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FRUIT QUALITY IDENTIFICATION USING IMAGE PROCESSING, MACHINE LEARNING, AND DEEP LEARNING: A REVIEW

NAGNATH AHERWADI and USHA MITTAL*

Department of Computer
Science and Engineering
Lovely Professional University
Punjab, India
E-mail: aherwadinagesh@gmail.com

Abstract

The agriculture sector is the most important source of economic development of the country worldwide. Appearance is the important part of the fruit as it describes its shape, size, and color; also it shows the quality of the fruit whether it is fresh or rotten. By the use of the quality of fruit, we can identify the life of it, which means how many days we can keep after buying it. From this farmers can estimate the right time of harvesting fruit to save it from over-ripening. This will also help in planning for reducing harvest losses and to increase farmers' income. In this paper, the well-known techniques of Image processing, Machine learning, and deep learning technologies in maturity classification, quality identification, and shelf life identification of fruit are discussed. Different algorithms and techniques used for all the above problems are discussed here. First Fruit is identified and further maturity classification is carried out then on the basis of fruit maturity status we can identify the quality as well as the shelf life of fruits.

1. Introduction

Nowadays keeping our immune system strong is very important for our health. For the same, we just have to get fresh and healthy food. Fruit life identification will help us to get healthy and fresh fruits for our health. In this will come across about fruits all information like, whether the fruit is

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*Corresponding author; E-mail: usha.20339@lpu.co.in

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ripe or non-ripe or over-ripe and what type of quality fruit it is? With the help of this information, we can predict the shelf life of fruit, which means how many days we can keep it after buying it. The different algorithms, techniques used for fruit maturity classification, quality identification are given below.

1.1 Image Processing (IP). Image processing is used to make some different operations on the images that are required before being sent to the training. Some operations of IP are Image enhancement, image cropping, Image classification, image feature extraction, image segmentation, image quality increasing, and image color space conversion. This is one kind of signal processing image that is provided to input, and image or features can be the outcomes of that particular image. Image segmentation is the process of distributing into specific segments or regions and getting extracted required target. Digital Image analysis of Harumanis mango for estimating non-destructive ripeness levels is carried out. RGB images of mangos are segmented as they are uniformly not distributed. Image analysis requires internal and external attributes for color image segmentation in image segmentation of multilevel threshold ding approach to extract 2 mango regions from the background. To evaluate and compare for the prediction color analysis and Total Soluble Solids (TSS) are used with, this achieved more than 92% accuracy [1].

Image Color Space Conversion is the process of converting a particular image color space into required color space as many color spaces are available. An automatic system that will help the agriculture industry of date fruits so that consumers and other peoples get the best quality date fruits. Maturity stages of date fruit are identified, classified, and counting of harvested fruits with labelling is done by using the image processing. Thermal image processing is used in this model, where thermal image cold areas were detected for defect dates identification [2]. Two important steps are used first color image segmentation and second comparison. Region of interest of color segmentation is the main technique for image segmentation and a red color image is separated. For comparison purposes they are using famous techniques, histogram matching and correlation. Images of input and reference are segmented when all are converted to L-A-B color. Histogram comparison and correlation are used to detect the maturity level of apple fruit [3].

1.2 Machine Learning (ML). It is part of artificial intelligence and the study of algorithms where an improvement is increased by previous experience and using the data or information regarding it. Supervised learning uses labelled data and predicts the output on the basis of that data. Input data with correct output is given in labelled data. Identification of bananas from banana peels, images according to types and levels of ripeness. By comparing three Machine_learning algorithms are: *k*-Nearest_Neighbour's (k-NN), Support_Vector_Machine (SVM), and Decision_Tree (DT). They put a banana on a white surface and captured images from 17 different positions within 0.6 meters. DT and *k*-NN are giving less accuracy than SVM in banana type detection is 99.1% and in ripeness level identification 96.6% accuracy is achieved by k-NN and SVM [4].

Principal Component Analysis (PCA) computes the main components and carries out a change of basis of a given data. Sometimes it uses a few of them and ignores all remaining. Linear Discriminant Analysis (LDA) is used in statistical analysis for finding linear combinations. It is the same as PCA as they both look for linear combinations. PCA, LDA, IDA, Multi-cluster characteristic selection, and Eigen-vector Centre characteristics selection are five multivariate knowledge fusion strategies used to sort the optical ripeness of Cape gooseberry. Classifiers such as neural networks, support vector machines, and nearest_neighbours use various color spaces to distinguish fruit samples. The color spaces are equal up to a transformation and changes in the distribution of pixels of samples allow a few classifiers to improve performance. They got the highest accuracy using the 7-dimensional PCA feature space [5].

1.3 Deep Learning (DL). The second name of DL is deep structured learning and it is one of the ML classes. It uses artificial neural networks to learn concepts. It consists of neural network architecture which is having the same structure as the human brain neuron structure. Deep learning architectures include deep neural networks, deep belief networks, RNN, and CNN networks have been used in fields including computer vision, machine vision, speech recognition, NLP, PCA, audio-recognition, social network filtering, machine translation, bioinformatics, drug design, and medical image analysis.

DL algorithms contain a Convolutional Neural Network (CNN), where input takes an image and extracts all features of that picture, and converts it into dimensions without losing its attributes. CNN architecture for simple and deep learning neural networks is given below in fig a. "Sonaka" local breed grape images separated into two categories are ripen and un3 ripen. Those images are subjected to the CNN and SVM classification model for ripeness estimation. They are using morphological feature shape, color features HSV, and RGB for the classification model. They achieved 74.49% accuracy for CNN and 69% for SVM [6]. For reduction of cherry fruit wastage and incrementing its export and marketing, an improved CNN algorithm is used to detect the cherry fruit appearance and provide a grading system for cherry fruit. Max and average pooling is used for CNN generalization. CNN with Image processing gives 99.4% accuracy for this model [7].

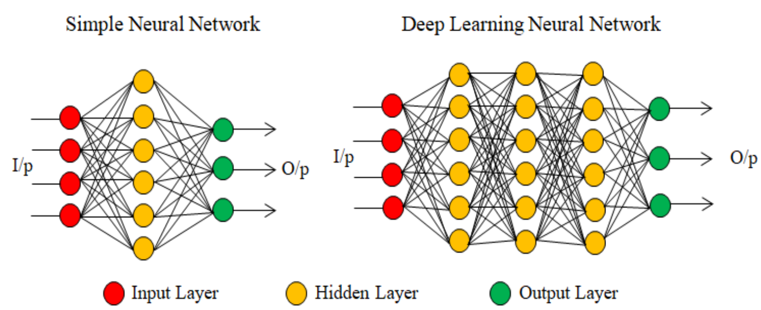

Figure 1. CNN Architecture.

2. Literature Review

Authors (Mauricio Rodriguez et al. [8]) had used CNN to classify the maturity level of the available fruit in their dataset. Oranges, red-apple, strawberries, green-apple, and bananas are the fruits available in their dataset. Two collections of images were created first. The data augmentation strategy was used next, followed by the training of the CNN using the images dataset as input. Performance of the system is checked by calculating all the metrics of the confusion matrix all metrics are calculated to know the performance of the system. The average precision achieved by the model is 96.34%. (Kaveri Kangune et al. [9]) proposes an automatic mangos teen ripening classification using the CNN framework which using the V3 Inception technique. The first model extracts the mangos teen features from images and using that, it will classify them. To train the model total of 800 images are used which gives validation accuracy 97%, training accuracy 99%, and testing accuracy 91.9%. With help of the Confusion matrix, they got values for precision is 0.88; recall is 0.96, and F1-score is00.92. The inception model has properly classified mangos teen into different ripening stages it. The classification model proposed by the author (Dhiya Mahdi Asriny et al. [10]) uses a Convolutional Neural Network (CNN) to classify images of Orange-fruit. 5 orange types are good_orange_grade_1, good_orange_grade_2, immature_orange, rotten_orange, and damaged_orange for classification using CNN algorithm. The dataset was created using mobile phone captured images; a total of 1000 orange photographs are taken and each class contains 200 images. In which they are using, 20, 20, and 60 percent of images for testing, validation, and training respectively. Model validated using K-fold cross-validation method. Tanh and ReLU activation functions are used with the Softmax classifier. ReLU function is giving 96% accuracy which is greater than Tanh function i.e. 93.8%.

For the classification of papaya maturity status, two approaches are proposed by Behera S. K. et al. [11]. The first is Machine learning and the second one is Transfer learning. Total 300 numbers of papaya fruit pictures are used for performing an experiment. All maturity levels individually having 100 images of papaya. In this model Local binary pattern (LBP), histogram of directed gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and k-NN, SVM, and Naive Bayes are the characteristics and classification approaches used in ML. On the other hand, 7 pre-trained models: Alex-Net, Res-Net-101, Res-Net-50, Res-Net-18, VGG-19, VGG-16, and Google-Net are used in Transfer Learning. The machine learning method gives 100% accuracy in 0.0995 seconds training time whereas Transfer Learning also gives 100%. They improved the 6% accuracy to the previous existing approach. (Rodrigo Pereira Ramos et al., [12]) Using DL techniques, this research identifies the grape maturation stage. VGG-19 is CNN, it is used to create a grape classification system in which grape pictures were gathered, processed, and categorized according to their maturity level. Images acquisition with various illuminants is used as classification model para-meters. For Syrah and Cabernet Sauvignon stages maturity-classification accuracy_score is 93.41% and 72.66% respectively. Authors conclude that using the computational intelligent algorithm, this model correctly classified wine grapes achieving maximum accuracy in terms of harvesting time. Author (Robert G. de Luna et al. [13]) discussed the design-plan and execution of a computervision observation method for detecting the presence of the flowers and fruits on tomato plants that are growing inside the chamber. The model also allows for tomato fruit maturity scoring. Single_Shot_Detector (SSD) and Regional-based CNN (R-CNN) are 2 pretrained transfer learning models used for the identification of the fruits and, flowers. The ANN, k-NN, and SVM are used to classify the maturity level of tomato fruit. The overall accuracy achieved by R-CNN is 1.67% for flower and 19.48% for fruit detection, where SSD achieved 100% for flower and 95.99 % for fruit detection. Training and testing accuracies by SVM are 97.78% and 99.81%; KNN gives 93.78% and 99.32% where ANN gives 91.33% and 99.32% for grading of tomato maturity.

Aaron Don M. Africa et al. [14] presented different techniques of fruit ripeness detection and its classification using machine vision and machine learning approaches. For pre-harvest and post-harvest analysis, required systems that can be utilized are presented here. To help the farmers in the evaluation of crops, authors are providing solutions for their problems using computer applications. They are capturing continuous images of fruits from trees and presented some most widely used and best-proven methods like faster CNN, image illumination, and deep learning. (Mohammed O. Al-Shawwa et al. [15]) Classifying the apple fruit using deep learning, also the author shared the useful benefits of the apple. He identified the type of apple based on the machine learning approach. For that using a dataset that carries 8,554 images of apples from that used for training 4488 pictures, for validation 1928 pictures, and for testing 2138 pictures. By using 70% photos for training and 30% for validation got 100% accuracy on the testing images set. The Kaggle-dataset was used for this approach which contains a set of 8554 images. They achieved 100% accuracy for the dataset. Author (Jasman Pardede et al. [16]) using the VGG-16 model implementing the Transfer Learning (TL) technique for fruit ripeness detection. Multilayer perceptron (MLP) block which contains a dense layer, flatten layer, and regularize was replaced by the top layer of the VGG-16 architecture. The author created their own dataset of fruit ripeness. The proposed model gives better performance when it is practically performed. MLP block achieved an increase in accuracy of 18.42% having a dropout of 0.5, Regularizes kernel and batch normalization 5 increase accuracy by 2.63% and 10.52% respectively. They conclude that reducing over-fitting in TL dropout is the best method. (Shuqin Tu et al. [17]) Five fruit maturity groups are: young, near_young, near_mature, mature, and after_mature are divided using data acquisition using Kinect-sensor. In the first stage of the algorithm, a faster region-based CNN (Faster R-CNN) is used for passion fruit identification by depth and color images, improvement of detection performance is done by integrating color-based and depth-based detections. In the second stage extraction and representation of features are taken by combining algorithms; dense scale invariant feature transform (DFSIT) with Locality_Constrained_Linear_Coding (LLC). Also for linear SVM input was the RGB-DSFIT-LLC features to identify the fruit maturity. Authors achieved detection accuracy is 92.71% and maturity classification accuracy is 91.52%.

Dr. T. Vijayakumar et al. [18] are presenting application for mellowness identification of dragon fruit using CNN RESNET-152. For training purposes, they used Python and tensor-flow. Developed model training was taken using different images of dragon fruit in its different mellowness stages and tested using confusion matrix and region of convergence using new 100 images. Epoch range taken between 10-500 for testing and results are maximum correct as compared to VGG16 or VGG19 in terms of accuracy in training and testing. The author (Anuja Bhargava et al. [19]) proposed an automatic fruit grading system for mono_colored and bi_colored apples in this article. Three levels: Segmentation, feature-extraction, and apple classification are used in this model. Defected regions are segmented using the Fuzzy_C-means, and different sets of “Statistical”/”Textural”, “Geometrical”, Gabor_Wavelet, and Discrete_Cosine_Transform are used for feature-extraction. Three classifiers were used for classification: k-NN, Sparse Representation Classifier, and SVM, and the model use 4 datasets of apple. 1st having 1120 samples in which defective 984, 2nd are having 333 samples in which 247 defectives, 3rd contain 100-samples in which 26 are defective, and 4th having 56 defectives. The accuracy_score achieved by the above datasets were: 95.21%, 93.41%, 92.64%, and 87.91%. (Rucha Thakur et al. [20]) discussed an automatic system that sorts and analyzes the strawberry fruit. A CNN is used to determine strawberry ripeness levels. Fruit_surface, fruit_color, fruit_size, and fruit_shape with other important features are extracted for proper classification using CNN, and the strawberry color of its surface predicts its ripeness level. With help of CNN proposed model has achieved an accuracy of 91.6%. An automated computer vision system is proposed by the author (Fatma M. A. Mazen et al. [21]) for bananas maturity classification. To begin, home-made 4 class database is developed. Second, an artificial neural network-based architecture that incorporates color, brown spot growth, and Tamura. To define and grade banana fruit ripening stages, statistical texture features are used. The naive Bayes, k-NN, decision tree, SVM, and discriminant analysis classifiers are used to compare the results and consistency of that proposed model. This model is having an accuracy of 97.75%, which is greater than other techniques. To reduce fruits classification faults by humans (Suganya et al. [22]) presenting a quality detection system. Detection and quality classification is done by using a Tensor-flow library, a faster R-CNN algorithm, and a softmax classifier. Objection task and all-region proposals generating task are performed by the faster R-CNN algorithm. To generate a convolutional map they feed images instead of on region proposals to CNN. They had got an accuracy of more than 95% for fruit quality detection which is greater than CNN and DL algorithms. The author (M. Shamim Hossain et al. [23]) proposed a fruit-classification frame-work using DL. Frame-work having 2 learning-architectures, the first one is a light-model six-layer CNN and the second one is fine-tuned VGG-16 pretrained DL model. This paper author used two 6 datasets in which dataset_1 consists of clear images of fruits and dataset_2 consists of challenging images to classify. They had got the accuracy for classification is 99.94 % and 99.75% using the dataset-I as well as 85.43% and 96.75% using dataset-II for the first and second model. (Wilson Castro et al. [24]) Cape gooseberry fruits are classified by using 4 ML algorithms and RGB, HSV, and LAB color-spaces combination. In 7 various maturity classes, 925-samples were manually classified. For training and validation, a 5-fold cross-validation approach was applied to categorize the colour of each fruit image in the three colour spaces and their related maturity states. The categorization of fruit based on their maturity level is adaptive to colour space and classification methodology. Performance is improved by the combination of color spaces using PCA. The author (Poshit Raj Gokul et al., [25]) proposed an approach for estimating the size and ripeness of sweet-lime. For this study, the only fruit with a spherical shape is taken into account the pictures were taken using digital-camera and mobile-phone. In MATLAB, the technique for calculating the size and ripeness of the sweet-lime is developed. The fruit volume is calculated by predicting the image-radius. Ripeness is observed using RGB colour-coding by ration of the RG. The outcomes are practically confirmed using vernier-calipers. In the end, they conclude that the proposed approach saves time and money and a generic algorithm for all types of citrus fruits can be developed. The author (John Carlo V. Puno et al. [26]) of this paper focused on Carabao Mango (Mangifera Indica) quality evaluation using a Convolutional Neural Network (CNN). A mechanical device that has a conveyor belt, rollers, and a camera was used to ensure all sides of the mango are considered for quality analysis and to collect videos for model training and validation. Frames extracted from videos are processed using the image processing technique and the background removed to get the only mango. The dataset contains good and bad quality mangoes images. The developed model used a total of 5550 training samples with an accuracy of 94.99 % and a total of 2320 validation samples with an accuracy of 97.21%.

Mohammed Faisal et al. [29] suggested an Intelligent_Harvesting_Decision_System (IHDS) from the fruit maturity level. To detect 7 separate maturity levels of date fruit, computer vision and DL techniques are used for this decision system. Maturity stages are Immature_stage-I, Immature_stage-II, Pre_Khalal, Khalal, Khalal with Rutab, Pre_Tamar, and Tamar. They created 6 different Deep Learning systems for IHDS, each of which achieved a separate accuracy_score 7 for different levels of ripeness. Data generated by the Center for Smart-Robotics-Research is used by IHDS. The accuracy achieved by the system is 99.4% and performance metrics are, F1 score: 99.4%, precision, and recall are 99.7% each. This study by (Rahul J. Mhaske et al. [30]) K-means clustering algorithm is used for quality detection of different types of apples. Comparative analysis is carried out, and the outcomes are much better compared to previous work. For training and testing, they are using the two datasets. One is created by the authors consisting of 220 images of apples. The second one is created by Computers and Optics in Food Inspection

(COFILAB). It contains three types of apples are: "Royal gala Apple", "Golden Apple" and "Royal Apple". They achieved maximum accuracy of 98.38% and minimum accuracy of 95.16%. provide sufficient detail to allow the work to be understood without too specialized references. This section should extend, not repeat, the background to the article already dealt with in the Introduction and laid the foundation for further work.

Table 1. Description of different techniques used for fruits analysis.

Year	Fruit	Application	Techniques used	Remarks and Results	Ref.
2021	Apple	Ripeness Classification	CNN, IP	To Reduce harvest losses. To help end-users like farmers or people who shop from supermarkets. 96.34% is the average precision score of this model	[8]
2021	Grapes	Ripeness Detection	VGG-19 CNN and IP	Wine grapes are classified using this technique. Cultivated and harvested at the right time. Model got 93.41% and 72.66% accuracy for both category grapes	[12]
2021	Mixed Fruit	Detection	ML, TL and VGG-16 CNN	Overfitting of the data is reduced Better performance than other techniques	[16]
2020	Orange	Classification	Deep Learning CNN, IP	Increased accuracy and consistency of quality orange selection. Reduces human workload,	[10]
2020	Mangosteen	Ripeness Classification	CNN, I I3 Inception model	To get quality mango-steen. To Initiate the Commercialization to help the mango-steen company. Accuracies for training is 99%,	[9]

				testing is 91.9%, and validation is 97%.	
2020	Papaya	Ripeness Classification	KNN, SVM, and Naive Bayes	Improved grading and Sorting system Cost and Time effective model Machine learning and transfer learning both achieved 100% accuracy	[11]
2020	Tomato	Growth Detection	SSD, R-CNN, ANN, KNN and SVM	Achieved high accuracy for grading on maturity level. For fruit SSD achieves 100% and for flower SVM achieves 99.81 % accuracy	[13]
2020	Mixed Fruit	Classification	ML and CNN	Provide solutions to help farmers using computer applications	[14]
2020	Dragon fruit	Detection	VGG16, VGG19 and RESNET 152	Smart farming accuracy increased Provides better prediction than the prevailing. This model achieved accuracy for 4 different datasets are 95.21%, 93.41%, 92.64%, and 87.91%.	[18]
2020	Strawberry	Ripeness Classification	CNN and IP	Human errors are reduced Reduced classification time This model achieved 91.6% accuracy.	[20]
2020	Cherry	Classification	CNN, ANN, KNN,	Increased exportability and marketability of cherry. Reduced wastage of cherry. Model achieved 99.4% accuracy.	[7]
2020	Mango	Ripeness Detection	IP	Improved analytical methods of classification. This	[1]

				model got 92% accuracy.	
2020	Dates	Maturity Classification	Deep Learning and Computer Vision	Fruit harvested at the appropriate time using this technique. Accuracy for this model is 99.4%.	[29]
2020	Mixed Fruit	Classification	Deep Learning CNN, VGG*16	To help industrial applications and automate the process of classification Model 1 and 2 got accuracy 99.94 %, 99.75% for dataset_1 and 85.43%, 96.75% for dataset_2	[23]
2019	Apple	Classification	Deep Learning CNN	It is good for bone health, weight loss, heart, and to prevent cancer. Accuracy is 100% for this model.	[15]
2019	Grapes	Ripeness Estimation	CNN, SVM IP	To reduce pre and post-harvesting loss. To make cost-effective. SVM and CNN got 69% and 74.49% accuracy.	[6]
2019	Banana	Ripeness Classification	ANN, SVM, naive Bayes, KNN and DT	Enhanced classification rate and minimized training and testing runtime of banana classification. Model gives 97.75% highest accuracy.	[21]
2019	Cape Gooseberry	Ripeness Classification	IP, PCA, LDA, and SVM	Fruits are properly sorted. Performance is good.	[5]
2019	Banana	Ripeness Detection And Classification	KNN, SVM and Decision Tree (DT)	Get the good quality banana. Faster processing and high accuracy. SVM got accuracy 99.1% for detection. k-NN, and	[4]

				SVM got achieved 96.6% accuracy for classification	
2019	Dates	Detection and Classification	IP	Provides better quality dates to the food industry. Improved date fruit quality.	[2]
2019	Mixed Fruit	Ripeness Detection	IP	Increased accuracy, consistency, and efficiency of grading system.	[3]
2019	Passion Fruit	Mellowness Detection	DFSIT, LLC and SVM	Accurately and efficiently recognizing maturity of fruit. Accuracy for detection is 92.71% and for classification 91.52%.	[17]
2019	Mixed Fruit	Ripeness Detection	R-CNN and IP	Overcomes human faults and problems They got more than 95% accuracy for this model.	[22]
2019	Cape Gooseberry	Ripeness Classification	ML, PCA and IP	Developed a perfect suitable classification model. Enhanced the accuracy of the sorting system	[24]

3. Discussion

A comprehensive review of the fruits Detection, Maturity classification, and quality assessment is presented to identify the shelf life of fruit. This study explores the uses of ML and DL algorithms with Image Processing techniques. The different techniques used in the detection and classification of fruits are given in the summary table. Fruits, applications, and remarks were also added to the paper.

4. Conclusions

Among the Image processing technique, Machine learning algorithms, and

Deep learning algorithms best techniques for fruit detection, maturity classification and quality assessment depend on the datasets used for that experiment. [5] CNN model achieved 79.49% accuracy whereas SVM achieved 69% accuracy, so in this case, the Deep learning technique is best. [20] Again here CNN got the highest accuracy 91.6% as compared to an image processing technique accuracy of 60%. So the working accuracy totally depends on the dataset and techniques used for detection and classification with quality assessment of fruits.

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