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A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: A survey

Mukesh Kumar Tripathi*, Dr. Dhananjay D. Maktedar

Department of CSE, Guru Nanak Dev Engineering College, Bidar, Karnataka, India

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ABSTRACT

Computer vision is a consistent and advanced technique for image processing, with the propitious outcome, and enormous potential. A computer vision has been strongly adopted in the heterogeneous domain including agriculture. During the study of existing research on the role of computer vision in fruits and vegetables among various horticulture products of agriculture fields it is noticed that, the existing survey paper has not focused properly on mathematical framework, feature descriptor, defect detection on multiple datasets of fruits and vegetables elaborately. This has motivated us to undertake an extensive survey. In this paper, we examine the paper broadly related to fruits and vegetables among various horticulture products of agriculture fields, specific model, data pre-processing, data analysis method and overall value of performance accuracy by using a particular performance metric. Moreover, we study the different type of disease present in various fruit and vegetable. We have also focused on the comparison of different machine learning approach with respect to different performance metrics on the same dataset. Thus, we have found that among all existing machine learning techniques SVM give better classification accuracy. A generalized framework to grade the quality and defect detection of multiple fruits and vegetables is also proposed in this survey. This paper covers the survey of ninety-eight papers closely related to computer vision in the agricultural field. By the survey, we have found that computer vision plays an important role and has a large potential to address the challenges related to the agricultural fields.

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E-mail addresses: mukeshtripathi016@gmail.com (M.K. Tripathi), dhananjay.maktedar@gmail.com (D.D. Maktedar).

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1. Introduction

India is a developing country. It is the sixth largest economy in the world [1]. US holds the first rank in a world with 19.39 trillion of GDP followed by China with 12.24 trillion of GDP, followed by Germany, Japan, UK and with 2.6 trillion of GDP, India stood the sixth rank across the world. Agriculture is the backbone of Indian economy. In India, more than 70% of the human resource directly or indirectly employed in agriculture [2]. In 1991, 64% of employment has been managed by agriculture. After 1991, the Indian market had open the door for industrialization, privatization etc. And adopt many models of development, such as PPP, even still agriculture producing 43% employment of the total population of the county [3] and also agriculture has a remarkable impact with an average 18% towards Indian GDP [4].

Due to the versatility of environment, India has the ability to cultivate a large variety of horticulture product of fruits and vegetables. In 2017–18, the production reaches up to 305.4 million tones which makes 33% of the agriculture production [5]. Fruits and vegetables account to 90% share of the total horticulture product. The other categories include flower, aromatic, plantation crop and spices etc. In the last decade, the production of fruits and vegetables increased by 35% [4]. In this, State Uttar Pradesh ranks 1st in the production of vegetables with 26.4 million tones, followed by state West Bengal with 25.5 million tones, which is 30% of the production of vegetables compared to other states of India. In the fruit production, state Andhra Pradesh produces 120.98 lakh tones followed by state Maharashtra 103.78 lakh tones which are together 24% of fruit production compared to rest the state of India.

The population of India is 1,355,388,325 which is equivalent to 17.744% of the total population of the world. Subsequentially, it is increasing day by day. China holds 1st rank with 18.54%, followed by India. According to the report, only 32.2% of the population of India are from an urban area, rest remaining 67.8% belongs to the rural area [6]. The total literacy rate in India is 72% and the rate of literacy rate of male and female is 80.6% and 62.8% respectively [7]. It shows that the literacy rate of female is very less compared to the male.

The farmer in a rural area is illiterate, resulting unawareness with the availability of advanced technology in the agricultural field, this lead one of the major challenge in adopting the advanced technology.

The development of agriculture is essential and should be propositional to the population to fulfil the demand. Also, India is one of a major country that exports many agriculture products so it is important that the quality of agricultural commodities must be sustained until it reaches to the end user. The government of India has launched many fruitful and beneficiary schemes to enhance the economic condition of farmers, but due to unawareness, only a few are able to take advantage of such scheme and able to employ this scheme for smart farming.

The farmer has to face some other major challenges due to the poor economic condition. One challenge is that most of the farmer need to take help from the middleman to sell the product. Another problem is that major of warehouses in India is situated at the district level. To reach to warehouse the farmer needs to hire some vehicle by giving some money that is the extra financial burden on the farmer. Even though after reaching to the center, they are not getting some trained resource person to help this farmer. One other major challenge is that the farmer is not able to adopt him in perceptive of advanced technology. In order to address these challenges, we require advanced technology in the agriculture field. The techniques based on computer vision to monitor, measure, analysis continuously various aspects and phenomena in agriculture product [8].

In the view of the above challenges, many researchers have done the work. In that few of them are closely related to computer vision domain are described in this survey paper. The author [9] has done the detail review of quality grading of fruits and vegetables applying computer vision techniques. The principal focal point of a research paper is on feature extraction based on Color, Texture, shape, and furthermore extracted feature is used by the classifier. The one major limitation of this survey is, they have only considered the single image of fruits and vegetables for grading, sorting and recognition and classification of disease.

The author [10] presents a paper based on computer vision to grade the delicious apple. In this, an apple data set is divided into two categories such as health and defect. To evaluate the quality of apple different classifiers such as SVM, KKN. 92.5% and 82.2% accuracy rate has been achieved with SVM classifier for healthy and defect categories. The drawback of the present paper is that they have considered only one direction of apple images. A review for fruit grading system based on color, texture, and size is also presented by the author [11].

Quality evaluation of tomato based on a computer is also presented by the author [12]. They have described the color statistical feature, color texture feature. In the experiments, they have gotten 100% and 96.47% accuracy rate for defective/non-defective and ripe/unripe tomato image. A framework of orange sorting using pattern recognition is also presented by the author [13]. The one disadvantage present in a paper, it could not able to identify the presence of disease in orange. Another survey has been presented by the author [14]. They all have highlighted the challenges and advantage of collaboration between human and robots in agriculture fields. One other survey based on machine vision technology to grade peels pistachios presented by the author [15]. In the experiments, they have utilized SVM as a classifier with an accuracy rate of 94.33%.

Serval type of available disease of citrus is described by the author [16]. They have done a comparison of all steps involved in a paper such as pre-processing, segmentation, feature extraction, classification is done. With the survey, they have concluded that K-means is a more suitable method for defect segmentation and texture feature is also a most useful feature that is utilized by Support Vector Machine and Neural -Network to detect the available disease in citrus leaves. A role and importance of statistical machine learning method are discussed by the author [17]. They have suggested many effective machine learning algorithms that can be utilized in agriculture fields. One limitation of the paper is that it covers only Machine Learning Techniques. It could not able to describe supervised and unsupervised techniques such as ANN and DL. A review of grading and sorting of fruits and vegetables is presented by the author [18]. They have also highlighted the various steps such as pre-processing, segmentation, feature extraction, and classification involved in grading and sorting. A grading system for strawberry is also discussed by the author [19]. They have utilized the K-means method for classification of a strawberry image based on based on color, texture, shape feature.

Grading, sorting and disease recognition is a key factor to evaluate the quality of fruits and vegetables during postharvest. Many research's has used application of the computer vision to quality level evaluation of fruits and vegetable during postharvest. The author [20] present the role of Post-Harvest Management of Fruits and Vegetables Storage They have additionally talked about significant of the key parameter for grading such as Packaging, Storage process and storage system. The author [21] present a review on the role and application of computer vision for quality grading of citrus fruits during post harvesting. They clarify the various available techniques to acquire the images and their use for the non-destructive inspection of internal and external features of these fruits. The role of machine vision is more effective

of classifying fruits and vegetables by color, texture, shape, weight, but other parameter such as good appearance and free from defect disease. The identification and classification of various available disease in citrus are still challenging task during post harvesting.

In the post-harvesting there are many factors that affect the quality and safety of the fruits and vegetables. The author [22] discuss the processing step for the production of fruits in postharvest. They have additionally given the spotlight on a different attribute that affect the quality of fruits and vegetables, how to maintain quality of fruits, Chemical-Based Microbial Control for Vegetables, role of physical treatment and importance of computer vision for value-added monitoring product quality and microbial contamination during the handling along with meeting the traceability requirements. One another author [23] present the detail review of postharvest quality evaluation system based on computer vision and composition of organically and conventionally produced fruits. The key Postharvest quality parameters including physicochemical properties, postharvest storage performance, microbiological, sensory and nutritional quality. They have also discussed several important problems in organic fruits to maintain the quality. One of the disadvantages of the review that it neglects to address significant of application of computer vision for storage quality of fruits and vegetables. One another author [24] discuss about the factor that impact the quality of fruits and vegetables. Appearance, Textural, Flavor, Nutritional, safety is some factor that affects the quality during post-harvesting.

Recently, the author [25] also present the assessment of mango quality, different technology during post-harvesting, non-destructive assessment criteria during mango supply chain. Heat treatment, cold storage management, controlled atmosphere storage, 1-methylyclopropen (1-MCP), ethylene is some assessment technique to quality grading during postharvesting. With this we found that there are need to adopt the application of computer vision to implement low cost structures for storage of fruits and vegetables. The author [26] has design and analysis the apple sorting machine the component of the machine such as a slider, brush, roller, sliders. The available feature is classified by C4.5 classifiers. The author [27] analysis the big data tool and method in agriculture fields. For the survey, we have chosen only fruits and vegetables from a variety of horticulture product. Comparisons of this survey and existing survey are presented in Table 1.

We have analyzed the differing aspect and the role of computer vision for fruits and vegetables. From the existing method, the most common one is satellite-based, Thermal and near-infrared cameras and mobile and sensor device etc. [28]. Some other techniques to extract the feature of an image based on color, texture, and shape are the sum and different histogram, GCH, CCH, CCV, CLBP, ZM, structure element [29,30]. At the last, the most popular techniques used to analyze image include Machine Learning which consists of various methods such as DL, K-Means, SVM, MSVM, ANN, PNN, KNN, LP, WBF and RA [31,32]. Besides the all available techniques, Deep Learning techniques have recently gotten more attention [33].

The above challenges present in agriculture motivated us to do the survey on in fruits and vegetables among various horticulture products of agricultural fields. Based on the

| Table 1 – Comparisons of this survey and existing survey. | rvey. | | | | | | | | | | |
|---|------------|--------------|---------|--------------------|-------|------|-----------|----------------|------------|----------------------|------|
| Year Application | Pre- | Segmentation | Feature | Feature Extraction | nc | | Defect | Classification | Similarity | Performance | Ref. |
| | Processing | | Color | Texture | Shape | Size | detection | | Measure | Evaluation Metric | |
| 2019 This Survey | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | |
| 2019 Application of statistical machine learning in | 7 | 7 | × | | × | × | ' | 7 | × | × | [17] |
| agriculture | | | | | | | | | | | |
| 2018 Grading of Fruits and Vegetables | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | × | × | 6 |
| 2018 Detection and Classification of citrus disease | 7 | 7 | 7 | 7 | 7 | × | 7 | 7 | × | × | [16] |
| 2018 Human-robot interaction in Agriculture | 7 | 7 | × | × | × | × | × | 7 | × | × | [14] |
| 2017 Grading of golden delicious Apple | 7 | 7 | 7 | 7 | × | × | ' | 7 | × | × | [10] |
| 2017 Evaluation of peeled pistachios | 7 | 7 | 7 | 7 | × | × | × | 7 | × | × | [15] |
| 2016 Quality evolution of Tomato | 7 | 7 | 7 | 7 | × | × | ' | 7 | × | 7 | [12] |
| 2016 Orange Sorting by pattern recognition | 7 | 7 | × | × | × | 7 | × | 7 | × | × | [13] |
| 2016 Apple sorting system | 7 | 7 | 7 | 7 | 7 | × | ^ | × | × | × | [56] |
| 2012 Sorting and Grading of Fruits and Vegetables | 7 | 7 | 7 | 7 | 7 | 7 | × | 7 | × | × | [18] |
| 2010 Strawberry quality grading system | 7 | 7 | 7 | 7 | 7 | × | 7 | 7 | × | × | [19] |
| 2011 Fruits Grading System | 7 | 7 | 7 | 7 | × | 7 | × | 7 | × | × | [11] |
| | | | | | | | | | | | |

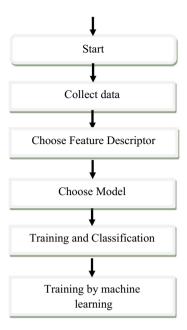


Fig. 1 - Flowchart of the proposed methodology.

discussion above, this review paper will try to give the comparison of the present survey with existing survey. This paper covers the numerous application of computer vision in agriculture fields. This survey has conjointly potential to compare the various method of different phases of computer vision such as Pre-processing, Segmentation, Feature extraction, Defect detection, Classification, Similarity measure, Performance evaluation metric. One limitation of the present survey that it could not able to cover the require time to recognition and classification of fruits and vegetables. It would be a great challenge and scope for other research's to do the deep literature survey and implementation for less recognition time.

The all procedure is represented in the form design cycle refer Fig. 1. The rest paper is organized as follows: Section 2 describes the methodology of the survey followed by Section 3, which give broadly cover all aspects of the application of computer vision in fruits and vegetables of agricultural fields. This session covers the various subtopic from 3.1 to 3.3. In Section 3.1 Recognition systems are described, followed by Defect detection, Data preprocessing in 3.2 and 3.3 respectively. Section 4 explains distinguish available feature extraction based on the various available descriptors followed by Performance Metric symbols used for classification, Overall Performance, Performance comparison with another approach, advantage, and disadvantage in respective Sections 5.1-5.4 presented. Section 6 present the deep review of assessment quality of fruits and vegetables using computer vision. In Section 7, describe the future scope in details and the last conclusion is presented in Section 8. Also, a list of abbreviations is represented by Appendix A.

2. Methodology

All the reference paper is collected and deeply analysis in two-step:

| Phase | Techniques | This paper | Ref. [50] | Ref. [66] | Ref. [30] | Ref. [56] | Ref. [57] | Ref. [60] | Ref. [58] | Ref. [64] | Ref. [69] | Ref. [40] | Ref. [38] | Ref. [90] | Ref. [37] | Ref. [45] | Ref [36] |
|---------------|--|------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|
| Year | | 2019 | 2018 | 2018 | 2017 | 2017 | 2017 | 2016 | 2015 | 2015 | 2015 | 2014 | 2013 | 2012 | 2010 | 2010 | 199 |
| Segmentation | Thresholding | 1 | | | | | | | | | | | | | | | |
| | K-Means | ~ | | | | | | | | | | | | | | | |
| | Spatial Weighted Method Median Filter | <i>V</i> | <u> </u> | | | | | | | | | | | | | | |
| | Watershed Method | | | | | | | 100 | | | | | | | | | |
| | Grab Cut | 1 | | | | 1 | | • | | | | | | | | | |
| | Otsu's Thresholding | ∠ | | | 1 | | | | | | | | | | | | |
| eature | GCH | ∠ | | | | | | | | 1 | | 1 | 1 | <u> </u> | <u> </u> | | |
| xtraction | CCH | 1 | | | | | | | | ŕ | | • | ŕ | · | · | | |
| | CCV | 1 | | | 1 | | | | | 1 | | 1 | 1 | | 1 | | |
| | CDH | ∠ | | | | | | | | | | | | | | | |
| | LBP | 1 | | | | | | | | | | | | | | | |
| | CLBP | <u> </u> | | | | | | | | | | | | - | | | |
| | SSLBP LTP | 1 <i>a</i> | | | | | | | | | | | | | | | |
| | SEH | | | | 100 | | | | | | | | | | | | |
| | HIST | 1 | | | 1 | | | | | | | | | | | | |
| | UNSER | 1 | | | 1 | | 1 | | | | | | | | | | |
| | ISHAD | ∠ | | | | | | | | | | | 1 | | | | |
| | GLCM | / | | | | | | | | | | | | | | | |
| | ZM BIC | <i>I</i> | | | / | | | | | | | | | | | | |
| | WDH | | | | | | | | | | | | | | | | |
| | SIFT | 1 | | | • | | | | ✓ | | | | | | | 1 | |
| | Statistical Feature | / | / | | | | | | | | | | | | | | 1 |
| lassification | KNN | ✓ | ✓ | | ✓ | | | | | | | | | | | | 1 |
| | SVM | 1 | | 1 | 1 | / | 1 | | 1 | | | / | 1 | | | | |
| | Non-Linear SVM | 1 | | | | | | | | | | | | | | 1 | |
| | MSVM | 1 | | | | | | | | | | | | | | | |
| | ANN | | | | _ | | | | | | | | | | | | |
| | PNN GA | 10 10 | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | | |
| imilarity | Euclidean distance L1 Distance | | | | <i>I</i> | | | | | | | | | | | | |
| neasure | Cosine distance | | | | 1 | | | | | | | | | | | | |
| | Canberra distance | 1 | | | 1 | | | | | | | | | | | | |
| | The Di distance | 1 | | | 1 | | | | | | | | | | | | |
| | Chi-square Distance | ∠ | | | 1 | | | | | | | | | | | | |
| erformance | Precision | ∠ | ~ | | | | | | | | | | | | | | |
| valuation | Recall | | | | | | | | | | | | | | | | |
| netric | Mean | " | | | | | | | | | | | | | | | |
| | Variance | | | | | | | | | | | | | | | | |
| | Equal Error rate Classification Accuracy | | | | | | | | | | | | | | | | |

1: Collection of all paper by using keyword based on a search of journals, conference, a new paper by a different site such as Google Scholar, ACM, Science direct, Research gate, IEEE explore, Google etc.

We have used the following keyword to search the paper is represented by syntax such as:

["Recognition"] AND ["Classification"] AND [Fruits or Vegetables or Agriculture] = Results.

With this syntax, we have gathered numerous papers through given link. We have downloaded three hundred fifty papers by using all keyword. Out of all research papers, we have access to two hundred thirty papers. In that one hundred thirty-three paper has been discarded and 97 papers are cited which are relevant to our domain and finally, all selected papers have been deeply analysis as per requirement and suitability of the domain.

2: In this step, all the selected paper has been analyzed, based on all research questions. Some important question is listed below:

- What is the major problem for recognition of the image of agriculture fields?
- Which techniques have been used to detect the fruits and vegetable disease?
- What is the suitable approach for classification of disease of fruits and vegetables?
- Why the preprocessing method is required?
- How to extract the feature of images using color, shape, texture?
- What are the available datasets in agriculture field?
- Which type of the metric has been adapted to measure the performance of the system?
- Is an analysis of their performance on the different datasets?
- Is any author comparing their own method accuracy with another?
- Is the author applying similarity measure method, evaluation criteria to match the performance criteria?
- What is the major disease in a different category of fruits and vegetables?

All the answer to the question asked in the methodology section is presented in Table 2. In that, we have shown the different method used by researchers in all phases. All the answer to the question asked in the methodology section is presented in Table 2. In that, we have shown the different method used by researchers in all phases. In the segmentation section, various method has been analysis for prepossessing. This method is Thresholding based, K-Means, Spatial Weighted Method, Median Filter, Watershed Method, Otsu's Thresholding. GCH, CCH, CCV, CDH, LBP, CLBP, SSLBP, LTP, SEH, HIST, UNSER, ISHAD, GLCM, ZM, BIC, WDH, SIFT, Statistical Feature method is used to analysis in feature extraction phase. For the classification KNN, SVM, Non-Linear SVM, MSVM, ANN, PNN, GA classifier has been utilized. Euclidean distance, L1 Distance, Cosine distance, Canberra

distance, Di distance, Chi-square Distance is some few methods to measure the similarity. Finally, Precision, Recall, Mean, Variance, Equal Error rate, Classification Accuracy Metric are used to evaluate the performance of the system. As we know that computer vision covers numerous method in all phase. But in this survey, author could not able to consider other techniques due to limitation of the application. So, this would be great opportunity for research's to explore other techniques in agriculture fields.

3. Computer vision application in agriculture

In this part, we have described a computer vision related research in fruits and vegetables, indicating various findings for recognition and classification system, defect detection, data preprocessing.

3.1. Recognition and classification systems

In the section, we have focused on a brief review of the work done by many researchers in the domain of the recognition and classification of fruits and vegetables. Many researchers are working on recognition of image, but initially, the author [34,35] proposed the effective image recognition approach based on color, texture, classification. The author [34] compute the to process the CCV, the technique finds the associated parts of the image and characterize the pixels inside a given shading container either coherent or incoherent. Subsequent to grouping the CCV pixels, CCV obtains two color histograms: one for coherent pixels and another for incoherent pixels. The two histograms are put away as a solitary histogram. Image pixel is classified by border/interior classification [35], considering two color histogram, one as border pixel and second one as only interior pixels.

Veggie Vision is the first automatic produce ID system introduce by [36]. They have used a Histogram, Color and texture method to evaluate the accuracy of the recognition system. For the experimental purpose, they have considered apple and orange as a case study and results are evaluated by the histogram method in the form of Hue, Saturation, and Intensity. Color features having accuracy 72% and 90% correct choice in top four selections. They also used the two texture method named as Texture Measure A and Texture Measure B to measure the convolves and center surrounding respectively. The combine Texture produces accuracy with 33% and 63% correct choice is in the top four selections and a combination of color, texture feature having 84% and 96% top four choices.

The author [37] uses many descriptors for feature extraction. They have also fused some descriptor and implemented on supermarket dataset which consists of 15 types of fruits and vegetables with a different pose, illumination, and variability. In the experiments, BIC, CCV and UNSER feature are fused, for a SVM classifier, more than 95% accuracy rate has been achieved in the proposed system. The author [38] proposed a framework for recognition and classification of fruits and vegetables. The framework consists of three steps such as Image Segmentation, Feature Extraction, and final classification of fruits and vegetables using MSVM techniques. The dis-

tinctive feature extraction method such as GCV, CCV, BIC, UNSER, ISADH is implemented and evaluated in HSV color space. 93.62%, 95.27%, 95.82%, 96.96%, 98.90% accuracy rate is achieved for respective descriptor. The learned classifier is applied to detect the image used to compare the accuracy rate of images [39]. To assess the outcomes different execution metric, for example, Recall, Precision, F-measure, False-Positive has been used for the experiment. They utilize two different set of image, one is for single scale case with containing 170 images of car, second dataset case with multiscale case with 108 images of car with different size and rotation. With the test, they express that recall- precision curves are more appropriate than ROC curves for measuring the performance of object detection approaches.

The author [40] has used 15 different categories of fruits and vegetables for a case study. This dataset has also different pose, variability, cropping, and partial occlusion effect. Different descriptor based on color, texture, shave has been used to extract the feature of the image. This extracted feature is used for classification. The MSVM is used for training and classification. Finally, they have shown 93.84 accuracy rates. The author [41] also used various feature extraction techniques such as ACC, BIC, CCV, GCV, LAS, QCCH, EOAC based on color, texture, and shape on the 15 different categories of fruits and vegetable dataset. They have combined two lowcot classifier such as support vector machine (SVM) and learned classifier such as Naive Bayes, Decision Tree, Simple Logistic, Naive Bayes Tree, k-Nearest Neighbors (KNN). The proposed framework to combine two classifiers is totally depending on term diversity measures to find detect which base learning classifiers are suitable to be consolidated.

A mathematical framework has been introduced for the detection of the image based on the probability method by the author. The probability method is useful for decision making. They have also used other parameter such as shape and appearance to detect the images. For the experimental purpose 101 different categories of object and each category contains between 45 and 400 images. The proposed system is able to produce a performance of around 70% to 95% for different category of a dataset. Another author [43] describes unsupervised learning techniques for image categories. In this approach, image categorization is based on the clustering method. Based on this approach unrelated or inhomogeneous image are categorized. The one limitation of this proposed system is that it totally depends on the shape and color of the local feature and also how to weight of different type of feature in the case of local or global. Also, the author [44] used effectively code-blocks for visual recognition and also used SVM and Naive Bayes two linear classifier for categorization of the image. In this, they have used three different classes of the dataset. First contain side views of cars. Precision and recall metric is used to evaluate the performance on the same dataset. The second data set is in seven different categories by name Xerox 7 contain 1776 images. The third dataset ETH80 is in four categories such as cars, horses, dogs and cows. The best performance has been achieved on the Xerox 7 dataset by the linear SVM classifier. With 4.8% error rate and a standard deviation is 1.2%.

The author [45] also presents a method for an extension of image categorization and also classification based on a bag of

the feature, which represent an image as an order less distribution of features. Two different descriptors Scale Invariant Feature Transform and SPIN is employed and evaluated in different categories of the dataset. Non-linear SVM is utilized for classification. The highest accuracy is achieved by (HS + LS) -SIFT descriptor with a value of 96%. The SPIN technique is additionally evaluated by an author, however excluded in a paper since it fails to produce a quality outcome. The parallel and distributed techniques also play important role in agriculture field by [46]. In their work, they have done a comparison between parallel and serial execution. The results show that parallel execution is quite useful for image recognition compares to serial execution and also They have also proposed image processing on a massively parallel computer using single-instruction, multiple-data (SIMD) computer and multiple-instruction multiple-data (MIMD) parallel processing computers. The result indicates MIMD implementation is at least four times faster than the SIMD implementation.

The author [47] present progressive randomization descriptor for image categorization. One most important characteristic, its low dimensionality and its unified approach for different applications the advantage of progressive randomization descriptor is its low dimensionality and its unified approach for different application. One major drawback is that it uses LSB Value of the image which does not contain all information under MSB. The learning algorithms for the constellation model to recognize the image is proposed by the author [48]. The accuracy rate is 87%, 90% in the case of face and car image separately. They have mentioned key factor is how to derive optimal detector, this detector important because of two reasons, first, it requires to inspect a possible joint extensive number of conceivable joint part positions, second it is not invariant as for interpretation, pivot, or scale. The main advantage of the proposed method is that it can detect the image with illumination, occultation and also invariance effect. The cost of the experiment is very high, is one of the disadvantages of the proposed system.

TFRS fruits recognition system as proposed by the author [49]. They have tested 123 images of thirty-nine species of Thai fruit. For feature extraction they utilize three various features based on color, size, edge shape. RGB histogram and Sobel edge detection based on color and edge shape feature is used to extract the feature of images. With the experiment they are able to achieve 93.5%, 86.67% accuracy rate for trained and untrained dataset respectively. Also, they calculate the average access time with a value is 54.68 s per image.

The author [50] presents a different form of KNN classifier such as Fine-KNN, Medium-KNN, Coarse -KNN, Cosine- KNN, Weighted-KNN. In the experiment, the feature of fruits is extracted by first and second order statistical method. The accuracy rate of the proposed classifier is 96.3%, 93.8%, 25%, 83.8%, 90% and 95% respectively. The results clearly show that Fine-KNN has quality output, whereas coarse- KNN has the lowest accuracy rate. The footboard machine is proposed by the author [51]. They have used SVM for classification. To evaluate the performance of a proposed machine, Precision and recall metric is used. The performance of the machine is 82.76% and 78.77% respectively.

Deep Learning base architecture is also an effective method to recognize the fruits and vegetables [52,53]. Neural

Network based fruits recognition system is also presented by the author [54]. They have utilized Deep Learning architecture and achieved 85.11% accuracy rate. Also a novel approach to recognition of images based on DL techniques has been also proposed by the author. The author also [56] describe the color and texture descriptor for recognition of fruits. Color Features (Mean, Standard Deviation, Skewness, and Kurtosis) and GLCM feature extraction method with SVM classifier is evaluated to test the accuracy of the system. The author has achieved quality, accuracy rate with a value of 91.67% accuracy for apple dataset, with 75% strawberry dataset able to produce a lower accuracy rate.

The author [57] has also used texture and shape feature for green apple recognition. Some parameter such as contrast, entropy, means used to describe the characteristics of the texture of image 90% accuracy rate has been achieved by using a combination of color and texture descriptor for recognition of green apple. A framework for plant species detection proposed by author [58]. They have utilized the color, texture, shape-based descriptor to extraction the feature of images. Five different categories of a dataset are evaluated by SVM classifier. With fruits dataset, the system shows poor accuracy rate with an estimation of 67.3% and highest exactness rate 98% is accomplished in leaf subcategory datasets. Also Hybrid RGBD feature is proposed by [59] to detect the image of the fruit. Additionally, they have presented the comparison table to recognize the accuracy based on color, fused color with shape descriptor. The accuracy of color and fused color, shape with a value of 97% and 99% respectively.

The author [60] present the modified fruits-fly optimization techniques to recognize the fruits. Classification Accuracy, True Negative, False Positive are utilized as a performance evaluator metric. The highest accuracy rate with a value 98.95% is achieved on a WBC dataset with Classification Accuracy metric by GAFOVFS techniques.

The Watershed Image method for background subtraction is described by [61]. They have done the comparisons between neural network, Naive Bayes and decision tree algorithms. The decision tree has the highest accuracy rate with a value of 93.13% using CA as the metric. The Naïve Bayes and a neural network have produced 91.94%, 92.84% accuracy rate individually to identify orange image condition such as ripe, unripe, and scaled. Precision and Sensitivity are also used as a performance metric to evaluate the system for all three classifiers. Decision tree classifier with Precision and Sensitivity metric has the highest accuracy rate 93.45% and 93.24% compared to the neural network, Naive Bayes classifier.

The author [62] used a CNN to classify the fruits and vegetables. The outcomes demonstrate a 95.6% accuracy rate has been accomplished by VGG model. The Common Publicly-available datasets related to agriculture are shown in Appendix B. The outline of this section is presented in Table 3. This table highlight description of the problem, Preprocessing techniques, feature extraction method, various classifiers, metric and value of accuracy of the system. In this section, various feature extraction method is used to extract the feature and also discuss about different classifier to classify the image. In this, author has also described the existing problem in details. One major disadvantage of recognition and classification system is the unavailability of a dataset of

fruits and vegetables and other limitation is utilization of new trend classifier such as ML, ANN, Fuzzy logic, Artificial intelligence etc. In future, all researchers should utilize various and current feature extraction and classification method for recognition and classification.

3.2. Defect detection

In agriculture, the disease is one major factor for loss of quality of fruits and vegetables. The economic condition of the farmer is directly proportional to the quality of fruits and vegetables. For example, soybean rust is a fungal disease in soybean has significant economic losses to the farmer. If we are able to identify the disease, the report says that the farmer may get benefit approx. 11 million-dollar profit [63].

In a recent year, a lot of work has been a car out to detect and classify the disease. The disease can appear in both possibilities such as pre-harvesting and post-harvesting. With the help of pesticide and other chemical product, we can control the disease. In the aspect of economic various factors is responsible for the loss, such as storing and sorting management system. As early as possible if we could detect and classify the disease, we can prevent the loss of fruits and vegetables. That can lead to a strong economic background so their life will be with health and prosperity. One major problem is that disease may be spread over the part of the image of fruits and vegetables within short spam. Due to this, the application of computer vision to the detection and classification of the different type of disease is crucial in agriculture fields. Many researchers are trying to design and develop effective and computer vision model to detect the disease and to overcome those challenges.

The traditional approach to detect the disease is totally based on an expert opinion by using eye, smell, and observation. One major drawback of this it is time-consuming, the cost will be more and the last most time we need to rely on expert opinion. One limitation of this method is that results cannot be authenticated to overcome this limitation many researchers have widely used advanced techniques to detect the disease in agriculture [30,56,64,65].

A survey has done on the application of image processing of fruits disease detection and classification by the author [29]. In that, they have proposed a framework to detect the disease based on color, texture and shape descriptor. Additionally, they have used the Multiple Support Vector Machine classifier to achieve an average accuracy more than 99%. Average accuracy more than 99%. Author [56] proposed an automatic system to recognize various categories of fruits based on color and texture feature. All images are classified by the Support Vector Machine classifier and produces high accuracy rate with a value of 83.33%. Also, the author [64] have proposed fused descriptor based on color, Texture, shape to classify the disease of apple. The fusion of CCV + CLBP descriptor has accomplished the most noteworthy accuracy with an estimation of 95.93%.

Some of the authors [30,65] has described the basic parameter of disease detection such as Ratio of Infected Area, Lesion Color Index, Damage Severity Index. In the experiments, they have calculated the total infected region and the total area of images. They have also given the details of soybean disease

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| Table | 3 – Application of com | puter vision in fruits and v | regetable and used | techniques. | | | | | |
|-------|--|--|------------------------------|---|----------------------------|---|----------------------------|----------------------------|------|
| Year | Application | Problem description | Data pre-processing | dataset used | Descriptor details | Data analysis method | Performance metric used | Value of metric used in %. | Ref. |
| 2018 | Fruits and vegetable classification | Classification based on CNN model. | Learning Techniques | 26 different set of fruits and Veggies. | CNN | CNN | CA | 95.60 | [61] |
| 2017 | Automatic fruit recognition system. | Recognition of fruits based on color and texture. | Grab cut segmentation | 8 different set of fruits. | GLCM | SVM | CA | 91.67 | [56] |
| 2017 | Recognition of apple | Recognition of apple based on fused texture and shape. | Thresholding | Apple Data-set. | Contrast, Entropy, Mean | SVM | CA | 88.25 | [57] |
| 2017 | Fruit recognition | Fruits recognition Using Multi-class classifier. | Discrete Cosine Transform | 32 different set of fruits data-set. | Hybrid RGBD | Hierarchical multi feature classification | CA | 97 | [59] |
| 2016 | Image Recognition | Image recognition and classification. | Learning Techniques | Handwritten data- set. | Bilinear-Deep model | SVM | Mean | 87.25 | [55] |
| 2016 | Recognition of Ripe, Unripe and Scaled Condition | Recognition of Ripe, Unripe and Scaled Condition based on ML techniques. | Watershed method | Orange data-set. | Border Interior | Naïve Bayes, ANN, Decision Tree | CA | 91.94,92.84,93.13 | [60] |
| 2015 | Plant species recognition | plant species recognition based on Texture feature discriptor. | K-means | Fruits Data-set. | SIFT | SVM | CA | 67.33 | [58] |
| 2013 | Detection of fruits and vegetables | Detection of fruits and vegetables using ISADH feature algorithm. | K-means | Supermarket Produce data-set. | GCH,CCV, ISHAD, BIC | SVM | CA | 96 | [38] |
| 2010 | Classification of fruits and veggies | Fruits and vegetables classification based on multi-class classification. | K-means | Supermarket Produce data-set. | GCH,UNSER, CCV, BIC | MSVM | CA | 95 | [37] |
| 2010 | Recognition of image | Recognition of image using Spatial Weighting for Bag-of-Features. | Spatial weighting | Sets of car, bicycles, and motorbikes. | SIFT | Nonlinear SVM | Equal error rate | 96 | [45] |
| 2007 | Recognition of fruits and image | Recognition of fruits and image using PR Statistical descriptor | LBB Based method | Arts Scenario. | PR | NBDC_BLDA | CA | 88.30 | [47] |
| 2000 | Identification of fruits | Identification and classification of fruits KNN. | Median Filter | Fruits Data-set. | Statistical Feature | Fine-KNN, Coarse- KNN | Precision & Recall | 96.3, 25 | [48] |
| 1992 | Recognition system | Recognition of image based on color and Texture. | Thresholding | Fruits image data- set | RGB Color | KNN | CA | 84 | [36] |

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| Year | Application | Problem Description | Data Pre-processing | Data-set used | Descriptor Details | Data analysis method | Disease Type | Performance metric used | Value of metric used in %. | Ref. |
|------|-------------------------------------|---|----------------------------------|---|----------------------------------|-------------------------|--|----------------------------|----------------------------|------|
| 2018 | Disease Classification. | Classification of disease in papaya. | K-means | Data-sets of papaya | GLCM | SVM | Black Spot, Brown Spot, Powerdary mildew | CA | 95.2 | [66] |
| 2018 | Recognition and classification | Recognition and classification to of citrus diseases. | Weighted segmentation | Fruits data set | GRB,GLCM | SVM | Anthracnose, Black spot, Canker, Scab, Melanose. | CA | 96.9 | [72] |
| 2017 | Disease detection. | Detect the disease based on image processing techniques. | Otsu's Thresholding method | Soybean leaf diseased image | BIC,CCV, CDH, LBP, SSLBP, LAP | SVM | Soybean Rust, Bacterial Blight, Sudden Death, Downy Mildew, Brown Spot, Frog Eye | CA | 95 | [30] |
| 2016 | Disease detection & classification. | Classify disease based on the various descriptors. | K-means | A diseased apple | GCH, CCV, LBP.CLBP | RF Classifier | Blotch, Rot, Scab | CA | 76.25 | [70] |
| 2016 | Classification of defect | Compute the infected level of cocoa farms | Clustering-based Segmentation | data set of diseased cacao pods | RGB Feature | SVM | Black Pod Rot, Vascular Streak Dieback, Cacao Pod Borer, | CA | 85 | [71] |
| 2015 | Classification of disease. | Classification of disease in apple based on color, texture | K-means | Data-set of diseased apple | GCH, CCV, LBP, CLBP, ZM | MSVM | ROT, SCAB, BLOTCH | CA | 95.94 | [64] |
| 2015 | Fruits Classification. | Classification of pomegranate fruits and leaf. | K-means | Data-sets of diseased pomegranate | GLCM | NEURAL NETWORK | Bacterial light, Rot, Spot | CA | 90 | [69] |
| 2014 | Detection of disease. | Detection of disease based on color, texture. | K-means | Apple Data-set. | GCH, CCV, UNSER, BIC | SVM | ROT, SCAB, BLOTCH | CA | 92.98 in RGB, 97 in HSV | [40] |
| 2012 | Apple Disease classification | Apple Disease classification based on color, Texture, Shape. | K-means | Apple data set | GCH, CCV, LBP, CLBP | MSVM | Blotch, Rot, Scab | CA | 95 | [90] |
| 2006 | Detection of the defect. | Classify the healthy and disease with crop. | NA | Arable diseased crop | NA | NEURAL NETWORK | Yellow rust on wheat | NA | 99 | [68] |

categorize in six major forms such as Soybean Rust, Bacterial Blight, Sudden Death, Downy Mildew, Brown Spot, Frog Eye. In the experiments, they classified the soybean disease with different classifiers such as SVM, KNN, and PNN Classifier. With the experiment, they found that CCV and BIC descriptor deliver 90%, 95% performance accuracy. With, KNN classifier and 90%, 92% accuracy rate have been accomplished.

Common diseases in papaya fruit are a black spot, powdery mildew, brown spot, phytotron blight, and anthracnose are described by the author [66]. A framework based on a machine based on an agro medical expert system is presented. Additionally, for the experiments, evaluation, they have implemented the Co-occurrence matrix feature and statistic feature. SVM, Decision tree and Naive Bayes classifier have been utilized for classification of disease. The average accuracy of all the classifiers 97.03%, 88.93%, and 80.89%.

The author [67] has done the detail review the losses in fruits and vegetables in both pre-harvest and post-harvest due to fungal infection. They have stated that nears about 25% loss of total production. An automatic identification of plant stresses and diseases in arable crops using proximal optical sensing and self-organizing maps is proposed by [68]. They have utilized the neural network architecture to train the feature. Additionally, Artificial Neural Networks has utilized by the author [69] to detect and classify the disease in pomegranate fruit. They also describe the type of disease present into pomegranate fruit such as bacterial blight, fruits spot, fruit rot, and leaf rot, they have achieved a good accuracy rate of more than 90%.

A hybrid approach to detect the disease in apple fruit is proposed by [70]. With the experiment, CLBP and LTP with Gabor classifier give better result compare with another method. Gabor classifier with CLBP descriptor produces the highest accuracy at 70%, 80%, 80% and 100% for a respective disease present in apple such as apple rot, apple scab, apple blotch, normal apple. Due to disease 40% loss has been recorded due to the only presence of disease in cacao farms [71].

The author proposed a framework for recognition and classification of citrus disease based on color, texture, geometric feature. RGB, GLCM and area, solidity, orientation feature is used to extract the feature. They have also discussed the disease present in citrus such as Anthracnose, Black spot, Canker, Scab [72]. Also, some framework to detect the disease is introduced by the author [73,74]. The Table 4 provides the different disease present in fruits and vegetables. The different classifier method and evaluated metric with accuracy rate is also presented in Table 4.

The present work in this section deal with description of various fruits and vegetables. Different segmentation method, feature extraction method and data analysis to obtain the accuracy of the system. Author has also listed various available data-set of fruits and vegetables with various disease. One limitation of present survey, it could able to detect and classify the defect on only train data-set. It is advisable to all the researchers to consider this limitation and try to come with new experiential solution to recognize and classify the defect in real-time.

3.3. Data preprocessing

Preprocessing is an essential step in computer vision. In our finding, the large amount of related work 80% involved some basic preprocessing step. Further, process image is applied in next step such as extraction of the feature based on color, texture, shape. The most common preprocessing techniques were image resizing such as 256×256 , 128×128 , 96×96 and 60×60 pixel. K-mean is very effective and popular image segmentation techniques related to agriculture [40,44,55,66,70,75,76]. In our survey, we have observed that 70% the author has used K-mean technique. Some author has also used thresholding techniques [46,77]. Some other techniques are also categories such as region based, edgebased, attribute-based, model-based and graph-based method [25].

Background subtraction [65,74] and foreground pixel extraction [78] is also used to process the image. Watershed segmentation [79,80] edge-based segmentation techniques [81,82] were used to detect the boundary of the image. In histogram-based segmentation, the histogram is calculated from the frequency of occurrence of the various color levels in the image [83,84,85]. Other than that, some author has used this process images into feature extraction [65] such as Gray level co-occurrence method, Local linear model, linear discriminate analysis. Some author has also used the processed image to extract the feature by combing color, texture, shape [64].

In this section, various strategy is involved for background subtraction of image. Most of author has used segmented techniques in one color space. To overcome of this limitation, it is advisable to all researcher to perform background subtraction of image in number of available color space for same data-set. One major disadvantage of pre-processing that it is time consuming and further phase of recognition is totally depended on prepossessing. In future, all researcher should apply effective and efficient solution for background subtraction of image.

Feature extraction based on the various available descriptor

In the present survey, we have given focus to extract the images feature are mostly based on color, texture, shape descriptor. Color is most basic feature extraction descriptor contain a different variety of methods such as RGB histogram, Opponent histogram, Hue histogram, RG histogram, Transform Color Distribution, Color Moment and Color Moment Invariants and others [86].

Texture descriptor is also having a various category of methods such as mean, variance, energy, correlation, entropy, contrast, cluster shade. Fourier descriptor, Space descriptor, angular transform, image moment etc. are categorized under the shape descriptor [87].

Many descriptors are available and review based on a large number of the application using color, texture, and shape. The descriptor is very helpful in answering some question listed such as.

- How to recognize the different variety of fruits and vegetables?
- How to detect the disease available in fruit image?
- How will it differentiate the face of human from the image?
- · How will it do the pattern recognition?

The accuracy of training and classification depends upon the goodness of the descriptor. That's why we need various descriptors which can able to extract the feature of images efficiently. Thus the good quality of descriptor plays a major role in the most recognition and classification problem.

These are the following three questions to answer to develop an effective and powerful descriptor. The question is listed below.

- Where to compute the descriptor?
- How to compute the descriptor?
- How to compare the descriptor?

4.1. Where and how to compute the descriptor?

Depends upon the type of the application, there is a various way to compute the descriptor. In our paper, we have limited our scope based on color, texture, and shape parameter to compute the descriptor. Effective descriptor should have following characteristics [88,89].

- Locality
- Pose invariance
- Distinctiveness
- Repeatability

4.2. How to compare the descriptor?

Similarity measure and evaluation criteria are two major categories to compare the performance of the descriptor. Similarity measures are calculated by finding the distance measure between the descriptor. In our finding, we have identified some important and different distance [30] are listed in Table 5.

We also have searched some method for evaluation criteria. This method is helpful to identify the top match. Average retrieval precision (ARP), Average retrieval rate (ARR), Average retrieval accuracy (ARA) method category under evaluation criteria is defined following expression [30] such as (see Table 6).

5. Discussion

In this part, we will present a computer vision related research in fruits and vegetables, indicating various findings for Performance Metric symbols used for classification, Overall performance, Performance comparison with another approach, Advantage and disadvantage.

5.1. Performance metric symbols used for classification

In our finding, we have to survey many papers to obtain the accuracy of the proposed system. SVM and KNN are two com-

Table 5 – Similarity measure.

$$\begin{array}{l} \text{Euclidean distance} \\ \text{Euclident} \ (D^a, D^b) = \big(\sum_{k=1}^{dim} D^b(k) - D^a(k)^2 \big)^{1/2} \\ \text{L1 distance} \\ \text{L}_1 \ (D^a, D^b) = \sum_{k=1}^{dim} \left| D^b(k) - D^a(k) \right| \\ \text{Cosine distance} \\ \text{Cosine} \ (D^a, D^b) = \frac{\big(\sum_{k=1}^{dim} D^b(k) + D^a(k)^2 \big)^{1/2}}{\big(\sum_{k=1}^{dim} D^b(k)^2 \big)^{1/2} * \big(\sum_{k=1}^{dim} D^a(k)^2 \big)^{1/2}} \\ \text{EMD distance} \\ \text{Emd } (D^a, D^b) = \sum_{k=1}^{dim} \left| cdf(D^b(k)) - cdf(D^a(k)) \right| \\ \text{Canberra distance} \\ \text{Canberra} \ (D^a, D^b) = \sum_{k=1}^{dim} \left| \frac{D^b(k) - D^a(k)}{|D^b(k) + D^a(k)|} \right| \\ \text{The Di distance} \\ \text{di} \ (D^a, D^b) = \sum_{k=1}^{dim} \left| \frac{D^b(k) - D^a(k)}{1 + D^b(k) + D^a(k)} \right| \\ \text{Chi-square distance} \\ \text{chisq} \ (D^a, D^b) = \frac{1}{2} \sum_{k=1}^{dim} \left| \frac{D^b(k) - D^a(k)}{D^b(k) + D^a(k)} \right| \\ \end{array}$$

Table 6 – Evaluation criteria.

```
Average retrieval precision (ARP): ARP = \frac{1}{N} \sum_{i=1}^{N} P(X_i) \\ P(X_i) = \frac{l_n}{l_i} * 100 Average retrieval rate (ARR): ARR = \frac{1}{N} \sum_{i=1}^{N} R(X_i) \\ R(X_i) = \frac{l_r}{l_{db}} * 100 Average retrieval accuracy (ARA): ARA = \frac{1}{N} \sum_{i=1}^{N} A(X_i), where A(X_i) is the accuracy for query image X_i and define as: A(X_i) = \begin{cases} 100, & \text{where Ir is in majority among It} \\ 0, & \text{else} \end{cases}
```

mon classifiers used by many researchers [30,37,40]. Another classifier such as a PNN, GA, Decision Tree, DL, ANN, etc. are widely used a classifier to measure the accuracy of the proposed system and also we have found that none of the researchers have been given the definition and symbol of performance, due to unavailability we have to describe the performance metric is shown in Table 7.

5.2. Overall performance

In this section, we will present how the authors show the final performance value of the evaluated algorithms. The overall performance that is considered as a keyword of this survey utilizes distinguish performance metric to measure the accuracy of the proposed system. Selection of performance metric totally depends upon the type of application and dataset used by the author.

The author [90] used a variance metric (σ) to get the recognition accuracy of the dataset with consist 15 different sets of fruits and vegetables. The overall accuracy is more than 90%, which indicate good performance. Also, they used the CA metric to recognize the disease of apple. In this, they have implemented many feature extraction methods in both RGB and HSV color space.

| Table 7 – D | escription of various metric s | symbols used to ca | lculate the accuracy of the system. |
|-------------|--------------------------------|--------------------|--|
| Sr. No. | Performance metric | Symbol used | Definitions |
| 1 | Precision | P | It is Called positive value and defines by P = TP/ (TP + FP) where TP denote correct Prediction and FP denotes False Positive |
| 2 | Recall | R | It is calculated by R = TP/(TP + FN) Where TP denotes correct prediction and FN denotes False Negative. |
| 3 | Quality Measure | QM | It is calculated by QM = TP2/(TP + FP) (TP + FN) where FN is false negatives, FP is False Positive and TP denotes correct prediction |
| 4 | Mean | μ | It is calculated by $\mu=1/n$ $\Sigma(Xi)$, Where $\Sigma(Xi)$ is a total number of the sum of all other number and n is a number of counts |
| 5 | Variance | σ | It is calculated by $\sigma \equiv \sqrt{1/n(X-\bar{X})}$, \bar{X} Where is a mean value, X is sample value |
| 6 | Standard Deviation | X^2 | It is calculated by $X^2 = \frac{(n-1)S^2}{\sigma^2}$. where S is sample size, n is a count of sample and σ is variance |
| 7 | Mean Relative Error | MRE | The mean error between estimated and predicted values, in percentage |
| 8 | Mean square error | MSE | It is an error between the estimated and predicted values |
| 9 | Root Mean Square Error | RMSE | Standard Deviation of difference between estimated and predicted values |
| 10 | Intersection over union | IOU | IOU is calculated by the union of the overlapping box, intersection box. Where is the intersection of the box is divided by the union of the area box and it is defining by IOU = TP/(FP + TP + FN), where FP, TP, FN are True positive, False Positive, False Negative respectively |
| 11 | Classification accuracy | CA | The percentage of the total number of the image correctly classified divided by the number of the image for Testing |

ISADH feature extraction produces a higher accuracy rate (>93%) in both RGB and HSV color space and UNSER has the lowest accuracy rate among all feature extraction. Mean and standard variance performance metric are also used by the author [91].

Mean and standard variance are applying to get a performance by the author [92] They have also compared the performance of the proposed system with another metric such as sensitivity, specification, accuracy, mean and last Square error. The CA metric is used by the author [66] that show good accuracy rate with 96.70%. Various performance accuracy metric such as Precision, FPR, FNR to recognize the disease in papaya applying various classifiers such as SVM, Decision Tree, Naive Bayes classifier. The results show that System produces better accuracy compare to the other classifier.

ARP and ARR performance metric used by the author [65] to detect the disease of Soybean. The author [93] use classification accuracy metric to identify the fruits images using ANN_ABC and ANN_HS techniques and achieved 96.70%, 94.28% accuracy. The author [74] use precision and recall metric to measure the accuracy of the proposed system. He has considered 3811 amount of litchi as a dataset. One drawback is that when a number of images are less for training and testing is less than its precision and recall proportionally will be less. The same performance metric has been used by other researcher's [39,76,94,95,96].

Various performance metric has been used to evaluate the overall accuracy of the system. With the review, it has concluded that classification accuracy (CA) is most popular metric among all available metric. We likewise have found that among all existing machine learning techniques SVM produce higher accuracy. In future, researcher should have fused the various data analysis techniques to improve the performance of the recognition system.

5.3. Performance comparison with another approach.

One objective of this paper is to examine how computer vision using various techniques performs in comparison to other existing methods. In this, we focus on comparative analysis between techniques used for the same dataset as well as including various performances metric in the same paper. Many authors have used machine learning techniques to obtain the accuracy of the proposed system. MSVM show 93.84% where 86.04% accuracy rate compared to minimum distance on the same dataset with the same performance metric [29], which show 7–8% higher accuracy rate.

Evaluation of performance based on different metric applying three classifier SVM, Decision Tree, Naïve Bayes has been used. All this classifier with different metric is tested on Papaya dataset. An SVM classifier with the Specification metric has produced highest accuracy and metric such as sensitivity, precision using Naïve Bayes to show worst performance by the author [66].

The author [93] has used KNN, ANN-ABC, ANN-HS classifier with CA metric to evaluate the performance of the system. ANN-ABC has achieved the highest accuracy rate with a value of 96.70% and ANN-HS, KNN produced 94.28%, 70.88% respectively. The most effective method is deep learn-

ing which is part of machine learning produced 15% higher accuracy rate compared to another method by the author [42]. Color based method gives better results computer to texture [56].

Precision metric with elimination algorithms is superior compared than Recall and F-Measure [39]. The accuracy of K-means classifier is 2–20% higher compared to other KNN, LDA, and SVM. Also, neural network has shown better results in many experiments [67]. RIA, RSI based techniques [65], GA and random decision forest-based techniques [95,67], LDA Classifier [74], ANN- based algorithms [62] are effective techniques for identification of the image. Border and interior pixel classification [35] also be superior compared to the unsupervised learning method [43]. In the survey, it has found that fused descriptor is superior compared to a single with SVM classifier [19]. Also, Deep learning is getting more attention from all inter-discipline and intra-discipline domain. The author [97] use multimodel deep learning for the detection of the image.

They have utilized multimodel deep learning on public avail dataset such STISEN, GAIT, Sleep-Stage, Indoor-Outdoor. In some case, it is also observed that MSVM showed poor results with GCH descriptor and improved sum and

difference histogram [40]. In the only case, deep learning has shown worst performance with 20% accuracy compared to other Classifier such as KNN [98]. Table 8 show difference in performance using the same performance metric in agriculture. Different performance metric is used for recognition and classification of fruit and vegetables. Different combination of classifier is also additionally implemented on the same dataset in this section. There exist numerous tools and platform permitting researchers to experiment with computer vision for fruits and vegetables. Deep leaning is more popular for data analysis now days. In future work, researchers must utilize the current available techniques to achieve good performance accuracy.

5.4. Advantage and disadvantage

In this Survey, our principle concentration is the accuracy of recognition and classification of fruits and vegetable and also detection of disease in fruits and vegetable among the horticulture product under agriculture field (see Sections 3.1 and 3.2). The advantage of computer vision is that provides rapidness, persistence, and non-destructiveness. Detection of fruits and vegetables [38] the method is robust under a

| Year | Application in agriculture | Performance metric | Difference in performance (%) | Re |
|------|---------------------------------------|----------------------------------|---|---------------------|
| 2018 | Recognition of Papaya disease | CA | SVM:95.2, Decision tree:88.6 Naïve Bayes:77.78 | [66 |
| | | Sensitivity | SVM:85.6, Decision tree:66.0 Naïve Bayes:33.33 | [66 |
| | | Specification | SVM:97.12, Decision tree:92.00 Naïve Bayes:86.67 | [66 |
| | | Precision | SVM:85.6, Decision tree:60.0 Naïve Bayes:33.0 | [66 |
| | | False Positive rate | SVM:2.88, Decision tree:8.0 Naïve Bayes:13.3 | [60 |
| | | False negative rate | SVM:14.4, Decision tree:40.0 Naïve Bayes:66.67 | [66 |
| 2018 | Identification of orange varieties | CA | KNN:70.88, ANN-ABC:96.70 ANN-HS:94.28 | [9: |
| 2017 | Apple Recognition | CA | GA:92.30, SVM:87.18 KNN:80.34, RF:83.76 | [9! |
| 2017 | Branch Recognition | CA | GA:88.03, SVM:84.61 KNN:90.59, RF:85.47 | [9 |
| 2017 | Identification of leaf | CA | GA:80.03, SVM:75.21 KNN:74.35, RF:77.78 | [9 |
| 2014 | Recognition of leaf image | CA | KNN:64.4, LDA:67.4, SVM:82.4, K-Mean:84.6, MSVM:84.6 | [9 |
| 2011 | Fruits recognition and classification | CA | SVM: GCH + LBP:93.84 KNN: GCH + CLBP:92.98 | [1 |
| 2004 | Recognition of image | Recall Precision F-measure | Elimination:80.58 (Recall) Elimination:100 (Precision) Elimination:44.4 (Measure) | [39 [39] [39] |

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challenging condition such as illumination, different poses, variability, cropping, and partial osculation. Also in the detection of disease in soybean [30] robust to the image effect with blurring, scaling, illumination.

The one other advantage of using computer vision in fruits and vegetables in the term of reducing effort/labor. The conventional procedure required adequate time, automatic processing takes place in computer vision with reducing the time. More ever fruits and vegetables are tested shown in Tables 3 and 4. The accuracy of all framework is generally high. By the survey, it is seen that SVM classifier is mostly used for testing compared to other classifiers such as KNN, PNN, and ANN etc. And also KNN widely used for the segmentation of fruits and vegetables. The paper [8] indicates that DL has the potential to apply in a variety of agriculture product. The testing time is also less with DL compared to other methods such as SVM, KNN, PNN etc.

One other advantage of computer visions is the availability of a vast range of feature descriptor. The accurate feature of fruits and vegetables is more important that is utilized by the classifier to obtain the accuracy. With the survey, we can say that color and texture based descriptor is mostly used to compare to other descriptors. The other advantage of computer vision in fruits and vegetables is that it detects the disease earlier. The author [64] classifies the disease available in apple data set, due to that farmer can save the cost of the product.

One major disadvantage in the use of Computer Vision is the preparation of dataset, that is Hercules task and it is too much time-consuming. Another disadvantage is the high computation time to process the image with an effect of osculation.

In the computer vision, a number of tasks such as preprocessing, segmentation, feature extraction, training, and testing. Each individual step depends on the previous task. At any step, if we could not able to measurable action we could not able to recognize and classify the fruits and vegetables in agriculture fields. One major disadvantage is that fruits and vegetables have more dependability on the environment, due to that it may possible that same approach of computer vision produces different accuracy on the same dataset.

Computer vision system to evaluate the quality level of fruits and vegetable

Computer vision has rich application and potential to evaluate the quality level of fruits and vegetable. Many researchers [99–101] have proposed numerous techniques to grade the agriculture product based on computer vision. An author [102] has proposed an automatic detection and classification system to grade the quality of apple. SVM data analysis techniques have been used to recognize apple fruits. One advantage of the proposed system that it consumes less recognition time. An interesting work presented by author [103] for quality inspection. The test has been done dynamically. The experiment results show that 95% image is classified. A quality infection of grape-based on computer vision system is presented by author [104]. In the experiment automatically feature selection give better accuracy compare to

manual selection. One limitation of the system is how to fix the ideal temperature for storage of grapes.

From the literature, it has found that poor administration of distribution center is one of the key factors for losses. To solve this problem, the author [105] has come with a solution with the Universal Turing Machine. This technique is used to calculate the effect of cultivar stacking heading, stacking bearing, stacking speed, the anxiety and energy proportion. The one limitation of the present system that determines the properties of only one class of fruits and vegetables. That why it is advisable for all researchers to explore this new trend topic in future and try to provide some solution to measure the mechanical properties of various fruits and vegetables.

Extended to storage issues of quality of fruits and vegetables, the author [106] presents reviews of the application of internal and external quality analysis of fruits. The various mechanisms have been utilized such as NIRS, Optical tomography, Multispectral and hyperspectral imaging. These all available techniques have the capability to measure the internal and external quality. In India, due to a large population, there is a huge demand for better quality, safe nutritious and fresh product without defect. That is why in future there is a considerably more requirement for non-damaging estimation and low-cost techniques for quality assessment.

Another author [107] also uses a non-destructive method to assess the quality of fruits and vegetable. They have explored the various methodologies to obtain the size of the fruits. They have also explored the application of computer vision to determine the size of the image. A novel approach is proposed by the author to estimate the feature of potato image. In this, they have determined some feature of potato image that is length and width, thickness, maximum square area, and volume. The experiment results show 93% showed 93% accuracy grading in volume thickness modal and 73% by area region thickness model.

Author presents [108] a novel algorithm to estimate the quality of citrus fruits. They have considered volume and mass of the product are two key attributes to assess the quality. The conventional way to deal with to calculate the volume and mass is time-consuming. To overcome this problem, an image processing based technique is used. First, all fruits image is in RGB get converted into HSI. The value of hue will be probably constant. Water displacement method (WDM) is taken to calculate the volume and R2 value has been calculated that indicate the mass information of fruits and vegetables in multi-product sizing product system. To satisfy the consumer need we all should adopt the new techniques for quality assessment, sorting and proper management of the warehouse. In this, the author [109] has given the solution to assess the quality based on computer vision. As we are all aware that colour is a key attribute to identify the quality. Manual inspection of colour will be time-consuming and have a high chance of error. To overcome this author has given the automated system to the recognition of colour.

The author [110] has done the classification of cashew product to access the quality by using computer vision. First, background subtraction and enhancement operation are done on capture images. They have utilized the morphology

operation to extract the background. In this, three different class of cashew is present such as whole, split up and split down. After that various feature of the product is extracted. These features are max, min, mean, standard derivation, area under a curve and finally the length of the curve. Further, all the extracted feature used for training and classification. The system produces a 100% accuracy rate in all three different class of cashew.

Presence of the defect is responsible to decrease the quality. The author [111] presents an efficient and effective methodology to detect the defect in citrus. They have used two different classifiers such as neural network and CART for training and testing. Both classifier produces good accuracy rate with a value 98.30% and 93.71% respectively. Computer vision framework speaks to an appropriate instrument for a quality assessment of fruits and vegetable in agriculture fields. It covers to large domain of agriculture. The computer vision able to give answer of all question which

has been asked in methodology section with efficiency, accuracy, lost cost and user friendly.

7. Future scope

Within the study, we have mostly covered the various existing applications of computer vision in fruits and veggies among various horticulture products of agricultural fields.

We have described in brief about how to extract the feature using the various descriptors. We have additionally examined the various machine learning techniques to find the accuracy of the proposed system. With the existing study, we have developed the framework for recognition and classification of veggies and fruits for future work described in Fig. 2.

In the study, we have observed following future scope listed below.

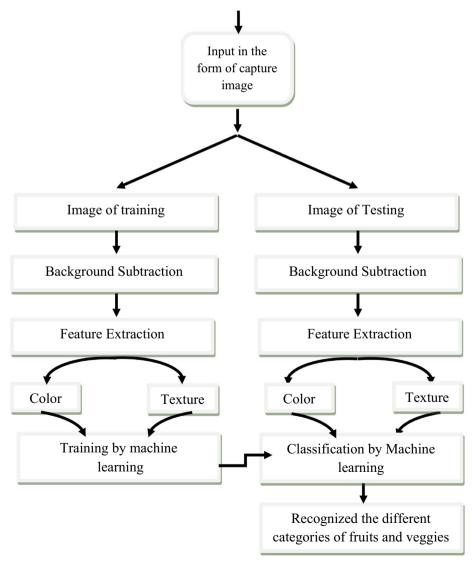


Fig. 2 - Framework for recognition and classification of veggies and fruits.

- Consider the different area of dataset under agriculture field.
- Fused the color, texture, shape descriptor to extract the feature.
- Same performance metrics can be used in the different dataset to measure accuracy.
- Recently, deep learning getting more focus of many researchers due to its potential to produce high and accurate results. This may be one of the future works for recognition and classification problems.

8. Conclusion

In this paper, we have done a survey based on the role of computer vision in fruits and vegetables among various horticulture products of agricultural fields. We have identified ninety-eight paper related to fruits and vegetables in the agricultural domain, identify the particular area, the dataset used and various challenges in the agriculture domain. In the previous work reported by researcher's in literature, quality grading and defect detection of fruit and vegetable are done on a single dataset of fruit and vegetables. In this, a generalized framework is proposed to grade the quality and defect detection of multiple fruits and vegetables. We have discussed comparative analysis of the performance of particular single feature like color, texture, shape with fused feature. Likewise, a comparative performance study is an analysis of various machines learning method with another

current technique on the same dataset with the same performance metric.

We have also given concern on the technical aspect of various frameworks employed, data preprocessing, details of descriptors used to extract the feature of images and also detection of a defect of multiple fruits and vegetables using various techniques. More ever, we also discuss a different type of disease present in various fruits and vegetables. Different performance metric symbols used to calculate the performance of the proposed system has been discussed in the survey. With this survey, SVM gives a better accuracy rate and classification accuracy is a widely used performance metric outperforms other metrics.

In future work, we want to use a different descriptor based on color, texture, shape, size and fused them to achieve more accuracy, also apply the deep learning techniques concept to detection and classification. Our main aim of this survey is to motivate the most researchers to gain knowledge of computer vision. Researchers should use this information to address the challenge in agriculture fields. The overall advantage of computer vision is motivating for its future implementation of modern farming, more accurate and efficient sorting and monitoring systems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. List of abbreviations

| Name | Abbreviation | Name | Abbreviation |
|------|---------------------------------------|-------|--------------------------------------|
| ANN | Artificial Neural Networks | ACC | Color Autocorrelogram |
| ACM | Association for Computing Machinery | ARP | Average Retrieval Precision |
| ARA | Average Retrieval Accuracy | ARR | Average Retrieval Rate |
| BIC | Border Interior Classification | CCH | Color Coherence Histogram |
| CDH | Color Difference Vector | CCV | Color Coherence Vector |
| CLBP | Complete Local Binary Pattern | DL | Deep Learning |
| DSI | Damage Severity Index | EOAC | Edge Orientation Autocorrelogram |
| FNR | False Negative Rate | FPR | False Positive Rate |
| GDP | Gross Domestic Product | GCH | Global Color Histogram |
| GLCM | Gray Level Co-occurrence Matrix | GA | Genetic Algorithms |
| ISHD | Improved Sum and Difference Histogram | KNN | k-Nearest Neighbors |
| LAS | Local Activity Spectrum | LTP | Local Ternary Patterns |
| LDA | Linear Discriminant Analysis | LBP | Local binary pattern |
| LP | Linear Polarization | LDA | Linear Discriminant Analysis |
| LSB | Least Significant Byte | LCI | Lesion Color Index |
| MSVM | Multiple Support Vector Machine | MSB | Most Significant Byte |
| PPP | Public Private Partnership | PR | Progressive Randomization |
| PNN | Probabilistic Neural Network | QCCH | Quantized Compound Change Histogram |
| RIA | Ratio of Infected Area | RNN | Recurrent Neural Networks |
| RA | Regression Analysis | RSI | Severity Index for Rust |
| SD | Standard derivation | SEH | Structure Element Histogram |
| SVM | Support Vector Machine | SSLBP | Scale selective Local binary pattern |
| SIFT | Scale Invariant Feature Transform | TFRS | Thai Fruit Recognition System |
| WBF | Wavelet Based Filtering | WDH | Wavelet Decomposed Color Histogram |

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Appendix B. Publicly-available data-sets related to agriculture

| No. | Organization/data-set | Description of data-sets | Source |
|-----|--|---|---|
| 1 | Supermarket Data-set | 15 different categories of fruits and vegetables | http://www.ic.unicamp.br/ ~rocha/pub/downloads/tropical- fruits-DB-1024x768.tar.gz. |
| 2 | Image-Net Data-set | Image of various plants (trees, Vegetables, flowers) | http://image-net.org/explore? wnid=n07707451 |
| 3 | Leaf snap Data-set | Leaves of 185 tree species | http://leafsnap.com/data-set/ |
| 4 | Life CLEF Data-set | Geographical and use of plants | http://www.imageclef.org/2014/ lifeclef/plant |
| 5 | Image-Net Large Scale Visual Recognition challenge (ILSVRC) | The image that allows image localization | http://imagenet.org/challenges/ LSVRC/2017/#det |
| 6 | Crop/weed Field Image Data-set | Crop/weed images | https://github.com/cwfid/data- set |
| 7 | Flavia leaf Data-set | Leaf image of 32 plants | https://flavia.sourceforge.net/ |
| 8 | Syngenta crop Challenge 2017 | Corn images | https://ideaconnection.com// syngenta-crop-Challenge/ challenge.php |
| 9 | Plant data-set | Herbicide injury image data-set | https://plants.uaex.edu/ herbicide https://www.uaex.edu/yard- |
| 10 | Malaya Kew Data-set. | Image of leaves from 44 species class | garden/resource-libary/disease/ https://web.fsktm.um.edu.my/ ~cschan/downloads_ mkleaf_data-set.html |

REFERENCES

- [1] The economic times. GDP data; 2018. Link https://economy-means-little-for-indias-future/articleshow/64966415.cms.
- [2] India at a glance. FAO in India. Food and Agriculture Organization of the United Nations; 2018. Link: http://www.fao.org/india/fao-in-india/india-at-a-glance/en/.
- [3] Singh A, Ganapathysubramanian B, Singh AK, Sarkar S. Machine learning for high-throughput stress phenotyping in plants. Trends Plant Sci 2016;21(2):110–24.
- [4] Mamta S, Hemanga B, Bhawna T, Sweta J, Moreshwar K, Ranbir S, Pankaj G. Horticultural statistics at a glance. Link: http://nhb.gov.in/statistics/Publication/Horticulture%20At%20a%20Glance%202017%20for%20net%20uplod%20(2).pdf.
- [5] Press Information Bureau Government of India. ECONOMIC SURVEY; 2018. Link: http://www.pib.nic.in/indexd.aspx>.
- [6] India Population. Worldometers n.d data; 2018. Link: http://www.worldometers.info/world-population/india-population/>.
- [7] Literates and Literacy Rates; 2018. Link: http://www.nlm.nic.in/literacy01_nlm.htm/>.
- [8] Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. Comput Electron Agric 2018;147:70–90.
- [9] Bhargava A, Bansal A. Fruits and vegetables quality evaluation using computer vision: a review. J King Saud Univ – Comput Inf Sci 2018;1–15.
- [10] Moallem P, Serajoddin A, Pourghassem H. Computer vision-based apple grading for golden delicious apples based on surface features. Inf Process Agric 2017;4(1):33–40.
- [11] Al Ohali Y. Computer vision based date fruit grading system: design and implementation. J King Saud Univ – Comput Inf Sci 2011;23(1):29–36.
- [12] Arakeri MP, Lakshmana. Computer vision based fruit grading system for quality evaluation of tomato in

- agriculture industry. In: Proc ICCCV '16 Proceedings of the 2016 International Conference on Communication, Computing and Virtualization, Mumbai, India; 2016. p. 426–433.
- [13] Jhawar J. Orange sorting by applying pattern recognition on colour image. In: Proc. ICISP '15 Proceedings of the 2015 International Conference on Information Security & Privacy. Nagpur, India; 2016. p. 691–697.
- [14] Vasconez JP, Kantor GA, Auat FA. Human -robot interaction in agriculture: a survey and current challenges. Biosyst Eng 2018;179:35–48.
- [15] Nouri-ahmadabadi H, Omid M, Mohtasebi SS. Design, development and evaluation of an online grading system for peeled pistachios equipped with machine vision technology and support vector machine. Inf Process Agric 2017;4 (4):333–41.
- [16] Iqbal Z, Attique M, Sharif M, Hussain J, Habib M, Javed K. An automated detection and classification of citrus plant diseases using image processing techniques: a review. Comput Electron Agric 2018;153:12–32.
- [17] Rehman TU, Mahmud S, Chang YK, Jin J, Shin J. Current and future applications of statistical machine learning algorithms for agricultural machine vision systems. Comput Electron Agric 2019;156:585–605.
- [18] Mahendran R, Gc J, Alagusundaram K. Application of computer vision technique on sorting and grading of fruits and vegetables. J Food Process Technol 2012;3(8):1–7.
- [19] Liming X, Yanchao Z. Automated strawberry grading system based on image processing. Comput Electron Agric 2010;71 (S1):S32–9.
- [20] El-ramady HR, Domokos-szabolcsy E, Abdalla NA, Taha HS, Fari M, editors. Sustainable agriculture reviews: postharvest management of fruits and vegetables storage. Switzerland: Springer Cham; 2013. p. 65–152.
- [21] Cubero S, Lee WS, Aleixos N, Albert F, Blasco J. Automated systems based on machine vision for inspecting citrus fruits from the field to postharvest—a review. Food Bioprocess Technol 2016;9(10):1623–39.

- [22] Erkan M, Yildirim I. editors. Minimally processed refrigerated fruits and vegetables. Postharvest Quality and Safety of Fresh-Cut Vegetables, USA: Springer; 2002. p. 271– 326.
- [23] Mditshwa A, Magwaza LS, Tesfay SZ, Mbili N. Postharvest quality and composition of organically and conventionally produced fruits: a review. Sci Hortic (Amsterdam) 2017;216:148–159.
- [24] Brasil IM, Siddiqui MW, editors. Preharvest modulation of postharvest fruit and vegetable quality: quality of fruits and vegetables: an overview. UK: Academic Press Elsevier; 2017. p. 1–40.
- [25] Ntsoane ML, Zude-Sasse M, Mahajan P, Sivakumar D. Quality assessment and postharvest technology of mango: a review of its current status and future perspectives. Sci Hortic (Amsterdam) 2019;249:77–85.
- [26] Sofu MM, Er O, Kayacan MC, Cetis B. Design of an automatic apple sorting system using machine vision. Comput Electron Agric 2016;127:395–405.
- [27] Kamilaris A, Kartakoullis A, Prenafeta-Boldu FX. A review on the practice of big data analysis in agriculture. Comput Electron Agric 2017;143:23–37.
- [28] Ishimwe R, Abutaleb K, Ahmed F. Applications of thermal imaging in agriculture—a review. Adv Remote Sens 2014;3 (3):128–40
- [29] Dubey SR, Jalal AS. Application of image processing in fruit and vegetable analysis: a review. J Intell Syst 2015;24 (4):405–24.
- [30] Shrivastava S, Singh SK, Hooda DS. Soybean plant foliar disease detection using image retrieval approaches. Multimed Tools Appl 2017;76(24):26647–74.
- [31] Saxena L, Armstrong L. A survey of image processing techniques for agriculture. In: Proc. AFITA '14 Proceedings of the 2014 Asian Federation for Information Technology in Agriculture, Perth, Australia; 2014.p. 401–13.
- [32] Dubey SR, Jalal AS. Robust approach for fruit and vegetable classification. In: Proc. ICMOC '12 Proceedings of the 2012 International Conference on Modelling, Optimization and Computing, Tamil Nadu, India; 2012. p. 3449–53.
- [33] Lecun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521:436–44.
- [34] Pass G, Zabih R, Miller J. Comparing images using color coherence vectors. In: Proc ICOM '96 Proceedings of the 1996 ACM international conference on multimedia, New York, USA; 1996. p. 65–73.
- [35] Stehling RO, Nascimento MA, Falcao AX. A compact and efficient image retrieval approach based on border/interior pixel classification. In: Proc. CIKM '02 Proceedings of the 2002 ACM CIKM International Conference on Information and Knowledge Management. McLean VA, USA; 2002. p. 102– 109
- [36] Bolle RM, Connell JH, Haas N, Mohan R, Taubin G. Veggie vision: a produce recognition system. In: Proc. WACV '96 Proceedings of the 1966 IEEE Workshop on Applications of Computer Vision, Sarasota, FL, USA; 1996. p. 244–251.
- [37] Rocha A, Hauagge DC, Wainer J, Goldenstein S. Automatic fruit and vegetable classification from images. Comput Electron Agric 2010;70(1):96–104.
- [38] Dubey SR, Jalal AS. Species and variety detection of fruits and vegetables from images. Int J Appl Pattern Recognit 2013;1(1):108–26.
- [39] Agarwal S, Awan A, Roth D. Learning to detect objects in images via a sparse, part-based representation. IEEE Trans Pattern Anal Mach Intell 2004;26(11):1475–90.
- [40] Dubey SR, Jalal AS. Fruit disease recognition using improved sum and difference histogram from images. Int J Appl Pattern Recognit 2014;1(2):199–220.

- [41] Faria FA, Dos Santos JA, Rocha A, Da S. Torres R. Automatic classifier fusion for produce recognition. In: Proc. SIBGRAPI '12 Proceedings of the 2012 IEEE Conference on Graphics, Patterns and Images, Ouro Preto, Brazil; 2012. p. 252–9.
- [42] Fei-Fei L, Fergus R, Perona P. One-shot learning of object categories. IEEE Trans Pattern Anal Mach Intell 2006;28 (4):594–611.
- [43] Heidemann G. Unsupervised image categorization. Image Vis Comput 2005;23(10):861–76.
- [44] Jurie F, Triggs B. Creating efficient codebook for visual recognition. In: Proc. ICCV '05 proceedings of the 2005 IEEE international conference on computer vision, Beijing, China; 2005. p. 604–10.
- [45] Marszaek M, Schmid C. Spatial weighting for bag-of-features. In: Proc. CVPR '06 Proceedings of the 2006 IEEE computer society conference on computer vision and pattern recognition, San Francisco, California; 2010, p. 2118–2125.
- [46] Fakhri A Nasir A, Nordin M Rahman A, Rasid Mamat A. A study of image processing in agriculture application under high performance computing environment. Int J Comput Sci Telecommun 2012;3(8):16–24.
- [47] Rocha A, Goldenstein S. PR: More than meets the eye. In: Proc.ICCV '07 Proceedings of the 2007 IEEE international conference on computer vision. Rio de Janeiro, Brazil; 2007. p. 1–8.
- [48] Weber M. Unsupervised learning of models for recognition. Doctor thesis. California Institute of Technology; 2000. Link: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1. 336.5737&rep=rep1&type=pdf>.
- [49] Pornpanomchai, Chomtip, Khomkhwan Srikeaw, Voranun Harnprasert KP. Thai Fruit Recognition System (TFRS). In: Proc. ICIMCS '09 proceedings of the 2009 proceedings of the first international conference on internet multimedia computing and service. New York, USA, 2009. p. 108–112.
- [50] Nosseir A, Eldin S, Ahmed A. Automatic identification and classifications for fruits using k-NN. In: Proc ICSIE '18 Proceedings of the 2018 ACM international conference on software and information engineering Cairo, Egypt; 2018. p. 62–67.
- [51] Pham C, Jackson D, Schoning J, Bartindale T, Plotz T, Olivier P. Food board: surface contact imaging for food recognition. In: Proc. UbiComp '13 proceedings of the 2013 ACM international joint conference on pervasive and ubiquitous computing. Zurich, Switzerland; 2013. p. 749–752.
- [52] Fan S, Wang X. Vegetation recognition based on deep learning with feature fusion. In: Proc. ICAIP '17 proceedings of the 2017 ACM international conference on advances in image processing, Bangkok, Thailand; 2017. p. 19–23.
- [53] Patil O, Gaikwad PV. Classification of vegetables using tensor flow. Int J Res Appl Sci Eng Technol 2018;6(4):2926–34.
- [54] Sundararajan K, Woodard DL. Deep learning for biometrics: a survey. ACM Comput Surv 2018;51(3):1–34.
- [55] Zhong S-H, Liu Y, Hua KA. Field effect deep networks for image recognition with incomplete data. ACM Trans Multimed Comput Commun Appl 2016;12(4):1–22.
- [56] Jana S, Basak S, Parekh R. Automatic fruit recognition from natural images using color and texture features. In: Proc. devLC '17 Proceedings of the 2017 IEEE conference on Devices for Integrated Circuit, Kalyani, India; 2017. P. 620–4.
- [57] Li D, Shen M, Li D, Yu X. Green apple recognition method based on the combination of texture and shape features. In: Proc. ICMA '17 Proceedings of the 2017 IEEE International Conference on Mechatronics and Automation. Takamatsu, Japan; 2017. p. 264–9.
- [58] Purohit S, Viroja R, Gandhi S, Chaudhary N. Automatic plant species recognition technique using machine learning approaches. In: Proc. CoCoNet '15 proceedings of the 2015

- IEEE international conference on computing and network communications. Trivandrum, India; 2015. p. 710–9.
- [59] Rachmawati E, Supriana I, Khodra ML. Toward a new approach in fruit recognition using hybrid rgbd features and fruit hierarchy property. In: Proc. EECSI '17 Proceedings of the 2017 international conference on electrical engineering, Computer Science and Informatics, Yogyakarta, Indonesia; 2017. p. 202–7.
- [60] Ye FEI, Lou X, Han MIN. Evolving support vector machine using modified fruit fly optimization algorithm and genetic algorithm for binary classification problem. In: Proc. ICCWAMTIP '16 Proceedings of the 2016 IEEE International Computer Conference on Wavelet Active Media Technology and Information Processing .Chengdu, China; 2016. p. 38–46.
- [61] Wajid A, Singh NK, Junjun P, Mughal MA. Recognition of ripe, unripe and scaled condition of orange citrus based on decision tree classification. In: Proc. iCoMET '18 proceedings of the 2018 IEEE international conference on computing, mathematics and engineering technologies, Sukkur, Pakistan; 2018. p. 1–4.
- [62] Zeng G.Fruit and Vegetables classification system using image saliency and convolutional neural network. In: Proc. ITOEC '17 proceedings of the 2017 IEEE information technology and mechatronics engineering conference, Chongqing, China; 2017. p. 613–7.
- [63] Roberts Michael J, Schimmelpfennig David E., Ashley Elizabeth, Livingston Michael J, Ash Mark S, Vasavada U. The value of plant disease early-warning systems: a case study of USDA's soybean rust coordinated framework. Econ Res Rep 7208;2006:1–38.
- [64] Dubey SR, Jalal AS. Apple disease classification using color, texture and shape features from images. Signal Image Video Process 2015;10(5):819–26.
- [65] Shrivastava S, Kumar S, Hooda DS. Color sensing and image processing-based automatic soybean plant foliar disease severity detection and estimation. Multimed Tools Appl 2015;74(24):11467–84.
- [66] Habib MT, Majumder A, Jakaria AZM, Akter M, Uddin MS, Ahmed F. Machine vision based papaya disease recognition. J King Saud Univ – Comput Inf Sci 2018.
- [67] Liu J, Sui Y, Wisniewski M, Droby S, Liu Y. Review: Utilization of antagonistic yeasts to manage postharvest fungal diseases of fruit. Int J Food Microbiol 2013;167(2):153–60. https://doi.org/10.1016/j.ijfoodmicro.2013.09.004.
- [68] Moshou D, Bravo C, Wahlen S, West J, McCartney A, De Baerdemaeker J. Simultaneous identification of plant stresses and diseases in arable crops using proximal optical sensing and self-organising maps. Precis Agric 2006;7 (3):149-64.
- [69] Dhakate M, Ingole AB. Diagnosis of pomegranate plant diseases using neural network. In: Proc. NCVPRIPG '15 Proceedings of the 2015 National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics, Patna, Bihar; 2015. p. 1–4.
- [70] Samajpati BJ, Degadwala SD. Hybrid approach for apple fruit diseases detection and classification using random forest classifier. In: Proc ICCSP '16 proceedings of the 2016 international conference on communication and signal processing Melmaruvathur, India; 2016. p. 10015–1019.
- [71] Tan DS, Leong RN, Laguna AF, Ngo CA, Lao A, Amalin D. A framework for measuring infection level on cacao pods. In: Proc. TENSYMP '16 Proceedings of the 2016 Region 10 Symposium, Bali, Indonesia; 2016. p. 384–389.
- [72] Sharif M, Attique M, Iqbal Z, Faisal M, Ullah MI, Younus M. Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. Comput Electron Agric 2018;150:220–34.

- [73] Padol PB, Yadav AA. SVM classifier based grape leaf disease detection. In: Proc. CASP '16 proceedings of the 2016 IEEE conference on advances in signal processing, Pune, India; 2016. p. 175–179.
- [74] He ZL, Xiong JT, Lin R, Zou X, Tang LY, Yang ZG. A method of green litchi recognition in natural environment based on improved LDA classifier. Comput Electron Agric 2017:140:159–67.
- [75] Faria FA, Dos Santos JA, Rocha A, Torres RDS. A framework for selection and fusion of pattern classifiers in multimedia recognition. Pattern Recognit Lett 2014;39:52–64.
- [76] Jawale D, Deshmukh M. Real time automatic bruise detection in (Apple) fruits using thermal camera. In: Proc. ISSCP '17 proceedings of the 2017 IEEE international conference on communication and signal processing. Chennai, India; 2017. p. 1080–1085.
- [77] Tripathi MK, dr. Maktedar D. A framework with OTSU'S thresholding method for fruits and vegetables image segmentation. Int J Comput Appl 2018;179(52):25–32.
- [78] Yuan Y, Liu Y, Dai G, Zhang J, Chen Z. Automatic foreground extraction based on difference of Gaussian. Sci World J. 2014;2014:1–9.
- [79] Li J, Chen L, Huang W. Detection of early bruises on peaches (Amygdalus persica L.) using hyperspectral imaging coupled with improved watershed segmentation algorithm. Postharvest Biol Technol 2018;135:104–13.
- [80] De Smet P. Optimized high speed pixel sorting and its application in watershed based image segmentation. Pattern Recognit 2010;43(7):235923–66.
- [81] Marmanis D, Schindler K, Wegner JD, Galliani S, Datcu M, Stilla U. Classification with an edge: improving semantic image segmentation with boundary detection. ISPRS J Photogramm Remote Sens 2018;135:158–72.
- [82] Wang X, Deng Y, Duan H. Edge-based target detection for unmanned aerial vehicles using competitive Bird Swarm Algorithm. Aerosp Sci Technol 2018;78:708–820.
- [83] Caraiman S, Manta VI. Histogram-based segmentation of quantum images. Theor Comput Sci 2014;529:46–60.
- [84] Qin K, Xu K, Liu F, Li D. Image segmentation based on histogram analysis utilizing the cloud model. Comput Math with Appl 2011;62(7):2824–33.
- [85] Siang Tan K, MatIsa NA. Color image segmentation using histogram thresholding Fuzzy C-means hybrid approach. Pattern Recognit 2011;44(1):1–15.
- [86] Van De Sande K, Gevers T, Snoek C. Evaluating color descriptors for object and scene recognition. IEEE Trans Pattern Anal Mach Intell 2010;32(9):1582–96.
- [87] Amanatiadis A, Kaburlasos VG, Gasteratos A, Papadakis SE. Evaluation of shape descriptors for shape-based image retrieval. IET Image Process 2011;5(5):493–9.
- [88] Lowe DG. Distinctive image features from scale invariant keypoints. Int J Comput Vis 2004;60(2):91–110.
- [89] Tuytelaars T, Mikolajczyk K. Local invariant feature detectors: a Survey. Found Trends® Comput Graph Vis 2007;3(3):177–280.
- [90] Dubey SR, Jalal AS. Adapted approach for fruit disease identification using images. Int J Comput Vis Image Process 2012;2(3):44–58. https://doi.org/10.4018/jjcvip.2012070104.
- [91] Choi D, Lee WS, Ehsani R, Schueller J, Roka FM. Detection of dropped citrus fruit on the ground and evaluation of decay stages in varying illumination conditions. Comput Electron Agric 2016;127:109–19.
- [92] Kumar RA, Rajpurohit VS, Nargund VB. A neural network assisted machine vision system for sorting pomegranate fruits. In: Proc. ICECCT '17 Proceedings of the 2017 Second International Conference on Electrical, Computer and Communication Technologies. Coimbatore, India; 2017. p. 1–9.

- [93] Sabzi S, Abbaspour-Gilandeh Y, García-Mateos G. A new approach for visual identification of orange varieties using neural networks and metaheuristic algorithms. Inf Process Agric 2018;5(1):162–72.
- [94] Singh N, Dubey SR, Dixit P, Gupta JP. Semantic image retrieval by combining color, texture and shape features. In: Proc. ICCS '12 proceedings of the 2012 IEEE international conference on computing sciences. Phagwara, India; 2012. p. 116–120.
- [95] Tao Y, Zhou J. Automatic apple recognition based on the fusion of color and 3D feature for robotic fruit picking. Comput Electron Agric 2017;142:388–96.
- [96] Shao MW, Du JX, Wang J, Zhai CM. Recognition of leaf image set based on manifold-manifold distance. In: Proc. ICIC '14 Proceedings of the 2014 international conference on intelligent computing. Nanning, China; 2014. p. 332–7.
- [97] Radu V, Tong C, Bhattacharya S, Lane ND, Mascolo C, Marina MK. Multimodal deep learning for activity and context recognition. In: Proc. IMWUT '18 proceedings of the 2018 ACM on interactive, mobile, wearable and ubiquitous technologies. New York, USA; 2018. p. 1–27.
- [98] De Los Reyes A, Augenstein TM, Wang M, Thomas SA, Drabick DAG, Burgers DE. The validity of the multiinformant approach to assessing child and adolescent mental health. Psychol Bull. 2015;141(4):858–900.
- [99] Ilic ZS, Fallik E. Light quality manipulation improves vegetable quality at harvest and postharvest: a review. Environ Exp Bot 2017;139:79–90.
- [100] El Khaled D, Castellano NN, Gazquez JA, García Salvador RM, Manzano-Agugliaro F. Cleaner quality control system using bioimpedance methods: a review for fruits and vegetables. J Cleaner Prod 2017;140:1749–62.
- [101] Lin H, Ying Y. Theory and application of near infrared spectroscopy in assessment of fruit quality: a review. Sens Instrum Food Qual Saf 2009;3:130–41.
- [102] Ji W, Zhao D, Cheng F, Xu B, Zhang Y, Wang J. Automatic recognition vision system guided for apple harvesting robot. Comput Electr Eng 2012;38:1186–95.

- [103] Benalia S, Cubero S, Prats-Montalbán JM, Bernardi B, Zimbalatti G, Blasco J. Computer vision for automatic quality inspection of dried figs (Ficus carica L.) in real-time. Comput Electron Agric 2016;120:17–25.
- [104] Pietro Cavallo D, Cefola M, Pace B, Logrieco AF, Attolico G. Non-destructive and contactless quality evaluation of table grapes by a computer vision system. Comput Electron Agric 2019;156:558–64.
- [105] Jafari Malekabadi A, Khojastehpour M, Emadi B, Golzarian MR. Development of a machine vision system for determination of mechanical properties of onions. Comput Electron Agric 2017;141:131–9.
- [106] Magwaza LS, Opara UL, Nieuwoudt H, Cronje PJR, Saeys W, Nicolaï B. NIR spectroscopy applications for internal and external quality analysis of citrus fruit a review. Food Bioprocess Technol 2012;5:425–44.
- [107] Moreda GP, Ortiz-Cañavate J, García-Ramos FJ, Ruiz-Altisent M. Non-destructive technologies for fruit and vegetable size determination – a review. J Food Eng 2009;92:119–36.
- [108] Omid M, Khojastehnazhand M, Tabatabaeefar A. Estimating volume and mass of citrus fruits by image processing technique. J Food Eng 2010;100: 315–21.
- [109] Pace B, Pietro Cavallo D, Cefola M, Colella R, Attolico G. Adaptive self-configuring computer vision system for quality evaluation of fresh-cut radicchio. Innovative Food Sci Emerg Technol 2015;32:200–7.
- [110] Sunoj S, Igathinathane C, Jenicka S. Cashews whole and splits classification using a novel machine vision approach. Postharvest Biol Technol 2018;138:19–30. https://doi.org/10.1016/j.postharvbio.2017.12.006.
- [111] Gomez-Sanchis J, Martín-Guerrero JD, Soria-Olivas E, Martínez-Sober M, Magdalena-Benedito R, Blasco J. Detecting rottenness caused by Penicillium genus fungi in citrus fruits using machine learning techniques. Expert Syst Appl 2012;39:780–5.