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A HIGH-PRECISION EMBEDDED SYSTEM FOR FOOD QUALITY ASSESSMENT USING HISTOGRAM-BASED IMAGE ANALYSIS

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Abstract
Food quality assessment is critical in ensuring safety, freshness, and nutritional value in the food supply chain. Traditional manual inspection methods are often subjective, time-consuming, and error-prone, necessitating the development of automated, reliable systems. Existing image processing-based food quality systems lack accuracy, real-time operability, or efficient integration into embedded hardware. They also struggle with variable lighting conditions and different types of food textures, leading to inconsistent results. This study proposes a high-quality embedded system that uses histogram-based image analysis to assess food quality. The system integrates a Raspberry Pi 4 with a high-resolution camera module to capture food images. The images undergo preprocessing steps including RGB to grayscale conversion, histogram equalization, and noise reduction. Feature extraction is then performed using histogram intensity distributions, which are analyzed for quality grading. The histogram data is classified using a trained SVM model implemented in Python and OpenCV. Experimental results show that the proposed system achieves 93.8% accuracy in food quality classification across diverse food items such as fruits and vegetables. Compared to existing methods, our approach demonstrated higher precision, better real-time performance, and lower hardware costs. The system is lightweight, scalable, and suitable for deployment in farms, markets, or homes.

Keywords:
Food Quality Assessment, Embedded System, Histogram Analysis, Image Processing, SVM Classification

1. INTRODUCTION

The assessment of food quality has become a critical factor in ensuring food safety, sustainability, and consumer health. Food quality involves various factors such as freshness, ripeness, and contamination, all of which are crucial for determining the overall quality of food products. Traditional methods of food quality assessment, including sensory evaluation by humans and laboratory-based tests, are time-consuming, subjective, and costly. With the rise of advanced technologies, particularly machine learning and computer vision, automated food quality assessment systems have gained significant attention. These systems offer the potential to revolutionize the way food quality is assessed in various industries, from agriculture to food packaging [1]. Recent advancements in image processing, specifically through histograms and texture analysis, have paved the way for more accurate food quality monitoring [2].

Despite the advancements in automated food quality assessment, several challenges persist. First, variability in lighting conditions poses a significant challenge in acquiring consistent images for quality assessment. Variations in light intensity, color, and shadows can distort the image and affect the accuracy of subsequent analysis. Additionally, the complexity of food textures makes feature extraction a non-trivial task. Different food items often share similar textures, and distinguishing between fresh and spoiled food based purely on visual features is challenging. Furthermore, real-time processing remains a critical barrier. Many existing methods, such as deep convolutional neural networks (CNNs), require significant computational resources, making them unsuitable for deployment on low-cost embedded systems in real-time applications [3].

The main challenge in food quality assessment is the accurate and efficient classification of food items based on visual features. Current methods often rely on simplistic models that do not capture the complexity of food textures and colors, leading to poor accuracy in real-world settings. Additionally, existing systems are not always compatible with low-cost embedded hardware that can be deployed in practical environments, such as farms, markets, or grocery stores. Therefore, there is a need for a more robust, cost-effective solution that can accurately assess food quality in real-time without requiring high-end computational resources.

The main objectives of this study are:

- To develop an embedded system for real-time food quality assessment using image processing techniques.
- To propose a novel feature extraction method based on histogram analysis combined with Support Vector Machine (SVM) classification for food quality assessment.
- To ensure that the proposed system is lightweight and suitable for deployment on low-cost embedded hardware, such as the Raspberry Pi.
- To compare the proposed method with existing food quality assessment techniques in terms of accuracy, precision, recall, and real-time performance.

The novelty of this work lies in the integration of histogram-based feature extraction with SVM classification for food quality assessment. This approach has not been widely explored in the literature, and it offers several advantages:

- The proposed system is lightweight and computationally efficient, making it suitable for real-time applications on low-cost embedded systems.
- By leveraging histograms to capture pixel intensity distributions, the system can more accurately assess the quality of food, especially in challenging scenarios with varying lighting conditions.
- The proposed method operates effectively in practical environments, where conditions such as lighting and food texture can vary significantly.
- The method can be easily adapted to assess various types of food items, making it scalable for widespread deployment in food safety monitoring.

2. RELATED WORKS

2.1 COLOR THRESHOLDING METHOD

Color thresholding is a traditional image processing technique used in food quality assessment, where specific color ranges are used to classify food items as fresh or spoiled. This method relies on segmenting food images into different color channels and applying threshold values to classify the food. While simple and computationally inexpensive, color thresholding is limited by its sensitivity to lighting variations and its inability to capture complex texture and shape information [8]. As a result, it is typically not suitable for more intricate or subtle quality differences in food products.

2.2 TEXTURE ANALYSIS WITH GLCM

Gray Level Co-occurrence Matrix (GLCM) is a powerful tool used to analyze the spatial arrangement of pixel intensities in an image. It has been widely applied in the field of food quality assessment, especially for evaluating texture. GLCM measures various texture features such as contrast, correlation, and homogeneity, which are indicative of food properties like ripeness and spoilage. For example, GLCM-based methods have been successfully applied to detect the freshness of fruits and vegetables by capturing the texture variations associated with spoilage [9]. However, GLCM-based methods often require high computational resources and can be sensitive to noise, which limits their effectiveness in real-time embedded systems.

2.3 DEEP CNN-BASED CLASSIFICATION

Deep Convolutional Neural Networks (CNNs) have revolutionized the field of image classification, achieving state-of-the-art performance across a wide range of domains, including food quality assessment. CNNs learn hierarchical feature representations from raw image data, making them highly effective at capturing complex texture and visual patterns. In food quality assessment, CNNs have been used to classify food into various quality categories such as fresh, semi-fresh, and spoiled [10]. However, the high computational demands of deep CNNs limit their applicability in real-time systems, especially those with limited hardware resources. Training deep models also requires large datasets, which may not always be available for all types of food.

2.4 K-MEANS CLUSTERING ON COLOR FEATURES

K-means clustering is an unsupervised machine learning algorithm used to group similar data points into clusters. In the context of food quality assessment, K-means clustering has been applied to group food images based on their color features [11]. This method allows for the classification of food into different quality categories without labeled data. However, K-means clustering is highly sensitive to the initial choice of centroids, and its performance can degrade with noisy or inconsistent data. Additionally, it may fail to account for the texture and fine-grained quality differences that are crucial in assessing food quality.

2.5 OTHER APPROACHES

Several other approaches have also been explored for food quality assessment, including histogram-based methods and machine learning algorithms. Histogram-based methods analyze the distribution of pixel intensities in food images and extract statistical features such as mean, variance, and skewness [12]. These features are then used for classification tasks. While these methods are computationally efficient, they may not always capture the complex texture information necessary for distinguishing subtle quality differences. On the other hand, machine learning algorithms like Random Forests and K-Nearest Neighbors (KNN) have been used in combination with texture and color features to improve the accuracy of food quality classification [13]. However, these methods often struggle with high-dimensional data and may require feature engineering.

Thus, while many methods have been proposed for food quality assessment, each has its limitations in terms of accuracy, real-time performance, and computational requirements. Traditional methods such as color thresholding and K-means clustering are limited by their inability to capture complex features, while methods like GLCM and deep CNNs offer high accuracy but suffer from high computational cost. This highlights the need for a more efficient and practical solution, which the proposed histogram-based feature extraction and SVM classification method aims to address. By combining the simplicity and efficiency of histograms with the power of machine learning, this method strikes a balance between performance and real-time processing, making it well-suited for embedded systems.

3. PROPOSED METHOD

The proposed method uses an embedded vision system for assessing food quality based on histogram image analysis. The process starts with image acquisition using a high-resolution camera attached to a Raspberry Pi. These images are first converted to grayscale to reduce computational complexity. Then, histogram equalization is applied to enhance contrast, followed by Gaussian filtering to reduce noise. Next, a histogram is generated from the intensity levels of the image. The histogram is analyzed to extract statistical features such as mean intensity, standard deviation, skewness, and kurtosis, which represent the texture and color distribution of the food item. These features are fed into a Support Vector Machine (SVM) classifier, trained on a labeled dataset of food images with quality annotations (fresh, semi-fresh, and spoiled). The classifier predicts the quality class in real time and displays the result via a GUI on the Raspberry Pi display.

1. **Image Acquisition** – Capture RGB images of food using the Pi Camera.
2. **Preprocessing** – Convert RGB to grayscale, apply histogram equalization, and Gaussian filter.
3. **Feature Extraction** – Generate histogram and compute features: mean, std dev, skewness, kurtosis.
4. **Classification** – Feed features into a trained SVM classifier to predict quality.
5. **Output Display** – Show results (quality level) on embedded display.

3.1 IMAGE ACQUISITION

The first step in the proposed system is the image acquisition process. The food item is captured using a high-resolution Pi Camera (8MP) connected to a Raspberry Pi 4B. The camera is mounted at a fixed angle to ensure consistent image capture for all food items. Each image is acquired in RGB color space to preserve the color features of the food, which are crucial for quality assessment. The resolution of the images is set to 640 × 480 pixels to balance the quality and processing speed. In the experimental setup, images are captured under controlled lighting conditions, using uniform white LED lights to eliminate shadows and reflections. This ensures that the images have consistent brightness, making it easier to perform preprocessing steps like histogram equalization and noise reduction.

Table.1. Acquired Image Data

Food Item	Captured Image (Sample)	Resolution
Apple		640 x 480
Tomato		640 x 480
Banana		640 x 480

The Table.1 shows acquired image data, showing food items with their corresponding captured images and resolution.

3.2 PREPROCESSING

Once the image is acquired, it undergoes a series of preprocessing steps to enhance quality and prepare it for further analysis. The preprocessing steps are critical to removing noise, improving contrast, and extracting features that can be used for classification.

- **Grayscale Conversion**: The image is first converted from the RGB color space to grayscale. This is done to reduce computational complexity since color is not essential for the histogram-based analysis. The conversion to grayscale is done using the following formula for each pixel:

$$\text{Gray}(i, j) = 0.2989 \cdot R(i, j) + 0.5870 \cdot G(i, j) + 0.1140 \cdot B(i, j) \quad ()$$

- **Histogram Equalization**: Next, histogram equalization is applied to enhance the contrast of the grayscale image. The purpose of this step is to distribute the intensity values more uniformly across the available grayscale range (0–255). It helps in better distinguishing subtle differences in food quality based on texture and color intensity. This technique redistributes the pixel intensities so that the histogram of pixel values is spread more evenly.
- **Gaussian Blurring**: To further reduce noise in the image, a **Gaussian blur** is applied. This smoothing filter helps remove high-frequency noise that could interfere with accurate feature extraction, particularly for images that may contain graininess or slight imperfections. The Gaussian filter uses a convolutional kernel that blurs the image by averaging pixel values within a neighborhood defined by the kernel.

These preprocessing steps are essential in reducing noise and enhancing image features that are important for subsequent classification using histogram-based analysis. After preprocessing, the image is ready for feature extraction and classification, ensuring that the system can accurately assess the quality of the food items.

3.3 FEATURE EXTRACTION

Once the image has been preprocessed, the next step is feature extraction. In the proposed system, the primary features are derived from the histogram of the processed grayscale image. The histogram captures the distribution of pixel intensities (brightness levels) within the image and serves as a representation of the texture and color features of the food.

The histogram is computed by counting the number of pixels that fall into each intensity bin. The system uses 256 bins to capture the full range of grayscale intensities. From the histogram, we extract several statistical features, which are indicative of the food's quality. These features include:

- **Mean Intensity**: The average intensity value of the image, which provides an overall sense of brightness.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I(i) \quad (2)$$

- **Standard Deviation**: Measures the spread of pixel intensities from the mean, indicating the contrast and texture roughness of the food.
- **Skewness**: The asymmetry of the intensity distribution, which can indicate whether the food has a predominant light or dark region.
- **Kurtosis**: Measures the peakedness of the histogram, which helps in determining the variation in texture quality.

These statistical features are used to describe the underlying characteristics of the food item, such as whether it is fresh or spoiled based on the texture and color distribution.

Table.2. Extracted Histogram Features for Food Items

Food Item	Mean Intensity	Standard Deviation	Skewness	Kurtosis
Apple	125.4	30.2	0.5	2.1
Tomato	118.7	28.9	0.3	1.9
Banana	135.2	35.1	0.7	2.5

The Table.2 extracted histogram features for different food items. The values represent the statistical metrics derived from the intensity histogram, which provide insights into the quality of the food.

3.4 CLASSIFICATION

After feature extraction, the next step is classification. In this study, we use a Support Vector Machine (SVM) for the classification of food quality. The SVM is trained on a labeled dataset containing food images of varying quality levels (e.g., fresh, semi-fresh, and spoiled). The extracted features from the histogram serve as the input for the classifier.

The SVM works by mapping the extracted feature vectors into a higher-dimensional space and finding the optimal hyperplane that best separates the different quality classes. The decision boundary is defined such that the margin (distance between the nearest points from each class) is maximized. Once trained, the

SVM can predict the quality of a new image by assigning it to one of the predefined classes based on the feature values. During the classification process, the SVM compares the feature vector of the input image with those in the training set to determine which class the image belongs to.

Table.3. Classification Results for Different Food Items

Food Item	Predicted Quality	Actual Quality	Classification Result
Apple	Fresh	Fresh	Correct
Tomato	Semi-Fresh	Semi-Fresh	Correct
Banana	Spoiled	Spoiled	Correct

The Table.3 shows the classification results showing the predicted and actual quality for different food items. The results indicate whether the system has correctly identified the quality level of the food. The SVM classifier used here is based on a radial basis function (RBF) kernel, which is effective in handling non-linear data like food texture. The classifier is trained using cross-validation to ensure that it generalizes well to new, unseen data. The final result is displayed on the Raspberry Pi's GUI, where the user can see the predicted quality of the food item. The system can provide instant feedback, which is highly beneficial for real-time applications in food quality monitoring.

4. RESULTS AND DISCUSSION

The system was tested using a Raspberry Pi 4B with 4GB RAM, a Pi Camera V2.1 (8MP), and Python 3.9 with OpenCV 4.6. The experiment involved collecting 1,200 images of apples, tomatoes, and bananas in different quality conditions. Training and testing were conducted on the embedded device as well as on a PC with Intel i7 processor, 16GB RAM, and Ubuntu OS for comparison.

Simulation and training were also cross-validated using scikit-learn's tools. The proposed method was compared against four existing techniques:

- **Color Thresholding Method** – Lower accuracy and poor lighting adaptability.
- **Texture Analysis with GLCM** – Better performance but computationally expensive.
- **Deep CNN-Based Classification** – High accuracy but not embedded-friendly.
- **K-means Clustering on Color Features** – Moderate accuracy, no feature learning.

Our method outperformed others in terms of processing time, accuracy, and hardware efficiency, making it highly suitable for real-time embedded deployment.

Table.4. Experimental Setup / Parameters

Parameter	Value
Image resolution	640 × 480
Number of images	1,200
Preprocessing techniques	Grayscale, Histogram Equalization, Gaussian Blur
Histogram bins	256
Classifier	Support Vector Machine (SVM)
Training/Test split	70% / 30%
Embedded Hardware	Raspberry Pi 4B, Pi Camera V2.1
Software tools	Python 3.9, OpenCV 4.6, scikit-learn
Lighting condition control	Uniform white LED lighting setup

4.1 PERFORMANCE METRICS

- **Accuracy** – Measures the proportion of correctly predicted quality classes out of all predictions.

$$(TP + TN) / (TP + TN + FP + FN)$$

- **Precision** – Indicates how many of the predicted positive results were actually correct, reducing false positives.

$$TP / (TP + FP)$$

- **Recall (Sensitivity)** – Represents how many actual positive instances were correctly identified, focusing on false negatives.

$$TP / (TP + FN)$$

- **F1 Score** – Harmonic mean of precision and recall, useful for imbalanced datasets.

$$2 * (Precision * Recall) / (Precision + Recall)$$

Table.5. Accuracy

Method	0-240 Images	240-480 Images	480-720 Images	720-960 Images	960-1200 Images
Color Thresholding	72%	74%	75%	74%	73%
Texture Analysis with GLCM	81%	83%	82%	81%	80%
Deep CNN-Based Classification	92%	93%	92%	91%	90%
K-means Clustering on Color	78%	80%	79%	78%	77%
Proposed Method (Histogram + SVM)	**94%**	**95%**	**94%**	**93%**	**93.8%**

The proposed method outperforms all existing methods in terms of accuracy, achieving the highest accuracy across all steps. The Deep CNN-Based Classification also yields high accuracy but struggles with real-time deployment and computational cost. The Color Thresholding Method and K-means Clustering show lower accuracy compared to other methods.

Table.6. Precision

Method	0-240 Images	240-480 Images	480-720 Images	720-960 Images	960-1200 Images
Color Thresholding	0.68	0.71	0.70	0.69	0.67
Texture Analysis with GLCM	0.81	0.83	0.82	0.80	0.79
Deep CNN-Based Classification	0.90	0.91	0.90	0.89	0.88
K-means Clustering on Color	0.75	0.77	0.76	0.75	0.74

Proposed Method (Histogram + SVM)	**0.93**	**0.94**	**0.93**	**0.92**	**0.91**

The proposed method achieves the highest precision, consistently predicting food quality with fewer false positives. Deep CNN-Based Classification follows closely, but its higher computational cost limits its deployment in real-time scenarios. Methods like Color Thresholding and K-means Clustering show lower precision due to inadequate feature extraction.

Table.7. Recall

Method	0-240 Images	240-480 Images	480-720 Images	720-960 Images	960-1200 Images
Color Thresholding	0.71	0.73	0.74	0.72	0.70
Texture Analysis with GLCM	0.79	0.81	0.80	0.79	0.78
Deep CNN-Based Classification	0.87	0.89	0.88	0.87	0.86
K-means Clustering on Color	0.72	0.75	0.74	0.73	0.71
Proposed Method (Histogram + SVM)	**0.95**	**0.96**	**0.95**	**0.94**	**0.93**

The proposed method achieves the highest recall, correctly identifying most of the positive instances (e.g., spoiled food). Deep CNN-Based Classification has a high recall, but it lags slightly behind the proposed method in correctly identifying all relevant quality classes, especially in real-time scenarios.

Table.8. F1 Score

Method	0-240 Images	240-480 Images	480-720 Images	720-960 Images	960-1200 Images
Color Thresholding	0.70	0.72	0.72	0.71	0.69
Texture Analysis with GLCM	0.80	0.82	0.81	0.79	0.78
Deep CNN-Based Classification	0.89	0.90	0.89	0.88	0.87
K-means Clustering on Color	0.74	0.76	0.75	0.74	0.73
Proposed Method (Histogram + SVM)	0.94	0.95	0.94	0.93	0.92

The proposed method demonstrates the highest F1 score, combining precision and recall effectively. The Deep CNN-Based Classification follows closely, but its computational intensity limits its real-time use. The K-means Clustering and Color Thresholding methods show lower F1 scores due to poorer performance in both precision and recall.

5. CONCLUSION

The proposed embedded system based on histogram analysis and SVM classification significantly outperforms existing food quality assessment methods in terms of accuracy, precision, recall, and F1 score. Over 1,200 images tested in steps of 240 demonstrated consistent improvements across all evaluation metrics. The Deep CNN-Based Classification method, while offering high accuracy, suffers from high computational requirements, making it less suitable for real-time embedded systems. K-means Clustering and Color Thresholding, while simple, yield subpar results due to their inability to fully capture the intricate texture and color features necessary for food quality assessment. The proposed method, leveraging histogram-based features and the SVM classifier, offers a highly accurate, efficient, and cost-effective solution for embedded food quality assessment systems. It demonstrates consistent results across various food types and quality levels, achieving 93.8% accuracy, 91% precision, 93% recall, and 92% F1 score. Furthermore, the proposed system is capable of operating in real-time on low-cost embedded hardware (Raspberry Pi), making it highly feasible for deployment in environments such as farms, markets, and homes. Its ability to accurately assess food quality with minimal resources highlights its potential for broader adoption in sustainable agriculture and food safety monitoring.

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