Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7684040

DESIGN AND IMPLEMENTATION OF FCM BASED ENHANCED METHOD FOR SEGMENTATION OF IRREGULAR SHAPE FRUIT IMAGE CAPTURED IN NATURAL LIGHT TO IDENTIFY ARTIFICIALLY RIPENED FRUIT

Amit R. Welekar[1], Dr. Manoj Eknath Patil[2]
Research Scholar[1], Research Guide [2]
[1,2]Department of Computer Science & Engineering, Dr.A.P.J.Abdul Kalam University, Indore(M.P) welekar.amit@gmail.com[1],mepatil@gmail.com[2]

Abstract
In recent years, people have been using their eyes more and more to grade fruit. Image segmentation is an important part of developing a system for grading fruit because it lets the fruit be automatically analysed. Segmenting an image is a way to get the foreground of a digital photo while getting rid of the background that doesn't matter. Image segmentation can be done on both analogue and digital images. Object recognition has already been done with a number of different segmentation techniques. Methods like thresholding and cluster analysis are two examples of these kinds of approaches. Because natural light doesn't light up an object's surface in the same way, it's hard for standard algorithms to separate different parts of a picture of fruit. Having multiple lights on the objects of interest changes how they look, which can lead to wrong object analysis. The results of the study led to the development of a new way to divide up images of fruit. This method makes segmentation more accurate. The new method (DSDL-FCM) is made up of three algorithms: Fuzzy C-Means, adaptive K-means and modified thresholding. Combining the two methods is the only way to get more accurate results when separating images of fruits with different colours on the surface. The results showed that the new way of doing things worked well and accurately extracted individual fruits from photos.
Keywords: Shape Fruit Image , Ripened Fruit , FCM.

Introduction

Fruits give off ethylene gas when they breathe, which speeds up the rate at which they ripen as time goes on. It's tough to handle. ripe fruits because they turn into a mushy, fragile mess that can't handle being moved. Since this is the case, these fruits are picked when they are fully grown, even though they are still rough and green. A small amount of ethylene is enough to start the ripening process, which happens in carefully controlled conditions of temperature and humidity close to where the food will be eaten. Some examples are the mango, guava, fig, apricot, banana, kiwi, apple, plum, pear, and passion fruit. All other kinds of fruit aren't thought to have a climacteric stageThey are chosen at the exact time when they are needed. reached its final destination without any problems. Even though they are exposed to ethylene, they do not change in any way.

Because of this, they don't make very much ethylene gas. Oranges, grapes, litchis, watermelons, and blackberries are among the fruits in the package. We solved the problem of a training dataset that wasn't big enough by using techniques that make data better. When there isn't enough data to go around, you can easily and effectively use data enhancement technology to improve the quality of training samples, strengthen the model, and prevent overfitting. Using data augmentation technology to change the training samples makes it possible to make the model less sensitive to a certain set of characteristics or features. A process called "data augmentation," which made an existing dataset better and more valuable, led to a better and more valuable dataset. As a direct result of this, the model became more stable and worked better. So that data augmentation could be done faster, the image resolution was changed from 1920 by 1080 pixels to 780 by 1040 pixels, and the resulting photos were zoomed by a factor of four. There were only a certain number of pictures from each category that were shown.

Related work

Ramudu,et al.(2021) The goal of this study was to test a proposed method for segmenting medical image data, such as MRI brain and CT colonoscopy images. It has been shown that the algorithm works very well, getting the highest level of accuracy and overcoming the noise effect and border leakages. With this segmentation, the representation of the image can be looked at in more depth. In the field of medical image analysis, segmenting a picture is often seen as a difficult task because there are so many possible therapeutic uses.

Yueshuang Qi et al.(2022) In this work, an FCM-based method for image refinement segmentation is given so that these problems can be solved quickly. To start, we use a new way to measure how similar pixels are based on the results of pre-classifying picture sub-blocks. The process of putting pixels into groups is then improved by combining the spatial and grayscale properties of the local windows. This is done through voting and refinement. After everything is said and done, we give our results.

Hong Zhu et al.(2018) A new way to segment medical images is to use the density peaks clustering (DPC) algorithm and the fruit fly optimization algorithm together. Here are just a few of the good things about this plan. First, it doesn't have the problem that DPC does, which is that you have to pick parameters (like the number of clusters) in its decision graph at random. Instead, it can figure out their values automatically. Second, our method allows for some uncertainty in the steps taken, which is different from the way fruit flies are optimised, which uses a constant step size. In this way, the system is kept from getting stuck in a "local optimum" state. In a strange twist, our method chooses the threshold distance and cluster centres based on the imageentropy value. This lets it capture the image's underlying structures more accurately.

Anuja Bhargava et al.(2021) This study looks at the different ways that freshness, colour, texture, size, shape, and overall quality of fruit and vegetables are measured. This article takes a close look at the different ways that researchers have come up with to figure out how good fruits and vegetables are.

Zhen Yu et al.(2021) Images from the Berkeley database and MR images of the brain downloaded from the Brain online are used to test the theory. The authors of this work also suggest a thorough way to choose superpixel methods for colour photographs, one that can measure how important two different sets of criteria are. The idea of entropy from information theory was used as the basis for creating an evaluation metric that uses the internal entropy of superpixels. Most of the time, this criterion is used to evaluate groups of medical images. The results of the tests show that this method works better than the current method for both natural photos and medical images.

Methodology

There is evidence that a lot of work has been done to make an automated system for classifying fruits and vegetables even though there are no commercial uses of such systems right now. Most of the previous efforts have been based on the same basic idea: using one or more types of sensors along with a machine learning technique to find characteristics of the produce items, such as shape, colour, texture, and size, in order to classify them. Because fruits and vegetables can be different sizes, shapes, and colours, it can be hard to tell what they are when you are trying to identify them. A lot of research has been done to find answers to these problems. Nearly every part of a fruit or vegetable's shape, size, colour, and texture that can be seen from the outside has been thought of as a possible way to classify it correctly. When people first tried to classify things, they used global characteristics like shape and colour. Later, they focused on local characteristics like texture. Many different types of sensors, from simple black-and-white cameras to cutting-edge hyperspectral cameras, have been used to record the unique characteristics of fruits and vegetables [3]. Because of this, researchers have looked into both empirical and Neural Network (NN)-based approaches to machine learning and they are always trying to improve both. When it comes to real-world systems, there are a number of things that make it hard to get high accuracy and speed. Constraints include background environments that change, lighting that changes, specular reflection, and recognition that changes. In the parts of object recognition that deal with classifying, recognising, and finding fruits and vegetables, there have been a lot of problems that have had to be solved. Methods from related fields, like the classification of leaves, have also helped move the classification of fruits and vegetables forward. Most of the work being done in this area is focused on image analysis as feature description and machine learning algorithms for classification and recognition Using machine vision, the results of the analysis are shown in the form of a "feature description." A physical trait is taken into account in the analysis. These traits are given to the classification algorithm as inputs so that it can make a correct decision. Even though many ways to describe and classify features have been looked into, they still need a lot of work and improvement before they can be used in a way that leads to effective classification. To make a system that reliably sorts fruits and vegetables, we need to look at the problems raised by features, sensors, and classification algorithms from a different point of view.

Data acquisition is the process of taking pictures of the physical environment and putting them into a digital format. A sample dataset is the set of data that comes from this process. To reach this goal, it was necessary to use both active and passive sensors, but it worked out in the end. You can further divide these sensors into those that can see and those that can't. Both of these ways of classifying are good. There are a lot of things to think about when choosing a sensor. They include the application's environment, the characteristics being looked for, the lighting, the colour camouflage, and the way the environment blocks the view. The first ones used sensors made from black-and-white cameras. Light Detection and Ranging (LiDAR) technology is also often used in agriculture to classify different types of fruit and vegetable crops. Light Structured Sensors, also called LSS, are the focus of a lot of research because they can use depth data along with information about colour, shape, and texture. In the year researchers started looking into how different kinds of fruits and vegetables should be grouped together for harvesting with the help of robots. A lot of research has been done in this area, and a lot of research is still being done. In the agricultural and food processing industries, colour, temperature, spectral, auditory, tactile, and depth sensors have all been used to collect data for sorting and recognising. For example, both the amount of light and the colour of the background have a big effect on colour (RGB) photographs. Reviewing all of the relevant research that has been published shows that the reflectance properties of objects can be mapped onto a wavelength, and that hyperspectral cameras can be used to capture this data. This method is less sensitive to a lot of different factors and can tell the difference between things with backgrounds or colours that are similar to each other. Recent research has shown that adding data from other fruit characteristics to the data from hyperspectral imaging can make it work better. For judging the quality of food, this method has been used to solve a wide range of classification problems. But it has been found that the high dimensionality of hyperspectral data makes it hard to use in effective systems, because classifying hyperspectral images takes a lot of processing power. This means that it may not be possible to use hyperspectral data in systems that work well. When an object with a temperature above 0 Kelvin gives off radiation, it depends not only on how well it gives off radiation, but also on how hot its surface is. This quality can also be used to sort different kinds of produce into different groups. Fruits and vegetables can be put into different groups based on how much heat they take in compared to how big their leaves are and what's going on around them. It is hard to tell the difference between a green fruit and a leafy green vegetable because the temperature of the vegetables and the background are pretty similar. Recently, thermal analysis has been used in a number of different ways, such as to figure out if a plant has a disease, to figure out if chilling the fruit in storage hurt it, to figure out if it is ready to be harvested, and to figure out how much it might yield . Some other recent uses of thermal analysis are: Other problems with this technology are the canopy effect and the fact that it is sensitive to temperature . But, depending on the circumstances, heat fingerprints might not be able to be found until the fruit has been severely damaged . Scientists have used the basic ways that acoustic waves can be absorbed, reflected, and bent to classify fruits and vegetables. This has helped them classify a wider range of fruits and vegetables. Acoustic signals have been used to judge the quality of fruits and vegetables because the way they bend is a good way to tell how much water they have. We can figure out how hard an apple is and, by extension, how fresh it is by pressing on it and listening to the sound wave that comes out of it. This makes it easier to figure out the acoustic properties.

The process of collecting and organising raw data

When visual sensors are used to take a picture, the picture will always have some level of noise and distortion. Raw images are images that haven't been changed in any way, so computer vision or image processing software can't use them to figure out what the image is about. To make the effects of distortions and noise less noticeable, a lot of preprocessing is needed, as we'll see in the next section.

Pre-processing

Raw information that RGB matrices collect is redundant, so it needs to be processed statistically in order to get rid of unwanted data and find where data is missing. This is because noise, distortion, and different sensor sensitivity to the same physical input from the environment all contribute to this redundancy. Raw photos can be preprocessed at a high level of abstraction or a low level of abstraction. In the case of simple processing, the pixel is the low level of abstraction. Estimating pixel values can be limited in either a spatial or non-spatial way, and both have a wide range of applications and possible benefits. When it comes to still photos, the amount of geometric distortion depends on how far away the camera is from the subject of the photo. But when mobile robots are used, the amount of geometric distortion depends on how the camera moves, how it is oriented, and how fast it moves. When doing geometric pre-processing on an image, you can use groups of two or more pixels. A lot of basic preprocessing is done on pixels next to each other so that the differences between them stand out. Using gradients to make an image look smoother and find edges are two common examples. Because of this, a lot of filters have been made in the field of signal processing. At the sub-holistic level, values that aren't known can be estimated by using a convolution of filters. The fact that you can't use information you already know suggests that the convolution is either a random or a statistical function.

Segmentation

Image segmentation must be done first in order to get a Region of Interest, which is a distinct part of an image (ROI). When it comes to computer vision systems, being able to divide images into parts is a big challenge that, in the end, determines how well more advanced image analysis works. Many different segmentation methods, such as those based on luminance, hue, saturation, grayscale, texture, and edges, have been described in the research that has been done. On the other hand, as computing power keeps getting better, better ways to divide things up are being made. A rough segmentation of an image can be done by using edge detection and background subtraction. A technique that has been used a lot is to get rid of the local breaks that happen at each pixel of a filtered image. This is where the intensity and direction of the pixels become important. When extracting edge pixels from complex images, the lower and upper thresholds need to be carefully thought out so that a break in continuity can be found. Also, many edge detection methods tend to find a false edge in images that have already been processed. Edge-based segmentation does not work well with images that have a continuous background, occlusion, or mixed edges. This is because of the things that have already been said. With threshold-based segmentation, thresholds are used at the pixel level to make regions in an image. By applying threshold to each of the three channels separately, most greyscale algorithms have been made to work with RGB images. For computer vision tasks, a fully automated threshold value convergence is needed for segmentation. However, estimating the threshold is still very important, so many algorithms use "hit and try" to do this. The presentation of a segmentation method based on an adaptive threshold selection can be found in . To find the best cutoff point, an iterative process that converged on the mean value of the grey scale was used. In a way that the Otsu method can be used with RGB images is described. The Otsu approach was used to figure out the convergent intraclass variance, which is the threshold for this adaptation.

Characteristics: Getting Them Out

A feature descriptor is a piece of data that describes a specific dynamic aspect of an object in a digital image from a higher-level perspective, such as recognition, classification, retrieval, or reconstruction. Feature descriptors can be used for many things, such as recognition, classification, retrieval, and reconstruction. To put fruits and vegetables into groups, many identifying signs or traits are looked at. Color, shape, size, and texture are the most common ways to recognise and sort fruits and vegetables. Feature descriptors can be categorised as either global or partial, depending on whether or not they can give a full or insufficient picture of a feature. When it comes to recognising objects, a global feature is a high-level, all-encompassing description of the object, like its shape. On the other hand, a local feature is a low-level and patch-level description of many different places of interest within the object. For instance, an object's shape is a global feature, but its texture is a local feature. When doing a job that involves recognition, the areas of interest are not always the same. Instead, they can change from one sample to the next.

collecting pictures and figuring out what the hidden meanings of their colours are by using every colour in a shot.

The main goal of this experiment was to find out how easy it is to find mature pomegranates in their natural habitats.

Color Analysis: Traits of Colors

Figures 1(a), 1(b), and 1(c) show that the pomegranate fruits in the pictures are a very bright colour. But there are a lot of shadowy parts in the background, and the image as a whole isn't very good. At best, the edges are about average in how sharp they are. Since there isn't much light during the day, the dark parts of the background aren't as noticeable as they would be at night. But the colour of the fruit isn't as striking as it is at night. There are dark spots, and the lines aren't as clear as they used to be. When shooting with natural light, the pomegranate fruit could be hidden by a number of things, making it hard to pick it out for precise processing. That makes it hard to shoot.

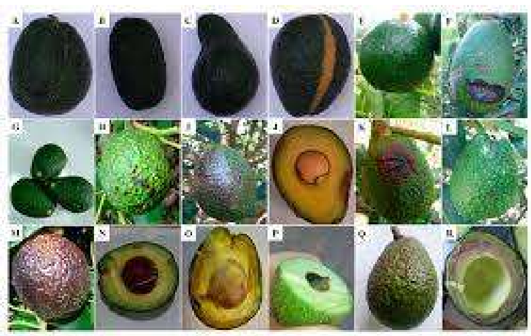


Figure 1 - Irregular Shape Fruit Image Captured In Natural Light To Identify Artificially Ripened Fruit

The fuzzy C-means method for clustering

For the food industry to make a fruit sorting machine that works on its own, it must be able to recognise fruits based on their quality. This is the most important technology, according to most people. In this article, we explain how to rate fruits using a tiered system that we've made. The goal of this study is to see how well Python can tell the difference between healthy and unhealthy fruits. First, we take the image of a fruit that was given to us and pull out its features. Then, we build linked databases using different methods, such as thresholding, segmentation, and k-means clustering. By comparing several different sets of data from experts, we can find an exact range for both good and bad harvests. This means we can make better decisions. With the help of the recommended range, we will be able to tell the difference between good and bad options. With the help of image processing, this article can tell the difference between high-quality and low-quality fruit in a very accurate way. Because of this, the article is able to tell the difference between good fruit and bad fruit.

The standard FCM clustering method uses a weighted similarity measure between image pixels and cluster centres so that the objective function can be improved over and over. This method tries to find the best cluster by lowering the value of the objective function. The objective function of the FCM algorithm often looks like this:

$$J(u,v)=\sum_{i=1}^{N}\sum_{j=1}^{C}u_{ij}^{m}\|x_i-v_j\|^2$$

where m is a number that shows how important the factor is (Fuzzy coefficient).

Keep in mind what I just said. For this analysis, we set m = 2, where uij is the percentage of the i-th sample that belongs to the j-th class, Xi is the i-th sample, Vj is the j-th clustering centre, and || xi - vj || is the distance norm between sample Xi and cluster centre Vj. Sample I is shown by the letter xi, and a sample's level of membership in a group is shown by the letter uij. The Euclidean distance is used as part of this study. The Lagrangian conditional extreme value optimization theory can be used to get the iterative formulas for Uij, the fuzzy membership degree, and Vj, the centre of the cluster. Both of these things are in the previous sentence.

$$u_{ij}=\left[\sum_{k=1}^{C}\left(\frac{\|x_i-v_j\|^2}{\|x_i-v_k\|^2}\right)\right]^{-1}$$

$$v_j=\frac{\sum_{i=1}^{N}u_{ij}^2x_i}{\sum_{i=1}^{N}u_{ij}^2}$$

Using a kernel fuzzy C-means method to group things together

We can find out what the KFCM's goal function is by using the kernel method.

$$J=\sum_{i=1}^{N}\sum_{j=1}^{C}u_{ij}^{m}\|\phi(x_i)-\phi(v_j)\|^2$$

Defined by the Mercer core

$$d^2(x_i,v_j)=\|\phi(x_i)-\phi(v_j)\|^2=K(x_i,x_i)+K(v_j,v_j)-2K(x_i,v_j)$$

In the next paragraph, we'll talk about how the KFCM algorithm needs to do calculations over and over again.

We need to come up with a more advanced FCM-based algorithm that can deal with photos of fruits with natural lighting and different shapes.

Going Ahead The steps that went into this improved FCM will be called "DSDL-FCM-related activities," and the results we'll talk about will be called "enhanced FCM."

Step1: In the first step of the process, pictures of round (Apple) and long (Banana) fruits are taken in both natural light and even (artificial) light. Then, Original FCM is used to tell the difference between the two types of forms.

(As a first result, we have divided fruit pictures into groups that show how natural and artificial ripening are different from each other.)

Step2: Second, our improved FCM method will also take pictures of both regular-shaped (Apple) and irregular-shaped (Banana) fruits in both natural light (Natural Sunrays) and uniform light (artificial Light source). Then, an improved FCM algorithm, called DSDL-FCM, will be used to separate the parts of these images.

The second result is segmented pictures of apples and bananas with signs of when they are ready to eat (Natural and Artificial)

Step 3: Look at the differences between the three to four values from the Original FCM and the parameters from Step 2 to figure out which set of numbers is more accurate (DSDL-FCM)

Third, a table that compares FCM and DSDL-performance FCMs should show that the latter is better for images of fruits with regular (Apple) and irregular (Banana) shapes that are lit by natural light or artificial light. If the table is made right, this should be the case.

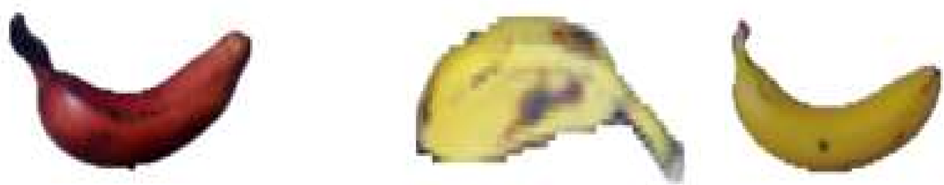
Step 4: We call this process "improved" because one of our main goals is to fix FCM's most important problems. This is why this step in the process is called "better."

Before we move on to anything else, we want to keep the amount of time it takes to run the FCM to a minimum. We also want to avoid having to specify the number of clusters before the fuzzy c-means technique can be run (FCM).

In the end, we use this information to fix an image of a fruit with the wrong shape that was taken with natural light.

The fourth thing that happens is: The Two and Three Plots Side by Side Compare how well the Original FCM and our improved FCM (i.e., DSDL-FCM), which was made later, work.

(a) (b) (c)



(d) (e) (f)

(g) (f)

Figure 2: Segmentation Of Irregular Shape Fruit Image Captured In Natural Light To Identify Artificially Ripened Fruit

Table 1: Results analysis

Model	Precision	Recall	F-Score	Accuracy	TP	FP	FN
K-means	0.98	1.0	0.98	.88	1343	19	3
FCM	0.96	1.0	0.97	0.95	1306	36	5
DSDL-FCM	*0.99*	*1.0*	*0.99*	*0.99*	*1309*	*1*	*1*

Conclusion

So, the suggested enhanced FCM method (DSDL-FCM) identifies fruits that have been ripened naturally so that people can keep eating them to stay healthy. The method being used is an Android app that can tell the difference between fruit that has been ripened naturally and fruit that has been ripened in a lab. The app takes a picture of the fruit with the phone's camera, analyses it by figuring out the histogram value, and then labels it as either naturally ripened or artificially ripened. Improved FCM (DSDL-FCM) method also performs better in Precision and accuracy as compared to K-Means and FCM.

Reference

1. Ramudu, Kama, et al. "An Efficient Segmentation of Biomedical Images Using Optimized Level Set Method via Enhanced Possibilistic FCM Clustering." SSRN Electronic Journal, 2021, 10.2139/ssrn.3852922. Accessed 19 Nov. 2021.
2. Lu, Jue, and Rong Qiang Hu. "A New Image Segmentation Method Based on FCM and Ant Colony Algorithm." Applied Mechanics and Materials, vol. 380-384, 30 Aug. 2013, pp. 1705–1709, 10.4028/www.scientific.net/amm.380-384.1705.
3. Hong Zhu ,Hanzhi He,Jinhui Xu,Qianhao Fang, Wei Wang. Medical Image Segmentation Using Fruit Fly Optimization and Density Peaks Clustering.December 2018Computational and Mathematical Methods in Medicine 2018:1-11,DOI:10.1155/2018/3052852
4. Anuja Bhargava, Atul Bansal. Fruits and vegetables quality evaluation using computer vision: A review. https://doi.org/10.1016/j.jksuci.2018.06.002, Volume 33, Issue 3, March 2021, Pages 243-257.
5. Zhen Yu, Cuihuan Tian, Shiyong Ji, Benzheng Wei, Yilong Yin, "SMBFT: A Modified Fuzzy -Means Algorithm for Superpixel Generation", Computational and Mathematical Methods in Medicine, vol. 2021, Article ID 1053242, 12 pages, 2021. https://doi.org/10.1155/2021/1053242

6. Sharifah Lailee Syed Abdullah,Hamirul'Aini Hambali,Nursuriati Jamil. Segmentation of Natural Images Using an Improved Thresholding-Based

TechniqueDecember2012,Procedia Engineering 41:938-944,DOI:10.1016/j.proeng.2012.07.266,License,CC BY-NC-ND 3.0

7. Yueshuang Qi,Anxin Zhang, Hua Wang,Xuemei Li. An efficient FCM-based method for image refinement segmentation.July 2022The Visual Computer 38(1):1-16,DOI:10.1007/s00371-021-02126-1.
8. Yu, Gui Shui, and Ke Li. "Watershed Image Segmentation Based on PSO and FCM." Advanced Materials Research, vol. 1070-1072, Dec. 2014, pp. 2041–2044, 10.4028/www.scientific.net/amr.1070-1072.2041.
9. Wu, Zong Jia, and Li Kun Liu. "The Improved Membership Matrix Initialization Method of FCM for Image Segmentation." Advanced Materials Research, vol. 989-994, July 2014, pp. 3743–3746, 10.4028/www.scientific.net/amr.989-994.3743.
10. S, Sadagopan. "Brain Tumor Segmentation Using Improved Kernel Weighted FCM." Journal of Advanced Research in Dynamical and Control Systems, vol. 11, no. 0009-SPECIAL ISSUE, 25 Sept. 2019, pp. 899–905, 10.5373/jardcs/v11/20192649.
11. "Brain Tumor Detection and Segmentation by Fuzzy C–Means (FCM) Algorithm Using LabVIEW." International Journal of Recent Trends in Engineering and Research, vol. 4, no. 2, 1 Mar. 2018, pp. 104–107, 10.23883/ijrter.2018.4072.je8vm.
12. L. Wang, R. Liu, and S. Liu, "An effective and efficient fruit flyoptimization algorithm with level probability policy and itsapplications," Knowledge-Based Systems, vol. 97, pp. 158–174,2016.
13. H. Kachariya,K. Vasaniya, S. Dhameliya, R. Savant, "A Review of Volume Estimation Techniques of Fruit", International Journal of Engineering Research & Technology (IJERT) , Vol. 4 Issue 01,January-2015,pp.217- 221.
14.] D. Kakadiya, N. Shah, M. Patel, R. Shah, C. Kachariya, K. Sukhwani, " Shape Extraction Methods for Fruits: Technical Review" , International Journal of Computer Applications(0975 8887) , Vol.111, No.1, Feb.2015, pp.43-48
15. Acuña, R. G. Gonzalez, Junli Tao, and Reinhard Klette. "Generalization of Otsu's binarization into recursive colour image segmentation." In Image and Vision Computing New Zealand (IVCNZ), 2015 International Conference on, IEEE, 2015 pp. 1-6.
16. D. Jasani, P. Patel , S. Patel, B. Ahir, K. Patel, and M. Dixit, " Review of Shape and Texture FeatureExtraction Techniques for Fruits", International Journal of Computer Science and InformationTechnologies, Vol.6, 2015,pp.4851-4854.
17. Ramírez-Gil, J.G.; López, J.H.; Henao-Rojas, J.C. Causes of Hass Avocado Fruit Rejection in Preharvest, Harvest, and Packinghouse: Economic Losses and Associated Variables. Agronomy 2020, 10, 8. https://doi.org/10.3390/agronomy10010008
18. GONG, M.; et al. Fuzzy C-means clustering with local information and kernel metric for image segmentation [J]. IEEE Transactions on Image Processing, 2013, 22 (2):573-584. Available from: . Accessed: Nov. 09, 2017. doi: 10.1109/TIP.2012.2219547.
19. LEI, X.; OUYANG, H. "Image segmentation algorithm based on improved fuzzy clustering," Cluster Comput., 62(1), 1-11 (2018). Available from: . Accessed: Jun. 12, 2018. doi: 10.1007/ s10586-018-2128-9.

20. YANG, X., HUANG, S. Multi-view clustering algorithm based on fuzzy C-means[J]. Journal of Central South University (Science and Technology), 2015, 46(6):2128-2133. Available from: . Accessed: Aug. 23, 2018. doi: 10.11817/j.issn.1672-7207.2015.06.
21. XU, H., et al. Identification of citrus fruit in a tree canopy using color information [J]. Transactions of the Chinese Society of Agricultural Engineering, 2005, 21(5):98-101. Available from: . Accessed: Dec. 15, 2017. doi: 10.3321/j.issn:1002-6819.2005.05.023.
22. M. Q. Li, L. P. Xu, Shan Gao, Na Xu, and Bo Yan, "Remote sensing image segmentation based on a robust fuzzy C-means algorithm improved by a parallel Lévy grey wolf algorithm," Appl. Opt. 58, 4812-4822 (2019).
23. Kumar, Ram and Patil, Manoj, Improved the Image Enhancement Using Filtering and Wavelet Transformation Methodologies (July 22, 2022). Available at SSRN: https://ssrn.com/abstract=4182372
24. Ram Kumar, Manoj Eknath Patil ," Improved the Image Enhancement Using Filtering and Wavelet Transformation Methodologies", Turkish Journal of Computer and Mathematics Education ,Vol.13 No.3(2022), 987-993.
25. Ram Kumar, Jasvinder Pal Singh, Gaurav Srivastava, "A Survey Paper on Altered Fingerprint Identification & Classification" International Journal of Electronics Communication and Computer Engineering ,Volume 3, Issue 5, ISSN (Online): 2249–071X, ISSN (Print): 2278–4209.
26. Chetna kwatra, Bukya Mohan Babu, M.Praveen, Dr T.Sampath Kumar, Ram Kumar Solanki ,Dr A V R Mayuri. (2023). Modified Cnn Based Heart Disease Detection Integrated With Iot. Journal of Pharmaceutical Negative Results, 993–1001. https://doi.org/10.47750/pnr.2023.14.S02.120