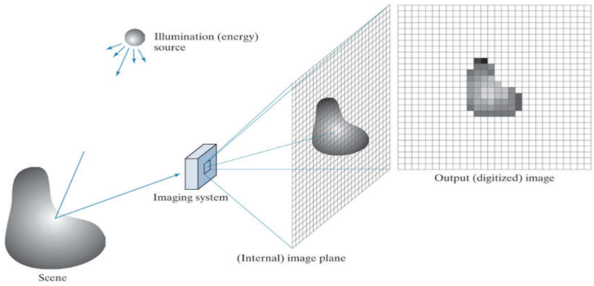

Fig. 1: An example of image acquisition

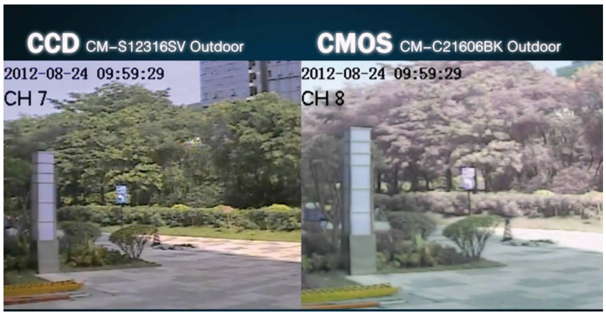

Fig. 2: Representing the difference between CCD sensor and CMOS sensor

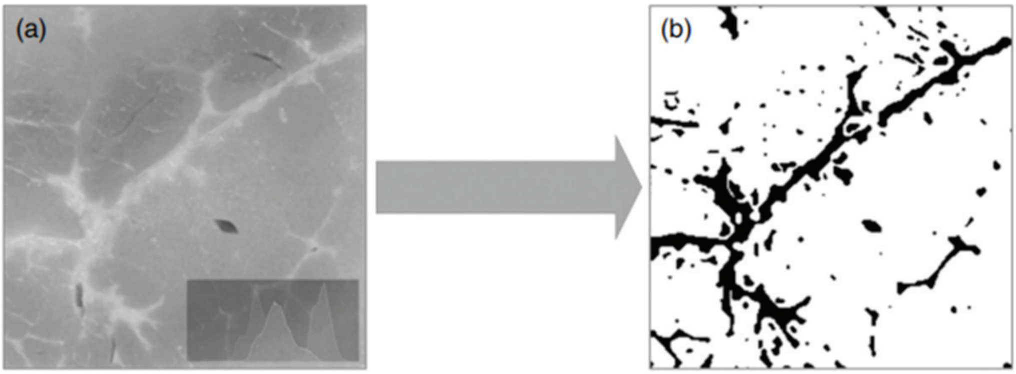

Fig. 3: Representative central section of a medium quality pork ham: (a) original RGB (Red, Green, Blue) color model image and (b) binarized version of pores/defects and fat-connective tissue after segmentation (Guilherme & Rodrigues, 2013).

Feature Extraction

This process focuses on identifying and isolating key characteristics from images, such as textures, shapes, and colors, which are essential for effective analysis and decision-making. It involves transforming raw image data into a reduced set of representative features that retain the most critical information. For example, Local Binary Patterns (LBP) are effective for texture classification, aiding in applications such as detecting surface irregularities or differentiating materials. Advanced techniques like wavelet transforms and Principal Component Analysis (PCA) further optimize feature extraction by enhancing feature representation and reducing computational complexity (Mirmehdi *et al.*, 2008).

Feature Processing

Feature processing in Digital Image Analysis (DIA) is a vital step for extracting and analyzing meaningful attributes from images, such as edges, corners, textures, shapes, and colors. These attributes play a key role in enabling machines to detect patterns, recognize objects, and interpret images across various applications, including medical imaging, autonomous systems, and quality control in industries. The main steps in feature processing include:

- **Feature Detection**: This involves identifying significant elements like edges, corners, or blobs within an image. Techniques such as edge detection (e.g., Sobel or Canny algorithms) and corner detection (e.g., Harris corner detector) help isolate these critical features, forming the basis for further analysis.
- **Feature Description**: Once detected, these features are represented using descriptors that encapsulate their unique properties. Methods like Scale-Invariant Feature Transform (SIFT) or Histogram of Oriented Gradients (HOG) create robust representations that are invariant to scaling, rotation, and lighting changes.
- **Feature Matching**: This step compares features across images to find correspondences or similarities. By using techniques like nearest-neighbor search or brute-force matching, it enables tasks such as image stitching, object tracking, and 3D reconstruction.

- **Feature Extraction**: In this stage, raw data is transformed into a reduced set of representative features while preserving essential information. Techniques like Principal Component Analysis (PCA) reduce dimensionality, while wavelet transforms capture localized frequency information, making analysis computationally efficient.
- **Feature Selection**: To enhance accuracy and reduce noise, this step involves choosing the most relevant features for a specific task, such as classification or segmentation. Statistical or machine learning-based methods like Recursive Feature Elimination (RFE) are commonly employed.

These processes collectively lay the foundation for advanced pattern recognition, object detection, and image interpretation, enabling machines to analyze visual data effectively for diverse applications (Gonzalez & Woods, 2018).

Applications of DIA in The Quality Control and Analysis of Food

Detection of Pesticide Residue in Grapes

Traditional pesticide testing in grapes requires laboratory analyses, which are costly and time-intensive. An image-processing method was developed to differentiate pesticide-treated and untreated grapes. This technique involves segmenting grape images to identify Regions of Interest (ROI) and using Haar wavelet filters for feature extraction. Through Support Vector Machine (SVM) classifiers, this method achieved high accuracy, making it an efficient option for real-time, non-destructive pesticide detection in grapes (Baigvand *et al*., 2021).

Grading of Dried Figs

A machine vision system was created to automate the grading of dried figs based on color, size, and split area. The system includes a CCD camera and image processing algorithms, allowing for high-throughput, accurate sorting. Using color intensity and equivalent diameter measurements, the system classified figs into five quality grades with 95.2% accuracy, supporting post-harvest quality control without the need for manual inspection (Baigvand *et al*., 2015).

Acrylamide Detection in Potato Chips

Acrylamide, a harmful compound found in fried starchy foods, can be detected using DIA. Conventional detection methods are destructive and resource-intensive. Acrylamide presence is detected by analyzing color changes in the wavelet domain. The method segments the chip's Region of Interest (ROI) and extracts discriminatory features using the Haar filter, achieving a 97% accuracy in acrylamide detection. This approach shows promise for non-invasive quality assessment of potato-based products (Dutta *et al*., 2022).

Detection of Milk Adulteration Using Smartphone-Based Colorimetry

Smartphone-based colorimetry provides a portable, low-cost solution for milk adulteration detection. This method uses copper sulphate($CuSO_4$) for protein precipitation, analyzing the remaining Cu (II) concentration after reacting it with Ethylenediaminetetraacetic acid (EDTA) giving a blue color that is measured through RGB (Red, Green, Blue) color values.This setup allows for efficient, sustainable adulteration testing without costly laboratory equipment and low relative error (Table 1) (Silva *et al.*, 2021).

Table 1: Accuracy assessment of the proposed procedure in comparison to Near Infrared Spectroscopy (NIR) reference procedure. Mean values and uncertainties of the protein content (% m/v) estimated from triplicate measurements.

Sample	Proposed procedure	Reference procedure[a]	Relative error (%)	Estimated F value[b]
1	3.79±0.09	3.50	+8.4	6.6
2	3.17±0.09	3.29	–36	7.5
3	3.39±0.03	3.29	+30	0.8
4	3.33±0.06	3.26	+21	3.4
5	3.40±0.2	3.25	+4.6	37.9
6	3.06±0.07	3.22	–5.0	4.7
7	3.1±0.2	3.20	–3.1	39.1
8	3.0±0.1	3.19	–5.9	9.8

a Coefficient of variation typically of 1.0% (FOSS Analytics).
b Critical F value (95% confidence level): 19.0

Determination Ascorbic Acid in Amazon Fruits

An innovative method for quantifying ascorbic acid (AA) using smartphone-captured colourimetric spot tests. This method relies on AA's reduction of ferric Fe(III) to ferrous Fe(II), forming a red complex with 1,10-phenanthroline that can be quantified through color decomposition in RGB channels. The low-cost setup and quick processing (approximately 1.6 minutes per sample) provide a valuable tool for rural areas and small-scale producers, especially in the Brazilian Amazon. The method is precise, eco-friendly, and correlates well with traditional titration methods, proving that smartphone-based digital imaging is effective even in complex food matrices in comparison, with other analytical methods as shown in Table (2) it had low relative error (Dos Santos *et al*., 2019).

Predicting Moisture Content in Pepper During Drying

This study focuses on using digital images combined with laser light to predict the moisture content and color of bell peppers during the drying process. A (CCD) camera and laser diodes emitting at specific wavelengths (532 nm and 635 nm) were employed to monitor the changes in moisture content and color. The findings showed that scattering area and light intensity could predict moisture content, with better accuracy for yellow-colored samples (Romano *et al*., 2012).

Quantification of Ethanol in Distilled Beverages Using a Smartphone-Based Procedure

This research introduces a cost-effective, green, and fast method for determining ethanol concentrations in distilled beverages through smartphone-based DIA. It utilizes the effect of ethanol on the color intensity of phenolphthalein in an alkaline medium. A 3D-printed holder optimized image capture, and RGB values were measured using a smartphone camera as shown in Figure (4). The procedure showed a linear response from 10.0 to 70.0% (v/v) ethanol(r =0.998, n=7), a coefficient of variation of 1.2% (n=8) and a limit of detection (99.7% confidence level), offering an eco-friendly alternative to conventional approaches that require toxic reagents. It proved to be accurate and practical for point-of-care applications(Marinho *et al*., 2020).

Table 2: Representing comparison of DIB spot test method with other analytical methods in determination of ascorbic acid content in sample.

Sample	Analytical Methods	Value[a]
Bacuri[b]	DIB	74.56±4.64
Cashew	Titration, AOAC	121.0±18.2
	HPLC/UV	155.40±4.22
	DIB	151.81±7.24
Cupuaçu	HPLC/UV	30.00±5.00
	HPLC/UV	96.00±8.00
	DIB	52.25±3.75
Mango	HPLC/UV	19.99±0.75
	Spectrophotometry	19.3±4.8
	DIB	26.33±2.71
Orange	Amperometry	44.93±5.59
	HPLC/UV	46.12±1.96
	DIB	37.03±1.84
Vitamin C Tablet[d]	Spectrophotometry	1000±40
	DIB	1000±100
	DIB	1040±56

a Mean ± D b Data not found in the literature.

c Standard deviation not calculate. d As model sample and for comparison purpose, expressed in mg/tablet

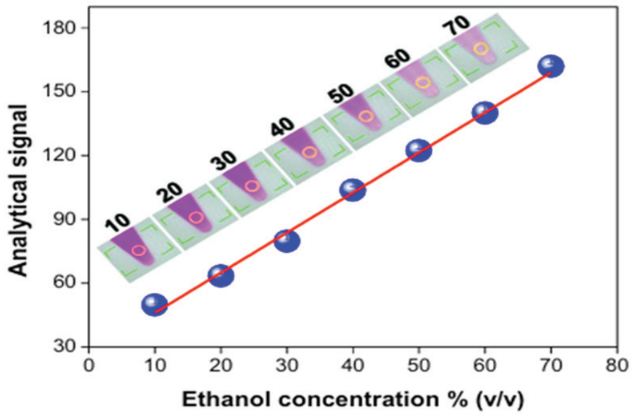

Fig. 4: Analytical curve for the determination of ethanol in distilled beverages. Images refer to the vials with ethanol standard solutions. G-channel values were taken as the analytical signal.

Estimating Live Pig Weight Using DIA

A system that estimates live pig weights using digital images taken in a farm environment without stressing the animals. The approach integrates boundary detection, feature extraction, and pattern recognition *via* a Vector-Quantized Temporal Associative Memory (VQTAM) algorithm. By extracting features like the average distance from the pig's centroid to its body boundary, the system could estimate weights with less than 3% error. The study suggests that DIA could be an efficient, non-invasive method for weight estimation on farms(Wongsriworaphon *et al*., 2021).

Coupling of DIA and Three-Way Calibration for Nitrite Detection in Food Samples

An innovative method that combines DIA with three-way calibration for detecting nitrite in food samples using a paper-based sensor. The sensor, impregnated with Griess reagent (sulfanilamide and N-1-naphthyl-ethylenediamine), changes color in the presence of nitrite, producing a red dye whose intensity correlates with nitrite concentration. Images of the sensor were captured using a SONY Xperia Z5, and MATLAB was used to analyze the red pixel intensities. The method employed two calibration models: unfolded partial least squares-residual bilinearization (U-PLS/RBL) and multiway-PLS/RBL (N-PLS/RBL). U-PLS/RBL outperformed N-PLS/RBL, offering higher accuracy in predicting nitrite concentrations in test samples. The developed method was validated against HPLC, showing good agreement with the reference method, and was applied successfully to real food samples like cabbage, carrot, and sausage. This approach provides a fast, cost-effective alternative for nitrite detection in food (Almasvandi *et al*., 2020).

CHALLENGES AND FUTURE DIRECTIONS

Smartphone-based DIA methods offer accessibility and affordability but are affected by lighting variability and device differences. Enclosed setups or standardized conditions could mitigate these issues, ensuring reproducibility. Future DIA advancements in AI and machine learning promise further automation and enhanced accuracy, transforming food safety and quality control practices.

THE CONCLUSION

DIA applications are revolutionizing food quality control, enabling rapid, non-invasive testing that aligns with industry demands for safety and compliance. By integrating smartphone-based tools and machine vision systems, DIA provides solutions that are both accessible and effective, setting a new standard in food quality and safety assessments worldwide.

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التحليل التصويري الرقمي (DIA) في تكنولوجيا الغذاء: نظرة عامة

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التحليل التصويري الرقمي (DIA) هو تقنية حديثة ومتطورة تُستخدم في علوم الأغذية لتحسين جودة المنتجات وسلامتها من خلال الفحص غير المحطم والفعّال. تعتمد التقنية على معالجة الصور الرقمية واستخراج الخصائص المميزة مثل اللون والملمس باستخدام أدوات متقدمة مثل أجهزة استشعار CCD وخوارزميات الذكاء الاصطناعي. تتيح هذه التقنية تطبيقات متعددة تشمل كشف بقايا المبيدات وتصنيف الفواكه المجففة وكشف غش الحليب وقياس الرطوبة وتقدير أوزان الحيوانات الحية بدقة عالية. ومع وجود تحديات مثل تأثير الإضاءة واختلاف الأجهزة، تُظهر التطورات الحديثة في التعلم الآلي والذكاء الاصطناعي إمكانات واعدة لتحسين الكفاءة وتعزيز معايير الجودة والسلامة في قطاع الأغذية.