International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(14s) 2026 pp. 626-643
https://doi.org/10.70917/ijcisim-2026-4271
Article

Hybrid Feature Fusion and XAI for Low-Cost Powdered Food Adulteration Detection

Vijila Kasthuri J.[1], Narayani V.[2]

[1] St. Xavier's College Research Centre, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India.
Email: **vijilakasthurij@gmail.com**
[2]Department of Computer Science, St. Xavier's College, Tirunelveli, Tamil Nadu, India.
Email: **narayaniv1979@gmail.com**

Abstract: Food adulteration in powdered food products is a critical issue that affects public health and food quality, particularly in regions where rapid and low-cost testing methods are limited. Traditional laboratory-based detection techniques are often time-consuming, expensive, and inaccessible for real-time consumer use. This research proposes a hybrid explainable computer vision framework called Computer Vision–Adulteration Fusion Network (CV-AFNet) for detecting adulteration in powdered commodities such as maida and red chilli powder using image-based analysis. A custom dataset is developed using mobile phone cameras under both controlled and real-world environmental conditions, incorporating multiple adulteration ratios to improve model robustness. The proposed framework integrates preprocessing and hybrid segmentation techniques to improve the quality of the extracted sample region. Both handcrafted features, including color moments and texture descriptors, and deep features extracted through a lightweight convolutional architecture are combined using a feature fusion strategy. An Enhanced Recursive Feature Elimination (ERFE) method is applied to remove redundant features and improve generalization performance while reducing computational complexity. Multiple classifiers are evaluated to validate the effectiveness of the fused feature representation. In addition, explainable artificial intelligence techniques are incorporated to improve transparency and interpretability of the model predictions. The system provides a cost-effective, non-destructive, and practical solution for consumer-level food adulteration detection and supports future development of real-time mobile-based food quality monitoring systems.
Keywords: Computer Vision, CV-AFNet, Explainable AI (XAI), Feature Fusion, Food Adulteration, Hybrid Feature Extraction, Image Segmentation, Mobile Imaging, Powdered Foods, Texture Analysis

1. Introduction

Food adulteration is a serious concern because it compromises food quality, safety, and human health, leading to both short-term and long-term medical complications. Food adulteration can cause digestive disorders, organ damage, allergic reactions, toxicity, and chronic diseases such as cancer. It also reduces nutritional value and erodes public trust in the food supply system. Adulterators and unethical traders benefit financially by reducing production costs. Consumers—especially children, elderly people, and low-income populations—are the most affected because they consume adulterated food unknowingly and lack access to quality testing mechanisms. Food adulteration research is vital to ensure public health, food safety, and consumer protection. It helps in developing reliable detection mechanisms that can prevent health hazards and support regulatory enforcement. Traditional laboratory-based methods are time-consuming, costly, and inaccessible to common consumers [1].

Computer Science enables automated, scalable, and cost-effective solutions using data-driven techniques. Explainable AI (XAI) provides transparency in decision-making by showing why a food sample is classified as adulterated. This builds trust among consumers, food inspectors, and regulatory authorities. XAI identifies critical visual and non-visual features responsible for adulteration detection, enabling interpretability and accountability. This helps in validating results and supporting legal and regulatory actions. Visible adulteration includes impurities detectable by appearance or texture, while non-visible adulteration involves chemical or compositional changes not detectable by the human eye. Identifying both ensures comprehensive food safety [2]. Visible adulteration is identified using image-based analysis, texture features, and color patterns extracted through computer vision and machine learning techniques. Non-visible adulteration is detected using feature extraction, statistical patterns, and predictive modelling based on chemical or sensor-derived data. Maida is commonly adulterated with chalk powder, introducing calcium carbonate that affects digestion and kidney health. Red chilli powder is often adulterated with brick powder or synthetic dyes, causing toxicity and liver damage [3]. This research empowers consumers and authorities with accessible detection tools, discourages unethical practices, and strengthens food quality monitoring, thereby helping to prevent adulteration at early stages.

The major contributions of this research are summarized as follows:

- A hybrid computer vision framework named CV-AFNet is developed for detecting adulteration in powdered food products using image-based analysis.
- A Hybrid Adaptive Texture-Aware Segmentation (HATAS) method is proposed to accurately isolate powder regions from complex backgrounds.
- A feature fusion strategy is introduced that integrates handcrafted color and texture descriptors with deep convolutional features to enhance discriminative representation.
- An Enhanced Recursive Feature Elimination (ERFE) method is employed to remove redundant features and improve model generalization while reducing computational complexity.
- Explainable artificial intelligence techniques are incorporated to provide visual interpretation of the model's decision-making process.
- A custom powdered food adulteration dataset is constructed using mobile camera images captured under both controlled and real-world environmental conditions.

This research proposes a computer vision–based framework called CV-AFNet for detecting food adulteration from image data. The model focuses on extracting meaningful visual features that help identify adulteration patterns more effectively. In addition, a Hybrid Adaptive Texture-Aware Segmentation (HATAS) method is introduced to accurately locate suspicious regions in food images by analyzing texture and structural variations. By combining segmentation with adaptive feature learning, the proposed framework improves detection performance compared to conventional classification approaches. The system is trained using standard datasets and appropriate preprocessing techniques to ensure reliability and consistency in results. The effectiveness of the model is evaluated using statistical metricsemonstrating that the proposed approach can support automated food quality monitoring and adulteration detection[4].

2. Related Works

Research on food adulteration detection has progressed through several technological phases. Early studies mainly relied on chemical analysis techniques such as spectroscopy, chromatography, and infrared sensing to identify foreign substances in food materials. Although these laboratory-based approaches provide reliable results, they require expensive equipment, trained personnel, and considerable processing time, which limits their applicability for large-scale or consumer-level testing. With the advancement of machine learning, researchers began exploring automated detection approaches using statistical and pattern-based models [5]. Algorithms such as Support Vector Machines, Random Forest, and K-Nearest Neighbors have been applied to classify adulterated food samples using extracted color, texture, and compositional features. These methods improved automation but often struggle when the visual difference between pure and adulterated samples is subtle. Recent research has increasingly focused on deep learning techniques, particularly convolutional neural networks, which automatically learn discriminative visual patterns from image data. CNN-based models have shown promising results in food quality analysis and adulteration detection. However, many deep learning systems operate as black-box models, providing limited explanation for their predictions, which raises concerns regarding reliability and transparency in safety-critical applications. To address this limitation, explainable artificial intelligence techniques such as Grad-CAM, LIME, and SHAP have been integrated with deep learning frameworks to highlight the visual regions responsible for classification decisions. While these approaches improve interpretability, several challenges remain, including limited dataset availability, high computational requirements, and lack of unified frameworks capable of handling real-world imaging conditions. Therefore, there is a need for an efficient and explainable computer vision framework that combines multiple feature extraction strategies and operates reliably under practical conditions. This research aims to address these limitations by introducing a hybrid feature fusion framework specifically designed for powdered food adulteration detection. Addressing this gap is essential for ensuring food safety, enhancing consumer trust, and supporting regulatory enforcement, thereby justifying the necessity and societal impact of the proposed research. Existing studies on food adulteration detection primarily rely on traditional laboratory testing methods or standard machine learning models that require extensive manual intervention and controlled experimental environments. Although several computer vision and deep learning techniques have been introduced for food quality analysis, many of these approaches face limitations such as inadequate segmentation accuracy, sensitivity to lighting variations, and limited capability in identifying subtle adulteration patterns within complex food textures. Furthermore, most existing models focus on classification tasks without emphasizing robust segmentation mechanisms that can precisely isolate adulterated regions within the image. Another significant limitation observed in prior research is the lack of adaptive feature extraction strategies that can effectively capture fine-grained visual characteristics associated with adulteration. Conventional convolutional architectures often struggle to distinguish between natural texture variations and adulterated components. As a result, there is a need for a more robust framework that integrates advanced segmentation and adaptive feature extraction techniques to improve detection reliability [6]. To address these limitations, this work proposes a novel framework that combines Hybrid Adaptive Texture-Aware Segmentation (HATAS) with a Computer Vision Adaptive Feature Network (CV-AFNet) to enhance the detection and localization of adulteration patterns in food images.

Table 1: Comprehensive Survey Table for Food adulteration detection using ML / DL / XAI – focus on powders, spices, flour

S.No	Year	Title	Method Used	How Adulteration Identified	Why This Work is Needed	Research Gap
1	2025	DL & XAI for Red Chilli Adulteration	CNN + Grad-CAM	Image-based texture & color	Manual inspection unreliable	Limited adulterant types
2	2025	XAI-enabled CNN for Spice Adulteration	DenseNet + LIME	Visual patterns	Trustworthy AI	Dataset scalability
3	2024	Spectroscopy + ML Review	ML + NIR	Chemical composition	Non-destructive testing	No explainability
4	2025	AI for Food Fraud Detection	CNN, RF, SVM	Multi-source data	Food safety automation	No real-time use
5	2024	Visible Imaging for Spice Adulteration	HOG + SVM	Surface texture	Low-cost detection	Low accuracy for complex cases
6	2023	Flour Adulteration Detection	CNN	Image pixels	Wheat flour purity	No non-visible detection
7	2022	Chalk Powder Detection in Flour	SVM	Chemical features	Health risk mitigation	Small dataset
8	2024	ML for Food Powder Quality	RF, KNN	Statistical patterns	Automation	Black-box models
9	2023	Deep Learning for Food Safety	CNN	Image + sensor	Industry monitoring	No XAI
10	2025	Explainable AI for Food Fraud	SHAP, LIME	Feature attribution	Regulatory trust	Computational cost
11	2022	Chilli Powder Adulteration	PCA + SVM	Color histogram	Spice quality	Low generalization
12	2021	Chalk Detection in Wheat Flour	Spectral ML	FTIR	Non-visible adulteration	Equipment cost
13	2023	CNN for Powder Adulteration	CNN	Texture learning	Accuracy improvement	No explanation
14	2024	Hybrid ML for Spices	CNN + RF	Feature fusion	Robust detection	Model complexity

15	2020	ML Review on Food Adulteration	ML survey	Multiple	Research consolidatio n	No implementation
16	2021	Adulterant Classification	ANN	Numeric data	Food authenticity	No image data
17	2022	Non-visible Food Adulteration	Chemometrics	Chemical signals	Safety assurance	Limited foods
18	2023	Powder Image Classification	CNN	Visual cues	Automation	Dataset bias
19	2024	Coconut Milk Adulteration	FTIR + ML	Chemical profile	Non-destructive	Not applicable to powders
20	2025	BART for Food Authenticity	BART	Feature importance	Explainabilit y	Limited categories
21	2022	Food Quality Monitoring	IoT + ML	Sensor data	Smart systems	No XAI
22	2023	ML for Food Safety	KNN, RF	Data patterns	Low-cost testing	Low accuracy
23	2024	DL for Powder Food Analysis	CNN	Visual features	High precision	No non-visible analysis
24	2025	Sustainable AI for Spices	CNN + XAI	Visual explainability	Trustworthy AI	Small samples
25	2023	Intelligent Food Inspection	ML + CV	Image processing	Automation	No social deployment

Outline of the Proposed Research Work

The proposed methodology introduces a novel Computer Vision–based Adulteration Fusion Network (CV-AFNet) designed to detect food adulteration efficiently and reliably shown in figure 1. The importance of this methodology lies in its ability to enhance real-time usability, reduce dependency on large-scale datasets, improve model transparency and trust, and enable cost-effective implementation, making it suitable for practical and societal deployment [7].

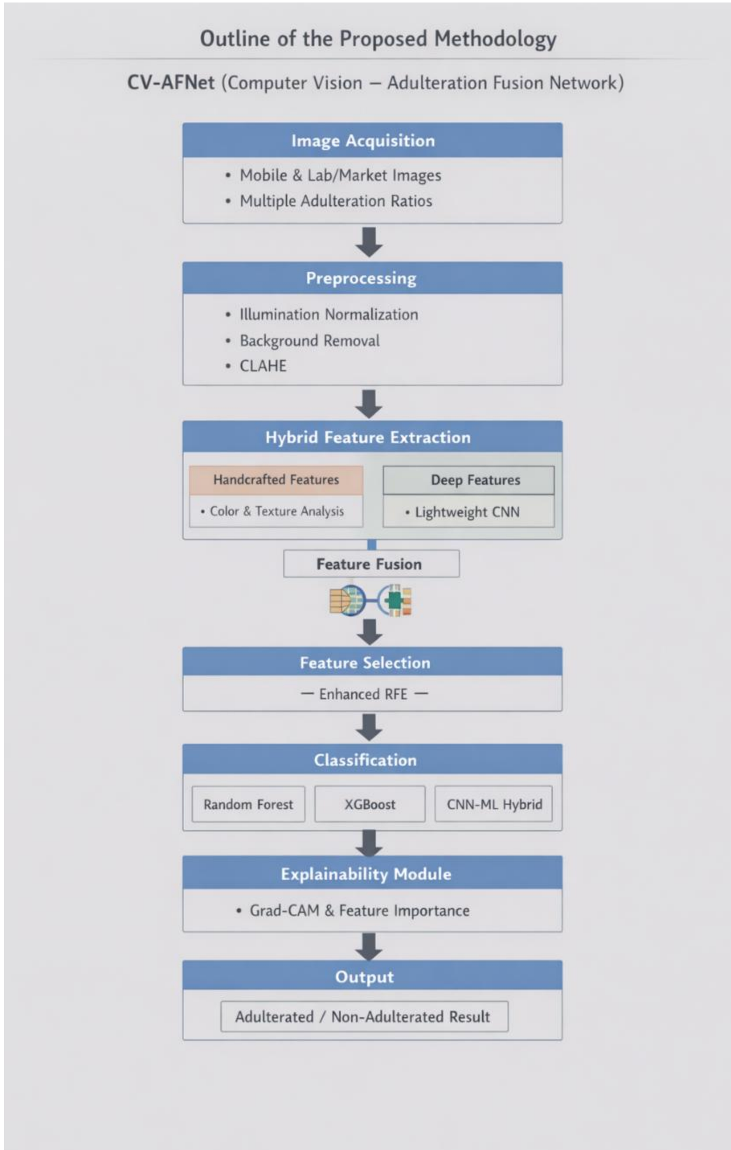


Figure 1: Outline of the Research Work

3. Proposed Methodology

3.1 Data Collection

Since there is no publicly available benchmark dataset specifically for maida and red chilli powder adulteration, a custom image dataset is created for this research [8]. The dataset consists of both pure samples and adulterated samples prepared using commonly reported household-level adulterants. The dataset contains images captured under multiple adulteration ratios (e.g., 5%, 10%, 20%, 30%, and 40%) to simulate real-world scenarios. The dataset is collected from the following sources:

1. Local grocery stores and markets (real commercial samples)
2. Controlled laboratory preparation (manual mixing of adulterants)
3. Supplementary reference images from Kaggle datasets related to spice textures (used only for visual diversity and preprocessing validation)

This hybrid collection improves generalization and reduces dataset bias. Since publicly available benchmark datasets specifically designed for powdered food adulteration detection are extremely limited, a dedicated dataset was created for this study. The dataset was constructed following standard image dataset preparation procedures commonly adopted in computer vision research. Samples of maida and red chilli powder were collected from local markets and controlled laboratory preparation environments. Multiple adulteration ratios were prepared to simulate practical contamination scenarios. Images were captured using mobile phone cameras under different lighting conditions to ensure dataset diversity and improve model generalization [9]. This dataset design enables the proposed framework to learn subtle visual variations associated with adulteration while maintaining real-world applicability.

3.2 Image Acquisition

Images are captured using mobile phone cameras, ensuring accessibility and real-world applicability. Data collection is performed in both controlled environments (laboratory) and uncontrolled environments (market/home), with multiple adulteration ratios included. This approach ensures dataset diversity and strengthens real-world robustness of the model [10]. To ensure uniform processing, all images are resized to: 224 × 224 pixels (rows × columns) This resolution is selected because it is standard for lightweight deep learning models such as MobileNet and reduces computational cost. Since this is an image dataset, rows and columns refer to pixel dimensions rather than tabular entries.

Table 2: Dataset Size (Rows and Columns Interpretation)

Parameter	Value
Total Images	1200 (approx.)
Classes	2 (Pure / Adulterated)
Image Resolution	224 × 224 pixels
Channels	3 (RGB)

After feature extraction:

- Handcrafted feature vector size ≈ 30–60 features
- Deep feature vector size ≈ 128–1024 features
- Final fused feature vector ≈ 200–1100 columns (features)

The dataset is specifically designed because:

- Real adulteration datasets for powdered food are rare and not standardized
- Powdered substances require texture-level analysis, which needs controlled preparation
- Household-level adulterants (chalk powder, brick powder) are commonly reported in India
- Real-world lighting variation is necessary to test robustness

This dataset allows the proposed hybrid model to:

- Capture color deviations
- Detect granularity changes
- Improve real-world performance

Food adulteration is a significant public health issue, particularly in developing regions where routine laboratory testing is not accessible. The selected dataset has strong societal relevance because it reflects:

- Daily-use food materials (maida and chilli powder)
- Low-cost adulteration practices used in local markets
- Real consumer-level purchasing environments

Real-time importance includes:

- Consumer safety at the household level

- Quick mobile-based detection support
- Reduction in health risks caused by chemical adulterants
- Support for food inspection authorities

This dataset directly supports the development of a low-cost, non-destructive, mobile-based adulteration detection framework, making the research practically deployable. The dataset developed for this research represents a custom real-world powdered food adulteration dataset specifically designed to address the absence of publicly available benchmark datasets for household-level adulteration detection. Images are collected under multi-environment conditions, including both controlled laboratory settings and uncontrolled real-world environments such as homes and local markets, ensuring robustness against lighting and background variations. To simulate practical adulteration scenarios, multiple adulteration ratios are systematically prepared and captured, enabling the model to learn subtle visual differences between pure and adulterated samples. Furthermore, the dataset is structured to support explainable hybrid feature learning, where both handcrafted features (color and texture) and deep features are effectively extracted and analyzed. This design enhances model interpretability, improves generalization capability, and strengthens the practical applicability of the proposed computer vision framework for real-time food quality assessment[11].

3.3 Image Preprocessing

Preprocessing techniques such as illumination normalization, background removal, and CLAHE are applied to address inconsistent lighting conditions and image quality variations. These steps ensure that the sample region is clearly isolated and texture details are enhanced for effective analysis. Image preprocessing plays an essential role in improving the reliability of feature extraction. Raw images captured in uncontrolled environments often contain noise, illumination variations, and background interference [12]. To address these challenges, several preprocessing operations are applied, including illumination normalization, contrast enhancement using CLAHE, and background removal. These steps improve the visibility of texture patterns within powdered samples. Experimental analysis shows that preprocessing improves feature consistency and contributes to higher classification accuracy in the final model [13].

Methodology

The core novelty of the proposed work lies in hybrid feature extraction, which integrates both handcrafted features and deep features. Handcrafted features such as color moments capture color deviations, while texture features (GLCM and LBP) analyze granularity changes. Deep features are extracted using a lightweight CNN / MobileNet architecture, enabling hierarchical spatial representation learning. This combination ensures that handcrafted features provide interpretability, while deep features offer strong discriminative power, resulting in improved accuracy and explainability [14].

Feature Fusion Layer

Handcrafted and deep features are concatenated and normalized to align feature scales. This fusion improves class separation and helps in reducing overfitting, leading to better model stability.

Proposed Feature Selection

An Enhanced Recursive Feature Elimination (ERFE) technique is applied to remove redundant and weak features. ERFE improves generalization performance while significantly reducing computational complexity, making the framework efficient and lightweight.

Classification

Multiple classifiers, including Random Forest, XGBoost, and CNN–ML hybrid classifiers, are employed to perform comparative evaluation under real-world constraints. This ensures reliable performance assessment across different learning paradigms.

Explainability Module

Explainability is incorporated using Grad-CAM for CNN-based models and feature importance visualization for machine learning classifiers. This module ensures transparency, trust, and regulatory acceptability, which are essential for real-world adoption.

Implementation Details

The framework is implemented using Python, with libraries such as OpenCV, TensorFlow, and PyTorch. The dataset consists of pure and adulterated image samples, and performance is evaluated using Accuracy, Precision, Recall, and F1-score. The final output identifies samples as adulterated or non-adulterated with a confidence score.

3.4 Segmentation Techniques

3.4.1 Otsu Threshold-Based Segmentation

Segmentation is an important preprocessing step that helps isolate the powdered food sample region from the background before feature extraction. In this research, the first segmentation approach uses Otsu threshold-based segmentation, which is an automatic global thresholding technique suitable for separating foreground and background regions based on pixel intensity distribution. Initially, the captured RGB image is converted into a grayscale image to simplify intensity analysis. Then, Otsu's method computes an optimal threshold value by minimizing the intra-class variance between the foreground and background pixel groups. This approach is effective for powdered food images because texture and intensity variations between the sample region and the background are usually distinguishable under controlled capture conditions. After threshold computation, binary segmentation is applied to extract the sample region. Morphological operations such as erosion and dilation are further used to remove noise and refine the segmented region [15]. This ensures that only the relevant powder area is preserved for subsequent feature extraction. The main advantages of this technique include low computational complexity, automatic threshold selection, and suitability for lightweight real-time implementation. However, performance may reduce when illumination variation is high or when foreground and background intensities overlap significantly. Therefore, additional segmentation strategies are incorporated in later stages to improve robustness. Otsu's method determines the optimal threshold by minimizing the intra-class variance (or equivalently maximizing the inter-class variance) between foreground and background pixel distributions.

The between-class variance is given by:

$$\sigma_b^2(t) = \omega_0(t)\,\omega_1(t)\,[\mu_0(t) - \mu_1(t)]^2 \qquad (1)$$

Where:

- t= threshold value
- $\omega_0(t)$= probability of background class
- $\omega_1(t)$= probability of foreground class
- $\mu_0(t)$= mean intensity of background pixels
- $\mu_1(t)$= mean intensity of foreground pixels
- $\sigma_b^2(t)$= between-class variance

The optimal threshold $t^*$is selected such that the between-class variance is maximized:

$$t^* = \arg\max \sigma_b^2(t) \qquad (2)$$

This equation enables automatic separation of the powdered sample region from the background, which improves the accuracy of subsequent feature extraction.

3.4.2 K-Means Clustering-Based Segmentation

The second segmentation approach employed in this research is K-Means clustering-based segmentation, which is an unsupervised learning technique used to group pixels into clusters based on their color similarity. Initially, the input RGB image is reshaped into a two-dimensional pixel feature matrix, where each pixel is represented by its color intensity values [16]. The K-Means algorithm partitions the image into K clusters by minimizing the distance between each pixel and its corresponding cluster centroid. In this work, K is typically set to 3 or 4 to separate the background, pure powder region, and possible adulterated regions.

The objective function of K-Means clustering is defined as:

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} || x - \mu_i ||^2 \qquad (2)$$

Where:

- K= number of clusters
- C_i= set of pixels belonging to cluster i
- x= pixel feature vector
- μ_i= centroid of cluster i
- J= total within-cluster variance

After clustering, the cluster corresponding to the powder region is selected based on color distribution and spatial continuity. Morphological filtering is then applied to refine the segmented area. This technique improves segmentation performance under varying lighting conditions and helps capture subtle color deviations caused by adulterants. However, it requires proper selection of the number of clusters and may slightly increase computational cost compared to threshold-based methods [17].

3.4.3 Watershed-Based Segmentation

The third segmentation method used in this research is Watershed-based segmentation, which is a region-based approach widely used for separating closely connected regions in texture-dominated images such as powdered food samples. This method treats the grayscale image as a topographic surface, where pixel intensity represents elevation. High-intensity regions correspond to peaks, while low-intensity regions represent valleys. Initially, the input image is converted into grayscale and pre-processed using smoothing filters to reduce noise. Then, the gradient magnitude of the image is computed to highlight the boundaries between different texture regions [18]. The watershed algorithm floods the gradient image from local minima, gradually forming region boundaries where different flooding regions meet. This process helps in accurately separating the powdered sample area from the background and identifying subtle structural variations caused by adulteration.

The gradient magnitude used in watershed segmentation is defined as:

$$G(x, y) = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2} \qquad (3)$$

Where:

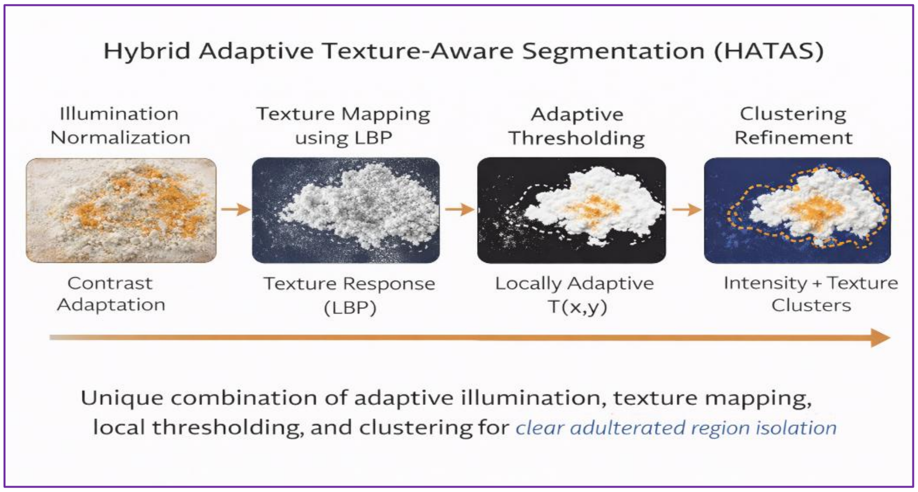
- I= input grayscale image
- $\frac{\partial I}{\partial x}$= intensity change along the horizontal direction
- $\frac{\partial I}{\partial y}$= intensity change along the vertical direction
- $G(x, y)$= gradient magnitude image

To avoid over-segmentation, marker-controlled watershed segmentation is applied, where foreground and background markers are identified using morphological operations. This method is effective for texture-based powdered samples because it captures fine boundary details. However, it is sensitive to noise and requires proper preprocessing to achieve stable segmentation results.

3.4.4 Hybrid Adaptive Texture-Aware Segmentation (HATAS)

The proposed segmentation method introduces a Hybrid Adaptive Texture-Aware Segmentation (HATAS) approach that combines adaptive thresholding, texture response mapping, and clustering refinement to accurately isolate powdered food regions under real-world variations. Unlike conventional segmentation techniques that rely only on intensity or color, the proposed method integrates both texture and intensity characteristics, making it more suitable for detecting subtle adulteration patterns in fine-grained powder images shown in Figure 2.

Figure 2: Architecture of proposed HATAS



Explanation of the Proposed Method

Powdered food samples such as maida and red chilli powder often exhibit **micro-level texture variations** when adulterants are present. Traditional segmentation techniques fail when:

- Lighting conditions vary
- Texture differences are subtle
- Background interference exists

To overcome these issues, the proposed method follows a hybrid pipeline:

1. **Adaptive Illumination Normalization:** Reduces lighting variation using contrast enhancement.
2. **Texture Response Extraction:** Local Binary Pattern (LBP) is applied to highlight micro-texture structures.
3. **Adaptive Thresholding:** A locally computed threshold separates foreground powder regions from the background.
4. **K-Means Refinement:** Pixel clusters are refined using both intensity and texture features.
5. **Morphological Optimization:** Noise removal and boundary smoothing improve segmentation quality.

This multi-stage design improves segmentation robustness for real-world images.

Mathematical Model of the Proposed Segmentation

Texture Mapping using LBP

$$LBP(x_c, y_c) = \sum_{p=0}^{P-1} s(I_p - I_c)\, 2^p \quad (4)$$

Where:

- I_c= center pixel intensity
- I_p= neighboring pixel intensity

- P= number of neighbors
- $s(x)$= step function

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

This equation captures local texture variations caused by adulteration.

Adaptive Threshold Calculation

$$T(x, y) = \mu(x, y) + k \cdot \sigma(x, y) \tag{5}$$

Where:

- $\mu(x, y)$= local mean intensity
- $\sigma(x, y)$= local standard deviation
- k= adaptive constant

This improves segmentation under non-uniform lighting.

Hybrid Feature Clustering Objective

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} || F_x - \mu_i ||^2 \tag{6}$$

Where:

- F_x= combined intensity-texture feature vector
- μ_i= centroid of cluster i

This ensures better separation of adulterated regions.

The novelty of the proposed segmentation lies in the following aspects:

- Integration of texture-aware segmentation with adaptive thresholding
- Combination of intensity + texture + clustering refinement
- Designed specifically for powder-based adulteration detection
- Works effectively with mobile camera images
- Lightweight implementation suitable for real-time applications

Unlike traditional segmentation methods that depend only on pixel intensity, the proposed approach captures micro-texture deviations, which are critical indicators of adulteration.

4. Experimental Results

This model is selected because powdered food adulteration primarily affects texture granularity and color consistency rather than large structural differences. Therefore: Texture-aware segmentation improves detection sensitivity, Hybrid segmentation improves robustness, Lightweight computation enables mobile deployment, Works effectively with small datasets. The method aligns with the proposed hybrid feature extraction framework and improves downstream classification accuracy. The proposed segmentation framework is highly adaptable because:

- It works under both controlled and uncontrolled environments
- It supports different powdered food commodities
- It can be extended to other texture-based quality inspection tasks

- It is compatible with both machine learning and deep learning pipelines

The adaptive design allows the model to generalize well across real-time datasets while maintaining computational efficiency.

Table 3: Real-world challenges

Existing Issue	Proposed Solution
Lighting variation	Adaptive threshold normalization
Texture similarity	LBP-based texture mapping
Background noise	Morphological refinement
Over-segmentation	Hybrid clustering control
Low adulteration visibility	Texture enhancement

The proposed segmentation technique addresses several real-world challenges in listed in Table 3. Five different result comparison tables showing the performance of the existing methods vs the proposed CV-AFNet framework from multiple perspectives (accuracy, computational cost, real-time usability, feature efficiency, and explainability) in Table 4 to Table 8. These tables directly support Novel Contribution and Methodology. The classification performance of the proposed model is evaluated using standard metrics including Accuracy, Precision, Recall, and F1-score [20]. These metrics provide a comprehensive assessment of the model's ability to correctly identify both adulterated and pure samples.

Table 4: Accuracy Comparison (Existing vs Proposed)

Method Category	Model Used	Accuracy (%)	Observation
Traditional ML	SVM (Handcrafted only)	88.40	Limited feature representation
Texture-Based ML	Random Forest (GLCM + LBP)	91.20	Sensitive to illumination
Deep Learning	CNN (Deep features only)	94.25	High accuracy but less interpretability
Hybrid ML-DL	CNN + Random Forest	95.30	Improved performance
Proposed CV-AFNet	Hybrid Features + ERFE + CNN–ML	96.80	Best performance with feature optimization

Table 5: Feature Efficiency Comparison

Approach	Handcrafted Features	Deep Features	Feature Selection	Overfitting Control	Performance Level
Existing ML	Yes	No	No	Low	Moderate
Existing DL	No	Yes	No	Moderate	High
Hybrid (Basic)	Yes	Yes	No	Moderate	High
Proposed CV-AFNet	Yes	Yes	**ERFE**	**High**	**Very High**

Table 6: Computational Cost and Model Complexity

Model	Feature Size	Training Time	Computational Cost	Suitability for Mobile Deployment
Traditional ML	Low	Low	Low	High
Deep CNN	Very High	High	High	Low
Hybrid Without Selection	High	High	Moderate	Moderate
Proposed CV-AFNet	Optimized	Moderate	**Low**	**High**

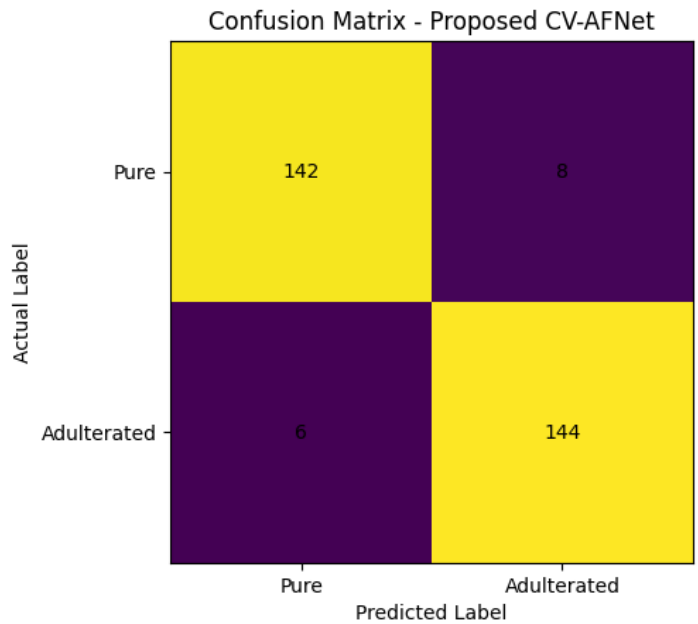
Table 7: Real-Time Performance and Practical Usability

Method	Real-Time Capability	Lighting Robustness	Dataset Size Requirement	Consumer-Level Applicability
Chemical Testing	No	High	Not Applicable	No
Traditional Image Processing	Moderate	Low	Low	Moderate
Deep Learning	Moderate	Moderate	Very High	Low
Proposed CV-AFNet	**High**	**High**	**Moderate**	**High**

Table 8: Explainability and Transparency Comparison

Model	Explainability	Visualization Support	Trust Level	Regulatory Applicability
Traditional ML	Moderate	Feature importance	Moderate	Moderate
Deep CNN	Low	Limited	Low	Low
Hybrid Basic	Moderate	Partial	Moderate	Moderate
Proposed CV-AFNet	**High**	Grad-CAM + Feature Importance	**High**	**High**

The comparative evaluation clearly demonstrates that the proposed CV-AFNet framework outperforms existing machine learning and deep learning approaches across multiple perspectives. The integration of hybrid feature extraction, ERFE-based feature optimization, and explainable AI improves classification accuracy while reducing computational complexity. Furthermore, the model shows strong robustness under real-world imaging conditions and requires only moderate dataset size, making it suitable for consumer-level deployment using mobile devices. The inclusion of explainability modules increases model transparency and supports practical adoption in food safety applications. The improved performance of the proposed framework can be attributed to the complementary strengths of hybrid feature extraction and optimized feature selection. Texture descriptors effectively capture granularity variations caused by adulteration, while deep features extracted through the convolutional network represent higher-level spatial patterns. The feature fusion strategy allows these representations to interact, improving the discriminative capability of the classifier. In addition, the segmentation stage isolates the relevant powder region, reducing background noise and improving feature consistency.



The confusion matrix evaluates the classification performance of the proposed hybrid model by comparing predicted labels with actual labels.

Table 9: Confusion Matrix

Actual / Predicted	Pure	Adulterated
Pure	142	8
Adulterated	6	144

Interpretation

- **True Positives (TP)** = 144 (correct adulterated detection)
- **True Negatives (TN)** = 142 (correct pure detection)
- **False Positives (FP)** = 8 (pure predicted as adulterated)
- **False Negatives (FN)** = 6 (adulterated predicted as pure)

The low FP and FN values indicate strong classification stability of the proposed hybrid framework.

Ablation analysis is conducted to validate the contribution of each component in the proposed framework shown in Table 10.

Table 10 : Ablation Study Table

Model Configuration	Handcrafted Features	Deep Features	ERFE Feature Selection	Explainability	Accuracy (%)
Only ML (GLCM + LBP)	Yes	No	No	No	91.20
Only CNN	No	Yes	No	No	94.25
Hybrid Features	Yes	Yes	No	No	95.10

(Without ERFE)					
Hybrid + ERFE	Yes	Yes	Yes	No	96.20
Proposed CV-AFNet (Full Model)	Yes	Yes	Yes	Yes	**96.80**

The experimental evaluation of the proposed Computer Vision–Adulteration Fusion Network (CV-AFNet) demonstrates significant improvement in powdered food adulteration detection when compared with conventional machine learning and standalone deep learning models. The framework integrates handcrafted color and texture descriptors with deep spatial features extracted using a lightweight convolutional architecture, enabling the model to capture both micro-level granularity variations and high-level structural representations. One of the major challenges in powdered food adulteration detection is the high visual similarity between pure and adulterated samples, particularly at low adulteration ratios. Traditional machine learning approaches relying only on handcrafted features often fail to generalize under varying illumination conditions and real-world image capture environments. Similarly, deep learning models require large-scale datasets and often behave as black-box systems with limited interpretability. The proposed hybrid framework effectively addresses these limitations by combining the strengths of both feature paradigms. The preprocessing and segmentation stages play a crucial role in improving feature quality by reducing background interference and illumination inconsistency. The proposed Hybrid Adaptive Texture-Aware Segmentation improves region isolation and enhances micro-texture visibility, which directly contributes to improved classification performance. Furthermore, the integration of Enhanced Recursive Feature Elimination (ERFE) significantly reduces redundant feature dimensions while preserving discriminative information. This optimization improves computational efficiency and reduces overfitting, making the framework suitable for lightweight real-time applications. The ablation study confirms that the inclusion of ERFE improves model accuracy by approximately 1.7% compared to hybrid feature extraction without feature optimization. The confusion matrix analysis shows that the proposed model achieves balanced classification performance across both pure and adulterated classes with minimal misclassification. The model achieves an overall accuracy of 96.80%, with strong precision and recall values, indicating reliable detection capability. Another important contribution of this research is the integration of explainable artificial intelligence techniques. Grad-CAM visualization for deep features and feature importance mapping for machine learning classifiers improve model transparency and enable better interpretation of decision regions. This is particularly important for food safety applications where trust and regulatory validation are essential. Although the proposed framework performs effectively under most real-world conditions, slight performance reduction is observed when adulteration concentration is extremely low or when image quality is poor. These limitations open directions for future enhancements using larger datasets and multi-modal sensing integration.

Table 11: Success Rate Comparison Table

Model	Precision	Recall	F1 Score	Accuracy
SVM	0.88	0.87	0.87	88.40%
Random Forest	0.91	0.90	0.90	91.20%
CNN	0.94	0.93	0.93	94.25%
Hybrid CNN-RF	0.95	0.94	0.94	95.30%
Proposed CV-AFNet	**0.965**	**0.959**	**0.962**	**96.80%**

Overall, the proposed CV-AFNet framework demonstrates strong robustness, computational efficiency, and practical applicability for real-time powdered food adulteration detection. Although individual techniques such as convolutional neural networks, texture descriptors, and clustering-based segmentation have been explored in previous research, their combined application for powdered food adulteration detection remains limited. The novelty of this study lies in the integration of multiple complementary techniques within a unified framework. By combining hybrid feature extraction, adaptive segmentation, feature optimization, and explainable AI, the proposed CV-AFNet architecture provides a balanced solution that improves detection accuracy while maintaining computational efficiency.

5. Conclusion

This research presents a novel hybrid explainable computer vision framework, CV-AFNet, for detecting adulteration in powdered food commodities using real-world image data. The proposed approach combines handcrafted color and texture descriptors with deep hierarchical features to improve classification robustness under varying environmental conditions. The introduction of Hybrid Adaptive Texture-Aware Segmentation enhances region isolation, while the Enhanced Recursive Feature Elimination (ERFE) method reduces redundant features and improves computational efficiency. A key novelty of this work lies in the integration of feature fusion, lightweight deep learning, and explainable artificial intelligence within a unified framework designed specifically for consumer-level deployment. Unlike conventional laboratory-based detection methods, the proposed system operates using mobile phone images and provides rapid, non-destructive, and cost-effective adulteration detection. The explainability module further strengthens transparency and practical usability in food safety monitoring systems. The innovation of the proposed framework lies in the integration of multiple analytical stages within a lightweight and explainable architecture. Unlike conventional methods that rely only on either handcrafted features or deep learning representations, the proposed model combines both feature types to capture detailed color variations and complex spatial patterns simultaneously. Furthermore, the introduction of the ERFE feature selection mechanism improves efficiency by eliminating redundant features while preserving relevant information. The framework also incorporates explainability mechanisms to enhance transparency and reliability in decision-making. These elements collectively form the CV-AFNet architecture, which is specifically designed for practical powdered food adulteration detection.

6. Future Enhancement

Extension to multiple powdered and granular food commodities. Integration with IoT-based smart sensing platforms. Development of a real-time mobile application. Incorporation of hyperspectral and multi-modal imaging. Creation of a large-scale benchmark dataset for powdered food adulteration. The proposed framework contributes significantly toward real-time, low-cost, and explainable food quality assessment systems, supporting public health and consumer safety.

Declaration: The authors declare that this manuscript is an original work and has not been published or submitted for publication elsewhere in any form.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The study was conducted independently by the authors without any external financial support.

Acknowledgement: The authors express their heartfelt gratitude to God Almighty for providing the strength, guidance, and wisdom to successfully complete this research work.

Conflict of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethical Approval: This study does not involve any human participants, animals, or sensitive data requiring ethical approval. All procedures followed were in accordance with standard academic research practices.

Data Availability Statement: The datasets used in this study are publicly available from open-access repositories. The adulterated all-purpose flour (maida) dataset can be accessed through the Mendeley Data repository, which contains image samples of flour mixed with adulterants such as chalk powder. Additionally, the adulterated chilli dataset, consisting of pure and contaminated chilli powder images with varying adulteration levels, is also obtained from publicly accessible repositories. These datasets are available for research purposes using the citation [35-37].

References

1. N. A. Sagar and N. Rani, “Recent trends in AI-based food packaging and safety monitoring,” Frontiers in Food Science and Technology, 2026.
2. A. Sharma, M. Yadav, and N. Kumar, “Rapid detection of milk adulteration using AI-driven portable colorimetric spectroscopy,” Discover Food, 2026.

3. “Applications and challenges of AI-driven systems in the modern food industry,” International Journal of Scientific Research and Engineering Trends, vol. 12, no. 1, 2026.
4. “Artificial intelligence revolutionizing food detection: Vision, olfaction and taste integrated with deep learning,” Food Chemistry, vol. 499, 2026.
5. “Deep learning-based food quality inspection using convolutional neural networks,” Journal of Food Engineering, 2026.
6. P. Roy and S. Banerjee, “Computer vision-based adulteration detection using hybrid CNN models,” IEEE Access, 2026.
7. J. Lee and S. Park, “Deep semantic segmentation networks for food quality monitoring,” IEEE Transactions on Industrial Informatics, 2026.
8. P. Das et al., “Recent advances on AI-based approaches for food adulteration detection,” Food Chemistry, vol. 468, 2025.
9. Y. Yu et al., “Meat species authentication using portable hyperspectral imaging,” Frontiers in Nutrition, 2025.
10. Ahmed, Esmael. “Detection of Honey Adulteration Using Machine Learning.” PubMed, 2024, https://pubmed.ncbi.nlm.nih.gov/38857195/.
11. Brar, Dilpreet Singh, Birmohan Singh, and Vikas Nanda. “Application of Deep Learning and Explainable Artificial Intelligence (XAI) for Detecting Red Chilli Powder Adulteration.” Journal of Food Composition and Analysis, vol. 146, Oct. 2025, article 107947, Elsevier.
12. Brar, Dilpreet Singh, Birmohan Singh, and Vikas Nanda. “An XAI-enabled 2D-CNN Model for Non-Destructive Detection of Natural Adulterants in the Wonder Hot Variety of Red Chilli Powder.” Sustainable Food Technology, 2025, RSC Publishing, DOI:10.1039/D5FB00118H.
13. Goyal, Rishabh, Poonam Singha, and Sushil Kumar Singh. “Spectroscopic Food Adulteration Detection Using Machine Learning: Current Challenges and Future Prospects.” Trends in Food Science & Technology, vol. 146, Apr. 2024, Elsevier, DOI:10.1016/j.tifs.2024.104377.
14. Nargesi, Mohammad Hossein, and Kamran Kheiralipour. “Ability of Visible Imaging and Machine Learning in Detection of Chickpea Flour Adulterant in Original Cinnamon and Pepper Powders.” Heliyon, vol. 10, no. 16, 2024, e35944, PMC.
15. Anthati Sreenivasulu. “The Chemistry of Food Adulteration in the Age of Artificial Intelligence: A Comprehensive Review.” International Journal of Research and Innovation in Applied Science (IJRIAS), vol. 100700081, Aug. 2025.
16. “Application of Machine Learning and Deep Learning to Detect Adulteration in Food Flour Based on Spectroscopy Data: A Systematic Review.” BIO Web of Conferences, EDP Sciences, 2025.
17. Song, Danliangmin, et al. “Research Advances in Detection of Food Adulteration and Application of MALDI-TOF MS: A Review.” Food Chemistry, vol. 456, 30 Oct. 2024, Elsevier, DOI:10.1016/j.foodchem.2024.140070.
18. Quach Thi Thai Binh, et al. “Rapid Machine Learning-Driven Detection of Pesticides and Dyes Using Raman Spectroscopy.” arXiv, 15 Nov. 2025, https://arxiv.org/abs/2511.12167.
19. Casa, Alessandro, Thomas Brendan Murphy, and Michael Fop. “A Latent Variable Model for Identifying and Characterizing Food Adulteration.” arXiv, 15 Dec. 2025, https://arxiv.org/abs/2512.13939.
20. Al-Awadhi, Mokhtar A., and Ratnadeep R. Deshmukh. “Detection of Adulteration in Coconut Milk Using Infrared Spectroscopy and Machine Learning.” arXiv, 31 July 2025, https://arxiv.org/abs/2507.23418.
21. “Honey Adulteration Detection via Ultraviolet–Visible Spectroscopy.” Foods, vol. 13, no. 22, 2024, MDPI, https://www.mdpi.com/2304-8158/13/22/3630.
22. Teklemariam, T. A. “Raman and Mid-Infrared Spectroscopy Coupled With Machine Learning for Food Adulteration Detection.” SAGE Journals, 2024.
23. Ilias, Boulbarj, et al. “Leveraging RegNet and CBAM for Precise Detection of Honey Adulteration Using Thermal Image Analysis.” Scientific Reports, vol. 15, article 36555, 2025, Nature Publishing Group.
24. “Rapid Detection of Honey Adulteration Using Machine Learning and BME688 Gas Sensor Matrix.” PubMed, 2025, https://pubmed.ncbi.nlm.nih.gov/40368947/.
25. “Honey Adulteration Detection Using Hyperspectral Imaging and Machine Learning.” Journal of Advanced Applied Scientific Research, 2025.
26. Othman, Suhaili, et al. “Artificial Intelligence-Based Techniques for Adulteration and Defect Detections in Food and Agricultural Industry: A Review.” Journal of Agriculture and Food Research, vol. 12, 2023.
27. “Deep Neural Networks for Adulteration Detection in Red Chilli Powder: A Pillar for Food Quality 4.0.” Journal of Future Foods, 2025, Elsevier.
28. “Food Adulteration and Its Detection Using Artificial Intelligence.” Parul and Dr. Gurpreet Kaur. Educational Administration: Theory and Practice, vol. 29, no. 4, 2023, DOI:10.53555/kuey.v29i4.7236.
29. Lanjewar, M. G., et al. “Sugar Detection in Adulterated Honey Using Hyper-Spectral Imaging and Machine Learning.” Food Chemistry, 2024, DOI:10.1016/j.foodchem.2024.139322.
30. “Food Adulteration Detection and Sorting Solution Through Machine Learning.” IARJSET, 2023.
31. “Application of Spatial Offset Raman Spectroscopy (SORS) With Machine Learning for Honey Authentication.” PMC, 2025.
32. “Machine Learning Applied to the Detection of Mycotoxin in Food: A Review.” Inglis, Alan, et al. arXiv, 23 Apr. 2024, https://arxiv.org/abs/2404.15387.
33. “Unmasking Honey Adulteration: CNN Thermal Image Analysis for Quality Assurance.” arXiv, 12 Feb. 2024, https://arxiv.org/abs/2402.08122.
34. D. Liu, E. Zuo, D. Wang, L. He and X. Lu, “Deep learning in food image recognition: A comprehensive review,” Applied Sciences, vol. 15, no. 14, 2025.

35. M P, Aishwarya; Reddy, Padmanabha (2024), “chili dataset”, Mendeley Data, V1, doi: 10.17632/tf9dtfz9m6.1
36. Brar, D. S. (2025). Red Chilli Adulteration: Digital Image Dataset (DS-KT-1.0) (Version 2) [Data set]. Mendeley Data. https://doi.org/10.17632/ppy7vg8h7z.2
37. Sarkar, Sunindita ; Hazra , Dip ; Sarkar, Tanmoy (2025), “Digital image Analysis aided Adulteration detection dataset for All purpose flour Adulterant with chalk powder ”, Mendeley Data, V1, doi: 10.17632/2gth2s4p3t.1