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AI-Based RGB Imaging and 14-Channel Multispectral Food Quality Scanner

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Abstract: Food-quality assessment plays an important role in food safety, agricultural processing, storage, and supply-chain management. Conventional inspection methods depend on visual judgement or laboratory-based testing, which may require considerable time, specialised equipment, and manual effort. Recent developments in computer vision, multispectral sensing, and artificial intelligence (AI) provide opportunities for automated, non-destructive food-quality assessment. This paper reviews the application of RGB imaging, multispectral sensing, machine learning, and deep learning for fruit-ripeness estimation, surface-defect detection, grain classification, and food-authenticity assessment. The reviewed literature demonstrates that RGB imaging can extract visible features such as colour, shape, and texture, whereas multispectral sensing provides wavelength-dependent information associated with food characteristics. Published studies have reported promising results in tomato-ripeness classification, apple-defect detection, rice-grain analysis, and honey-adulteration screening. Based on these findings, a compact food-quality scanner integrating an RGB camera, a 14-channel multispectral sensor, controlled illumination, and an embedded processing unit is proposed. The review discusses sensor integration, data preprocessing, feature fusion, classification methods, evaluation metrics, and implementation challenges. It also identifies the need for broader datasets, standardised illumination, independent validation, and resource-efficient AI models to improve the reliability of portable food-inspection systems.

Keywords: Artificial intelligence, RGB imaging, multispectral sensing, food-quality assessment, machine learning, fruit ripeness, defect detection, non-destructive testing, sensor fusion.

I. INTRODUCTION

Good food quality is an important consideration in agricultural production, food processing, distribution, and consumer safety. The quality of fruits, vegetables, and grains depends on several characteristics, including colour, shape, size, texture, ripeness, physical damage, and composition. Conventional food inspection often relies on manual examination or laboratory-based analytical techniques. Manual assessment can be subjective, while laboratory methods may require specialised instruments and sample preparation.

Computer vision and artificial intelligence have introduced new approaches to automate food inspection. Digital imaging allows food samples to be represented through numerical image data, from which features can be extracted and analysed. Machine-learning algorithms can use these features to classify food categories, estimate ripeness, and identify visible defects [1], [2].

RGB cameras are particularly useful because they capture visible colour information using red, green, and blue channels. These images can be processed to obtain colour distributions, texture patterns, shape descriptors, and surface-defect information. However, visible appearance does not always provide sufficient evidence of internal damage or subtle compositional changes. Spectral sensing can provide additional information by measuring the response of a sample at selected wavelengths [3], [4].

Multispectral sensors offer a practical alternative to complex hyperspectral imaging systems when only a limited number of wavelength bands are required. They can be integrated into compact devices for applications such as fruit-ripeness assessment and food-authenticity screening [5], [6]. Combining RGB imaging with multispectral measurements may therefore provide complementary information for food-quality classification.

This paper reviews the existing literature on RGB imaging, multispectral sensing, and AI-based food inspection. It also proposes an integrated scanner architecture and identifies the technical challenges that must be addressed before practical deployment.

A. Motivation

The motivation for this study is to investigate a portable and relatively low-cost approach to food-quality screening. A combined sensing system could potentially provide:

- Automated identification of food categories.
- Estimation of fruit-ripeness stages.

- Detection of visible surface defects.
- Quality grading based on learned features.
- Digital storage of measurements and scan history.

These functions are proposed capabilities and require experimental validation for each food category.

B. Objectives

The main objectives of this review are:

- To examine RGB-based food inspection and image-processing techniques.
- To study multispectral and hyperspectral sensing for food-quality assessment.
- To review machine-learning and deep-learning approaches used in food classification.
- To propose a combined RGB and 14-channel multispectral scanner architecture.
- To identify research gaps, implementation challenges, and future opportunities.

C. Scope of the Review

The review focuses on non-destructive optical inspection of fruits, vegetables, and grains, with additional consideration of food adulteration. It examines published methods and reported findings rather than presenting unverified experimental results from the proposed scanner.

II. LITERATURE REVIEW

The literature demonstrates the growing importance of combining optical sensing with machine learning for food inspection. The following studies provide the technical foundation for the proposed system.

A. RGB-Based Food Quality Assessment

- 1) AI-based food-quality analysis: Jatain *et al.* reviewed deep-learning approaches for food-quality assessment and discussed their application to fruit and vegetable classification. Their work examined the use of convolutional neural networks (CNNs), preprocessing methods, feature extraction, and classification techniques. CNNs can learn useful representations directly from image data, reducing dependence on manually designed features. However, dataset size, computational requirements, and generalisation remain important considerations [1].
- 2) Colour-based imaging for post-harvest assessment: Priyadharshini *et al.* reviewed colour-based imaging for post-harvest fruit-quality evaluation. The study discussed RGB imaging, colour-space representations, image-derived features, and machine-learning methods for predicting and classifying food characteristics. The review supports digital imaging as a cost-effective, non-destructive approach, while also highlighting the importance of consistent image acquisition and meaningful feature extraction [2].
- 3) Image processing for rice-grain analysis: Rani *et al.* developed a rice-grain quality-analysis system using digital image processing. Their approach involved image acquisition, thresholding, noise reduction, morphological operations, edge detection, and feature extraction. Grain dimensions and aspect ratios were used to distinguish rice categories. The reported analysis classified Sona Masuri and Basmati as bold types and Jasmine as a medium type according to the study's defined criteria [3].

B. Multispectral Sensing for Fruit Ripeness

- 1) Low-cost multispectral fruit-ripeness assessment: Lauretti *et al.* developed a multispectral device for in-field fruit-ripeness evaluation. Their system used controlled broadband illumination and visible-to-near-infrared spectral measurements. The researchers evaluated tomato samples at six ripeness stages using 450 spectral measurements and reported an average classification accuracy of 93.72%. The study also compared multispectral measurements with RGB-based analysis [4].

C. Multispectral Imaging for Defect Detection

- 1) CNN-based fruit-defect classification: Vintimilla *et al.* investigated apple-defect classification using multispectral images and CNN architectures. Their evaluation included DenseNet121 and MobileNet variants, with attention-enhanced models and a cascaded classification approach. The fine-tuned MobileNetV2 model with squeeze-and-excitation modules achieved 96.9% accuracy and an F1-score of 0.956 for multiclass classification on the evaluated dataset. The green spectral band was particularly discriminative, while red-edge and infrared bands provided complementary information [5].

D. Hyperspectral Imaging for Grain Quality and Safety

- 1) Review of hyperspectral grain inspection: Liang *et al.* reviewed hyperspectral imaging for grain-quality and safety assessment. Their review covered applications including disease detection, physicochemical-property analysis, pesticide-residue identification, and geographical-origin determination. Hyperspectral imaging combines spatial and spectral information, providing detailed measurements across numerous wavelength bands. However, high equipment cost, complex data processing, and the lack of standardised models remain significant barriers to widespread use [6].

E. Multispectral Sensing for Food Authenticity

- 1) Honey-adulteration detection: Biradar *et al.* investigated the detection of jaggery-syrup adulteration in honey using an AS7341 multispectral sensor and machine-learning algorithms. The study evaluated adulteration concentrations from 10% to 50% by weight. The measured spectral intensity changed with adulteration level, particularly in selected visible and near-infrared channels. Random Forest achieved 100% accuracy on the reported training and testing datasets, whereas the ANN model achieved 33.33% accuracy. [7].

F. Illumination and Spectral Measurement Stability

- 1) Monitoring the spectral behaviour of LEDs: Myland *et al.* investigated LED degradation monitoring using a multichannel spectral sensor. The study examined the reconstruction of LED spectral characteristics from sensor responses and compared the results with spectroradiometric measurements. It demonstrated that multichannel spectral sensing can be useful for monitoring changes in illumination output [8].

G. Comparative Analysis of Reviewed Studies

The studies collectively indicate that different sensing methods serve different purposes. RGB imaging is suitable for visible appearance, multispectral sensing provides selected wavelength-dependent measurements, and hyperspectral imaging offers more detailed spectral information at greater hardware and processing complexity.

The following table summarises their principal contributions.

III. RESEARCH GAP AND PROPOSED CONTRIBUTION

A. Research Gap

The reviewed literature identifies several limitations that motivate further research.

First, RGB imaging mainly describes visible appearance. Although it can reveal discolouration, bruising, and changes in texture, it may not distinguish conditions that produce similar visible appearances.

Second, multispectral sensing provides additional wavelength-dependent information, but the number and selection of channels influence the features available for classification. Results from a sensor operating at particular wavelengths cannot automatically be transferred to a different sensor.

Third, hyperspectral imaging offers richer spectral information but may involve higher equipment cost, larger datasets, and more demanding processing requirements [6].

Fourth, food-quality models are often trained on particular products and datasets. A model trained on apples, for example, should not be assumed to provide reliable quality estimates for grains or other fruits without appropriate training and validation.

Finally, controlled illumination, sensor calibration, sample positioning, and the separation of training and test samples are important for obtaining reliable results [4], [8].

B. Proposed Contribution

The proposed AI-based scanner investigates the integration of:

- An OV5640 5 MP RGB camera.
- An AS7343 14-channel multispectral sensor.
- White and near-infrared illumination.
- An embedded control and data-acquisition unit.
- An AI classification pipeline.
- A display and microSD-based data-storage interface.

The main research objective is to compare RGB-only, multispectral-only, and combined-feature approaches under consistent experimental conditions. The proposed system is intended to investigate whether combining visible appearance and spectral measurements improves food-quality classification.

The contribution should be evaluated experimentally rather than assumed from the accuracy values of previous studies.

IV. PROPOSED SYSTEM ARCHITECTURE

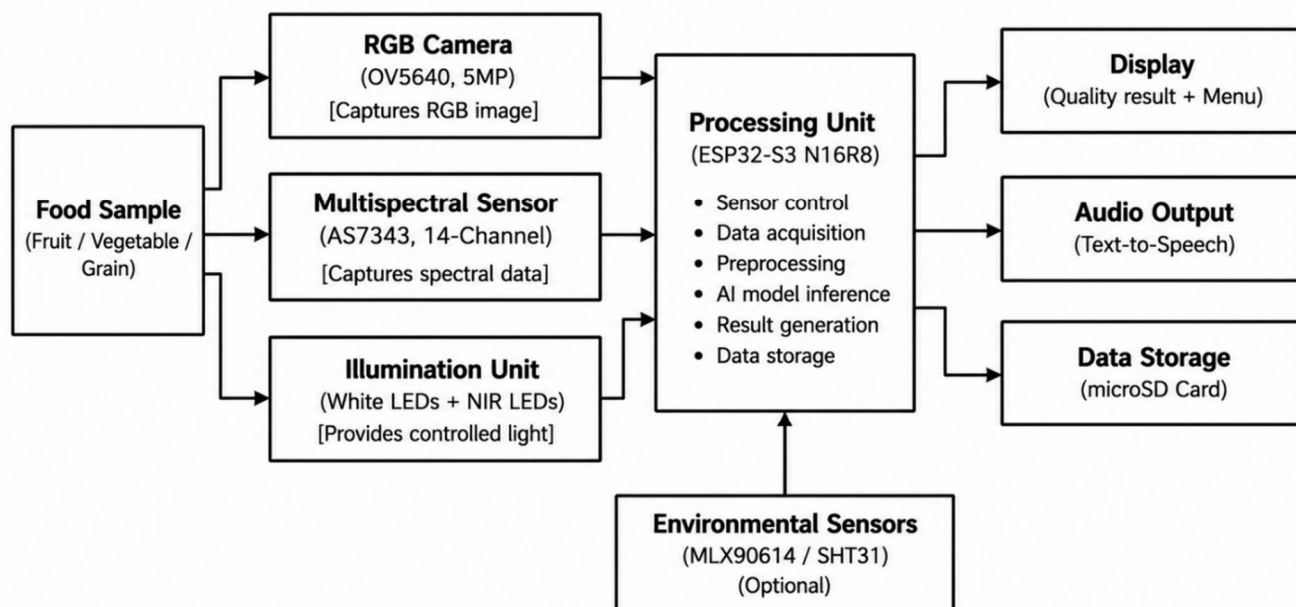


Figure 1. Block Diagram of the AI-Based RGB and 14-Channel Multispectral Food Quality Scanner

A. Hardware Components

- 1) RGB camera: The OV5640 camera captures the visible appearance of the food sample. The resulting image can be processed to identify colour distributions, boundaries, shape, texture, and visible defects.
- 2) Multispectral sensor: The AS7343 sensor measures light intensity across its supported spectral channels. These measurements provide a compact spectral feature vector that can be used with machine-learning algorithms.
- 3) Illumination unit: White LEDs support RGB image acquisition, while suitable near-infrared illumination may support spectral measurements where compatible with the sensor and measurement setup. The optical arrangement should minimise ambient-light interference and reflections.
- 4) Processing unit: The ESP32-S3 N16R8 can manage sensor communication, control the scanning process, acquire measurements, and handle user-interface functions. The suitability of this controller for the selected AI model must be verified through memory and timing tests. Larger models may require an external processor.
- 5) Output and storage: A display presents the predicted food category and quality result. A microSD card can store scan records, measurements, and associated metadata.
- 6) Environmental Sensors: MLX90614, The MLX90614 measures ambient temperature and humidity; the SHT31 measures infrared temperature. These readings may provide context for measurements but do not directly establish food freshness.

B. System Operation

The scanner operates through a sequence of sample placement, illumination, image capture, spectral measurement, preprocessing, classification, and result generation.

The sample is placed at a controlled distance from the sensing unit. The RGB camera captures an image, while the multispectral sensor records its channel responses. Both data streams are associated with the same sample identifier.

The collected measurements are preprocessed and supplied to the selected classification pipeline. The resulting prediction is displayed and stored for future comparison.

C. Data Acquisition

A reliable dataset should include multiple samples representing different quality categories. For fruit-ripeness assessment, samples may be labelled according to defined ripeness stages. For defect detection, labels may distinguish healthy samples from those with bruising, rot, or other specified defects.

For grain analysis, appropriate labels may include grain type, size category, or visible damage. These labels must be defined before data collection and supported by a consistent reference procedure.

For each sample, the dataset should contain:

- 1) RGB image or image features.
- 2) Fourteen-channel sensor measurements.
- 3) Sample category and reference label.
- 4) Illumination and acquisition conditions.
- 5) Sample identifier and acquisition date.

The dataset should include variation in sample size, orientation, natural appearance, and quality condition. Repeated readings of the same sample should not be treated as independent samples during evaluation.

V. METHODOLOGY

A. Image Preprocessing

The RGB image is first checked for blur, exposure problems, and unwanted background content. Image segmentation can isolate the food region from the scanning enclosure. Noise reduction and appropriate resizing may then be applied.

Colour features can be represented using RGB values or transformed colour spaces such as HSV and CIELAB. Texture and shape descriptors may also be extracted when relevant to the target food category [2], [3].

B. Multispectral Preprocessing

The multispectral sensor produces a set of channel-specific measurements. These measurements should be collected under consistent illumination and sensor settings. Dark measurements, reference measurements, and normalisation can be used where supported by the optical setup.

Measurements should be checked for saturation, noise, and unexpected variation. Since the AS7343 channels have defined spectral responses, their measurements should not be described as equivalent to arbitrary narrow wavelength bands without verifying the sensor specifications.

C. Feature Extraction and Fusion

The system can use two feature groups:

- 1) RGB features: Colour statistics, texture descriptors, shape information, and learned image features.
- 2) Spectral features: Normalised multispectral channel measurements and derived ratios or statistical features where justified.

In a feature-level fusion approach, both feature groups are combined into a single representation before classification. In a decision-level approach, separate models process RGB and multispectral inputs, and their predictions are combined.

The performance of each approach should be compared with the individual sensing methods to determine whether fusion provides a measurable benefit.

D. AI Classification

Several algorithms may be evaluated according to the dataset size and computational constraints.

- 1) Support Vector Machine (SVM): SVM can be suitable for structured feature vectors, particularly when the dataset is relatively small.
- 2) Random Forest (RF): Random Forest can classify tabular features and provide information about feature importance. Its performance should be evaluated using independent samples.
- 3) Convolutional Neural Network (CNN): CNNs learn visual features directly from RGB images. Lightweight architectures may be considered when inference speed and memory are important.
- 4) Hybrid classification: A hybrid model can combine image-derived features with multispectral measurements. Its usefulness must be determined experimentally rather than assumed.

For a small initial dataset, SVM and Random Forest can provide useful baseline models before more computationally demanding neural networks are considered [1], [5], [7].

E. Quality Classification

The system may be configured for different tasks, including:

- 1) Food-type classification.
- 2) Ripeness-stage classification.
- 3) Healthy-versus-defective classification.
- 4) Grain-category identification.
- 5) Food-authenticity screening for a specifically trained application.

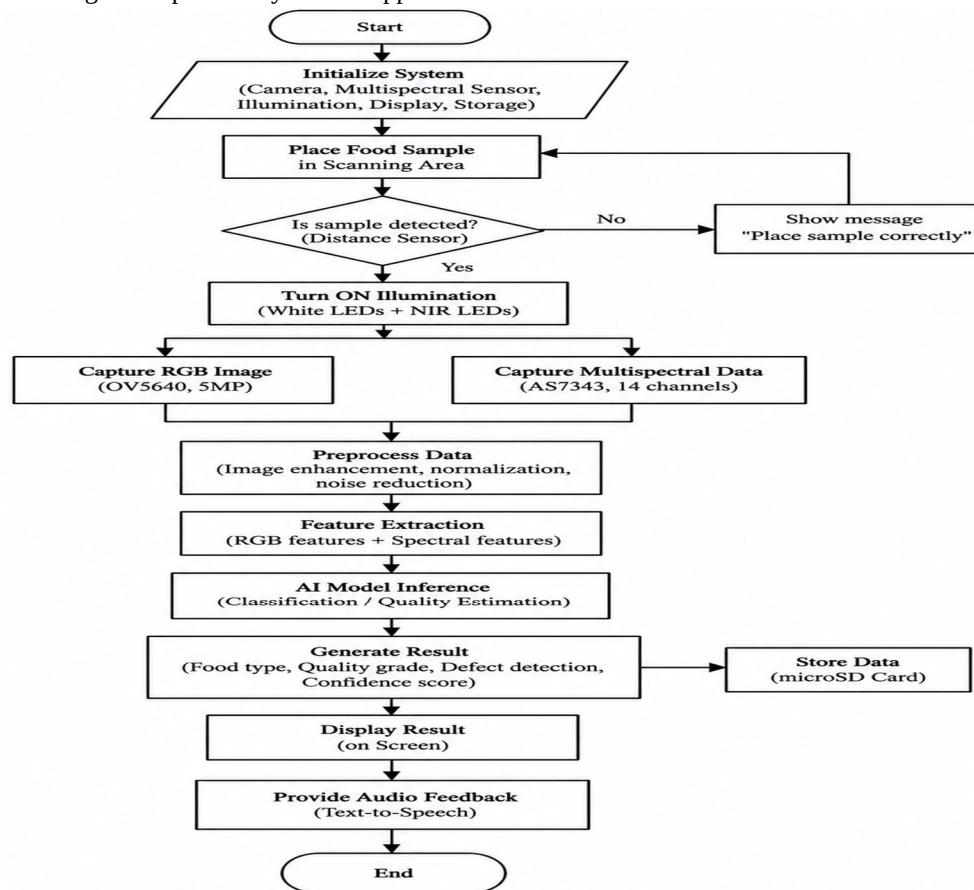


Figure 2. Flow Chart of the AI-Based RGB and 14-Channel Multispectral Food Quality Scanner

This flowchart illustrates an automated system that inspects and classifies food quality using computer vision and multispectral sensing:

- **Initialization & Detection:** The system boots up all hardware (sensors, camera, display, storage). When a food sample is placed in the scanning area, a distance sensor verifies its presence. If no sample is detected, it prompts the user to place it correctly.
- **Illumination & Data Capture:** Once detected, the system activates white and near-infrared (NIR) LEDs to illuminate the sample. Simultaneously, it captures a standard color image (5MP RGB) and spectral data across 14 channels (AS7343 sensor).
- **Preprocessing & Feature Extraction:** The raw visual and spectral inputs are cleaned (noise reduction, normalization, and enhancement) to extract key visual patterns and spectral signatures.
- **AI Inference & Analysis:** A trained AI model processes the extracted features to perform quality estimation, defect detection, and grain/food classification.
- **Output & Storage:** The system generates results (food type, grade, defects, and confidence score), saves the record onto a microSD card, presents the findings visually on a screen, and announces the outcome via text-to-speech audio feedback.

VI. DISCUSSION

A. Benefits of RGB and Multispectral Fusion

RGB imaging and multispectral sensing provide different types of information. RGB images are useful for visible characteristics, while multispectral measurements provide a limited set of wavelength-dependent responses.

Combining these data streams may improve classification when the two modalities contain complementary information. However, fusion can also introduce additional complexity, and not every task will benefit from using both sensors. Comparative experiments are therefore necessary.

B. Importance of Controlled Illumination

The light source affects the measurements recorded by both the camera and the multispectral sensor. Ambient light, shadows, reflections, distance, and changes in LED output can alter the observed features.

The spectral-sensing study by Myland *et al.* highlights the importance of monitoring illumination behaviour [8]. For food scanning, a controlled enclosure, repeatable sensor position, and suitable calibration procedure can help reduce measurement variation.

C. Embedded Processing Considerations

An embedded scanner must balance processing speed, memory requirements, energy consumption, and classification performance. Traditional machine-learning models operating on compact feature vectors may be easier to deploy than large CNNs.

The final processing architecture should be selected after measuring the model's memory footprint, inference time, and compatibility with the available hardware. If the embedded controller cannot run the selected model efficiently, inference may be performed on a more capable external processor.

D. Generalisation and Reliability

Food samples naturally vary in size, colour, surface texture, and composition. Models trained on a limited group of samples may learn dataset-specific characteristics rather than general quality indicators.

Reliable evaluation requires a sufficiently diverse dataset, consistent labelling, separate training and testing samples, and independent validation. Results should also be reported by class rather than relying only on overall accuracy.

E. Practical Limitations

The principal limitations include:

- Limited spectral information compared with hyperspectral systems.
- Sensitivity to illumination and sensor positioning.
- Dependence on representative and accurately labelled datasets.
- Processing and memory limitations of embedded hardware.
- Difficulty generalising across different food categories.
- Limited ability to establish internal quality or food safety from optical measurements alone.

These limitations should guide both hardware development and experimental evaluation.

VII. CONCLUSION

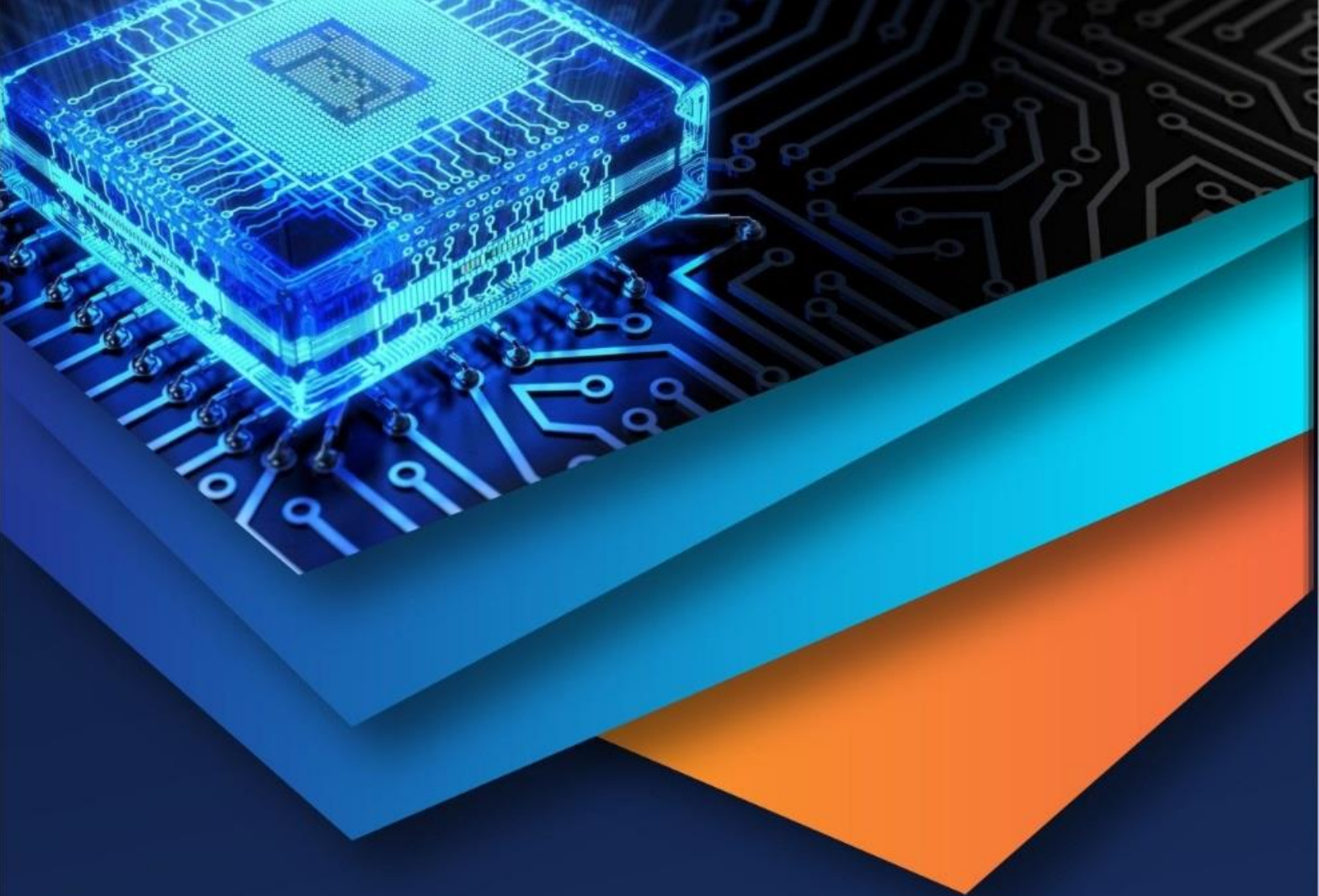
This paper reviewed the use of RGB imaging, multispectral sensing, and artificial intelligence for non-destructive food-quality assessment. Existing studies demonstrate the potential of RGB image processing for visible food characteristics, multispectral measurements for fruit-ripeness estimation and food-authenticity screening, and deep-learning models for defect classification. Hyperspectral imaging provides richer spectral information but introduces additional cost and processing complexity.

Based on these findings, an AI-based food-quality scanner combining an RGB camera and a 14-channel multispectral sensor has been proposed. The architecture integrates controlled illumination, data acquisition, preprocessing, feature extraction, AI classification, and result storage. The principal research objective is to determine whether combining RGB and spectral information improves performance compared with either sensing method alone.

Further experimental work is required to validate sensor integration, establish a representative dataset, compare classification algorithms, and evaluate generalisation under different scanning conditions

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