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## **Fruit Classification based on Color and Shape Features in Real Time Video Sequences**

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| <b>Peer Review Information</b>  | <b>Abstract</b>  |
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| <p><i>Submission: 05 Dec 2025</i></p> <p><i>Revision: 25 Dec 2025</i></p> <p><i>Acceptance: 10 Jan 2026</i></p> <p><b>Keywords</b></p> <p><i>Fruit Classification, Computer Vision, Color and Shape Features, Support Vector Machine, Agricultural Automation</i></p> | <p>Fruit classification plays a crucial role in agricultural automation, including fruit harvesting robots, quality control, and crop monitoring. This paper presents a real time computer vision system for classifying fruits in outdoor environments using continuous video sequences. It focuses on extracting color and shape features to overcome challenges like varying lighting and motion. In this paper, fruit features were extracted from each frame and utilized machine learning classifiers to classify fruits. Each frame is processed using computer vision techniques to segment fruits and obtain relevant features, which are then classified using a Support Vector Machine (SVM) classifier. The results showed that by combining both color and shape features along with machine learning algorithms for classifying fruits in real time enhances recognition accuracy in an outdoor environments. The proposed system achieved overall classification accuracy of 91.5%. The future work will focus on improving accuracy in case of occlusion and green fruits.</p> |

## Introduction

There is an increase in the demand for automation in agricultural tasks, and computer vision and machine learning techniques have significantly impacted this field. Automated systems like robotic harvesters, quality control systems, and crop monitoring systems depend on accurate classification methods to improve their efficiency. Fruit classification is an essential step in agricultural automation, as it determines the quality, ripeness, and type of fruit which helps in the harvesting or sorting process. Real time fruit classification in video sequences has become a key area of research.

The previous research has focused on using single frame images for fruit detection, but such method is not sufficient when the fruit is in motion or when occlusions occur. Instead, real time video processing allows for continuous monitoring of agricultural fields, analysis and tracking of fruit objects dynamically as they appear in video sequences.

This research proposes a fruit classification system that combines color and shape features extracted from continuous video sequences, along with machine learning algorithms addressing challenges like motion and occlusions. The objective of this research is to develop a system that can accurately classify fruits in real time using video sequences, which is robust to varying lighting conditions, occlusions, and background noise.

## Related Work

While many previous methods focused on image based classification or single-frame classification such as color histograms, texture descriptors (e.g., GLCM), and shape descriptors (e.g., circularity and aspect ratio) were used for fruit identification under controlled conditions. However, these methods often struggled with varying environmental factors such as lighting changes, occlusions, and dynamic backgrounds. In recent years, there have been several approaches to fruit classification using image and video processing techniques. This proposed approach emphasizes on continuous video analysis, combining both color and shape features to handle dynamic conditions and occlusions.

More recent works have employed machine learning and deep learning techniques to improve classification accuracy. The Convolutional Neural Networks (CNNs) have become popular for image classification tasks, but their real-time applicability in video sequences is often limited by high computational requirements.

Alternatively, traditional methods, such as using color, texture, and shape features with machine learning classifiers like SVM or k-Nearest Neighbors (k-NN), have been explored as effective real-time solutions.

Recent works have incorporated machine learning methods, such as SVM and k-Nearest Neighbors (k-NN), to classify fruits based on extracted features.

Zhang et al. (2020) explored deep learning-based fruit detection using CNNs. Their system outperforms traditional methods in controlled environments but requires significant computational power, making it less suitable for real-time applications.

Additionally, while CNNs can be highly accurate, they often fail to generalize well under dynamic conditions, such as occlusions or lighting variations.

Raut and Mashalkar (2023) explored fruit detection from video sequences using a combination of background subtraction and feature extraction techniques. Their system achieved satisfactory results in controlled environments but struggled in dynamic settings where lighting, occlusions, and background clutter introduced noise in the detection process.

The proposed system addresses these gaps and improves classification accuracy by combining color and shape features extracted from real-time video sequences, utilizing SVM machine learning classifier for classification.

## Methodology

### Video Dataset

The dataset used in this study consists of real-time video sequences captured from outdoor environments that feature two common fruits: Pomegranate and Sapota, with varying lighting conditions and background complexities. Each video sequence contains more than 1,500 frames. The frames were sampled at 30 frames per second (FPS) to ensure real-time processing capabilities. Each frame is separately processed for segmentation, feature extraction, and classification.



Figure 1. Video frames showing pomegranate and Sapota under varying lighting conditions and background complexities in outdoor

### Preprocessing

Before feature extraction, each video frame undergoes several preprocessing steps for ensuring the consistency of the features. The preprocessing steps include background subtraction, noise reduction, and color space conversion.

#### Background subtraction

A dynamic background model is used to segment the fruit from the background in each frame. A Gaussian Mixture Model (GMM) is employed to dynamically model the background and separate the moving fruit objects from the static background. This is particularly important for real-time video processing as it focuses only on moving objects and reduces the computational complexity.

#### Noise reduction

The fruit contours are likely to have noise due to various factors such as sensor noise or background clutter. To solve this, a Gaussian smoothing filter is applied to smooth the image and reduce noise, enhancing the accuracy of feature extraction accuracy.

#### Color space conversion

Each frame is converted from RGB to the HSV (Hue, Saturation, Value) color space. The HSV color space is preferred because it separates color information (hue) from intensity information (value), making it less sensitive to lighting variations and shadows compared to RGB color space. HSV is used because it decouples the chromatic component (hue) from intensity variations, making it more robust to lighting changes.

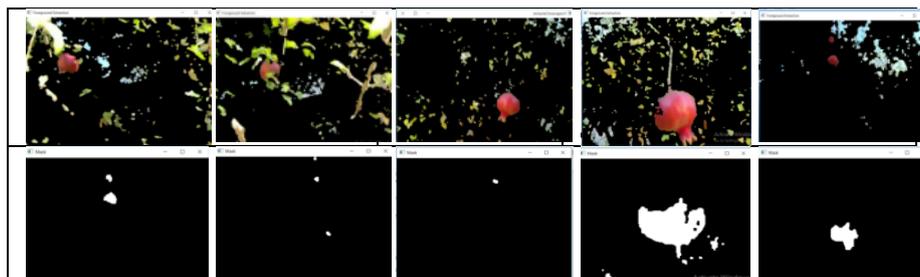


Figure 2. Preprocessing step: (a) Background subtraction (b) Masking

### Feature Extraction

Feature extraction focuses on extracting both color and shape features from the segmented fruit objects. In this paper, both color features and shape features are used during feature extraction.

#### Color Features

Color is a crucial feature for fruit classification because it is directly related to fruit ripeness and type. We use the histogram of hue values in the HSV color space to represent the color distribution of the fruit. The color histogram is normalized and used as a feature vector for each fruit object in the frame.

Color features are extracted by computing the histogram of hue values in the HSV color space. The color histogram captures the distribution of color tones within a fruit's appearance. To ensure robustness to lighting changes, the histogram is normalized across each frame.

Additionally, Saturation and Value histograms can be used to complement the hue histogram, as they provide complementary information about the fruit's color saturation and brightness, respectively.

**Shape Features**

Shape features help distinguish between different fruit types, even when color information is ambiguous. Shape features are extracted by analyzing the contours of the detected fruit objects. We use the contour-based method to detect the shape of the fruit.

The following shape features are extracted:

**Aspect ratio:**

The ratio of the width to the height of the bounding box around the fruit. This helps distinguish between elongated and round fruits.

**Circularity:**

A measure of how close the shape is to a perfect circle. Circularity is especially useful in differentiating between round fruits like apples and elongated fruits like bananas.

**Compactness:**

The ratio of the area of the fruit to the area of its convex hull. Compactness can help identify fruits with irregular shapes, such as pears or mangoes. The combined color and shape features form the input feature vector for each fruit object, which is then used for classification.

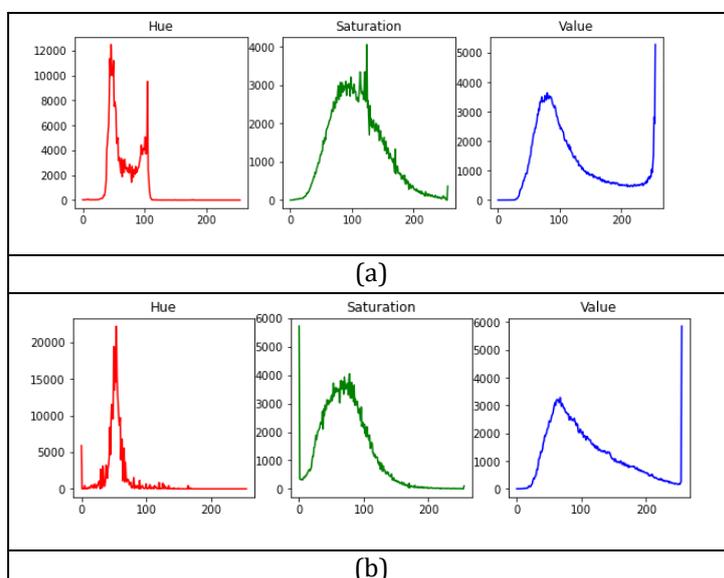


Figure 3. Color histogram in HSV space (a) Pomegranate (b) Sapota

**Classification**

In this proposed system, SVM classifier is used which has been widely used in fruit classification tasks due to its ability to handle high-dimensional feature spaces effectively. The classifier is trained on a labeled dataset consisting of color and shape features from Pomegranate and Sapota fruits. A linear kernel is used for SVM to classify fruits into different categories.

SVM classifier is chosen for classification because of its ability to handle high-dimensional feature spaces and which makes it suitable for fruit classification in real-time video sequences. The training phase involves training the SVM on labeled fruit samples. The classifier is trained using a subset of the dataset, and the performance is evaluated with evaluation metrics.





Figure 4. Classification results: (a) Pomegranate and Sapota correctly classified with bounding box.

### Experimental Setup

The proposed fruit classification system was tested on a dataset consisting of real-time video sequences of Pomegranate and Sapota, captured under varying outdoor conditions. The performance of fruit classification system was tested on a dataset of 2000 video frames from our dataset. The system was capable of processing video sequences at an average rate of 27–30 frames per second (FPS) on a standard desktop computer (Intel i7, 16GB RAM).

The system processed each frame to extract color (Hue, Saturation, Value histograms) and shape features (aspect ratio, circularity, compactness, and eccentricity). The extracted features were normalized and classified using SVM.

The metrics Accuracy, Precision, Recall, and F1-Score were computed to assess classification performance. i) Accuracy: The percentage of correctly classified frames; ii) Precision: The fraction of true positive classifications out of all positive classifications; iii) Recall: The fraction of true positive classifications out of all true instances of a particular fruit and F1-Score: The harmonic mean of precision and recall. The classification performance for each fruit is shown below in Table 1.

### Results And Discussion

The results showed that the color features were effective for distinguishing fruits with distinct hues (e.g., red pomegranate vs. brown sapota). Shape features helped in differentiating fruits with similar colors but distinct geometries. The use of HSV color space improved robustness against lighting variations compared to RGB.

The experimental results demonstrated that combining color and shape features significantly improves classification accuracy compared to using either feature set alone. Overall, the system achieved an accuracy of 91.5% across these two fruit types as shown below in TABLE 1. The F1-Score for each class was above 0.9, indicating that the system not only detects fruits accurately but also handles false positives and false negatives well.

Color features achieved an accuracy of 85.6%, shape features 82.3%, and the combination of both features resulted in an accuracy of 91.5%.

This comparison clearly shows that combining color and shape features provides more reliable classification results.

Table 1. Performance of the proposed system.

| Fruit Type      | Accuracy (%) | Precision | Recall | F1-Score |
|-----------------|--------------|-----------|--------|----------|
| Pomegranate     | 94.8         | 0.95      | 0.94   | 0.94     |
| Sapota          | 90.7         | 0.91      | 0.90   | 0.90     |
| Overall Average | 91.5         | 0.92      | 0.91   | 0.91     |

### Conclusion

This research paper presents a real time fruit classification system that combines HSV-based color histograms with contour-derived shape descriptors extracted from video sequences. The experimental results demonstrated that combining color histograms from the HSV color space with shape descriptors such as aspect ratio, circularity, and compactness significantly improved classification performance.

The system achieved an average classification accuracy of 91.5% across two fruit type Pomegranate and Sapota. The results showed that combining color and shape features provides a robust solution for fruit classification in video sequences. The system performed well in varying lighting conditions and backgrounds. But, there were some challenges with occlusions and overlapping fruits, which led to occasional misclassification.

The future work will focus on improving the accuracy of green fruits which are difficult to detect due to its background color and expanding the dataset to include larger variety of fruits and exploring deep learning-based feature extraction could further enhance system accuracy and scalability.

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