Comparative Study of ML Classifiers for Fruit Detection using Statistical Features

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ABSTRACT
The automation of fruit detection and classification has become a vital component of modern precision agriculture. Real-time video processing enables dynamic and continuous fruit identification, offering significant potential for sorting, grading, and quality assessment applications. This paper presents an efficient feature extraction approach for real-time pomegranate identification using first and second-order statistical measures. The statistical features mean, standard deviation, skewness, energy, entropy, contrast, homogeneity and correlation are derived from image frames captured in real-time video sequences using the Python OpenCV library. These features are then used to train and evaluate multiple machine learning classifiers, including Logistic Regression (LR), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Decision Tree (DT) and k-Nearest Neighbors (k-NN). These classifiers are evaluated using confusion matrix, accuracy, precision, recall, and F1-score metrics. The experimental results show that first and second-order statistical features provide a computationally efficient and reliable representation for real-time fruit classification. Among the evaluated models, Logistic Regression achieved the highest classification accuracy of 76.19%. The findings demonstrate that statistical feature based techniques can be lightweight alternatives to deep learning approaches for resource constrained agricultural automation systems.

General Terms
Computer Vision, Machine Learning, Pattern Recognition

Keywords
Feature Extraction, Statistical Measures, Real-Time Video Processing, Fruit Classification, GLCM, OpenCV, Machine Learning, Agricultural Automation

1. INTRODUCTION
The rapid advancement of automation technologies has significantly influenced modern agriculture. Automated fruit identification systems not only reduce labor costs but also improve productivity and product quality. Such systems commonly employ image processing and computer vision techniques to analyze visual features such as shape, color, and texture, enabling the classification and recognition of various fruit types in both static images and dynamic video environments.

In recent years, real-time video processing has emerged as a powerful tool for agricultural automation. Unlike static image-based systems, real-time video enables continuous monitoring and instant classification of fruits as they appear in live video streams. This capability is particularly valuable in applications such as automated sorting, yield estimation, and robotic harvesting. However, the implementation of real-time fruit recognition poses challenges related to computational cost, lighting variation, and background complexity.

Image features play an important role in object recognition systems. Among the various feature extraction methods, statistical feature extraction remains an effective and computationally inexpensive approach for representing texture and intensity information. First-order statistical measures (e.g., mean, standard deviation, skewness, energy, and entropy) describe the distribution of pixel intensities within an image, providing insights into its overall brightness, contrast, and randomness. In contrast, second-order statistical measures, typically derived from the Gray Level Co-occurrence Matrix (GLCM), capture spatial relationships between neighboring pixels and are essential for characterizing texture patterns through features such as contrast, homogeneity, correlation, and variance.

By integrating these statistical descriptors, fruit recognition systems can effectively capture both local and global texture characteristics while maintaining low computational complexity. While deep learning-based methods have recently demonstrated high accuracy in fruit detection, they often demand substantial computational resources and large annotated datasets, which may not be suitable for real-time applications or resource-constrained environments.

This research proposes a real-time fruit identification system that combines first- and second-order statistical measures with machine learning algorithms to achieve efficient classification performance. This study focuses on pomegranate detection and classification from real time video sequences captured using the Python OpenCV library. The extracted statistical features are evaluated using machine learning classifiers and their performance assessed using evaluation metrics such as accuracy, precision, recall, and F1-score.

2. LITERATURE SURVEY
Many early systems for fruit classification utilized traditional image processing techniques, relying heavily on color, texture, and shape features. These methods typically involve extracting low-level features directly from the image, such as histograms of color distributions, edge detection, or texture analysis using Gray Level Co-occurrence Matrix (GLCM). These approaches are computationally efficient and are often used in embedded systems with limited resources.

Ren et al. (2020) [2] used Gaussian Mixture Models (GMM) and texture features to identify various fruits, achieving high classification accuracy for different fruit types. These systems often struggle with dynamic real-time applications due to diverse environments.

Ghazal et al. (2021) [5] investigated the use of traditional texture and shape features for fruit classification, comparing multiple classifiers, including k-NN and SVM. Their study

demonstrated the effectiveness of using low-complexity image processing features for fruit recognition tasks.
Several studies have explored CNN-based models for fruit classification, showing significant improvements in accuracy, especially for large and diverse datasets. Chen et al. (2022) [4] combined traditional texture and color features with machine learning algorithms for fruit classification. Their hybrid system demonstrated the advantages of feature extraction over CNN-based approaches, particularly in terms of processing speed.
Similarly, Jia et al. (2023) [3] presented a method using YOLOX-m, an optimized variant of the YOLO object detection model, for detecting green fruits in complex environments. While CNN-based methods achieve high accuracy, they require significant computational resources and large labeled datasets, which may not be practical for many real-time applications in agricultural automation.

3. METHODOLOGY

The proposed real-time pomegranate classification system has followed the methodology as shown below in Fig 1 which includes steps: real-time video acquisition and frame extraction, image preprocessing, feature extraction, dataset creation and feature visualization, and machine learning-based classification.

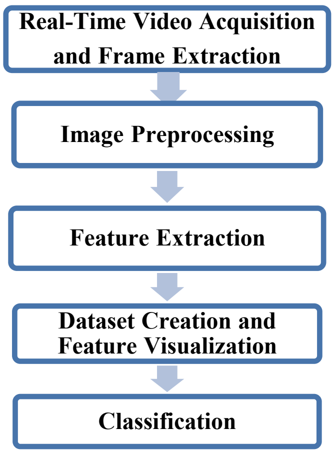


Fig 1: Methodology Steps

These steps work together to detect and classify pomegranates from live video sequences, leveraging statistical feature extraction combined with machine learning classifiers or efficient real-time performance.

3.1 Real-Time Video Acquisition and Frame Extraction

The first step in the proposed system involves capturing video sequences of pomegranates in real time. The video data is processed frame by frame to identify and classify the fruits. The OpenCV library in Python is employed for video capture, frame extraction, and image processing tasks. To facilitate real-time processing, the system operates in a dynamic environment, where pomegranates are detected within varying lighting conditions and backgrounds. The frame rate of the video capture is kept constant, and the system processes individual frames at a rate optimized for real-time performance. Using the Python OpenCV library, the system is able to capture video frames at a rate of 30 FPS. The frame rate may vary depending on the system's hardware.

Fig 2: Image frames extracted from video sequence of pomegranate in real time

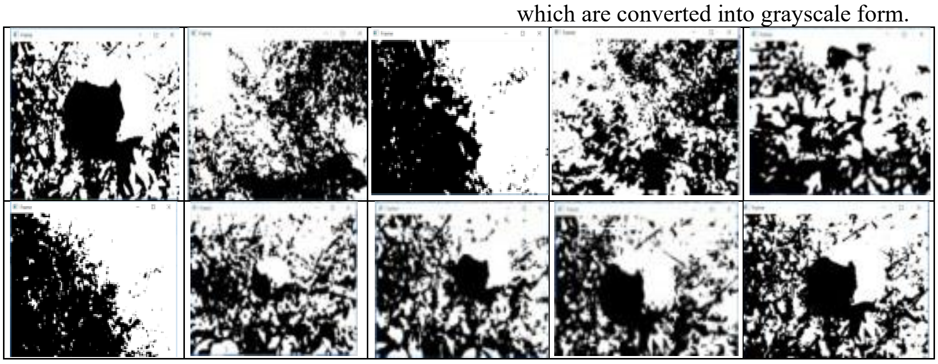
As shown in Fig 2, the Pomengranate image frames are extracted from real time video sequence. The total 2987 image frames are used as image dataset for this work.

3.2 Image Preprocessing

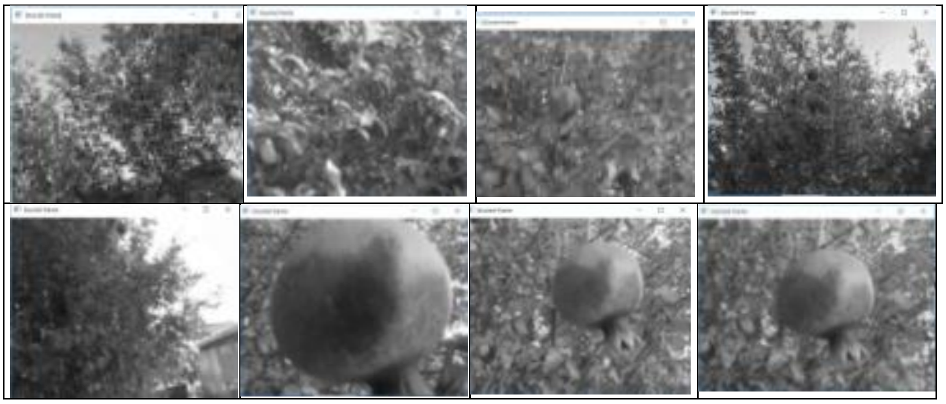
Image preprocessing is an important step to make input data suitable for feature extraction and classification. Such step is applied to reduce noise, enhance image quality, and simplify the image content for more effective feature extraction. The preprocessing, including grayscale conversion, Gaussian blurring, histogram equalization, and thresholding, was carried out on each frame before feature extraction.

3.2.1 Grayscale Conversion

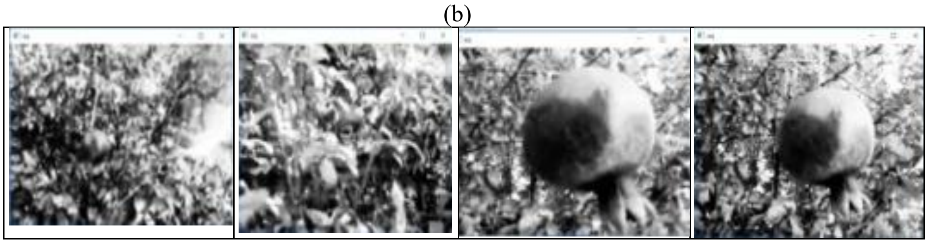
Converting the image to grayscale reduces the computational complexity by transforming the image into intensity values, thus eliminating the need to process multiple color channels. The following Fig 3 (a) shows the Pomegranate image frames which are converted into grayscale form.



(a)



(b)



(c)

Fig 4: (a) Grayscale conversion of Pomegranate image frames (b) Gaussian Blurring of Pomegrantae image frames (c) Histogram Equalized Pomegranate image frames

3.2.2 Histogram Equalization
To enhance the contrast of the image, histogram equalization is applied. This method redistributes the intensity levels across the image, improving the visibility of features that are critical for classification. The Table 3 below shows the enhanced Pomegranate image using histogram equalization.

3.2.3 Gaussian Blurring
A Gaussian filter is applied to the grayscale image to reduce noise and smooth out variations in intensity. This step helps in minimizing illumination problems and background noise that could otherwise affect feature extraction. The below Fig 3 (b) shows the Pomegranate image frames after applying Gaussian blurring.

3.2.4 Histogram Equalization
To enhance the contrast of the image, histogram equalization is applied. This method redistributes the intensity levels across the image, improving the visibility of features that are critical for classification. The Table 3 below shows the enhanced Pomegranate image using histogram equalization.

3.2.5 Thresholding
To isolate the pomegranate from the background, thresholding is employed. This technique converts the image to a binary format, distinguishing foreground objects (pomegranates) from the background. The thresholding value is selected dynamically based on the image content, allowing the system to adapt to varying lighting conditions and object appearances.

3.3 Feature Extraction
3.3.1 First-Order Statistical Features
First-order features are derived directly from the pixel intensities without considering the spatial relationships between pixels. These features describe the general distribution of pixel intensities and provide information about the brightness, contrast, and texture of the fruit.The first-order statistical features used in this study are mean, standard deviation, skewness, energy and entropy.

This Fig 1(c) presents the first-order statistical features extracted from the pomegranate images, providing a comprehensive overview of the intensity distribution across the image dataset.

3.3.2 Second-Order Statistical Features (GLCM)
Second-order features are derived from the Gray Level Co-occurrence Matrix (GLCM), which captures the spatial relationships between pixel pairs. The second-order statistical features contrast, homogeneity and coorelation were extracted from the pomegranate image frames. These features play a crucial role in analyzing the texture properties of images which is essential for distinguishing pomegranates from other / background objects.

3.4 Dataset Creation and Feature Visualization
To evaluate the classification performance, a dataset is created by extracting image frames from the real-time video sequence of Pomegranate. Each frame is processed to extract the statistical features. In order to better understand the distribution of these features and their relevance for classification, visualizations of the feature space are generated.

3.5 Classification
Once the features are extracted, a set of machine learning classifiers are employed to classify the fruit images based on the extracted statistical features. The five machine learning classifiers are used in this system. The Logistic Regression, a linear model for binary classification that estimates the probability of an image belonging to a particular class. Linear Discriminant Analysis, a technique that seeks to find a linear combination of features that best separates the classes. Support Vector Machine, a classifier that finds the optimal hyperplane to separate different classes in the feature space. Decision Tree, a tree-based model that makes decisions based on a series of feature thresholds. k-Nearest Neighbors**,** a non-parametric method where the class of a new sample is determined by the majority class of its k- nearest neighbors.

4. RESULTS AND DISCUSSION
The performance of the proposed system is evaluated using statistical features extracted from real-time video sequences.

To ensure a more comprehensive and reliable assessment, multiple evaluation strategies are employed. The classifiers are analyzed using standard performance metrics, cross-validation techniques, and comparative analysis under varying real-time conditions. The objective is to identify the most suitable classifier for real-time fruit detection.

Feature extraction plays a crucial role in the proposed system, as it derives meaningful representations from preprocessed images. In this study, first-order and second-order statistical features are utilized to capture both intensity distribution and spatial relationships among pixels, enabling effective discrimination between fruit and background.

4.1 Evaluation Metrics

The performance of each classifier is assessed using multiple evaluation metrics to provide a comprehensive analysis. Accuracy measures the proportion of correctly classified instances among the total samples. Precision indicates the proportion of true positive predictions among all predicted positives, while recall represents the proportion of true positives among all actual positive instances. The F1-score, defined as the harmonic mean of precision and recall, provides a balanced evaluation of the classifier performance.

In addition, a confusion matrix is used to analyze classification results in detail by comparing predicted and actual class labels. Based on confusion matrix, accuracy, precision, recall and F1-Score are calculated.

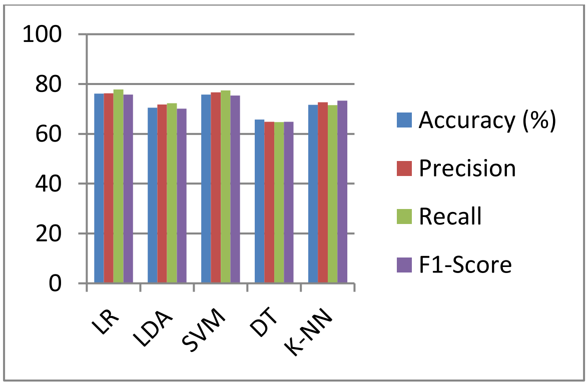
4.2 Performance Results

The evaluation results for each classifier are summarized below in Table 1:

Table 1: Classifiers, evaluation metrics and performance results

Classifier	Accuracy (%)	Precision	Recall	F1-Score
LR	76.19%	76.30%	77.78	75.81
LDA	70.48	71.85	72.36	70.17
SVM	75.71	76.67	77.50	75.38
DT	65.71	64.90	64.72	64.79
k-NN	71.71	72.67	71.50	73.38

Chart 1: Performance Results of Classifiers



The results indicate that Logistic Regression (LR) achieves the best overall performance among the evaluated classifiers, with an accuracy of 76.19%, precision of 76.30%, recall of 77.78%, and F1-score of 75.81%. Its superior performance suggests that the extracted statistical features are linearly separable to a certain extent, making LR a suitable choice due to its simplicity, computational efficiency, and suitability for real-time applications.

The SVM classifier also demonstrates competitive performance; however, its effectiveness is slightly limited, possibly because of noise and variations present in real-time video data. The LDA classifier shows comparatively lower performance, indicating that the assumption of class separability may not hold well for the given feature space. Decision Tree (DT) and k-NN classifiers exhibit moderate to lower performance, which may be attributed to overfitting (in DT) and sensitivity to noise and feature scaling (in k-NN).

To further strengthen the evaluation, the classifiers were analyzed under different real-time conditions, including variations in illumination, partial occlusion, and complex backgrounds. The results indicates that the combination of first-order and second-order statistical features yields better classification performance compared to individual feature sets.

5. CONCLUSION

This paper presented a real-time fruit detection and classification system for pomegranates using statistical feature extraction and machine learning classifiers. First-order and second-order statistical features were extracted from real-time video sequences and utilized for classification using Logistic Regression (LR), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Decision Tree (DT), and k-Nearest Neighbors (k-NN). Experimental results demonstrated that LR achieved the best performance among the considered classifiers, with an accuracy of 76.19%, precision of 76.30%, recall of 77.78%, and F1-score of 75.81%.

Apart from these results, the system performance is influenced by real-time challenges such as variations in illumination, occlusion, and similarity between fruit color and background, which limit its robustness in complex environments. Furthermore, the current evaluation is primarily conducted on a specific dataset.

To further strengthen the system, future work will focus on conducting more extensive evaluations across diverse datasets and real-world scenarios, including varying environmental conditions and larger-scale data. In addition, advanced feature extraction techniques and deep learning-based models such as Convolutional Neural Networks (CNNs) will be explored to improve classification accuracy and robustness. The proposed system can also be extended to multi-fruit detection and integrated with IoT-based smart agriculture systems for applications such as automated harvesting, yield estimation, and real-time monitoring.

6. ACKNOWLEDGMENTS

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