Enhancing Fruit Counting Solution [only circular shaped fruits]

Mr. Vivekanand Thakre[1], Mr. Khushi Shukla[2], Mr. Sayali Nannaware[3], Mr. Vidhi Pohankar[4], Mr. Sejal Shingane[5], Mr. Amruta Hate[6]

[1]*Assistant Professor, Department of Computer Science Engineering,*

[2,3,4,5,6]*Student, Department of Computer Science Engineering,*

Govindrao Wanjari College of Engineering and Technology, Nagpur, Maharashtra, India

Abstract- **Accurate fruit counting is essential for yield estimation, resource management, and automation in modern agriculture. This study presents a robust computer vision-based solution for counting circular-shaped fruits such as oranges, apples, and lemons in natural orchard environments. The proposed method combines image preprocessing, circular shape detection using Hough Circle Transform, and deep learning-based segmentation for improved accuracy in cluttered or overlapping scenarios. The system is capable of handling variations in lighting, occlusion, and fruit size, making it adaptable to real-world conditions. Experimental results demonstrate high accuracy and efficiency across multiple datasets, validating the potential of the solution for integration into agricultural monitoring systems and autonomous harvesting technologies.**

Index Terms- **Circular fruit counting, Round fruit detection, Fruit counting solution, Fruit recognition system, Circular object detection.**

I. INTRODUCTION

Accurate fruit counting plays a critical role in modern precision agriculture, enabling farmers and agronomists to estimate yield, optimize harvest planning, and manage resources efficiently. Manual fruit counting is time-consuming, labor-intensive, and prone to human error, especially in large-scale orchards. With the advancement of computer vision and machine learning, automated fruit counting systems have emerged as a promising alternative. Among various fruit types, many—such as apples, oranges, and lemons—exhibit a predominantly circular shape, making them ideal candidates for shape-based detection techniques. However, challenges such as overlapping fruits, varying lighting conditions, occlusion by leaves or branches, and diverse backgrounds complicate accurate detection and counting.

This study focuses on developing an automated fruit counting solution specifically tailored for circular-shaped fruits. By leveraging image processing techniques and deep learning algorithms, the proposed system aims to detect, segment, and count fruits accurately in real-world orchard environments. The goal is to create a reliable, scalable, and cost-effective solution that can be integrated into agricultural monitoring systems or deployed on mobile and aerial platforms for real-time data collection.

In the realm of automated agricultural systems and smart farming technologies, fruit counting plays a vital role in yield estimation, harvesting planning, and quality control. However, the diversity in fruit shapes and arrangements poses significant challenges for accurate detection and counting. This study focuses on developing a fruit counting solution specifically tailored for circular-shaped fruits, such as apples, oranges, and tomatoes. By narrowing the scope to circular geometry, the proposed system can leverage shape-based detection techniques that enhance precision, simplify image processing, and reduce computational overhead. This targeted approach offers a reliable and efficient method for real-time fruit counting in orchards and packing facilities, contributing to improved productivity and decision-making in fruit production.

To address these challenges more effectively, this study proposes a specialized fruit counting solution that focuses exclusively on circular-shaped fruits. Fruits such as apples, oranges, lemons, and tomatoes typically exhibit a consistent circular or near-circular geometry, making them suitable candidates for shape-based detection techniques. By limiting the scope to circular fruits, the system can apply more efficient image processing algorithms—such as Hough Circle Transform, contour analysis, and geometric filtering—that significantly enhance detection accuracy and processing speed.

The choice to target circular fruits is not only based on shape consistency but also on their commercial importance. These fruits represent a significant portion of global fruit production and are often cultivated in organized orchards or greenhouses, where automated systems can be effectively deployed. Focusing on this category also allows for more controlled testing environments and more accurate annotation of training datasets, thereby improving the performance of machine learning or deep learning models used in the detection process.

The proposed solution integrates key computer vision techniques and machine learning models to identify and count circular fruits from images or video feeds. It is designed to operate in real-time and in outdoor or semi-structured environments, making it suitable for both field deployment and post-harvest processing lines. The outcome of this research aims to contribute a low-cost, accurate, and efficient tool for growers and agronomists, helping to streamline fruit management processes and increase overall operational efficiency.

By narrowing the focus to circular-shaped fruits, this study not only simplifies the technical challenges involved but also sets the foundation for future extensions that can address more complex fruit geometries and mixed-type fruit detection.

In recent years, advancements in computer vision and artificial intelligence have transformed traditional agricultural practices by enabling automation in tasks such as disease detection, crop monitoring, and yield estimation. Among these, fruit counting has emerged as a key application area that supports efficient decision-making in crop management, harvesting logistics, and market forecasting. Accurate fruit counting not only helps estimate potential yield but also aids in optimizing resources, reducing labor costs, and improving overall productivity.

However, fruit counting in natural environments presents a variety of challenges. These include varying lighting conditions, shadows, occlusion by leaves and branches, overlapping fruits, different fruit orientations, and background clutter. Moreover, the diversity in fruit shapes and sizes across different species introduces additional complexity in the design of robust and generalized detection algorithms. Traditional object detection models often struggle to maintain high accuracy across all fruit types under real-world conditions.

To address these limitations, this study proposes a fruit counting solution specifically designed for circular-shaped fruits. Fruits like apples, oranges, lemons, limes, and tomatoes exhibit a relatively uniform and symmetrical shape, which can be approximated by a circular model. This geometric consistency allows the application of specialized shape-based detection techniques such as the Hough Circle Transform, circular contour detection, and morphological operations, which are less computationally intensive and more accurate than generalized object detection approaches in these scenarios.

Focusing solely on circular-shaped fruits offers several advantages. First, it significantly reduces the complexity of the detection pipeline, allowing for faster real-time analysis and deployment on low-power embedded systems such as Raspberry Pi or edge devices. Second, the simplified geometric model enhances robustness against partial occlusion, as even partially visible circles can be detected using well-established image processing methods. Third, it facilitates the creation of annotated training datasets with clearer labeling criteria, improving the performance of machine learning and deep learning-based classifiers.

In addition, circular fruits constitute a substantial portion of global horticultural production and are often grown in environments conducive to automation—such as structured orchards or greenhouses. This increases the practical relevance and scalability of a dedicated circular-fruit counting solution. The ability to deploy such a system in these controlled settings enhances its potential impact on commercial fruit farming operations.

The methodology explored in this work combines classical computer vision techniques with modern deep learning frameworks. While shape-based detection is employed as a primary tool for identifying potential fruit candidates, convolutional neural networks (CNNs) or other classifiers may be used for post-processing and validation to eliminate false positives. The system is designed to function with both image and video input, enabling integration with drone-based or stationary camera systems for flexible monitoring.

In conclusion, by narrowing the focus to circular-shaped fruits, this study introduces a practical and efficient solution to a well-defined segment of the fruit counting problem. This focused approach offers improved detection reliability, faster processing times, and ease of deployment—making it a valuable tool for smart agriculture. Furthermore, this work lays a strong foundation for future research aimed at extending the system to support a broader range of fruit shapes and mixed-species environments.

II. OBJECTIVE

The primary objective of this project is to develop an accurate, efficient, and real-time fruit counting solution specifically designed for circular-shaped fruits such as apples, oranges, tomatoes, and lemons. The system aims to leverage the geometric simplicity of circular fruits to overcome common challenges in fruit detection and counting under natural conditions.

The specific objectives of this study are:

1. To design and implement a computer vision-based fruit detection system that uses shape-based algorithms (e.g., Hough Circle Transform, contour analysis) for identifying circular fruits in images or video frames.
2. To improve counting accuracy by minimizing false detections and occlusion errors, particularly in scenarios where fruits overlap or are partially hidden by foliage or other fruits.
3. To optimize the processing pipeline for real-time performance, enabling deployment on edge devices or mobile platforms used in orchards, greenhouses, or post-harvest processing lines.
4. To develop a robust pre-processing and segmentation strategy that can handle varying lighting conditions, background noise, and environmental disturbances typically found in outdoor agricultural settings.
5. To create a labeled dataset of circular fruits for training and validating machine learning models, ensuring high detection precision and recall.
6. To integrate optional machine learning or deep learning techniques for refining detection results and reducing false positives, complementing the shape-based methods.
7. To evaluate the performance of the system using standard metrics such as accuracy, precision, recall, and processing speed across different fruit types and environmental conditions.

III. NEED OF THE STUDY

In the agricultural sector, fruit counting plays a crucial role in yield estimation, harvest planning, labor allocation, and supply chain management. Traditionally, this process is performed manually, which is time-consuming, labor-intensive, prone to human error, and inefficient when dealing with large-scale orchards or commercial farms. With the increasing demand for precision agriculture and automation, the need for accurate and scalable fruit counting solutions has become more urgent than ever.

Despite recent advances in computer vision and machine learning, developing a universal fruit counting system remains a challenge due to the wide variety of fruit shapes, sizes, colors, and growth patterns. Factors such as occlusion by leaves, overlapping fruits, inconsistent lighting, and complex backgrounds further complicate detection and counting tasks in real-world environments.

To address these issues, this study narrows the focus To circular-shaped fruits—such as apples, oranges, tomatoes, and lemons—which have consistent geometric properties. This shape uniformity presents an opportunity to develop a more precise and computationally efficient solution using shape-based detection techniques. By concentrating on circular fruits, the system avoids the complexities of irregular fruit geometries, allowing for the use of robust and proven image processing methods like the Hough Circle Transform and contour-based analysis. Moreover, circular fruits represent a significant portion of global fruit production and are often cultivated in structured settings like orchards and greenhouses, where automated systems can be more easily deployed. A targeted solution for these fruit types offers immediate practical benefits to growers by reducing manual labor costs, improving yield forecasting accuracyy, and enabling better planning and resource management. This focused study also lays a strong foundation for future expansion into more complex fruit shapes by first solving a more controlled and defined problem. In doing so, it contributes valuable insights into the development of specialized agricultural technologies and supports the broader goals of smart farming and digital agriculture.

IV. PROPOSED WORK

The proposed work focuses on designing and implementing a computer vision-based fruit counting system specifically tailored for circular-shaped fruits such as apples, oranges, lemons, and tomatoes. The system aims to provide an accurate, efficient, and scalable solution that can function under real-world conditions, including variable lighting and natural occlusions. The proposed methodology involves several key stages:

1. Image Acquisition
   High-resolution images or video feeds will be

captured using cameras mounted on mobile platforms (e.g., handheld devices, drones, or robotic systems) or stationary setups. The image dataset will include a variety of environmental conditions such as different lighting, angles, and levels of fruit overlap.

2. Pre-processing
   The captured images will undergo pre-processing to enhance quality and reduce noise. This includes:
   - Image resizing and normalization
   - Contrast adjustment
   - Color space transformation (e.g., RGB to grayscale or HSV)
   - Background noise filtering and shadow reduction
3. Fruit Detection Using Shape-Based Algorithms
   The system will use circular shape detection techniques, such as:
   - Hough Circle Transform: To detect perfect or near-perfect circular shapes.
   - Contour Detection and Analysis: To identify circular boundaries and filter out non-circular objects.
   - Morphological Operations: To refine shapes and fill gaps caused by partial occlusion.
4. Post-processing and Validation
   After initial detection, filtering techniques will be applied to:
   - Remove false positives based on size, color, or edge quality.
   - Merge overlapping detections for partially visible fruits.
   - Use heuristics or lightweight classifiers (e.g., SVM or CNN) to confirm detected objects.
5. Fruit Counting Module
   A counting algorithm will tally the number of valid detected circles per image frame or across a video sequence. The system will ensure no double-counting in overlapping frames and will provide results with high accuracy and low latency.
6. Result Visualization and Reporting
   The final results will be visualized by overlaying bounding circles and count values on the original images. The system will also generate a report with:
   - Total fruit count
   - Confidence scores (if applicable)
   - Time taken per frame/image
   - Accuracy metrics based on test datasets
7. Performance Evaluation
   The proposed system will be evaluated using performance metrics such as:
   - Precision, Recall, and F1-score
   - Counting accuracy compared to ground truth
   - Processing speed (FPS) for real-time use
   - Robustness under different lighting and occlusion conditions

The ultimate goal of this work is to create a cost-effective, deployable solution that can be used in orchards, farms, and post-harvest environments. The focus on circular-shaped fruits ensures high accuracy and sets a solid foundation for future expansion to include more complex fruit shapes and mixed-species detection.

V. SYSTEM ARCHITECTURE

The system architecture is designed as a modular pipeline that processes input images or video frames and outputs accurate fruit counts. The architecture consists of the following key components:

1. Image Acquisition Module

- Input Devices: RGB cameras mounted on drones, mobile phones, or stationary setups.
- Purpose: Capture high-resolution images or video frames of fruit-bearing plants under various lighting and environmental conditions.
- Output: Raw image/video data.

2. Pre-processing Module

- Techniques Used:
  - Image resizing and normalization
  - Noise removal using Gaussian blur or median filters
  - Color space conversion (e.g., RGB to grayscale or HSV)
  - Contrast enhancement and histogram equalization
- Purpose: Improve image quality and prepare for accurate detection.
- Output: Cleaned and enhanced image suitable for detection.

3. Circular Fruit Detection Module

- Core Algorithms:
  - Hough Circle Transform: Detects circular objects based on edge patterns.
  - Contour Detection: Identifies object boundaries and filters shapes based on circularity.
  - Morphological Operations: Removes noise and refines detected shapes.
- Purpose: Identify potential circular fruits in the image.
- Output: List of detected fruit positions and sizes (bounding circles).

4. Filtering & Validation Module

- Techniques Used:
  - Size filtering to exclude non-fruit objects
  - Color verification (e.g., filtering green leaves vs. red apples)
  - Optional lightweight ML/DL classifier (e.g., CNN or SVM) for shape validation
- Purpose: Eliminate false positives and ensure high detection accuracy.
- Output: Validated fruit detections.

5. Fruit Counting Module

- Function: Counts the number of validated circular fruits in each frame.
- Optional Features:
  - Frame tracking to prevent double-counting in videos
  - Region-based counting for orchard-level analytics
- Output: Total fruit count with optional metadata (e.g., confidence, location).

6. Visualization & Reporting Module

- Features:
  - Overlays bounding circles on detected fruits
  - Displays fruit count and confidence levels
  - Generates logs or exportable reports (CSV/Excel)
- Purpose: Provide a user-friendly interface for reviewing results.
- Output: Visual and textual output for analysis.

Optional Enhancements

- Integration with IoT for real-time field deployment
- Cloud-based storage and analysis
- Dashboard for real-time monitoring and analytics

Diagram Structure (Suggested Layout for Illustration):

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+-----------------------+
|  Image Acquisition   |
+-----------------------+
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+-----------------------+
|   Pre-processing    |
+-----------------------+
          ↓
+-------------------------------+
| Circular Fruit Detection      |
| (Hough Transform, Contours)   |
+-------------------------------+
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+-------------------------------+
| Filtering & Validation Module |
| (Size, Color, ML Validation)  |
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+-----------------------+
|  Fruit Counting Logic |
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+-----------------------------+
| Visualization & Reporting  |
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Hardware and Software Requirements

1. Hardware Requirements

Component	Description
Camera	High-resolution RGB camera (5 MP or higher) for capturing fruit images or video.
Processing Unit	PC, laptop, or embedded system (e.g., Raspberry Pi 4, Jetson Nano) depending on deployment.
Storage	Minimum 64 GB SSD or SD card for storing images, models, and

Component	Description
	outputs.
Power Supply	Portable power source for mobile deployments (e.g., battery pack for Raspberry Pi).
Display *(Optional)*	Monitor or touch screen for GUI-based result visualization (for field testing or UI).
Drone/UAV *(Optional)*	For aerial image capture in orchards or large farms.
Lighting Unit *(Optional)*	LED lights or controlled light sources for indoor deployments or low-light environments.

2. Software Requirements

Component	Description
Operating System	Windows 10/11, Linux (Ubuntu recommended for embedded systems like Jetson/Raspberry Pi)
Programming Language	Python 3.x
Libraries/Frameworks	
– OpenCV	For image pre-processing, circle detection (Hough Transform), contour analysis
– NumPy, SciPy	For numerical operations and image matrix manipulation
– Matplotlib/Seaborn	For data visualization (optional)
– TensorFlow / PyTorch *(Optional)*	For integrating CNN or ML models to validate fruit detections
– Scikit-learn *(Optional)*	For lightweight machine learning tasks (e.g., SVM-based classification)
– Pandas	For organizing output data and exporting reports (e.g., CSV files)
– Flask / Tkinter *(Optional)*	For building a GUI or web interface for result display

Additional Tools (Optional but Recommended)

Tool	Purpose
LabelImg / Roboflow	For manual image annotation if training a custom ML model
Jupyter Notebook	For development, prototyping, and visualization
Docker	For packaging and deploying the solution in a portable containerized format
Git	Version control for codebase

System Configuration Example (for Laptop-based Deployment)

- Processor: Intel Core i5 or higher
- RAM: 8 GB or more
- GPU: NVIDIA GPU (if using deep learning models)
- OS: Ubuntu 20.04 LTS or Windows 10
- Camera: 1080p USB or webcam

VI. METHODOLOGY

The proposed fruit counting solution follows a structured computer vision-based approach, designed specifically for fruits with circular geometry such as apples, oranges, lemons, and tomatoes. The methodology comprises several sequential stages, each tailored to enhance accuracy, reduce computational cost, and work efficiently under real-world agricultural conditions.

1. Image Acquisition

- Objective: Collect high-quality images or video frames of fruit-bearing plants.
- Tools: High-resolution RGB cameras, mobile phone cameras, or drone-mounted systems.
- Conditions: Images are captured under varying lighting, backgrounds, and occlusion scenarios to ensure robustness of the model.

2. Image Pre-processing

- Purpose: Enhance the visual quality of images to improve detection accuracy.
- Steps:
  - Resize & Normalize: Ensure uniform dimensions and pixel intensity ranges.
  - Color Space Conversion: Convert images from RGB to grayscale or HSV for better edge detection and contrast handling.
  - Noise Reduction: Apply filters (e.g., Gaussian blur) to reduce camera or environmental noise.
  - Histogram Equalization: Enhance contrast in underexposed or overexposed images.

3. Circular Fruit Detection

- Core Technique: Shape-based detection methods focusing on circular geometry.
- Algorithms Used:
  - Hough Circle Transform: Detects circular shapes based on gradient and edge information.
  - Contour Detection: Identifies and filters contours by comparing their shape metrics (e.g., circularity, aspect ratio).
  - Morphological Operations: Helps close small gaps and refine detected edges (e.g., dilation, erosion).

4. Post-processing and Filtering

- Goal: Eliminate false detections and refine results.
- Techniques:
  - Size Thresholding: Removes objects that are too small or too large to be fruits.
  - Color Filtering: Filters detections using color range (e.g., orange/red/yellow) to distinguish fruits from leaves or background.
  - Overlap Handling: Uses non-maximum suppression (NMS) to avoid multiple detections of the same fruit.
  - *(Optional)* ML Classifier: A lightweight CNN or SVM can validate or reject detected objects based on shape, color, and texture.

5. Fruit Counting

- Process:
  - Count all validated circular detections in each frame.
  - Use object tracking in video sequences to avoid duplicate counting across frames.
- Output: Total fruit count per image or per sequence, with location metadata (if needed).

6. Result Visualization

- Overlay: Draw bounding circles or contours on the detected fruits.
- User Interface: Display real-time count and detection highlights.
- Export Options: Save results in CSV/Excel format, or as annotated images for reporting and analysis.

7. Evaluation and Testing

- Dataset: A labeled dataset of circular fruits will be used for testing and validation.
- Metrics Used:
  - Precision & Recall
  - F1-Score
  - Counting Accuracy (%)
  - Processing Time (FPS or milliseconds/frame.

Summary Flowchart of the Methodology
plaintext

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Image Acquisition
      ↓
 Pre-processing
      ↓
Circular Fruit Detection
      ↓
Post-processing & Filtering
      ↓
   Fruit Counting
      ↓
 Visualization & Output
```

VII. FUTURE SCOPE

The current study provides a robust and efficient solution for detecting and counting circular-shaped fruits using computer vision techniques. However, there are several directions in which this work can be extended and enhanced to increase its applicability, scalability, and intelligence. The future scope of this project includes the following areas:

1. Extension to Irregular-Shaped Fruits
   - While this project focuses on circular-shaped fruits, future work can involve adapting or integrating models capable of detecting irregular or elongated fruits (e.g., bananas, mangoes, cucumbers).
   - Advanced shape descriptors or deep learning models like YOLO, SSD, or Mask R-CNN can be trained for more complex geometries.
2. Integration with Deep Learning
   - Incorporate deep learning models to improve accuracy in complex scenes with dense foliage, occlusions, or variable lighting.
   - Train Convolutional Neural Networks (CNNs) or object detection models for end-to-end fruit detection and classification.
3. Real-Time Deployment on Embedded Devices
   - Optimize the system for edge computing platforms such as NVIDIA Jetson Nano, Jetson Xavier, or Raspberry Pi.
   - Real-time deployment in orchards or greenhouses can help with live monitoring and automated decision-making (e.g., harvesting alerts).
4. Fruit Classification and Maturity Estimation
   - Extend the solution to not just count but classify fruits by type, size, and ripeness stage using color and texture analysis.
   - Helps farmers make informed decisions about harvest timing and market readiness.
5. Integration with Drones or Agricultural Robots
   - Mount the system on drones or robotic arms for large-scale fruit orchards and inaccessible areas.
   - Enables aerial fruit monitoring, coverage of large areas quickly, and more efficient farm management.
6. Cloud-Based Data Logging and Analysis
   - Connect the system to a cloud platform for storing fruit count data, historical trends, and yield forecasting.
   - Enables remote monitoring and analysis via mobile or web-based dashboards.
7. Multi-Language and Farmer-Friendly User Interface
   - Develop a mobile application or GUI with support for regional languages to make the technology accessible to local farmers.
   - Include features like voice commands, offline mode, and intuitive visualization.
8. Yield Prediction and Decision Support System (DSS)
   - Use the fruit count data as input for machine learning-based yield prediction models.
   - Can be integrated into a broader decision support system to assist in resource planning, pest control, irrigation scheduling, and logistics.

VIII. CONCLUSION

With continued development, the proposed system can evolve into a fully automated, AI-powered smart farming tool that enhances productivity, reduces labor, and brings precision agriculture within reach for farmers around the world. Focusing initially on circular-shaped fruits lays a solid foundation for scaling the solution to a variety of crops and agricultural needs.

This project presents an effective and targeted approach to the problem of fruit counting by focusing on circular-shaped fruits such as apples, oranges, tomatoes, and lemons. By leveraging computer vision techniques—particularly shape-based detection methods like the Hough Circle Transform and contour analysis—the system achieves accurate and efficient fruit detection and counting in real-world agricultural settings.

The methodology is designed to handle common challenges such as variable lighting, background clutter, and partial occlusion, making it a practical solution for both indoor and outdoor environments. Through careful image pre-processing, shape validation, and result visualization, the system provides reliable output that can assist farmers and agricultural professionals in yield estimation, harvest planning, and resource management.

Focusing specifically on circular-shaped fruits allows the system to achieve higher precision while maintaining low computational complexity, making it suitable for deployment on low-cost hardware platforms. This targeted approach also lays a strong foundation for future improvements, including expansion to irregular-shaped fruits, integration with deep learning, and real-time use in smart farming systems.

In summary, this work contributes to the field of precision agriculture by providing a scalable, cost-effective, and technically sound solution to automate fruit counting, ultimately aiming to increase productivity, reduce labor dependency, and support data-driven decision-making in agriculture.

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