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Healthy Fruits Image Label Categorization through Color Shape and Texture Features Based on Machine Learning Algorithm

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Abstract*: *The fruit categorization according to their visual quality has recently experienced tremendous growth in the field of agriculture and food products. Due to post-harvest loses during handling and processing, there is an increasing demand for quality products in agro industry which requires accuracy to predict the fruit. Various techniques of machine learning have been successfully applied for classifying the fruit built on binary class. In this paper, machine leaning technique is used to automate the process of categorization and to improve the accuracy of different types of fruits by feature selection. To categorized images domain specific features such as color, shape and textual features are considered. Statistical color features are extracted from the image, bounding box feature for shape features and gray-level co-occurrence matrix (GLCM) is used to extract the textual feature of an image. These features are combined in a single feature fusion. A support vector machine (SVM) classification model is trained using training set features on fruit360 dataset which includes six fruit categories (classes) with two sub category (sub-classes) which builds multiclass classification task. We present one-vs-one coding design of Error correcting output codes (ECOC) and apply to SVM classifier; validation followed a fivefold cross validation strategy. The result shows that the textual features combined with color and shape feature improved fruit classification accuracy.

Keywords* : *Categorization, SVM-ECOC, Machine learning

I. INTRODUCTION

India is considered as the second largest producer of fruits and vegetables. One of the challenging problem affecting the country's agriculture market is post-harvest loses. Annually the country suffer huge losses due to post-harvest loses. The various post-harvest losses from the producer to consume includes lack of proper harvest practices, transportation and cold storage which results in 35% to 40% of fruit and vegetable produced being wasted The research work at the department of nano science and technology at TNAU has been trying to reduce post-harvest losses of fruits by slowing down the ripening and control loses at farm level using Enhanced Freshness Formulation (EFF) by dipping fruit(mangoes and bananas) in EFF solution.

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It also adopt various methods for controlling losses in package houses, transportation and retail shops by placing a EFF based tablet in a fruit carton which results in increased shelf life[1]. The initial and most important process in post harvesting sequence is sorting and grading of harvested produce. In India manual sorting and grading is performed by human based on visual quality inspection. But it is costly, tedious and time consuming [2]. Huge losses occur in post-harvest during handling and processing, with the increasing demand for quality products in agro industry requires accuracy .The quality of the fruit is classified into internal and external factors [3]. The external quality factor includes size, image-color, image- shape and image-texture. In order to prevent losses of post harvesting there is a need to automate the process of categorizing the fruit using external factors. Automatic categorization of fruits from images is one of the most difficult tasks in an emerging domain of research that combines the aspect of computer vision and machine learning. One of the challenging researches in computer vision is to automatically categorize image using low level features [4]. Image categorization has been referred to as a process in which labeling of images is done into one of a number of predefined categories. Generally it depends on combination of approaches such as statistical (mean, variance and entropy), structural (part of the object) and spectral approach [5]. The human vision can easily categorized fruit images among various categories even though they are changes in numerous factors such as illumination, noise, viewing angle etc. The categorization of common fruits according to their visual features such as image-color, image-shape and image-texture are fundamental aspect for visual content. Human perception of certain visual features could be associated with different classes of fruit objects Images. Classification of image deals with multi class categorization based on image feature similarity by using the visual descriptor in large scale database. Multiclass categorization image classification problem is motivated by the need to classify fruit object based on their category.

The purpose research performs automation of fruit image categorization using external features through machine learning techniques. The paper presents two objectives. In the first case feature extraction is performed using color and shape feature. In the second case three features color, shape and texture are considered and finally the accuracy of each case is presented. A machine learning model is proposed where the feature extraction involves color, shape and texture algorithms of each image. The classification uses SVM (support vector machine) with ECOC framework. Evaluation

Table 1: Summarization of Binary and Multiclass SVM algorithms

Purpose & ref	Features	Images	Dataset	Classifier/Algorithm	accuracy	Finding
To classify dates fruit automatically [6]	Shape & color	120	(Web scraping)	Binary SVM	100%	It classifies the fruit type eatable or non- eatable using binary SVM. It is proven high degree of accuracy.
To classify different fruits automatically[11]	Color, texture & shape	1653 (18 categories)	On-site data collection &(web scraping)	Multiclass Kernel SVM (KSVM)	88.2%	It classifies the fruits with KSVM. It proved that multiclass kernel SVM perform accuracy with 88.2%.
Fruit recognition system with KNN [12]	Shape, size & texture	36	-	KNN	95%	It classify & identify several fruits with nearest neighbor (KNN) algorithm improve accuracy.
Fruit recognition with ANN[15]	Texture, color& shape.	150 (6 categories)	-	ANN	90%	It classifies several fruit with artificial neural network.
Fruit classification using statistical feature [14]	Color and texture	941 (10 categories)	Supermarket produce	Multiclass SVM	95.3%	Proposed fruit classifying using statistical and co-occurrence featured from the wavelet transform. It proves that Multiclass SVM perform accuracy with more than 95%
Fruit classification using surface and geometric information [15]	Color, texture ,size & shape	2633 (15 categories)	Supermarket produce	k-nearest neighbor	81.94%	
Fruit Recognition [16]	Color & texture	240 (30 images per class) (8 categories)	(web scraping)	Multiclass SVM	-	Proposed method uses Grabcut segmentation for background removal, glcm texture and statistical color feature. Multiclass SVM classify the fruit

of model is carried out using performance metric. The rest of the paper organized is as follows. In Section 2, methodology is presented. Section3, describe the SVM with ECOC framework. In Section 4, we discuss the classification steps, section 5, experimental results and Analysis, section 6; present the discussion and finally conclusion and probable future work.

In literature much research work is discussed in automation of fruit classification using binary class and multiclass SVM. In binary class to classify the dates whether it is eatable and non-eatable with an 100%accuracy [6], for multiclass such as date fruit classification with one against all method [7] ,fruit and branches identification with one against one method[8],Cape gooseberry fruit classification for visual ripeness[9], categorization of fruit using different classifiers[10]. Zhang & Wu, proposed a multiclass KSVM method for classification of fruits [11]. Fruit recognition with (K-nearest neighbors) KNN [12]. Naskar and Bhattacharya [13] proposed fruit recognition with ANN.

II. METHODOLOGY

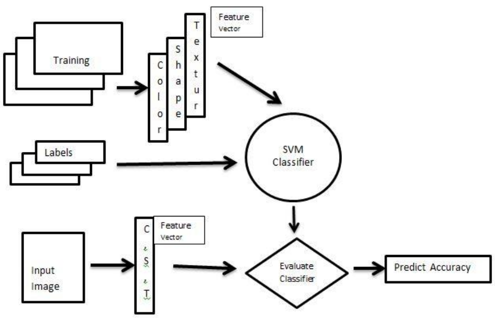

Fig1: Block Diagram of fruit Categorization Scheme

Image-Database

The Image-Database of 5817 images includes 6 different categories: Apples, Avocado, Bananas, Cherrys, Grapes and Lemons from Fruits360 dataset [17]. The Table 2: presents total fruit categories with sub category with in the same classes. The Fruit360 dataset consists of 81 distinct fruit object category folders, from which 12 category folders has been taken and designed as six fruit category along with its sub category.

Table 2: Total No of Image for Categories with Sub Category

Category	Apples	Avocados	Bananas	Cherrys	Grapes	Lemons
Sub category/ No of Image	Apple Red Delicious-490 Apple Golden 3-481	Avocado-unripe-427 Avocado- ripe-491	Banana -Green-490 Banana- Red-490	Cherry-Red-492 Cherry-Yellow-492	Grape Pink-492 Grape White 2-490	Lemon-492 Limes-490
Total	490+481=971	427+491=918	490+490=890	492+492=984	492+490=892	492+490=892

Feature Extraction and Preprocessing

Feature Extraction has been referred to as a process in which the raw image is represented in a reduce form in order to make decision making easier when performing image classification or recognition [18]. Feature extraction has been classified into two types: Low Level extraction refers to directly feature extraction from the image without any description of object. High level refers to feature extraction involving shapes and objects finding in image based on low level [19]. The Low Level feature can be further categorized into the following:

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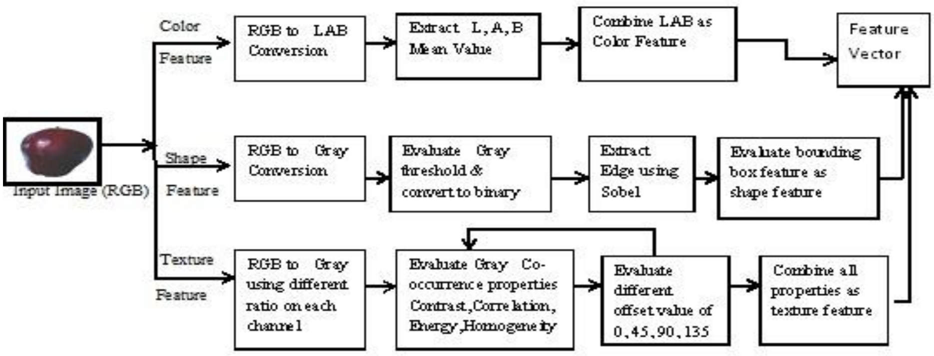


Fig2: Image Fruit-Feature Extraction Process

General feature (color, texture and subarea of image) and Global Feature (feature calculation on entire image or subarea of the image) and Domain specific feature (human image faces, image-fingerprints etc.)[20].

Color-Feature Extraction

The image-color is extensively measured visual descriptor [21]. The analysis of the image descriptor based on low-level- features from the image. Generally the color image descriptor is defined into color spaces of three dimensional such as RGB, LAB (luminance or intensity, chromaticity layer 'a', chromaticity layer 'b'), HSV (Hue, Saturation and Value). The propose work uses color features that has been are extracted with LAB Color components, where L refers to luminosity, 'A' signifies the color which falls along red-green axis and 'B' signifying the color falling along the blue-yellow axis.

Step1: Convert RGB-image to LAB results in the luminance or intensity of that image.
Step2: Evaluate the statistical measure, Mean value of L, A and B.
Step3: Combine LAB as Color Feature.

Shape-Feature Extraction

The image-shape is primitive visual descriptor for image description. To determine the shape of a given image object in image recognition and classification process, it has been stated by [22] that it must matches a model sufficiently.

Step 1: Convert an RGB image into Gray scale
Step2: Evaluate the Gray threshold and convert into Binary Image
Step3: Evaluate the Edges using sobel
Step 4: Evaluate bounding box as shape feature

Texture- Feature Extraction

Texture Feature is considered as one of the important feature that has been refers to as the inherent surface property of an image object and its relation to its surrounding. To extract texture feature co-occurrence matrix is used. The input image is converted into grey scale image using formulae [21] in equation (1).

$$Yc=0.29*Rc+0.589*Gc+0.114*Bc \qquad (1)$$

Yc refers to gray scale value, Rc- Red Component, Gc- Green Component, Bc -Blue Component.
The statistical measure used for texture features are as follows: Contrast, Energy, Homogeneity, Correlation.

Table 3: Statistical Texture Feature

$Contrast = \sum_{i,j} \lvert i-j \rvert^2 p(i,j)$	$Energy = \sum_{i,j} p(i-j)^2$
$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$	$Correlation = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$

The element (i, j) specifies the number of times the pixel value i occurred horizontally adjacent to a pixel with value j. The statistical properties are calculated using formulae in Table 3. The texture-feature extraction is as follows

Step1: Color- image to grey scale conversion performed using formulae (1).
Step2: Evaluate GLCM (the gray-level co-occurrence matrix) of gray scale image.
Step3: Evaluate GLCMs. Using four Different offsets (0, 45, 90,135)
Step4: Evaluate the four statistical properties Contrast, Energy, Correlation and Homogeneity from multiple glcms.
Step5: Evaluate the statistical measure, Mean for the above four properties.
Step 6: Combine all as Texture Feature.

Training Image for category classification using Training Set Features (Color, shape, texture) and SVM

Step1: The input dataset consisting of 5817 fruit- images with 6 categories along with two subcategory of each fruit with an image size of 100X100X3.
Step2: Extract three image features (color, shape and texture).
Step3: The fruit-images divide into 70% training-data and 30% test-data. The training-data is dealt with 5Fold Cross- Validation.
Step4: Train multi class SVM with training set features.
Step5: The test-data is built by random sample of each group and it is used for classifier performance analyzing and generating confusion matrix
Step6: The accuracy is presented.

III. SVM-ECOC CLASSIFICATION

SVM has been used in different application built on categorization like classifying points into disjoined planes [23], text categorization and pattern recognition [24]. In Today's world with huge data there is a need for multiclass classification [25].It is mainly for target categories greater than two. Dietterich *et al* (1995) proposed ECOC framework [26] for transforming multiclass into several binary problems. The SVM when combined with ECOC enriches the system failure when solving multiclass classification [27].

ECOC reduce multiclass problem to group of binary classifiers. It consists of two schemes. "Coding Scheme: *The coding design presents ways through which a multiclass problem reduced to a group of binary class problems. It describes the classes that the binary Learners are trained on*". "Decoding Scheme: *It presents ways to combine result obtained from binary learners*. Detail explanation available [28], [29]

SVM-ECOC Algorithm:

The steps are as follows

Step 1: load Dataset of fruit image.

Step2: Feature Extraction *w.r.t* color, shape and texture

Step3: Define the predictor data names and response data names

Step4: Create a SVM template and specify the predictor order

Step5: Train the ECOC classifier using SVM binary learner with coding design and specify the class order

Step6: Cross-Validate ClassificationECOC classifier using KFold

Step7: Predict classification accuracy for Test Data

Function to Train and Predict

To train we create a model using templateSVM [30] function that return a SVM template which is appropriate for training ECOC multiclass. The template object contains options for SVM Classification. It then trains the ECOC classifier using SVM binary learners with a one-vs.-one coding design. The function fitcecoc[29] is used for specifying SVM binary learners for ECOC multiclass learning, Cross validation is performed using 5 fold cross validation .

IV. FRUIT-IMAGE CLASSIFICATION-STEPS

Step 1: The input is a fruit-image.

Step2: Loading Database: After loading, it divide into 70% training-data and 30% testing- data.

Step 3: Fruit-Image preprocessing and feature Extraction: The processing of training–data-set and test-data- set is performed by SVM model. Preprocessing depending on the feature based requirement.

Step 4: The training feature extraction is done by training feature set (color, shape and texture) with function templateSVM

Step 5: Classifier trained with training feature set.

Step 6: The classifier evaluation achieved by accuracy metrics.

Step 7**:** Prediction Accuracy

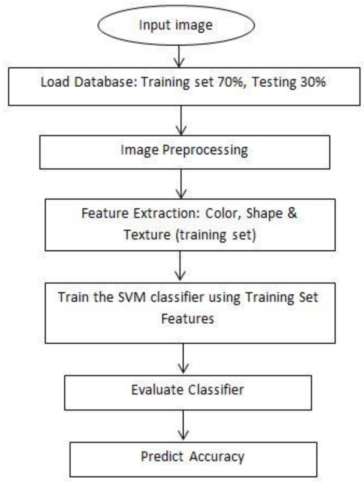


Fig 3: Fruit- Category- Classification steps

Performance Evaluation

The mostly used classification metric is Accuracy [25]. There are numerous performance metrics in literature for classification of image. The metrics of classification depends on the technique used and domain area.

Accuracy: The most widely used measure which signifies the total classification result not only individual category prediction [19]**.**

Accuracy = TP+TN/TP+FP+FN+TN (2)

The cell at the bottom (right side of the confusion matrix) represents the accuracy. The equation (2) presents the formulae. (TP, TN, FP, FN refers to true positive, true negative, false positive, false negative respectively)

V. EXPERIMENTAL RESULTS AND ANALYSIS

Multiclass image classification contains 5817 fruit-images dataset. The experiment contains 6 fruit image categories with two sub category taken from fruit 360 data set [17], it contains 70% training-data and 30% testing-data. The training-data is trained with SVM Classifier for identifying fruit category accuracy. The experiment is performed to extract the color feature by the mean (Statistical Feature) parameter value in the LAB color space presented in Table 4, Shape feature by the bounding box presented in Table 5and the Textual Feature by using GLCMs presented in Table 4.

The input is a fruit-image input, RGB image is preprocess depending on the feature extraction procedure. For color feature extraction the RGB-fruit- image is converted into LAB color space. The color image features are extracted using the

Table 4: Experimental results color & texture feature

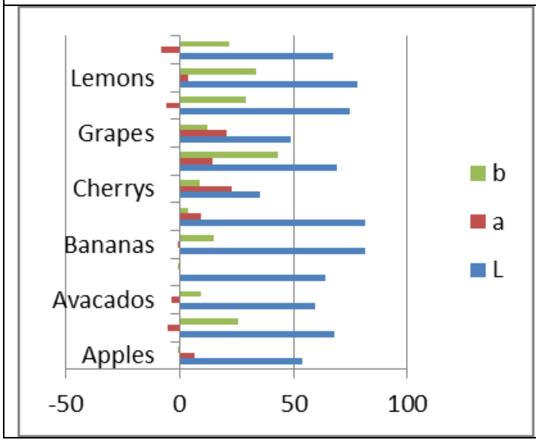
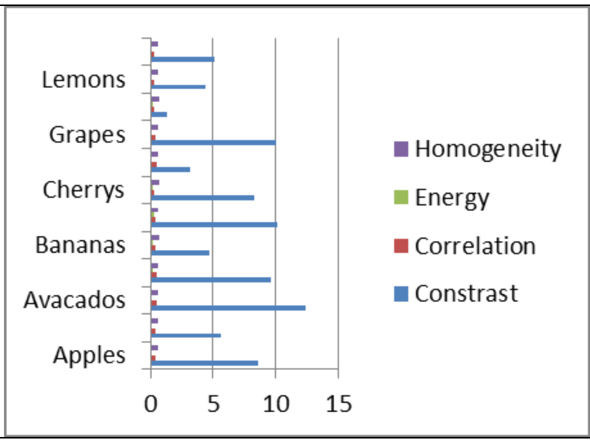
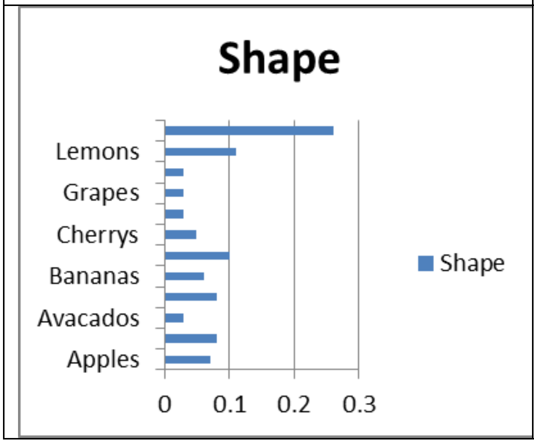
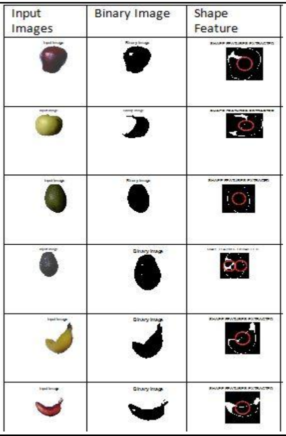
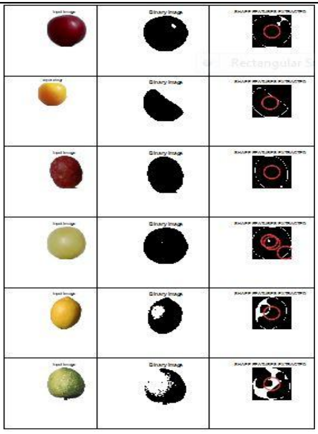
Color -Features	Texture- Feature
	

Table 5: Experimental result of shape feature

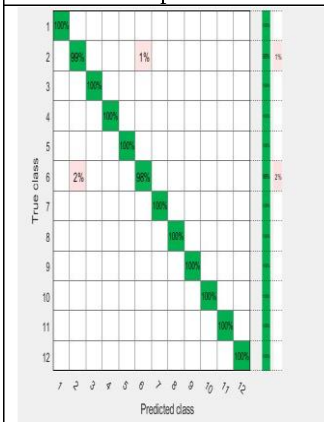
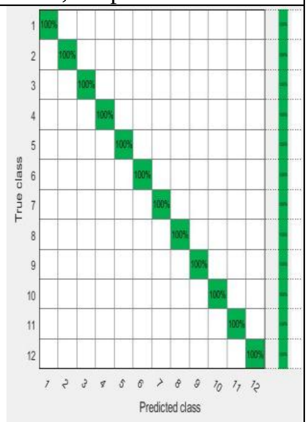
the mean. For Shape feature extraction the input image is converted into gray scale conversion and then the gray scale threshold is evaluated and converted into binary image. The next steps involve extracting the edges using sobel, finally evaluation of the boundary box is treated as a shape feature. The extraction of textual feature is attained by converting the image into gray scale using different ratios on each channel, then four textual characteristics (contrast, correlation, energy and homogeneity) are calculated in four angles (off sets) with GLCM

The feature fusion described in Fig 1 contains information about image colors such as L, A, B (Three Features) shape (one feature) and textual characteristics (contrast, correlation, energy and homogeneity - Four Features). These 8 measure features are given as an input to the SVM (Linear kernel classifier). SVM-ECOC performed better compare to SVM.

Evaluation of the model

The proposed research work uses confusion matrix to evaluate model accuracy. The confusion matrix represent correct vs. incorrect category labels. The initial twelve horizontal-lines (rows) in table represent the predicted class category and the initial twelve vertical-lines (columns) represent the true class (Target Class). The slant-line (diagonal) represents category classified correct. The non-diagonal cells represent categories classified incorrectly.

Table 6: Confusion Matrix for fruit categorization

Confusion matrix using color and shape	Confusion matrix using color, shape and texture
	

The model accuracy is evaluated and presented in Table 6 for each category. The table consists of twelve sub categories (six fruit with two sub category) from fruit360 dataset [17].The result showed accuracy range of 98to 100% in case of two features (color and shape) and accuracy of 100% in case of three features (color, shape and texture).

Table7: Comparative result in literature

Sno	Ref	Model	Features	Dataset No of image in Dataset	Accuracy (%)
1	Kumari and Gomathy [2018] [14]	SVM	Color & Texture	941 (10 classes)	95.3
2	Alzubi et al(2018)[6]	Binary SVM	Shape and color	120	100
3	Proposed System	Multiclass SVM with ECOC	Color and shape	5817 (6 classes with in 2 sub category)	98 to 100
4	Proposed System	Multiclass SVM with ECOC	Color, Shape & texture	5817 (6 classes with in 2 sub category)	100

VI. DISCUSSION

As shown in the Table 7, the classification of fruit database into categories is determined by both feature selection and classification technique used. The proposed work uses SVM with ECOC framework for categorization of fruit with one vs. one coding design to train the classifier. The result obtained shows accuracy ranges from 98 to 100% for different category of fruits where two feature color and shape are being considered for training the model and it shows an accuracy of 100% in all the categories when training set feature (color ,shape ,texture) are used . The result presented by Alzubi *et al* [6] uses binary SVM for classifying the date fruit into two categories whether it is eatable or non-eatable. Another study conducted by [14] with two feature color and texture resulted in lower accuracy than that of proposed work with feature fusion (color, shape and texture feature), using multiclass approach. The training set features improves the accuracy of the model therefore high accuracy is achieved when appropriate feature selection for multiclass classification problem.

VII. CONCLUSION

Automation of fruit image categorization has been a challenging research for reducing the post harvesting loses. In this study a machine learning technique based multiclass model is built for image classification. Input to the model is a fruit-image; feature selection includes color, shape and texture. The model is trained using training set features, multiclass SVM is used as a classifier and validation is performed using 5 fold cross validation strategy. The model was tested with two cases In first case model trained on two features and the second case with three features. It was observed that when using training set features the experiment showed the classification result with 100% prediction accuracy. The multiclass SVM resulted in better accuracy with three features color shape and texture when compared to two. The result shows that the texture feature improved the overall model accuracy. The research can be helpful for the farmers to reduce post-harvest loses that occur during sorting and grading produce, in various environment, such as transport center or hypermarket, trade market can make use of this system to make profit. Additionally this method can be useful to different category objects. Furthermore mobile application can be developed for senior citizen or visually impaired daily routine schedule where human inspection exists for categorization. The future work to this research is to study accuracy prediction with additional number of categories.

REFERENCES

1. https://timesofindia.indiatimes.com/city/coimbatore/reducing-post-harvest-losses-the-main-challenge-researchers/articleshow/63405223.cms accessed on 30 oct 2019
2. A.Ibrahim, A.Eissa, and A.Alghannam, “Image processing system for automated classification date fruit”. International Journal of Advanced Research, 2014, 2(1), 702-715.
3. M. S. M Alfatni, A. R. M.Shariff, M. Z. Abdullah, M. H. B. Marhaban, and O. M. B Saaed. “The application of internal grading system technologies for agricultural products”–Review. Journal of Food Engineering, 2013,116(3), 703-725.
4. Y.Chen, and J. Z. Wang. “Image categorization by learning and reasoning with regions. Journal of Machine Learning Research”, 2004, 5(Aug), 913-939.
5. A.Rocha, D. C.Hauagge, J.Wainer, and S. Goldenstein. “Automatic fruit and vegetable classification from images. Computers and Electronics in Agriculture”, 2010, 70(1), 96-104
6. R. Alzu’bi, A.Anushya, E.Hamed, E. A Al Sha’ar, and B. A. Vincy “Dates fruits classification using SVM”. In AIP Conference Proceedings, 2018, April, Vol. 1952, No. 1, p. 020078). AIP Publishing.
7. G. Muhammad, “Date fruits classification using texture descriptors and shape-size features”. Engineering Applications of Artificial Intelligence, 2015, 37, 361-367.
8. L. Qiang, C. Jianrong, L.Bin, D.Lie, and Z. Yajing,. “Identification of fruit and branch in natural scenes for citrus harvesting robot using machine vision and support vector machine”. International Journal of Agricultural and Biological Engineering, 2014, 7(2), 115-121.
9. W.Castro, J.Oblitas, M.De-La-Torre, C.Cotrina, K.Bazán, and H.Avila-George, “Classification of Cape gooseberry fruit according to its level of ripeness using machine learning techniques and different color spaces”. IEEE Access, 2019, 7, 27389-27400.
10. C.C.Patel, V.K. Chaudhari, “Comparative Analysis of Fruit Categorization Using Different Classifiers”. In: Venkata Rao R., Taler J. (eds) Advanced Engineering Optimization Through Intelligent Techniques. Advances in Intelligent Systems and Computing, 2020, vol 949. Springer, Singapore online available 1 july 2019
11. Y.Zhang, and L.Wu, “Classification of fruits using computer vision and a multiclass support vector machine”. Sensors, 2012,12(9), 12489-12505.
12. P.Ninawe, and S.Pandey, “A completion on fruit recognition system using k-nearest neighbors algorithm”. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2014, 3(7), 2352-2356.
13. S. Naskar, and T. Bhattacharya, “A fruit recognition technique using multiple features and artificial neural network”. International Journal of Computer Applications, 2015, 116(20).
14. R. S. S.Kumari, and V. Gomathy, “Fruit Classification using Statistical Features in SVM Classifier”. In 2018 4th International Conference on Electrical Energy Systems (ICEES), 2018, February. (pp. 526-529). IEEE.
15. J. C.De Goma, C. A. M.Quilas, M. A. B.Valerio, J. J. P.Young, and Z. Sauli,. “Fruit Recognition Using Surface and Geometric Information”. Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 2018,10(1-15), 39-42.

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16. S.Jana, S.Basak, and R.Parekh, "Automatic fruit recognition from natural images using color and texture features". In 2017 Devices for Integrated Circuit (DevIC) ,2017, March, (pp. 620-624). IEEE.
17. Fruits 360 Dataset on Kaggle. https://www.kaggle.com/moltean/fruits. last visited on 06.07.2019
18. H. A.Elnemr, N. M.Zayed, and M. A.Fakhreldein, "Feature extraction techniques: fundamental concepts and survey". In Handbook of Research on Emerging Perspectives in Intelligent Pattern Recognition, Analysis, and Image Processing, 2016, (pp. 264-294). IGI Global
19. M. S.Nixon, A. S. Aguado, "Feature Extraction & Image Processing for Computer Vision", 2013. (3rd ed.). Elsevier Ltd].
20. R. S. Chora's , "Image Feature Extraction Techniques and their Applications for CBIR and Biometrics Systems".International Journal of Biology and Biomedical Engineering, 2007, 1(1), 6–16.
21. D.Chandrakala, and S. Sumathi, "Image classification based on color and texture features using frbfn network with artificial bee colony optimization algorithm". International Journal of Computer Applications, 2014, 98(14).
22. M.Yang, K.Kpalma, and J.Ronsin, "A survey of shape feature extraction techniques" 2008.
23. Y.Ahuja, and S. K.Yadav, "Multiclass classification and support vector machine". Global Journal of Computer Science and Technology Interdisciplinary, 2012,12(11), 14-20.
24. J.Donahue, Y.Jia, O.Vinyals, J.Hoffman, N. Zhang, E.Tzeng, and T.Darrell, "Decaf: A deep convolutional activation feature for generic visual recognition". In International conference on machine learning , 2014, January, (pp. 647-655).
25. C. Demirkesen, and H. Cherifi, "A comparison of multiclass SVM methods for real world natural scenes". In International Conference on Advanced Concepts for Intelligent Vision Systems (pp. 752-763), 2008, October, Springer, Berlin, Heidelberg.
26. T. G. Dietterich, G.Bakiri, "Solving Multiclass Learning Problems via Error-Correcting Output Codes". Journal of Artificial Intelligence Research, 1995,2, pp. 263-286.
27. Z. Yan., & Y. Yang, "Application of ECOC SVMs in Remote Sensing Image Classification", The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 2014,40(2), 191
28. S.Fatima and M.Seshashayee,"Categorized Image Classification using CNN Features with ECOC Framework", International Journal of Recent Technology and Engineering, 2019.
29. Error correcting output codes https://in.mathworks.com/help/stats/fitcecoc.html accessed on 28 nov 2019
30. https://in.mathworks.com/help/stats/templatesvm.html accessed on 28 nov 2019

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