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AI&ML-based smart non-disruptive methods for post-harvest fruit grading: State-of-the-Art

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***Abstract*—Intelligent vision-based non-destructive evaluation solutions are built around visual criteria, which are fundamentally similar to the cognitive processes of looking, experiencing, watching, and making decisions in human perception. Among these factors, image processing stands out as a popular method for effective evaluation and grading, providing significant advantages in terms of time, expense, and resource use in a variety of fields, including agriculture. This study provides an extensive overview of state-of-the-art computer vision methods for non-destructive post-harvest fruit grading, with an emphasis on Machine Learning and Deep Learning techniques. It clarifies the changing terrain of visual assessment techniques by combining a variety of research endeavors. This study aims to present a comprehensive overview of the most recent methods, their uses, and their efficiency in fruit grading applications. This paper's main contribution is its methodical synthesis and analysis of the body of literature, which results in a tabular overview that emphasizes the different approaches and their significance to the area. By outlining the challenges, the paper directs future research efforts and paves the way for improvised fruit grading systems that are more precise and productive.**

***Index Terms*—AI-Ml, fruit grading, machine learning-based fruit grading, deep learning-based fruit grading, smart vision computing insert**

I. Introduction

India, a country renowned for its rich cultural diversity, depends heavily on agriculture. The agricultural industry is vital to rural households because it not only drives the country's economy but also provides a living for more than half of the people (Economic Survey of India 2020-21[1]). In addition to its economic benefits, agriculture is critical to maintaining food security because it produces a large amount of staple grains, as the National Sample Survey Office report [2] notes. India's agriculture is its backbone, given its diverse influence.

Recently, there has been a lot of interest in Computer Vision problems, particularly those involving digital photos and videos, particularly in the areas of object identification and image categorization [3]. Identifying things from different classes is the focus of object detection, a critical component of computer vision that poses a major challenge to image identification. This technology is widely used in many different applications, including image annotation, video co-segmentation, face recognition, video surveillance, crowd counting, transport management, and tracking the placements of cricket balls during matches, among others. The Object Detector algorithm functions by combining two essential elements: a classifier algorithm that assigns class labels to subregions based on the feature representation and an initial feature extraction algorithm that encodes picture regions as descriptors[4]. Feature vectors are first used to describe image regions to obtain informative representations [5]. Different machine-learning techniques are then used to detect objects in photos or movies [6]. Both machine learning (ML) and deep learning (DL) methods are used in object detection strategies. For feature detection, machine learning (ML) uses several types of machine learning algorithms in addition to conventional methods such as color extraction and histograms [7]. On the other hand, DL makes use of several neural network topologies to determine which detection algorithm works best [8][9]. DL, as an example, uses an unsupervised learning technique that does away with the need for independent feature extraction during model training. On the other hand, object categorization is essential for classifying things into various groups, making it easier to identify the contents of images. It frequently collaborates with other computer vision methods like segmentation and object localization. Object localization helps with later segmentation by locating certain objects in a picture. For every object in the photos, the segmentation procedure generates pixel-wise masks [10].

Combining the two previously described processes—object identification and classification—will enable non-disruptive post-harvest agricultural produce grading and assessment through the use of visual features. Given this, the remainder of the paper goes as follows: A thorough literature review of numerous methods founded on deep learning and machine learning independently is critically reviewed and given in Section II. A tabular summary and the conclusions from the literature review are discussed in Section III. Section IV summarizes the cumulative findings, contributions, and future scope.

II. LITERATURE REVIEW (STATE-OF-THE-ART)

Computer vision, a subfield of artificial intelligence, allows machines to carry out tasks that humans can perform, from simple math operations to complex cognitive processes. Artificial Intelligence (AI) and computer vision work together to enhance Natural Language Processing, Computer Vision, and Expert Systems. AI-powered systems that analyze many industries are becoming more prevalent and require reliable hardware and software to function well[44]. It uses algorithms to train machines for particular scenarios using either newly created or pre-existing datasets. When compared to human cognition, this intersection improves speed and reliability while revolutionizing computing capacities. Deep learning, machine learning, robotics, sentiment analysis, object identification, recognition, surveillance, and smart cars are all included in the increasingly popular topic of computer vision. It breaks down images into binary matrices that represent the pixels [11][12].

We have looked closely at the most important studies on fruit grading and evaluation in this area.

A. Approaches Utilizing Machine Learning for Fruit Classification Tasks

In 2006, Chherawala et al. [13] presented a non-destructive quality assurance method based on the fruit's exterior look. A key predictor of fruit quality was color, specifically within the CIELAB color space. Their technique offered a reliable way to anticipate quality. Lee et al [14] proposed using color mapping to automate the process of color grading. Their method required employing advanced color grading algorithms to estimate unique sets of color space using preselected colors in an application. In 2015, Matteoli et al. [15] presented an automated system for determining the peach fruit's maturity. To minimize operator intervention, they made use of sensors based on fiber optic spectroscopy and multivariate processing algorithms. To further avoid harm, non-destructive techniques were employed to gauge each fruit's maturity.

In 2016, Nandi et al. [16] proposed a fuzzy incremental learning algorithm-based automated fruit grading model. To evaluate quality, the model concentrated on characteristics like surface, shape, and size. One could submit individual fruits or movies as input. Marimuthu and Roomi [17] defined three categories for banana maturity using a fuzzy system: overripe, ripe, and unripe. They employed rule-based techniques and classification algorithms with regression trees for feature space interval modeling. The PSO algorithm was used to optimize parameters and fuzzy models. The results demonstrated its greater performance over other current methods.

In 2018, Kaur et al. [18] presented their findings on the variety checking of Satluj Purple plums. Their model distinguished between ripe and unripe forms by using JPEG photos of varied maturity stages. To extract texture and color information, discrete cosine transformation methods and mean RGB transformation functions were used. To identify the primary classification factors, they observed the correlation coefficient between images belonging to different classes. An important factor in the ultimate decision-making process was the MADM hypothesis.

In 2019, Castro et al. [19] developed a method to classify gooseberry fruit by combining four machine-learning techniques to assess three color spaces. Based on their stages of ripeness, the fruits were divided into ripe, unripe, and partially ripened groups. This method was developed using the SVM classifier. In 2020, Ren et al. [20] developed a non-invasive method that uses moisture content as a deciding factor to distinguish between high-quality fruits and those that are damaged. Using mango and apple slices in their studies, They employed three methods for machine learning.—SVM, Decision Tree, and KNN—for the classification procedure.The 10-fold validation demonstrated that SVM performed better than the other approaches.

In 2020, Nazulan et al. [21] developed a model that employs machine learning-based detection and classification techniques to evaluate the sweetness of fruits. To assess and forecast fruit sweetness, their system used the K-means clustering approach to process the watermelon's texture and shape. The system was tested using thirteen watermelon sample photographs to show its functionality. The system achieved an 84.62% detection accuracy, and the fruits were categorized into quality grades A, B, and C. In 2020, Champaneri et al. [22] presented a method for overcoming the difficulty of building a working prototype crop forecast system using the Random Forest algorithm. They showcased the Random Forest algorithm's better classification power, a powerful supervised machine learning method appropriate for both regression and classification applications. The suggested strategy performed better in categorization than other approaches, according to the results, with an accuracy of more than 75% for all crops.

In 2021, Rodrigues et al. [23] presented automated approaches that use Fruit ripeness assessment using machine learning and computer vision techniques. The approach uses an algorithm to categorize fruits according to their level of maturity, making it easier to analyze farming practices using robots and drones.

B. Approaches Utilizing Deep Learning for Fruit Classification Tasks

In 1996, Recce et al. [24] presented a surface feature-based method for rating orange fruit. They included a neural network classifier in their suggested architecture. To detect color variation, a neural network with rotation invariant transformations was used. A neural network-based classifier was used to evaluate the output photos after simulating the fruit in six orthogonal orientations. In 2015, Zhang et al. [25] created a CNN model with five layers to classify fruits. They used single and multiple food image tests to conduct evaluations. The outcomes of the experiment showed that color-based features did not always provide accurate findings. On the dataset with a single fruit and the dataset with multiple foods, the model's accuracy was highest at 80.8% and 60.9%, respectively.

In 2018, Wang et al. [26] built an eight-layer CNN architecture with dropout layers and parametric ReLU. They gathered a dataset of 3600 photos of eighteen different kinds of fruits that they got off the internet using a digital camera. They centered the fruit, cropped the backdrop, and resized the pictures as part of their preprocessing technique. With an accuracy of 95.67%, the model outperformed the HWE+GA method with 81.11% accuracy and the prior 6-layer CNN model with 94.94% accuracy. In 2018, Mure et al. [27] published the Fruits-360 dataset, which includes a variety of fruits. They evaluated the fruit detection capabilities of GoogleNet, AlexNet, and traditional NN. Their model outperformed existing approaches in terms of processing time and demonstrated a 99% accuracy rate.

In 2018, Lu et al. [29] presented a 6-layer CNN model for fruit classification utilizing a dataset of 1800 digital camera photos of 9 different fruit varieties. In the same year, Wang et al. [49] built a model, which they compared to various genetic algorithm (GA) techniques, wavelet entropy (WE), and VB-SVM. The model's remarkable 99% accuracy was demonstrated by the experimental results, which outperformed VB-SVM (86.56%), WE (82.33%), and GA (91.44%). In 2018, Patino-Saucedo et al. [30] presented a model for the classification of tropical fruits utilizing a dataset of 2633 photos from 15 distinct types of retail products. The collection included photos taken from different angles, some of which showed fruits enclosed in bags. They opted for a 5-layer CNN model to lower the complexity of the AlexNet framework, with the max pooling layer coming after the first, second, and fifth layers. After the first and second layers, the model included dropout layers in addition to fully connected layers. Their findings, which obtained 100% with texture descriptors and 99.56% with color descriptors, showed the model's great accuracy.

In 2017, Zeng et al. [31] suggested a revised version of the VGG model for dividing vegetables and fruits. They made use of 26 fruit and vegetable category photos. The fruit region is first located using a visual saliency model that is based on a bottom-up approach. Additionally, the features needed to accomplish classification are learned using a CNN model. In terms of feature matching and classification, the model is achieving 95.6% accuracy. In 2017, Hou et al. [32] utilizes the VegFru dataset to categorize fruits and vegetables. There are 160,000 photos of fruits and vegetables in the dataset. By contrasting the suggested model with VGGNet and CBP-CNN, they also suggested HybridNet with these two models for classification. While CBP-CNN achieves an accuracy of 82.11%, VGGNet achieves 77.12%, which is lower than the suggested HybridNet's 83.15% accuracy.

In 2019, Kumar et al [33] created a brand-new method that combines traditional grading criteria with precise quality metrics. The EQA algorithm, which includes a comprehensive system for pomegranate fruit quality assessment and grading, is provided. The suggested architecture makes use of artificial neural networks (ANNs), and its performance outperforms existing methods in terms of efficiency. In 2019 again, Nasiri et al. [34] suggested using their findings on date fruit to separate out faulty from high-quality fruit. They have put out a CNN model that uses the VGG-16 architecture, max pooling layer, batch normalization, dropout, and dense layers. The suggested model was trained and tested using a range of date fruits, including Tamar, Khalal, and Rutab. The improved accuracy of the suggested model demonstrates that the system performs better in categorization than several current methods.

In 2019, Lu et al. [35] suggested using various data expansion techniques in conjunction with CNN to choose 5822 color photos across 10 classes from the ImageNet collection. The model is contrasted with SVM and bag-of-features (BoF). BoF displays a 56% accuracy rate, whereas CNN achieved 74% accuracy rate without data augmentation and 90% accuracy rate with data augmentation methods.

In 2019, Steimbrener et al. [36] suggested their work, which classified fruits and vegetables using a modified version of GoogleNet. There are 2700 photos of fruits and vegetables in the GoogleNet dataset, representing 13 different fruit varieties. 2D cuts were made from each spectral band to reframe the images as 3D matrices. They integrated three models with their suggested neural network model: the pseudo-RGB, the convolutional kernel, and the linear combination. With these models, the CNN model's accuracy is 88.15%, 85.93%, and 92.23%, in that order. In 2019, Katarzyna et al. [37] constructed a 9-layer CNN using the same architecture as that of the study conducted by Steimbrener et al. [36]. To increase the advantages in the retail sector, they employed the method of classifying fruits. Fruit photos with backgrounds were classified by varying the weights. The model to identify apple fruits in a picture was trained and tested on 6161 photos in total. As per the operational procedure, the identified apple is stored as an independent image. The accuracy of the suggested model, which employs six apple types, is 99.78%.

In 2019, Zhang et al. [38] presented their research by evaluating the accuracy of three data augmentation strategies and max-pooling approaches. They made use of the dataset that Wang and Chen had previously used[26]. Their accuracy of 94.94% is the highest of the many systems now in use. They examined previous hybrid techniques, such as PCA+ kSVM (88.20% accurate), PCA+FSCABC (89.11% accurate), and WE+BBO (89.47% accurate). In 2019, Sakib et al. [39] analyzed and contrasted several CNN architectures for fruit categorization. For their work, they made use of the Fruit-360 dataset. They combined and compared each case to determine the results that were obtained by using hidden layers and epochs on different examples. First, two layers of CNN are utilized, each of which then a layer of pooling that has two completely connected layers. The accuracy of the model was 99.79%. In 2020, Xuan et al. [40] employed four deep learning architectures—YOLOv3, DarkNet53, Faster RCNN with AlexNet, and Faster RCNN with ResNet101—to accomplish object recognition. Red apple identification F1 values are 95.0%, 94.6%, and 94.1% for basic, inadequate, and overly bright illumination, respectively. It is determined that YOLOv3 is exhibiting good detection performance. In 2021, Ashtiani et al. [41] presented the findings of testing and creating a CNN-based computer vision application to categorize the ripening stages of mulberry fruit. The suggested model's prediction and accuracy are improved with the application of transfer learning.

In [42], For picture segmentation and feature extraction, this study largely uses a K-means clustering technique based on Enhanced Fuzzy. Furthermore, the Back propagation-based Discriminant Classifier (BBDC) is used for classification, and Maximally Correlated Principal Component Analysis (MCPCA) is used for feature selection. In [43], For picture and abnormality segmentation, feature extraction utilizing, Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP), Discrete Fourier Transform (DFT), and shape features, an enhanced fuzzy-based k-means clustering technique is utilized. An efficient method for feature vector optimization is Self-Adaptive Chicken Swarm Optimization (SA-CSO). A Convolutional Neural Network (CNN) is used to process fruit-segmented images, a Fuzzy Classifier is used for defect classifications, and the K closest neighbours (KNN) technique is used for classification. To increase accuracy and boost the overall efficacy of the intelligent mango fruit grading system, SA-CSO optimizes the hybrid classifier.

III. IMPACTFUL WORKS' TABULATED SUMMARY

Below given table Table-1 is a categorized (ML, DL-based works) summary of over-the-year progression summary under defined heads- (Year, Author), Methodology used, Evaluation Parameter as well as found research.

IV. FINDINGS AND OPPORTUNITIES

The challenges and gaps identified in machine learning-based works encompass the need for more robust methods for image segmentation and the exploration of alternative color spaces to enhance improvisation, along with challenges related to the necessity of creating mechanical systems for effective assessment (Chherawala et al., 2006), the complexity of high-dimensional space leading to optimization issues (Marimuthu and Roomi et al., 2017), and the absence of consideration for behavior-related elements crucial for comprehensive fruit quality assessment (Kaur et al., 2018). Additionally, scalability issues arise due to the method's inadequacy in handling huge datasets effectively (Castro et al., 2019), limitations in testing and training datasets affecting model robustness (Nazulan et al., 2020), and difficulties in achieving good accuracy with large amounts of data or live images, hindering real-time application scenarios (Rodrigues et al., 2021). In deep learning-based works, challenges revolve around the need for methodology enhancement in traditional neural network approaches (Recce et al., 1996), opportunities to enhance prediction accuracy through model architecture modifications (Zhang et al., 2015), limitations in prediction capacity for single types of images (Wang et al., 2018). Exploring pre-trained CNN models for architecture refinement (Patino-Saucedo et al., 2018), enhancing datasets with a broader variety of fruit images for improved model robustness (Zeng et al., 2017), and refining model architectures to address performance variations and improve detection accuracy (Steinbrener et al., 2019). In 2022, Kumari et al. highlight the potential for exploring alternative optimization techniques and attention modeling to address gaps in the current approach and enhance overall system performance.

V. CUMULATIVE ANALYSIS: UNIQUE CONTRIBUTIONS, SUMMARY, AND FUTURE SCOPE

The tallied comparison study includes a thorough investigation of Machine Learning (ML) and Deep Learning (DL) techniques for non-destructive fruit grading between 2006 and 2022. From basic machine learning (ML) techniques like Support Vector Machines (SVM) and Least Squares Regression to more sophisticated deep learning (DL) structures like Convolutional Neural Networks (CNNs) like AlexNet, GoogLeNet, and ResNet, there has been a clear progression throughout time. The aforementioned studies enhance the overall comprehension of intelligent visual inspection systems by presenting differing levels of achievement in tackling the principal obstacles mentioned, such as computing efficiency, dataset diversity, and scalability.

Studies in machine learning (ML) have improved fruit grading accuracy significantly by utilizing methods like fuzzy incremental learning algorithm, particle swarm optimization (PSO), and K-means clustering. Nevertheless, there are still issues with successfully and efficiently scaling these techniques to handle big datasets and with adjusting them to different fruit varieties and maturity stages. Furthermore, there is a noticeable deficiency in the incorporation of behavior-related components into machine learning frameworks, which may restrict their ability to accurately capture subtle traits that are essential for precise grading. On the other hand, deep learning techniques, especially CNNs, have proven to have very high accuracy rates; nevertheless, there are still difficulties in optimizing models to get better accuracy over a range of fruit types and ripeness levels. Even though DL models perform well, there are still issues with scaling and computational efficiency in architectural optimization, particularly when using them in situations with limited resources.

This work not only provides a comprehensive analysis of advanced computer vision in non-destructive fruit grading post-harvest but also serves as a guide for researchers concentrating on particular areas. The condensed results, presented in a tabular style, provide an extensive understanding of significant study methodologies and may direct future research efforts toward the creation of intelligent fruit grading systems.

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TABLE I
IMPACTFUL WORKS' TABULATED SUMMARY

a. Machine Learning Based Works			
Year, Author	**Framework/Methodology**	**Features/Evaluation Parameters**	**Challenges/Gap**
[2006], Chherawala et al.][13]	Least Squares Regression	Higher Correlation, R2 = 0.92	More robust methods for image segmentation are available, Other Color Spaces can also be tried for improvising
[2016, Nandi et al.][16]	Fuzzy Incremental Learning Algorithm	Grading	It is necessary to create a mechanical system to rotate the mango.
[2017, Marimuthu and Roomi et al.][17]	PSO	Accuracy	In high-dimensional space, it is quite simple to get trapped in local optima.
[2018, Kaur et al.][18]	MADM Theory	Colour Weightage, Achieves great performance and lowers the rate of misclassification	Behavior-related elements are not considered.
[2019, Castro et al.][19]	SVM	Has significantly improved performance, In high-dimensional space, hyperplanes.	It is not appropriate for huge datasets.
[2020, Nazulan et al.][21]	K-means clustering	Shape and texture-based detection is applied, System obtained 84.62% accuracy.	A limited number of images are used for the testing and training.
[2021, Rodrigues et al.][23]	Machine learning algorithms	Classification is done according to the ripeness.	System is not obtaining a good accuracy for large amounts of data or on live images.
a. Deep Learning Based Works			
[1996, Recce et al.][24]	ANN	Confusion Matrix Parameters.	Traditional Neural Network approach is used, Needs to be more enhanced concerning methodology.
[2015, Zhang et al.][25]	CNN model with 5 layers	Accuracy: 60.09% for many fruits and 80.8% for a single fruit.	More layers can be added to enhance the accuracy of prediction.
[2018, Wang et al.][26]	CNN model with 8 layers	Precision 95.67%	Prediction capacity is limited to single types of images only.
[2018, Mure et al.][27]	AlexNet, GoogLeNet proposed CNN models	Precision 99% all models,	Plan is to create a mobile application that takes pictures of fruits and labels them accordingly.
[2018, Hussain et al.][28]	Proposed CNN models	Precision 99%.	'More classes and sub-classes can be included.
[2018, Patino-Saucedo et al.][30]	Fruit-AlexNet	Precision of 99.56%	It may be possible that we can use some pre-trained CNN models by modifying some layers and parameters to design a new CNN model.
[2017, Zeng et al.][31]	Modified VGG	Precision 95.6%	Existing dataset must be enhanced with various types of fruit images.
[2017, Hou et al.][32]	CBP-CNN, VGGNet proposed HybridNet VGGNet	77.12%–84.46%–72.32%, CBP-CNN 82.21%–87.49%–84.91% HybridNet 83.51%–88.84%–85.78%.	VegFru, and HybridNet can be more inspired for advanced research on FGVC.
[2019, Lu et al.][35]	CNN MODEL with 5 layers	74% without data additionally, 90% with data augmentation	More layers need to be added to get efficient results.
[2019, Steinbrener et al.][36]	Modified GoogLeNet	88.15% with Pseudo-RGB images, 85.93% with linear combinations, 92.23% with convolutional kernels	The model is providing various accuracy rations in variant models. Need to create a hybrid model with more accuracy.
[2019, Katarzyna et al.][37]	CNN MODEL with 9 layers	Accuracy 99.78%.	Prediction capacity is limited to single types of images only.
[2019, Zhang et al.][38]	CNN MODEL with 13 layers	Accuracy 94.94%,	Accuracy is low with 13-layer CNN architecture.
[2020, Xuan et al.][40]	Faster RCNN with AlexNet, Faster RCNN with YOLOv3	Out of the four detection models, the enhanced YOLOv3 model demonstrated the strongest recognition effect, according to the findings.	It is possible to expand the existing work to include the classification of more than four ripeness stages.
[2021, Ashtiani et al.][41]	CNN with ResNet-18 using Transfer learning	Accuracy of 98.03%	To develop the models to improve the detection accuracy further.
[2022, Kumari et al.][43]	Enhanced fuzzy-based K-means clustering, SA-CSO, and a hybrid classifier with KNN, Fuzzy Classifier, and CNN	Confusion matrix and depending parameters,	In place of SA-CSO other optimization can be used for improvisation, Again attention modeling can be tried.