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Fruit Ripeness Detection Using Deep Learning

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Abstract:

The agricultural industry has been facing challenges in traditional and manual visual grading of fruits due to its laborious nature and inconsistent inspection and classification process. To accurately estimate yield and automate harvesting, it is crucial to classify the fruits based on their ripening stages. However, it can be difficult to differentiate between the ripening stages of the same fruit variety due to high similarity in their images during the ripening cycle. To address these challenges, we plan to develop an accurate, fast, and reliable fruit detection system using deep learning techniques. The modernization of crops offers opportunities for better quality harvests and significant cost savings. Our approach involves adapting the state-of-the art object detector faster R-CNN, using transfer learning, to detect fruits from images obtained through model colour (RGB). Spectroscopy analysis to predict the quality of fruit and categorization by using AS7265x Spectrophotometer. Our system's robustness will enable us to differentiate between fruit varieties and determine the ripening stage of a particular fruit with effectiveness and accuracy. The system will also efficiently segment multiple instances of fruits from an image and accurately grade individual objects

Keywords: RGB,Spectrophotometer,Spectroscopy,Transfer Learning,R-CNN.

1. INTRODUCTION

Although several researchers have addressed the challenge of fruit detection in the past, as evident in the works cited, the development of a fast and reliable fruit detection system remains an ongoing issue. This challenge arises due to the significant variability in the appearance of fruits in real-world field settings, including variations in color, shape, size, texture, and reflectance properties. Moreover, the fruits in these settings are often partially obscured and subject to changing illumination and shadow conditions. Many approaches proposed in the literature treat fruit detection as an image segmentation problem, where the goal is to distinguish fruits from the background. For instance, Wang et al. tackled the problem of apple detection for yield prediction by developing a system that relied on color and distinctive specular reflection patterns of apples. Additional information, such as the average size of apples, was used to filter out false detections and to split regions that may contain multiple apples. Another heuristic employed by the authors was to consider only those regions that were mostly round as valid detections. Bac et al. proposed a segmentation approach for sweet peppers using a multi-spectral camera with six bands. They utilized various features, including raw multispectral data, normalized difference indices, and entropybased texture features. Experimental results in a controlled glasshouse environment showed reasonably accurate segmentation results, although the authors noted that the accuracy was not sufficient for building a reliable obstacle map.In conclusion, while several works have addressed the challenge of fruit detection, the development of a fast and reliable fruit detection system remains a persistent issue due to the variability in fruit appearance in real-world field settings. Existing approaches often treat fruit detection asan image segmentation problem, leveraging color, texture, and other features. However, further advancements are needed to improve the accuracy and robustness of fruit detection systems, particularly in challenging conditions such as changing illumination and partial abstraction of fruits.

2. LITERATURE SURVEY

1. Multiple Convolutional Layers for Fruit Recognition:

- A detection model incorporating multiple convolutional layers, max-pooling, Global Average Pooling (GAP), and fully connected layers achieved a remarkable recognition rate of 99.8% for various fruits in unstructured environments, including green apples, nectarines, apricots, peaches, sour cherries, and amber-colored plums [2]. However, this model did not account for factors such as illumination and occlusion.

2. Nighttime Detection of Litchi and Litchi Stem:

- A method proposed for nighttime detection of litchi and litchi stem combined YOLOv3 and U-Net models, achieving impressive average accuracy (AP) rates of 89.30%, 99.57%, and 96.78% under low, normal, and high brightness conditions, respectively [3]. This approach addressed challenges associated with low illumination.

3. Spectroscopy Method for Banana Quality Grading:

- Utilizing spectroscopy, a method was employed to grade the quality of bananas, distinguishing healthy and unhealthy ones. The accuracy rates under various conditions were reported as 90.00%, 84.33%, and 78.60%. Data augmentation techniques were implemented to mitigate overfitting, and an 8-layer deep convolutional neural network achieved an overall accuracy of 95.67% [8].

4. Few-Shot Learning for Plant Disease Classification:

- A few-shot learning approach for plant disease classification utilized the Inception V3 network, Siamese networks, and Triplet loss. Trained and tested on 54,303 labeled images, the proposed method demonstrated an accuracy of approximately 94%. The uniqueness of the dataset, collected exclusively using smartphone cameras, added to the novelty of the approach [9, 11].In the realm of agricultural product detection, recent literature showcases a diverse range of models and methodologies tailored to address specific challenges. From multi-layered convolutional networks for fruit recognition to innovative approaches like nighttime detection using YOLOv3 and U-Net, these studies highlight the advancements in leveraging deep learning for agriculture. Additionally, techniques such as spectroscopy for banana quality grading and few-shot learning for plant disease classification signify the diverse applications and continuous evolution of technology in the agricultural domain. The ongoing exploration of unique datasets and the incorporation of advanced techniques contribute to the refinement and effectiveness of these detection models.

3. EXISTING SYSTEM

1. Maturity Assessment Based on Color:

- The current system relies on the maturity assessment of fruits primarily through color analysis. Fruit color is considered the prime parameter for evaluating maturity. This approach assumes that color variations in fruits of the same variety directly correlate with their ripeness levels.

Limitations:

- **Subjectivity in Color Perception:** Human perception of color can be subjective, leading to potential variations in the assessment of fruit maturity. Different individuals may interpret color variations differently, impacting the accuracy of the maturity evaluation.

- **External Factors Impacting Color:** Environmental conditions, such as lighting and background, can affect the perceived color of fruits. The system may not account for external factors that influence the appearance of fruit color, leading to potential inaccuracies in maturity assessment.

- **Limited Applicability:** This approach may have limited applicability to specific fruits, such as citrus fruits, where ripeness is associated with color changes. It may not be universally applicable to all fruit varieties, each of which may exhibit unique indicators of maturity.

2. Image Processing Using MATLAB:

- The first part of the proposed system involves image processing, particularly for the identification of ripeness in citrus fruits. MATLAB Image processing tools are employed to analyze and process images for color-based ripeness assessment.

Limitations:

- Dependency on Image Quality: The accuracy of ripeness identification relies on the quality of the input images. Factors such as image resolution and clarity may impact the system's ability to precisely assess fruit maturity.

- **Processing Time:** Image processing using MATLAB may introduce a time delay, especially if a large dataset of images needs to be analyzed. This could be a limitation for real-time or high-throughput scenarios.

3. Implementation with Raspberry Pi:

- The second part of the proposed system is implemented using Raspberry Pi, extending the functionality beyond image processing. Raspberry Pi is used to carry out certain tasks related to fruit maturity assessment.

Limitations:

- **Processing Power:** Raspberry Pi may have limitations in terms of processing power and memory, potentially restricting the complexity and scale of tasks it can perform. This could impact the overall efficiency of the system.

- **Scalability:** Depending on the complexity of the tasks performed by Raspberry Pi, the system may face challenges in scaling up to handle larger datasets or more intricate analyses, limiting its adaptability to broader applications.

4. Verification of Internal Quality Using Foldscope:

- The third part of the proposed system involves the verification of internal fruit quality using Foldscope, a portable and low-cost microscope.

Limitations:

Specific to Internal Quality: While Foldscope aids in examining internal fruit quality, it is limited to specific aspects of quality assessment. It may not provide a comprehensive evaluation of all internal attributes, potentially overlooking certain critical factors.

Usability and Training: The effectiveness of Foldscope relies on proper usage and user training. Lack of familiarity or training could lead to inaccuracies in internal quality assessment.

The existing system primarily relies on color-based maturity assessment, utilizing image processing with MATLAB and implementation with Raspberry Pi and Foldscope for additional functionalities. However, limitations related to subjectivity in color perception, dependency on image quality, processing power, scalability, and specific applicability to certain fruits highlight areas for improvement in the system's accuracy, efficiency, and versatility. Consideration of these limitations is crucial for refining the proposed system and enhancing its effectiveness in fruit maturity assessment.

4. PROPOSED SYSTEM

1. Utilization of Deep Learning Techniques:

- The proposed system employs two distinct deep learning techniques for fruit classification: convolutional layers and Transfer learning models. These techniques leverage the power of deep learning (DL) to enhance the accuracy and efficiency of fruit classification.

Advantages:

- Increased Accuracy: Deep learning techniques, especially convolutional layers and Transfer learning, are known for their ability to automatically learn hierarchical features from data. This can lead to increased accuracy in fruit classification compared to traditional methods.

- Adaptability to Diverse Environments: The system is designed to work with images acquired in the natural environment of bananas, showcasing its adaptability to diverse settings. This ensures that the classification model is robust and can handle variations in lighting, background, and other environmental factors.

2. Ripening Stage Estimation and Quality Assessment:

- The proposed system goes beyond mere classification and extends its capabilities to estimate the ripening stage of the fruit. Additionally, it incorporates Spectroscopy techniques for quality assessment, providing a comprehensive evaluation of both ripeness and quality.

Advantages:

- Comprehensive Fruit Evaluation: By combining ripening stage estimation with quality assessment using Spectroscopy, the system offers a more comprehensive and detailed evaluation of fruits. This aids in providing a holistic view of the fruit's condition.

- Enhanced Decision-Making: The ability to estimate both ripening stage and quality assists consumers and vendors in making informed decisions. This is particularly valuable in optimizing purchasing decisions based on individual preferences and requirements.

3. Integration of Virtual Images Using Regular Cameras:

- The proposed system introduces a practical feature that allows the insertion of virtual images of fruits using regular cameras. This enhances the user experience and extends the system's usability beyond physical fruit inspection.

Advantages:

- **User-Friendly Interface: The** integration of virtual images simplifies the user interface and interaction. Regular cameras can be used, making the system accessible and user-friendly for both consumers and vendors.

- **Efficient Fruit Segregation:** The system's capability to easily segregate fruits based on their ripening stage and quality streamlines the process for consumers. This can lead to more efficient fruit selection and purchase decisions.

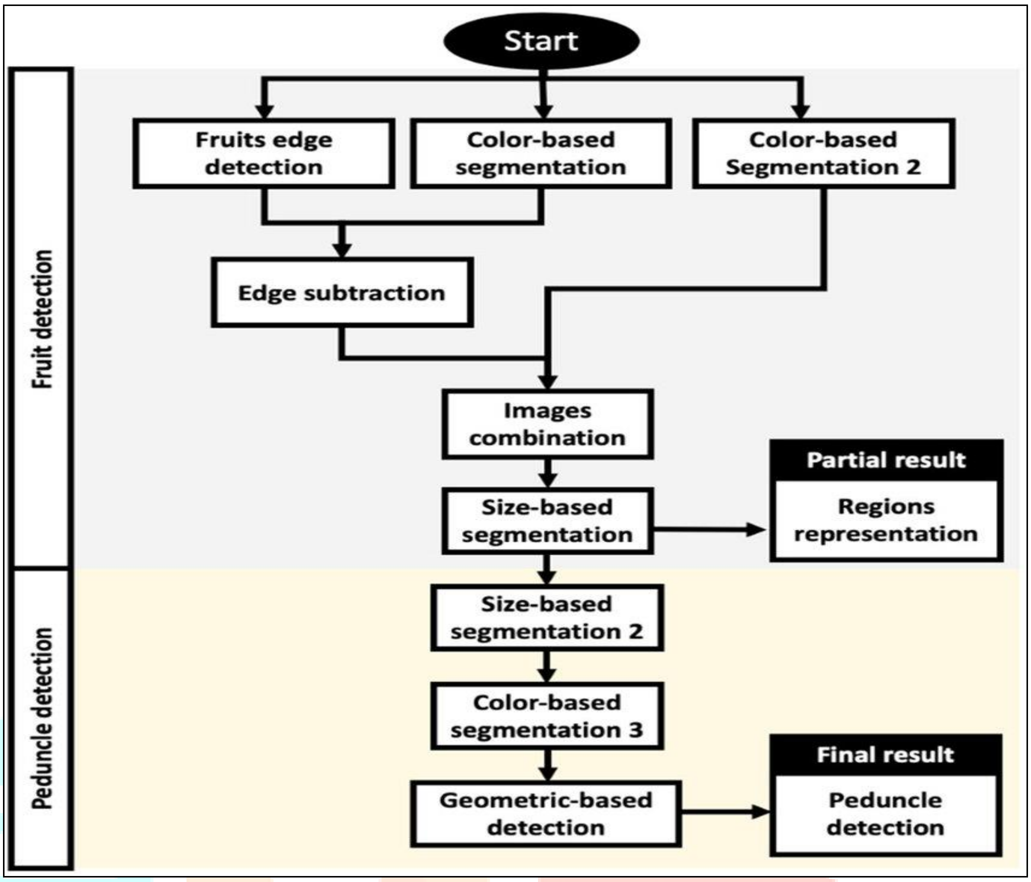
4. Addressing Everyday Consumer Needs:

- The proposed system recognizes the common scenario where fruits in general stores are typically judged for regular consumption. It aligns with the everyday needs of consumers who seek to make quick and informed decisions about the fruits they purchase.

Advantages:

- Time-Efficient Shopping: By providing quick and accurate information about the ripening stage and quality of fruits, the proposed system contributes to time-efficient and convenient fruit shopping experiences.

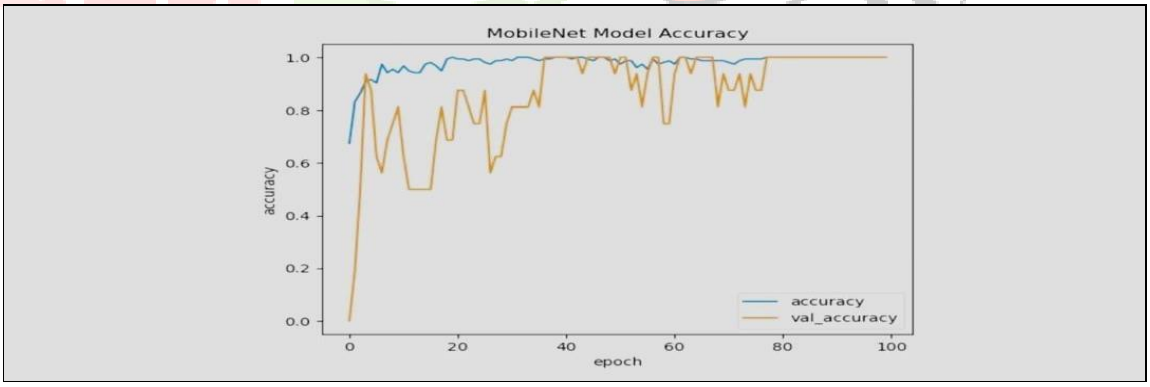
Basic Block Diagram

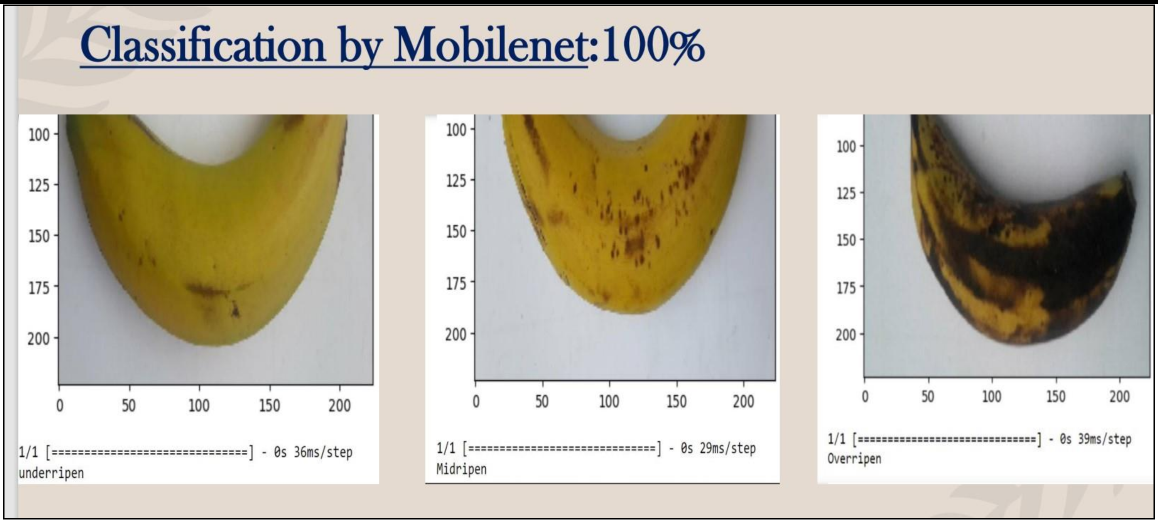


5. EXPERIMENTAL RESULTS

From the below figures it can be seen that proposed model is more accurate in order to prove our proposed system.

Main Window:





6. CONCLUSION

In this paper, we propose a methodology that utilizes Convolutional Neural Networks (CNNs) ,Transferflow models to classify Fruit Ripeness stages as Midripen, Overripen and Underripen classes. The Spectroscopy method using Sparkfun Spectrometer for better quality banana seperation from unuseful overripen banana class. The present study has explored and compared the performance of deep learning models, namely Convolutional Layers, VGG16, InceptionV3, ResNet50, NASNet Large, DenseNet201, EfficientNetB7, MobileNet for the classification of ripeness stages of bananas. The results indicate that the MobileNet model outperforms the other models in terms of accuracy and consistency. This finding highlights the potential of the MobileNet deep CNN model for accurately identifying the ripeness stages of bananas. Such a model can be employed in real-time image-based systems to help farmers identify the ripening stage of bananas and make informed decisions about harvesting. The Spectroscopy method utilised gave us better performance results in classifying the useful overripen banana.

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