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SHAPE AND TEXTURE BASED CLASSIFICATION OF CITRUS USING PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Citrus family consists of a variety of eatable, consumable and usable items with varying nutritional contents. Naked eye citrus classification needs expert human effort, which provides poor decision reliability. The unreliable classification decision may be extremely hazardous when the citrus is being classified for exports or usage in pharmacy products and various food items. In this paper, citrus fruit has been classified on shape and texture features. Principal Component Analysis (PCA) was used as a methodology to explore statistical findings. The average accuracy of the system proposed is 84%. This system can be implemented on pharmacy stores, food production units, or industries, and citrus export centers for reliable citrus fruit classification.

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INTRODUCTION

Pakistan is an agricultural country with a large, cultivated land supported by four seasons, natural and man-made irrigation systems, and other natural resources. The agriculture sector of Pakistan produces about 30 different types of fruits. Notable ones are citrus, mangoes, apples, dates, and guava, which are about 75% of the overall annual fruit production of Pakistan. Citrus is one of the leading fruits in Pakistan and is about 40% of the total fruit production of the country (Tahir, 2014; Ashraf *et al.*, 2020). About 2 million metric tons of citrus fruits are produced in Pakistan annually and kinnow is at top among citrus (Ashraf *et al.*, 2015). China is the leading producer of

citrus, while Pakistan is ranked at 16th position in the world with production of 2.28 million metric tons annually (Xinlu, 2001). It is estimated Pakistan produces 70 % of total world kinnow (Tahir, 2014). Citrus is cultivated across the Pakistan but Punjab has a lion share of 95% due to its diversity in an ecological environment conducive to citrus production and adequate water resources both natural and man-made. Within Punjab, Sargodha is the most citrus producing district. Being the central point of citrus production, the Sargodha district affects citrus marketing and pricing in the country on a large scale (Sharif *et al.*, 2005). Juicy, tasty, zesty, and delightful, citrus fruits are cultivated worldwide and provide numerous nutritious advantages

by eating as fresh or used in various drinks like squeezed for juice or food items like salads, puddings, sweets, jellies, and jams. Citrus fruit can also be used as part of cooking ingredients to flavor vegetables and meats. Even its by-products are of great value. Major health benefits include heart health, brain health, blood pressure control, digestive health, benefits for pregnant women and babies, skin and hair appearance, immunity against infections, reducing kidney stone, and have anti-ulcer, anti-carcinogenic and anti-anxiety, anti-bacterial, anti-typhoid, anti-fungal, anti-diabetic and anti-inflammatory properties (Marcene, 2021). Regular use of oranges increases HDL-Cholesterol (good cholesterol). These are also good for increasing appetite. Other notable medicinal effects of oranges are useful for patients having asthma, diabetes, gallstones, arthritis cholera, cataracts and lung infections, etc. (Milind and Dev, 2012).

Pakistan is regarded as the 10th largest citrus producer and largest Kinnow (a variety of citrus fruit) producer in the world (Nandi *et al.*, 2016). Kinnow is Pakistan's prime export fruit because of its unique juicy, scented, soft and refreshing qualities achieved through a series of hybridization and grafting research. As there are different varieties of citrus fruits and some varieties have close resembled with Kinnow because of similar characteristics. So, to achieve a large amount of Kinnow export targets, it's cumbersome to segregate Kinnow from other family members. Most farmers do it manually which requires huge labor, time, and cost. Failure in that affects quality and reputation also. So, it's very important to do all this work through a state-of-the-art automated system.

Computer vision is an attractive research topic for the recognition of objects using texture for the analysis of patterns. Objects are matched and mismatched based on pixel intensity. Computer vision (CV) is a complete discipline for using skin texture and shape features (Marcene, 2021). Talking about the application of CV towards images we can do many things such as morphing, exposure bracketing, stitching, Photo-based walkthroughs, 3D modelling, face detection, video match stabilization, movement, and visual authentication (Khan *et al.*, 2016). Computer science is, undoubtedly, helping in exploring newness in every walk of life, and agriculture is not far behind. Research has made it easy to find weeds, monitoring status and health conditions of various plants, fruits searches, determination of fruit

ripeness, fruit classification in terms of freshness, coarseness, solidness, shape, color, size, rot, acidity, sweetness, off-flavors, smell, dietary fiber and vitamins (Christodoulou *et al.*, 2003). The development of CV based applications is rapidly increasing to cope with the surging interest in commercial projects using machine learning techniques. There are numerous techniques in the CV which are widely used to detect and classify required objects out of an image with notable pros and cons. These techniques can provide a high accuracy of object detection and classification. Shape-based and color-based approaches are the most used techniques. We have also used these approaches in our research for the Shape and Texture based Classification of Citrus using Principal Component Analysis.

In this paper, four citrus fruits (Fruiter, Kinnow, Sour Orange, and Musambi) were classified based on the shape and texture. Fruits were classified on vertical and horizontal circumference. Another considerable parameter in classification were angular second moment and the other two values (contrast and correlation).

LITERATURE REVIEW

Jhawar has used Pattern recognition techniques to grade/sort lemon by processing image colors. He used three classifiers Linear Regression, Nearest Prototype, and Edited Multi-Seed. Linear Regression was found the most suitable classifier with 100% accuracy; however, Detection of damaged lemon was the notable limitation of that research (Jhawar, 2015).

A neural network algorithm was introduced for flower species classification based on texture features. Accuracy for flower species classification was achieved up to 98%. The accuracy was consistent on images with varying angles (Bhanuprakash *et al.*, 2016). They have introduced a novel DIP based system for automated mango grading based on attributes like size, shape, and peel defects and level of maturity like days-to-rot. The system was able to achieve 87% mango grading accuracy (Bhanuprakash *et al.*, 2016). Mango type's classification technique has been introduced by Iqbal for shape and texture features. The accuracy of the system was 78.94% (Abbas *et al.*, 2018). Khojastehnazh *et al.* (2010) worked on the grading of lemon fruits. They developed an efficient algorithm that worked based on color and size features. The average accuracy was reported as 94.04% for all lemon fruits. The algorithm can also be implemented for grading/inspection of

eggplant and cucumber etc (Khojastehnazh *et al.*, 2010). A classification system has been introduced which classifies coffee fruits (cherries) based on their ripeness. The system used Bayesian Classifier on texture, shape, and color feature of cherry. The system showed a 96.88% accurate performance (Sandoval *et al.*, 2010). A working-model has been introduced by Ohali for sorting and grading of date fruit. The system has been tested on preselected samples of date fruit. The accuracy achieved by the system is 80% (Golzarian and Frick, 2011).

Golzarian and Frick (2011) introduced a new framework using digital image processing technique. This framework was helpful to differentiate early narrow-leaf wheat from two common weeds. They used different combination of color, texture and shape features. Later on, Principal Component Analysis (PCA) model were induced to reduce to three descriptors. PCA model were evaluated on collected data and results shown 88% and 85% accuracy to distinguish between ryegrass and brome grass from wheat, respectively. Based on such results, a computer vision system was developed for automated weed management, which were very effective in such tedious job (Golzarian and Frick, 2011). Dubey and Jalal (2015) have been introduced a DIP-based classification of apple fruit diseases. A total of 13 classes were used with 70 images per class. The accuracy varies from class-to-class ranges from a minimum of 75.63% to a maximum of 95.94%. An apple (golden) grading system has been given by Moallem. The system presented 89.2% and 92.5% accuracy for first and second steps classification respectively (Moallem *et al.*, 2017).

Arlimatti (2012) introduced a classification system with nearest neighbour classifier. They proposed a classification based on the window and supervised classifier. The system incorporates pre-processing, image division into windows, features collection, window elimination and classification or decision-making step. Their study was helpful to distinguished between healthy and rotten apple. Proposed system achieves 80.00% accuracy in detecting rotten apples.

Arakeri and Lakshmana (2016) developed an automated grading system for tomato fruit to gear up the processing time and reduce the error rate in grading/categorization. The experimental results proved 96.47% accuracy of the system. Sabrol and Satish (2016) worked on tomato plant disease identification and classification. The classification accuracy achieved by the

system is 97.3%. Capizzi *et al.* (2015) developed an automated system to classify oranges based on 'surface defect', 'black mold', 'slight color defects', 'morphological defects', and 'good fruit'. The research produced an efficient and fast automatic classification system with a limited error rate of up to 2.75%. An automated orange skin defects detection system has been introduced which classifies oranges based on external appearance. The system expressed the best accuracy rate of 94.5% with ANN (Thendral and Suhasini, 2017). A novel system for automatic grading of citrus using shape and color was proposed in this research. Experimental results confirmed the accuracy of the system as for first grade 93.3%, for the finest grade 96.7%, for substandard 95.83%, and second grade 96.7% (Wen *et al.*, 2010). An integrated system has been introduced for citrus fruit sorting and grading based upon defects and color. The system showed good results for 12 samples out of a total of 20 samples, i.e. 60% accuracy (Kumar *et al.*, 2015).

Bhargava and Bansal (2021) developed an automated system based on k nearest neighbour algorithm (KNN), LR, Sparse Representations Classification (SRC), and Support Vector Machine (SVM) classifiers to distinguished fresh and rotten apple fruits. First, they used grab-cut method and fuzzy c-means clustering to segment the images. Later on, they extracted multiple features statistical, textural, geometrical, discrete wavelet transform, a histogram of the oriented gradient, and Laws' texture energy and selected by principal component analysis from the feature space. Later on, proposed cross validation techniques achieved 92.90% (k = 5), 98.42% (k = 10), and 95.27% (k = 15) accuracy by SVM classifier (Bhargava and Bansal, 2021).

METHODOLOGY

The research methodology of the system is quantitative where textural features are extracted and some quantification is applied to the extracted numerical values of texture features. Various experiments are carried out to compare the testing data with the training data to classify citrus types. Step-wise detail of the proposed methodology is explained as under:

Step 1- Acquisition of Image: Images of fresh citrus fruit were taken through digital camera. Measurements were performed manually and by using Corel Draw.

Step 2- Identification of ROIs: Region of Interest (ROI) selection was performed in IP software after conversion of images into BMP format using MaZda.

Step 3- Features extraction: After selecting the ROIs, features (PCA and raw data diagrams) are extracted and saved in a data file.

Step 4- Quantification of data: b11 was used for the quantification of the extracted features. The data was classified by using shape measurements and texture features

Step 5- Saving results in database: The results were saved in the database against the relevant citrus type.

Data Flow Diagram of the System

The data flow diagram of the proposed system is shown in figure 1.

Digital Camera Specifications

The use of the camera with varying quality in terms of pixels can bring a considerable change in the results. A low-quality camera produces poor images that could not be processed poorly.

But usage of a quality camera will ensure the production of quality images which will further lead towards better system performance in terms of accuracy. The formal description of a digital camera used in this project is as under:

Model	JV210	Depth	2.1 cm
Brand	Fujifilm	Height	5.6 cm
Operating Temperature	0- 40C	Width	9.4 cm
Suitable Humidity	10-80%		

Environment Setting for Image Acquisition

It was key to maintain a stable and similar environment for image acquisition to achieve optimum results because image acquisition in varying conditions can affect results reliability. All the images were acquired in the same environment which includes stable room light and specific camera distance from fruits. The camera while taking images was kept 10 inches away from the fruit and 8 inches high from the base.

Shape recognition and measurement

In this research project following tools have been used for recognition and measuring of shape:

- MS Paint for the conversion of images from jpg to BMP.
- MaZda for the conversion of images from color to grayscale.
- Corel Draw for picture manipulation and calculation of width and height in image of 4"x6".

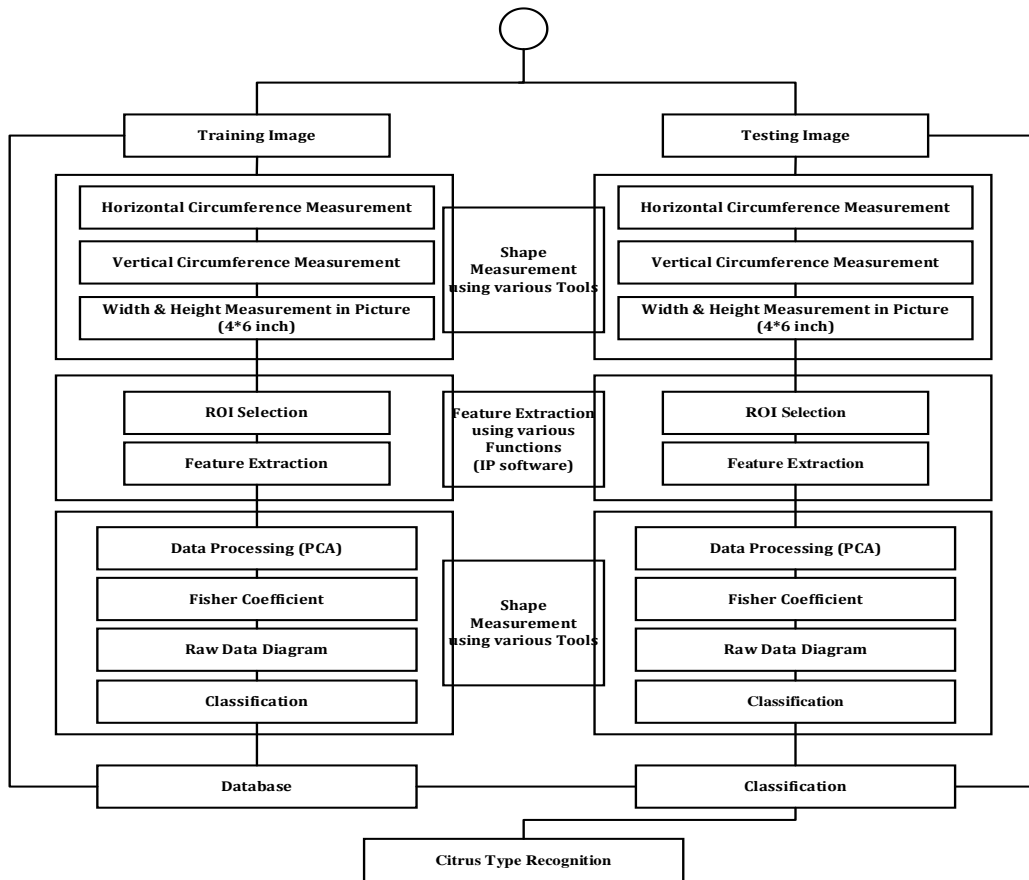


Figure 1. Data flow diagram of proposed system.









Type	Fruiter	Kinnow	Sour Orange	Musambi
Original Image				
Grayscale Image				

Figure 2. Original and grayscale image of each type citrus type.

Texture Analysis

MaZda supports 300 texture features including 3D and color ones. Moreover, Mazda allows 9 histogram-based, 5 inter-pixel distances, 20 co-occurrence matrices, 5 run-length-matrix-based, 4 different directions, 5 Gradient-map based 5-autoregressive model-based, and 20 on Haar-wavelet transform-based textural features (Szczypliński *et al.*, 2009). MaZda/Image Processing Software has been practiced for the extraction of textural features. Moreover, B11 software has been used for the quantitative analysis of texture features.

Texture Features used

In this research work, the following texture parameters were extracted using Image Processing Software.

Angular Second Moment

Angular Second Moment (ASM) is graded as a measurement of homogeneity or uniformity present in an image in terms of local grayscale distribution. An image having a homogeneous scene or texture contains relatively fewer gray levels. The value of P(i, j) will be high as well as the sum of squares. The following formula calculates the ASM:

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2$$

Contrast

The Black and White difference in an image is called its contrast. Contrast is one of the most important ingredients of texture because the absence of contrast flattens the image and creates a fully dark, completely light, or a particular shade of color or greyscale in the image. Differentiation between dark and light (contrast)

creates an attractive texture in the imagery. The following formula calculates contrast in an image:

$$Contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^G \sum_{j=1}^G P(i, j) \right\}, \quad |i - j| = n$$

Correlation

Correlation defines the measurement of pixels co-relationship with its neighbor pixels. It determines gray-tone linear dependencies out of an image. Correlation can be calculated by the following formula (Mohanaiah *et al.*, 2013; Raut *et al.*, 2016; Uyun *et al.*, 2013; Albregtsen, 2008);

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i, j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y}$$

B11 for Analysis and Classification

Program b11 is linked with MaZda and developed and designed for preprocessing, quantitative, exploratory analysis of texture data, and classification of MRI images. It can be called from MaZda or we can run it separately. *.sel files are loaded in as input and its interface is self-explanatory. The input panel is displayed on the left side of the interface window. The errors-containing file is indicated by the blue-color font. The analysis report is displayed on the right side of the interface window. The core value of the analysis report is the fisher coefficient. b11 reports are compatible to be saved in text formats. Texture features can be selected either manually or automatically in the report window of b11. The b11 menu items specified in the report window can be used for various analyses like LDA, PCA or NDA, etc.

```

b11 - texture data analysis
Files Options Analysis Classification About Exit
Input (data)                               Output (report)
*label
converted data: 9/24/2017 8:38:21 AM
*features
1 angularSecondMement
2 contrast
3 correlation
4 variance
5 inverseDifferenceMoment
6 sumAverage
7 sumVariance
8 sumEntropy
9 entropy
10 differenceVariance
11 differenceEntropy
12 info_measur_corr1
13 info_measur_corr2
*categories
1 1
2 2
*data
  1 1      0.00149717158564815
  2 1      0.00106206597222222
  3 1      0.00123302469135803
  4 1      0.00134906442901235
  5 2      0.00214844473379633
  6 2      0.00181003809799387
  7 2      0.00192064766589508
  8 2      0.00206426022376547
*end

* b11 report file [raw data analysis] <9/24/2017 8:39:43
* Data file name: ""
* Selected features [13 out of 13]
angularSecondMement [#1/#1]; p.mean= 1.63559E-003, p.std
contrast [#2/#2]; p.mean= 5.06111E+003, p.std= 3.15161E+
correlation [#3/#3]; p.mean=-5.18667E-002, p.std= 4.6438
variance [#4/#4]; p.mean= 2.39627E+003, p.std= 1.47629E+
inverseDifferenceMoment [#5/#5]; p.mean= 6.82257E-002, p
sumAverage [#6/#6]; p.mean= 2.51018E+002, p.std= 1.53864
sumVariance [#7/#7]; p.mean= 8.56769E+004, p.std= 7.8602
sumEntropy [#8/#8]; p.mean= 5.13276E+000, p.std= 2.19129
entropy [#9/#9]; p.mean= 6.89978E+000, p.std= 1.54391E-0
differenceVariance [#10/#10]; p.mean= 4.57691E+003, p.st
differenceEntropy [#11/#11]; p.mean= 4.49248E+000, p.std
info_measur_corr1 [#12/#12]; p.mean=-3.20994E-001, p.std
info_measur_corr2 [#13/#13]; p.mean= 9.58065E-001, p.std
Feature vector standardized: NO

* Results [raw-data analysis]
> Fisher coefficient, F = 46.9
> 1-NN classification of raw data
Missclassified data vectors: 0/8 [or 0.00%]
  
```

Figure 3. B11 Texture Data Analysis.

RESULTS AND DISCUSSION

Four citrus family members (Fruiter, Kinnow, Sour Orange, Musambi) were classified based on shape and texture parameters. Details of each extraction and calculations are explained in the following section:

Shape parameters extraction and calculation

250 images of each selected sample (Fruiter, Kinnow, Sour Orange, and Musambi) were captured using a digital camera. Each sample was measured horizontally and vertically to acquire circumference measurements. The difference between horizontal and vertical circumferences was also calculated. After analysis of data regarding shape measurements, the following are the findings:

Based on these findings the samples can be classified into two groups:

Group 1: Fruiter and Kinnow: Horizontal Circumference is always bigger than vertical

Group 2: Sour Orange and Musambi: Vertical Circumference is always bigger than Horizontal.

Texture parameters extraction and calculation

In texture features following two parameters were used to classify all four samples:

Raw Data Analysis Diagrams

Principal Component Analysis (PCA): Calculation of 'Fisher Coefficient'

Following are the raw data analysis diagrams of all samples:

A balanced relationship is found among correlation, contrast, and angular second moment.

Following are the findings regarding the data clusters. Data cluster means that majority of samples have a specific range of 'fisher coefficient' values.

Group 1: Fruiter and Kinnow

Horizontal Circumference is always bigger than Vertical Circumference

Fruiter: 224/250 has 'fisher coefficient' value from 0-9.

Kinnow: 211/250 has 'fisher coefficient' value of 10 or more.

Group 2: Sour Orange and Musambi

Vertical Circumference is always bigger than Horizontal Circumference

Sour Orange: 217/250 has 'fisher coefficient' value from 0 to 39.

Musambi : 197/250 has 'fisher coefficient' value of 40 or more.

Classification accuracy based on Texture Parameters
Following is the data of classification accuracy based on Texture Parameters:

Fruiter 224/250 = 89.6 %

Kinnow 211/250 = 84.4 %

Sour Orange 217/250 = 86.8 %

Musambi 197/250 = 78.8 %

Average Accuracy of the System = 84.9%

Results Comparison

Average Accuracy of the proposed system is 84.9%, which is much improved as compared to results of Arlimatti (2012), that were 80.00%.

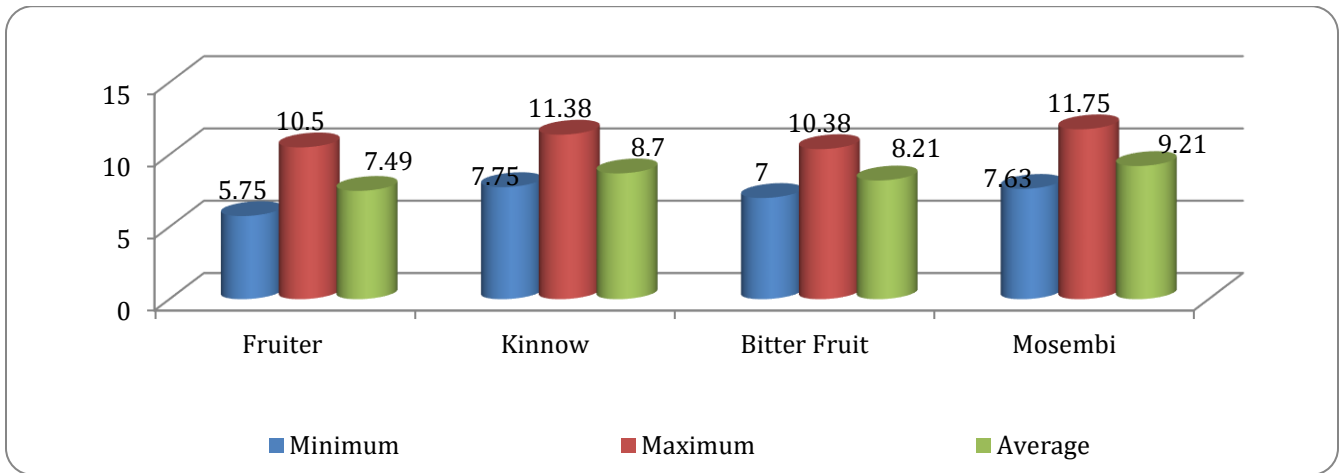


Figure 4. Horizontal Circumference (in cm).

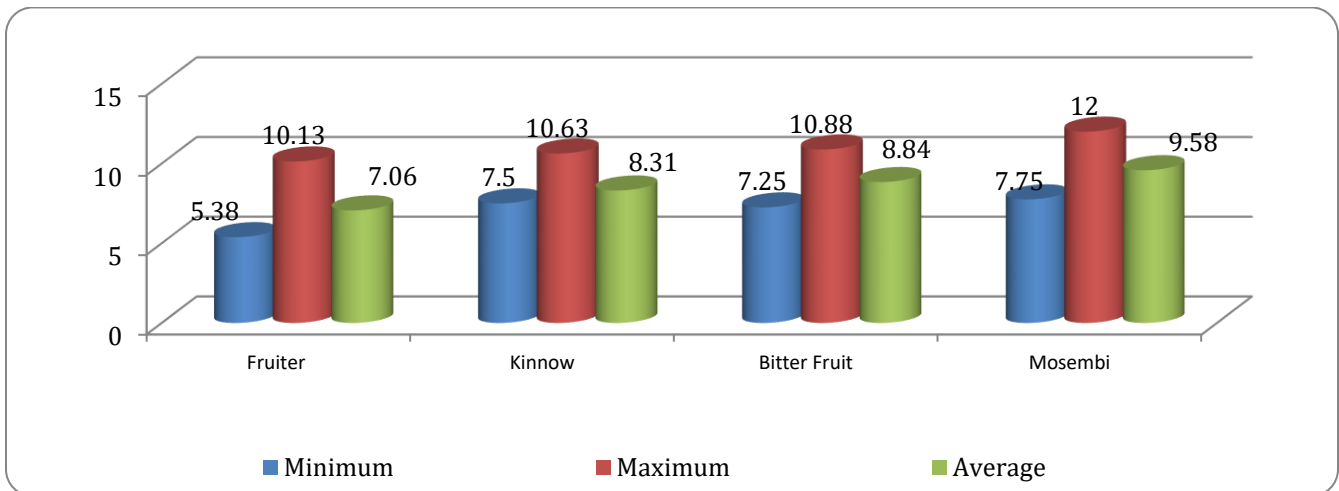


Figure 5. Vertical Circumference (in cm).

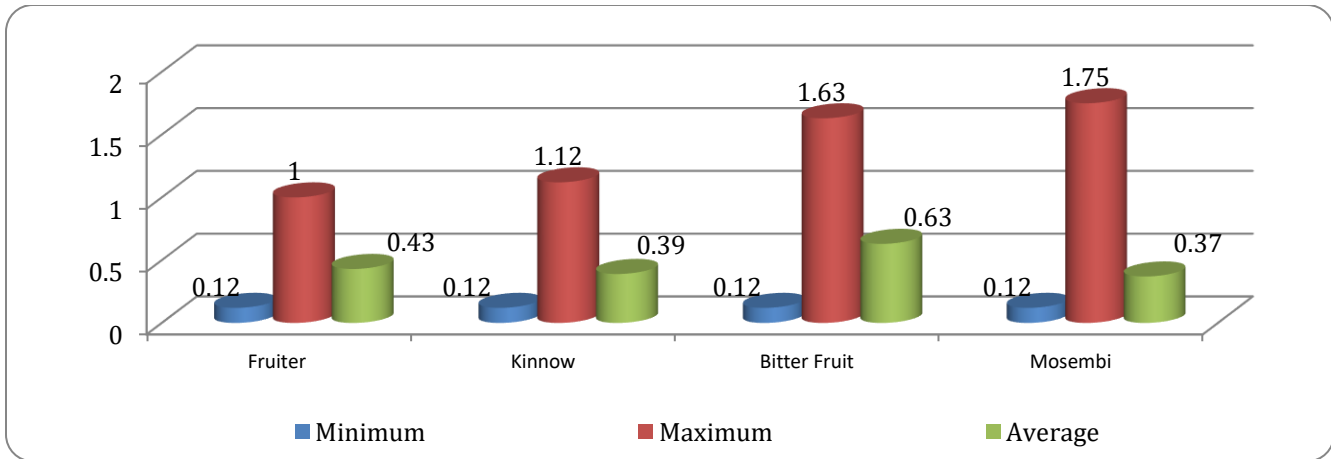
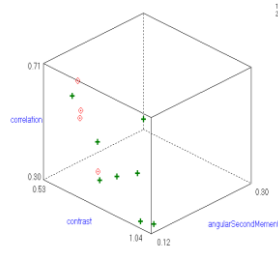


Figure 6. Difference between horizontal & vertical circumference (in cm).



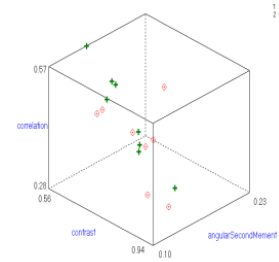
Fruiter Image



Fruiter Diagram



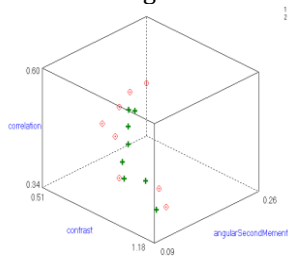
Kinnow Image



Kinnow diagram



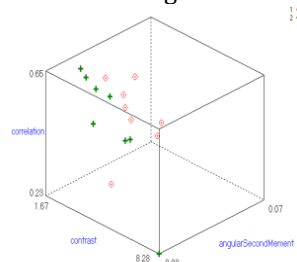
Sour Orange Image



Sour Orange Diagram



Musambi Image



Musambi Diagram

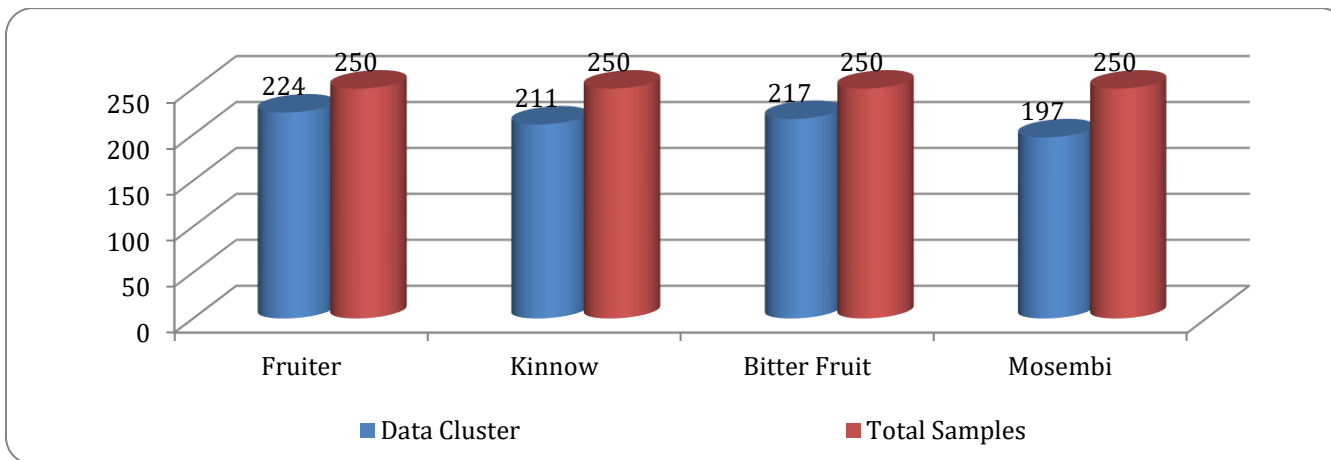


Figure 7. Comparison 'Fisher Coefficient' falling in a distinct range.

CONCLUSION AND RECOMMENDATIONS

In this research work, a system has been developed which classifies four categories of citrus family members (Fruiter, Kinnow, Sour Orange, and Musambi) based on shape and texture features. Shape features were brought in to work for the classification of four categories into groups of two categories each. The first group consists of Fruiter and Kinnow and the second group includes Sour Orange and Musambi as all samples of the first group have a bigger horizontal circumference and width in the image of 4"x6" while all samples of the second group have a bigger vertical circumference and height in image of 4"x6". Classification accuracy on texture-based features of Fruiter is 89.6%, Kinnow 84.4%, Sour Orange 86.8%, Musambi 78.8% and average accuracy of all categories is 84.9%.

This research work will surely encourage its implementation in the citrus forms, local market, export centers, food-product development centers, and pharmacy organizations which will resultantly reduce manpower, time, and cost of classification. Also, with same philosophy, we could use this application for identification of different vegetables and fruits as well as in small parts used in industry.

In future, classification accuracy can be improved by including more analysis and texture-based parameters like "Linear Discriminant Analysis", "Non-linear Discriminant Analysis", "Linear Dimensionality" and "Linear Separability". Moreover, the Mobile App of this system can be developed for instant use and operational efficiency.

REFERENCES

- Abbas, Q., M. M. Iqbal, S. Niazi, M. Noureen, M. S. Ahmad, M. Nisa and M. K. Malik. 2018. Mango classification using texture & shape features. *International Journal of Computer Science and Network Security*, 18: 132-38.
- Albregtsen, F. 2008. Statistical texture measures computed from gray level cooccurrence matrices. *Image processing laboratory, department of informatics, university of oslo*, 5: 01-14.
- Arakeri, M. P. and Lakshmana. 2016. Computer Vision Based Fruit Grading System for Quality Evaluation of Tomato in Agriculture industry. *Procedia Computer Science*, 79: 426-33.
- Arlimatti, S. R. 2012. Window based method for automatic classification of apple fruit. *International Journal of Engineering Research and Applications*, 2: 1010-13.
- Ashraf, S., G. A. Khan, S. Ali and M. Iftikhar. 2015. Socio-economic determinants of the awareness and adoption of citrus production practices in Pakistan. *Ciência Rural*, 45: 1701-06.
- Ashraf, S., R. Saqib, Z. Y. Hassan, M. Luqman and A. Rehman. 2020. Analysis of Intermediaries' Influence in Citrus Supply Chain in Pakistan. *Sarhad Journal of Agriculture*, 36: 210-16.
- Bhanuprakash, C., P. GK, A. G. Karegowda and C. Ramesh. 2016. Texture Based Flower Species Classification Using Neural Network. *International Journal of Advance Foundation and Research in Computer*, 3: 2348-4853.
- Bhargava, A. and A. Bansal. 2021. Classification and Grading of Multiple Varieties of Apple Fruit. *Food Analytical Methods*.
- Capizzi, G., G. L. Sciuto, C. Napoli, E. Tramontana and M. Woźniak. 2015. Automatic Classification of Fruit Defects based on Co-Occurrence Matrix and Neural Networks. *Proceedings of the 2015 Federated Conference on Computer Science and Information Systems*. IEEE.
- Christodoulou, C. I., S. C. Michaelides and C. S. Pattichis. 2003. Multifeature texture analysis for the classification of clouds in satellite imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 41: 2662-68.
- Dubey, S. R. and A. S. Jalal. 2015. Apple disease classification using color, texture and shape features from images. *Signal, Image and Video Processing*, 10: 819-26.
- Golzarian, M. R. and R. A. Frick. 2011. Classification of images of wheat, ryegrass and brome grass species at early growth stages using principal component analysis. *Plant methods*, 7: 28-28.
- Jhawar, J. 2015. Grading/sorting of lemons by applying pattern recognition techniques on color images. *International Journal of Advanced Computational Engineering and Networking*, 3: 26-29.
- Khan, F. U., N. Khan and F. Anjum. 2016. Farmers perception about yield losses of kinnow (Citrus reticulata) during its harvesting and post harvesting operations: A case study of tehsil Sargodha, Pakistan. *Journal of Pure and Applied Agriculture*, 1: 12-19.

- Khojastehnazh, M., M. Omid and A. Tabatabaeefar. 2010. Development of a lemon sorting system based on color and size. *African Journal of Plant Science*, 4: 122-27.
- Kumar, C., S. Chauhan, R. N. Alla and H. Mounica gurram. 2015. Classifications of citrus fruit using image processing -GLCM parameters 2015 International Conference on Communications and Signal Processing (ICCSP). IEEE.
- Marcene, B. O. 2021. Nutrition Facts and Health Benefits. [Online]. Available: <http://www.dovemed.com/healthy-living/natural-health/7-health-benefits-of-mandarin-orange/>. [Accessed 21 January 2021].
- Milind, P. and C. Dev. 2012. Orange: range of benefits. *International Research Journal of Pharmacy* 3: 59-63.
- Moallem, P., A. Serajoddin and H. Pourghassem. 2017. Computer vision-based apple grading for golden delicious apples based on surface features. *Information Processing in Agriculture*, 4: 33-40.
- Mohanaiah, P., P. Sathyanarayana and L. GuruKumar. 2013. Image texture feature extraction using GLCM approach. *International journal of scientific and research publications*, 3: 1-5.
- Nandi, C. S., B. Tudu and C. Koley. 2016. A Machine Vision Technique for Grading of Harvested Mangoes Based on Maturity and Quality. *IEEE Sensors Journal*, 16: 6387-96.
- Raut, M. A., M. M. A. Patil, M. C. P. Dhondrikar and M. S. D. Kamble. 2016. Texture Parameters Extraction of Satellite Image. *IJSTE-International Journal of Science Technology & Engineering*, 2: 13-18.
- Sabrol, H. and K. Satish. 2016. Tomato plant disease classification in digital images using classification tree 2016 International Conference on Communication and Signal Processing (ICCSP). IEEE.
- Sandoval, Z., F. Prieto and J. Betancur. 2010. Digital Image Processing for Classification of Coffee Cherries 2010 IEEE Electronics, Robotics and Automotive Mechanics Conference. IEEE.
- Sharif, M., U. Farooq and W. Malik. 2005. Citrus Marketing in Punjab: Constraints and Potential for Improvement. *The Pakistan Development Review*, 44: 673-94.
- Szczypiński, P. M., M. Strzelecki, A. Materka and A. Klepaczko. 2009. MaZda – The Software Package for Textural Analysis of Biomedical Images *Advances in Soft Computing*. Springer Berlin Heidelberg, pp. 73-84.
- Tahir, A. 2014. Forecasting citrus exports in Pakistan. *Pakistan Journal of Agricultural Research*, 27: 64-68.
- Thendral, R. and A. Suhasini. 2017. Automated Skin Defect Identification System for Orange Fruit Grading Based on Genetic Algorithm. *Current Science*, 112: 1704.
- Uyun, S., S. Hartati and A. Harjoko. 2013. Selection Mammogram Texture Descriptors Based on Statistics Properties Backpropagation Structure. *International Journal of Computer Science and Information Security (IJCSIS)* 11: 1-5.
- Wen, Z.-y., L.-m. Shen, H.-p. Jing and K. Fang. 2010. Color and shape grading of citrus fruit based on machine vision with fractal dimension 2010 3rd International Congress on Image and Signal Processing. IEEE.
- Xinlu, L. 2001. The past, present, and future of China's citrus industry. Online available at <http://www.fao.org/3/x6732e/x6732e01.htm>.

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