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Computer Vision in AgriTech: A Review

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Abstract. Harvesting and post-harvesting are two critical stages in the fruit farming process. Fruit size, colour, flavor, hardness, quality, maturation stage, market window, and fruit detection and classification are the most important elements to consider during these stages. Farmers' profits are determined by these factors. As a result, meticulous harvesting and grading are the most important aspects of farming. According to the findings of this survey, auto-harvesting robots, Machine Learning, and Deep Learning approaches are producing better outcomes and assisting farmers in minimizing losses throughout the harvesting and post-harvesting stages

1. Introduction

Agriculture is one of the oldest businesses that have yet to be digitalized. However, it is critical to the majority of the country's economy. To strengthen the economy and meet food demand, technological innovation is required in this industry. Agriculture duties in traditional farming can be broadly classified as pre-harvesting, harvesting, and post-harvesting. Farmers concentrate on seeds, soil, session, irrigation, crop growth, fertilizer, and pesticides during pre-harvesting. They concentrate on crop maturity during harvesting and post-harvesting, categorizing fruits and vegetables based on quality and determining the market window and demand. Technology progress in these three areas is required for efficient farming, meeting food needs, and saving farmers' lives. Fruit farming is the most important of many crops. Farmers can make a lot of money because of the demand. Therefore. Numerous research have been published in the last decade on various elements of the fruit industry, including as defect detection, fruit quality evaluation, grading, and volume and mass prediction. Again, computer vision, image processing, and machine learning techniques are commonly used in fruit classification. Furthermore, in the fruit sector, computer vision, machine learning, and deep learning are frequently used in the agricultural field. Many studies have been conducted in recent years to improve on-tree detection, classification, and grading of fruits. This paper focuses mostly on new technologies developed for the detection, identification, and classification of fruits in the field and after harvest.

2. Novel technologies that are applied in the pre-harvesting and harvesting of fruits

Farmers' profits are determined by yield. Yield is calculated by counting the number of fruits on the tree. Because future earnings are directly proportional to the quantity, size, form, and quality of fruits. All of these tasks are performed manually in traditional farming. Technology adoption may assist farmers in performing these tasks more efficiently and accurately in less time. Some of the technological developments covered in this section are related to yield mapping and harvesting. Table 1 summarizes the parameters of the examined papers, such as the type of fruit, dataset collection method, extracted features, methods or algorithms applied to the dataset, model evaluation technique, study output, and reference numbers. A fundamental technology for the fruit harvesting robot is fruit detection. Hetal N. Patel et al. [2] devised a method for detecting fruits that makes use of several attributes. The intensity, colour, orientation, and edge were extracted from the supplied image. The weights were then generated based on the integrated features of the image region. The binary map was created using a global threshold value. Fruits regions are recovered with 90% accuracy from the binary map. Shape and colour are two crucial features for detecting and locating fruits in photos; this is the first stage in constructing harvesting robots. The primary issue with color-based analysis is illumination. As a result, Kelman and Linker [4] suggested an alternative technique based on convexity for identifying apples in tree images. Convexity testing discovers apple edges that fall within 3D convex objects, eliminating false positives and duplicate apple detections. Si Yongshenga et al. [3] designed a machine vision system for robot harvesting in 2015 to locate apples in the tree. This algorithm recognizes apples using the colour difference (R-G) and colour difference ratio (R-G)/(G-B) mechanisms. This algorithm's unique feature is that it is never affected by light conditions. The Random Ring Method (RRM) was used to extract the circle feature from an apple. A matching algorithm based on epipolar geometry is used to identify apples in the tree. This study's experimental results were 95% accurate.Farmers cheer when they notice a large number of blooms in the tree during flowering and afterwards count the number of fruits in the tree. ArturJanowski et al. [20] examined three methods for counting the number of apples in a tree in order to estimate fruit yield. The first method utilized in this study was image filtration using the Hough Transform, which took into account the colour, shape, and size characteristics to detect apple fruits. The disadvantage of this procedure was that it took a long time to process and was inefficient (37%). The working idea of the second method, Viola-Jones Object Detection, is to train the framework with thousands of positive image datasets and look for target objects. This technique disregards colour and size, focusing solely on form aspects. The framework takes a medium amount of time to train, and the detection accuracy is also medium (55%). The final strategy employed by authors is You Only Look Once (YOLO). It employs a single CNN for classification and takes form features into account when training the network in real time. In comparison to the other two approaches, YOLO achieved 84% accuracy. A. Kongal et al. [8], have created a sensor-based system that predicts crop load using superficial machine vision. Using colour and a 3D camera from the apple orchard, they took photographs on both sides of apple trees to limit illumination and outside light conditions. Color and form characteristics were used to identify apples. Histogram equalization is used to differentiate apples, leaves, and branches, the Wiener filter is used to minimize the mean square error, and the colour image is converted into a grayscale image by subtracting the blue and green channels from the red channel, and binary images are obtained using Otsu's threshold method. Finally, the matured and green apples were identified using CHT and blob analysis. The co-registration of 2D and 3D camera pictures allows the apples to be located in 3D space. Apples in common coordinates are 3D registered to identify duplicates. To compare the results of apple identification with ground truth, a confusion matrix was built. This method counts apples with an accuracy of 82% in dual-side imaging. Nicolai Hani et al. [17] created a yield mapping system for apple orchards that detects and counts the apples. They used the three approaches listed below to accurately detect the fruit. The first is a semi-supervised colour-based clustering strategy based on the Gaussian Mixture Model (GMM) and Expectation-Maximization (EM). The second method, U-Net, is utilized for deep pixel-wise segmentation, and the third is Faster-CNN (FCNN), which serves as the network's backbone and is employed for object detection. Semi-supervised segmentation paired with a CNN-based counting approach yielded outstanding yield accuracies ranging from 95.56% to 97.83% for fruit counting.

TABLE 1. Analysis of pre-harvesting and harvesting parameters

Type Of Fruit	**Dataset Collection**	**Extracted Features**	**Models/Methods/ Algorithms Applied**	**Evaluation Model and Results**	**Outcomes/ Property**	**Ref. No.**
Not domain specific	Web sources	Intensity, Colour, Orientation & Edge	HSV, Elliptical colour filter, Gradient Magnitude, Binary map, Feature map	Simulation output. 95% accuracy	Extract the fruit region	[2]
Apple	Captured grey level Tree image	Shape	least square constrained optimization, Canny filter, Convexity test	Convexity test. 94% accuracy	Apple detection in the tree	[4]
Apple	Tree captured using camera	Colour and Shape	Colour difference, Colour difference Ratio, Random Ring Method (RRM) and epipolar geometry	Accuracy. 95%	Robot - Recognize and locate Apples	[3]
Apple	Tree image captured using mobile camera	Colour, Shape & Size	Image Filtration and Hough Transform (HT), Viola-Jones Object detection, YOLO	Accuracy. YOLO - 84% Viola-Jones – 55% HT – 37%	Yield mapping	[20]
Apple	Colour and 3D Camera	Colour & Shape	Wiener filter, Otsu's threshold, Circular Hough Transformation (CHT), Blob analysis & Mean Absolute Percentage Error (MAPE)	Confusion matrix. Apple counting 82%	Yield mapping	[8]
Apple	Colour Camera	Colour	Gaussian Mixture Model (GMM) and Expectation Maximization (EM), U-Net & Faster-CNN (FCNN)	Accuracy. 95.56% - 97.83%	Yield Mapping	[17]
Banana	Digital Camera	Colour & Size	Mean Colour Intensity (MCI) & Area algorithm	Accuracy. MCI- 99.1 % & Area algorithm – 85%	Classify the ripeness stage	[6]
Pineapp le	Digital Camera	Fruit Region	Median Filter, SURF, SVM & Connected component Labelling	Accuracy. Detection – 87.37% Counting – 85.25%	Yield Mapping	[15]
Pineapp le	Digital Camera	Colour, shape & texture	ANN, SVM, RF, NB, DT, KNN & ANOVA	Accuracy, Specificity, Sensitivity and Precision. Best – ANN – 94.4%	Yield mapping	[23]

Mango	hyperspectral camera & LIDAR sensor	Dry Matter (DM)	CNN & Partial Least Squares (PLS)	Accuracy. - doesn't mention it clearly	Predict – mango maturity	[12]

Fruits must be harvested at the right moment to retain their flavour and colour. These two parameters assess the quality of the fruits and boost farmers' profits. It is especially important to assess the maturity stage of banana fruits. Because after harvesting, banana fruits are moved to ripening champers. If the bunches are not matured, they are unable to create colour and flavour, and over-matured bananas split and spoil when they emerge from ripening champers. D.SuryaPrabha and J.Satheesh Kumar [6] proposed a solution to determine the maturity degree of the banana. The image-based classification algorithms rely heavily on two characteristics: colour and size. The mean colour intensity algorithm, which works on RGB histogram images, correctly categorized the matured banana 99.1% of the time. The area algorithm detects the unmatured banana with 85% accuracy using the area, perimeter, major axis, and minor axis length parameters of the size feature.Nancy C. Woods et al. [15] developed an automated technique for detecting and counting pineapples in a digital image of a field. The fruit photographs are captured using a digital camera in the pineapple field, and noise is minimized using the median filter approach. Following that, the interesting regions were subdivided, and the features were extracted using SURF. The SVM classifier was then used to train the system. SVM can detect fruits, and a connected component labelling technique was applied to count the matured pineapples in the image. Fruits are detected with 87.37% accuracy, while the total number of fruits is counted with an 85.25% success rate.

Wan NurazwinSyazwani et al. [23] created a model for identifying and classifying ripened pineapples using image processing techniques, as well as counting them using Machine Learning algorithms. Shape, colour, and texture are the primary characteristics used to identify the pineapple. Using an autonomous counting method to count the crown pineapple. To increase classification performance, the model was optimized using ANOVA. This model employs six classification algorithms: Artificial Neural Network (ANN), Decision Trees (DT), Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), and K-Nearest Neighbors (KNN). ANN is the best classification algorithm among them, producing results with up to 94.4% accuracy. A hand-held spectrometer is used in traditional farming to determine mango maturity using Dry Matter (DM) content. Instead of this formal strategy, Alexander Wendel et al. [12] proposed a new approach to maximize harvest time. This approach predicts fruit DM content using a hyperspectral camera, LIDAR sensor, and navigation system. To forecast the harvesting time and yield of the fruits, two regression approaches, Convolutional Neural Network (CNN) and Partial Least Squares (PLS), are applied. The authors declared that their model produced an efficient result and stated that more studies in the same field utilizing RGB cameras will be required due to the high cost of hyperspectral cameras.

3. Novel technologies applied in the post-harvesting of fruits

The influence of CNN on fruit classification, detection, and quality control in fruit image processing was studied by José Naranjo-Torres et al. [18] in 2020. The authors of [7, 9] provided a review of computer vision-based fruit classification and grading. According to their findings, fuzzy logic is simple to implement, SVM has the maximum accuracy, and the Adaptive Network-based Fuzzy Inference System gives the best results. Aside from that, a few more studies on fruit classification and grading are evaluated in this section. We look at a few more notable works. Table 2 contains a summary of the parameters of the examined articles, such as the type of fruit, dataset collection method, extracted features, methods or algorithms applied to the dataset, model evaluation procedure, study result, and reference numbers.

The fuzzy approach is used by Ab RazakMansor et al. [5] to categorize mango fruits using an RGB colour sensor. Using fuzzy rules, this model can classify mango fruits into three categories (unripe, ripe, and overripe). The categorization accuracy exceeded 85%. The authors proposed enhancing the algorithm's accuracy by taking into account the texture of the fruits and developing more fuzzy rules.

SenthilarasiMarimuthu et al. [11] used a fuzzy model to categorize banana fruit maturity as unripe, ripe, or overripe. The colour of the skin is important in the classification of banana fruits. The colour feature of the fruit was retrieved in two colour spaces: HSV and CIELa*b*. HSV is used to obtain colour vision that is invariant to illumination, similar to human perception. CIELa*b* is useful for detecting exterior flaws in fruit (e.g., brown area). The brown area was segregated using the K-Means clustering algorithm on the opponent colours of the CEILa*b* colour space. During the ripening stages of bananas, there is a possibility of colour and brown area overlap. Fuzzy logic use the Decision Tree (DT) knowledge base to deal with this ambiguity. The fuzzy model was then optimized using the particle swarm optimization technique, which yielded an accuracy of 93.11%.

Jiajun Zhuang et al. [16] proposed an optical-based approach for assessing banana ripeness stages. The colour, texture, and size of banana peel were extracted from different regions of the banana. Color properties were derived in this model utilizing the well-known approaches of Hue-Saturation-Value (HSV), CIEL*ch, and CIEL*a*b* colour spaces. The textural features were calculated using a Local Binary Pattern with Uniform Patterns (UP-LBP). To extract the shape characteristics, a Histogram of Oriented Gradients (HOG) was used. They used the Nave Bayes (NB), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM) classifier techniques to determine the maturity stage of bananas. The authors concluded that the colour characteristic is the best for classifying bananas, with total accuracy of 99.25, 100%, and 99.2% attained.

KwankamonDittakan et al. [13] proposed a grading structure for Pattavia pineapple (Keaw 1 and Keaw 2) utilizing texture analysis. This model is made up of three processes: feature extraction, feature selection, and classifier generation. The initial stage in feature extraction is to extract features from the training data set using a Local Binary Pattern (LBP). After the feature vectors were created, feature selection was used to reduce space. The classifier was then created using various classification methods (Decision Tree, Binary Decision Tree, Random Forest, Nave Bayes, Bayesian Network, Logistic Regression, SMO, and Neural Network). The predict operation is used to assess unseen pineapple photos. Among all classifier systems, the Neural network rated pineapple with 94% accuracy.

DevrimUnay and Bernard Gosselin [1] created a Neural Network-based system for apple quality classification and fault detection using Multi-Layer Perceptron (MLP). They retrieved the texture, colour, and wavelet properties of Jonagold and Golden Delicious apple photos, and Principal Components Analysis (PCA) was applied to classify the quality and discover the fault. The preliminary performance test was then carried out with single and multiple perceptron. This system had an accuracy of 83.7%.

TABLE 2. Analysis of post-harvesting parameters

Type Of Fruit	Dataset Collection	Extracted Features	Models/Methods/ Algorithms Applied	Evaluation Model and Results	Outcomes/ Property	Ref. No.
Mango	RGB Fiber optic Colour Sensor	Colour	Fuzzy Logic (Mamdani)	Accuracy. 85%	Grading (3 classes Overripe, Ripe and Unripe)	[5]
Banana	Digital Camera	Colour (Peak hue & Normalized brown area)	K-Means, Decision Tree, Particle swarm optimization, Fuzzy logic (Mamdani)	Accuracy. 93.11%	Ripening level (Unripe, Ripe & Overripe)	[11]
Banana	CCD Camera	Colour, Shape & Texture	HSV,CIEL*a*b*, CIEL*ch, Otsu thresholding algorithm, LBP, HOG, SVM, LDA & NB	The best result achieved 100% - Colour feature with LDA	Classification - Maturity Stage1, Stage2, Stage3 & Stage4	[16]
Pineap ple	---	Texture	LBP, Decision Tree, Binary Decision Tree, Random Forest, Naïve Bayes, Bayesian Network, Logistic Regression, SMO & NN	Accuracy, Area under the ROC curve, Sensitivity, Specificity & Precision. Best -NN – 94%	Grading (Keaw 1 &Keaw 2)	[13]
Apple	Colour Camera	Colour, Texture & Wavelet	Co-occurrence Matrices, Principal Components Analysis (PCA) & back-propagation	Single and multilayer perceptron. Best performance rate - 89.9%	Defect detection and Quality classification	[1]
Apple	Phone Camera	Colour and Size	Otsu method Naïve Bayes	Accuracy -91%, Specificity – 80% Precision – 100% and Sensitivity – 77%	Classification (Golden Delicious, Honey crips and Pink lady)	[10]
Papaya	Smartphone camera	Colour	LBP, HOG, GLCM, KNN, SVM, NB, ResNet101, ResNet50, ResNet18, VGG16, GoogleNet and AlexNet	Accuracy. VGG19 – 100%	Maturity status classification (Immature, Mature & Partially Mature)	[19]
Apple, Lemon & Mango	Fruits 360 dataset	Colour and Intensity	Median filter, CNN	Accuracy. 95%	Quality Grading (Good, Raw & damaged)	[21]
Multi-Fruits.	Video Camera	Colour, Count, & Weight	CNN	Propagation time (Max 20 seconds) & Accuracy (97%)	Self-Service system in the retail shop	[14]
Multi-Fruits	collected using calliper & spectrophot ometer	Colour & Size	KNN, Decision Tree (DT), Naive Bayes classification, RF and MLP	RF produces the highest accuracy – 94.3%	Fruits classification	[22]

Misigo Ronald and Miriti Evans [10] created a system for classifying apple varieties using image processing and Nave Bayes (NB) algorithms. They bought the apples (Golden Delicious, Honey Crisp, and Pink Lady) from the market and photographed them with their mobile camera. Color and size features from the collected photos have been retrieved and forwarded to NB for categorization. This system's performance was examined using accuracy, specificity, precision, and sensitivity, yielding results of 91%, 80%, 100%, and 77%, respectively.

Santi KumariBehera et al. [19] proposed a post-harvesting categorization methodology for determining papaya fruit maturity for packaging reasons. There are two methods for determining papaya maturity: 1. Transfer Learning, 2. Machine Learning Machine Learning is divided into two stages: feature extraction and classification. The authors utilized three techniques in the feature extraction stage: Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and Gray Level Co-occurrences Matrix (GLCM). 59, 37, and 13 features were extracted using the LBP, HOG, and GLCM, respectively. These properties are utilized for training and testing in the second stage (classification). K-Nearest Neighbours (KNN), Support Vector Machine (SVM), and Naive Bayes (NB) are used to classify the fruits during the classification step. Transfer Learning, the second way, is also a Machine Learning approach. Using a well-trained model, Transfer Learning can tackle a variety of problems. To categorize the maturation stages of papaya fruits, six pre-defined models are used: ResNet101, ResNet50, ResNet18, VGG16, GoogleNet, and AlexNet. VGG16 outperformed all other techniques, achieving 100% accuracy and requiring less training time (1:52 seconds).SarikaBobde et al. [21] created a fruit quality evaluation system based on Convolutional Neural Networks (CNN). The dataset was gathered from several web sources before being preprocessed. Using the ReLu procedure, the negative characteristics are replaced with the value zero. Pooling and flattening processes are used to extract the features from the dataset. In the fully linked layer, the Softmax activation function is employed for classification. The results of this CNN-based model were 95% accurate.

Frida Femling et al. [14] suggested a system for automating the identification of fruits and vegetables in the retail market by improving computer vision. Inception and MobileNet, two Convolutional Neural Network (CNN) architectures, were used. TensorFlow was used to create this model, which identified ten different types of fruits and vegetables. Clementines and kiwis are difficult for MobileNet to forecast. This model occasionally misinterprets fruits and vegetables.DilaraGerdanKoç and Mustafa Vatandaş [22] devised a technique to identify fruits based on their size and colour features. A caliper and spectrophotometer are used to measure the size and colour. For prediction, they used the K-Nearest Neighbor (KNN), Decision Tree (DT), Naive Bayes classification, and Multilayer Perceptron Neural Network (MLP) methods.

4. Discussion

Colour is a significant aspect of agricultural products. Most of the time, the maturity or ripeness degree of the fruits or vegetables has been detected using colour. This significant aspect is mostly concentrated by researchers once they have completed their effort to detect, identify, and classify fruits and vegetables. In this paper, 20 research studies were analyzed, 16 of which were entirely or partially based on colour [1-3, 5, 6, 8, 10, 11, 14, 16, 17, 19, 20 - 23]. Fruit quality cannot always be determined solely by colour. A few other criteria, such as size, shape, and texture, are also important. Shape [3, 4, 8, 16,20, and 23] and size [6, 10,20, and 22] variables are mostly employed in classification models to accurately classify fruits. The publications [1, 13, 16, and 23] investigated texture properties. Furthermore, the researchers rarely take into account the special features area [12], edge [2], wavelet [1], count [14], weight [14], and dry matter [12]. The authors can utilize several types of features, but the model construction processing procedures are nearly identical. They capture images or collect them from web sources, then convert the image into any colour space, segment the image, and extract the features. The extracted features are transferred as a piece of information into any domain, and the model is then classified or predicted. Finally, the system's performance is assessed using several techniques such as accuracy, sensitivity, recall, precision, and specificity.

5. Conclusion

This study provides an overview of various algorithms used in the detection, identification, and categorization of fruits. Computer vision algorithms are used in all aspects of agricultural processing. The majority of the datasets are collected by the authors, and common datasets are rarely used to execute the models. The majority of researchers focus on a single fruit or a certain piece of work. Purchasing a tool for each task is tough for farmers, and maintaining them is also difficult, therefore there is a need to build a common framework that can support farmers throughout the cultivation process.

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