Proposing Improved FCM based Method for Segmenting Irregular Shaped Fruit Image Captured in Natural Light

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Abstract

The latest improvements in computer vision have made it possible to use this technology in almost every aspect of human life. This has made a lot of new things possible. Since putting fruits and vegetables into groups has been shown to be a difficult task that needs more research and development, this application sector has become very important. Because of how similar things are within the same class and how different things are within the same class, trying to classify fruits and vegetables presents a number of problems that must be solved before success can be reached. Because there are so many different uses, it is important to choose the right sensors for gathering data and a way to represent features. Even though methods have been made to classify fruits and vegetables so that their quality can be judged and they can be picked by robots, the current state of the art can only be used with small datasets and a small number of classes. One of the biggest problem that modern machine learning algorithms have to deal with is that the problem is often multidimensional and there is often a lot of input that is very high dimensional. A lot of time and effort has been put into making and analysing classifiers for hyperdimensional characteristics, which need a lot of computing power to be optimised. In real-world applications over the past few years, many different feature description methods and machine learning techniques, such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Trees, Artificial Neural Networks (ANN), and the model being proposed here, have been used to classify fruits and vegetables. In this paper, we look at all of the new computer vision approaches to classify fruits and vegetables that have been proposed by the scientific community. People have said that these ideas are on the cutting edge.

Keywords :FCM ,Support Vector Machine (SVM) ,K-Nearest Neighbor (KNN) ,

Introduction

This article gives a full and up-to-date review of the research on how to classify fruits and vegetables and what makes them up. People have said that one of the biggest problem is the lack of good tools for collecting data, representing features, and making classification algorithms. Sensors used in the food industry to collect data are limited in many ways. Some of these limits are that the sensors are not destructive, that the environment can block them, that there are similarities between and within classes, and that the features are complicated. Using many sensors for the same purpose in fruit and vegetable research presents a number of problems. One of the most important is that the information from the different detectors is not the same. Also, the different kinds of data make it impossible to combine them with information from different points of view. In a similar way, the most recent feature descriptors are not right for the job. Also, RGBD sensors, which are the most recent type of sensors, don't have enough feature descriptors. Because they are sensitive to some of the pheromones that are naturally present and that are made when an image is taken, feature descriptors also have a number of major flaws. These qualifications are listed in the publication, and they are also clear from the research done before. Machine vision algorithms that are based on what we already know don't work well enough for categorising multi-feature, high-dimensional data. There are a lot of different kinds of fruits and vegetables, and each one is different from the others in its own way. Large datasets that are easy to get hold of are a big problem for the classification methods that have been found. It has been found that most of the published experiments have limits on either the number of classes that were tried or the size of the dataset. By using deep learning to train FCM (Fuzzy C- Means), the current work helps to improve the system's ability to offer ready-made parts that can be used in computer vision applications. Even though pretrained deep learning FCM are data-dependent, it's not easy to get a large enough dataset of fruits and vegetables. Taking into account the thorough study of how to classify fruits and vegetables, it is possible to say that computer vision needs to be rethought in a big way before it can be used better in the food business. Based on the results of the study, this could be done. This paper describes a deep learning fuzzy c-means (FCM) clustering-based method for separating 3D breast lesions from a contrast-enhanced FRUIT IMAGE.

Related work

X. Liu et al. [1]Most ripe apple skins are only partly red; they also have some green and pale yellow. This makes it harder for machines to recognise apples as they get older. We talk about a way to find these apples that uses both their colour and shape. Using a technique called simple linear iterative clustering (SLIC), photos of orchards are turned into super-pixel blocks. Because we use the colour of the blocks to find candidate regions, we can get rid of a lot of blocks that don't have fruit, which makes our detection more accurate.

Rui Wang; et al. [2]

In this piece of research, it is suggested that the task for roads be done with RD-Net, which is a network for semantic segmentation. Reflection padding and a "convolution and pooling" stack are used to pull out features. A dilated residual transition unit is also used to add more depth to the network, and upsampling is used to bring back lost detail at larger sizes. In evaluating the proposed network, aerial unstructured road datasets are used along with four other cutting-edge deep learning-based road extraction networks. When the recommended network is used to solve the problem of road segmentation, the results are encouraging, showing that the accuracy of segmentation has improved. This shows both how useful it is and how easy it is to use on unstructured roads.

Anita Kausar et al . [3]

Object classification is important for the automation of industries like robotic harvesting, farming, healthcare, and education. This can be done with the help of techniques like machine learning and computer vision. Because fruits are so similar to each other in size, shape, and texture, it can be hard to put them into different groups. We came up with a Pure Convolutional Neural Network that has the fewest parameters possible so that a wide range of fruits can be found more accurately (PCNN). The PCNN is made up of seven convolutional layers, and some of them follow the stride. We also used the recently made Global Average Pooling (GAP) layer, which did a good job of reducing overfitting and averaging out all of the feature maps.

Yong-Xianga Sun et al. [4]

In this article, a new way of using chain codes to trace the edges of pictures of fruit is shown. The image of a fruit is used to figure out the circumference, area, circular degree, inscribed circle radius, graph complexity, concave rate, and graph parameter. This is done so that the chain code is reflected. The image is also used to figure out the height and width. The results of the experiments show how simple, accurate, and effective this technology is, and how little space it needs to store information.

Akin, C., et al. [5]

If only colour information was used, it would not be possible to make a good algorithm for finding pomegranates. Because of this, a detection method will need to include more than just the colour of the pomegranate in order for it to be reliable. A normal pomegranate is round, which is different from the shape of tree branches and leaves, which are both long and thin. Most pomegranates don't have seeds either. If you want to find some kind of fruit, you might just have to look for round things. Using machine vision to divide fruit into sections is not always easy (lighting and occlusion). All of these questions are also looked into in the solution that has been given.

A. Gokul, P. R., et al.[6]A good evaluation of the fruit's quality is good for both the grower and the person who buys it (see [6]). In this study, an image processing method is described for figuring out how many sweet limes there are and how old they are. The only types of fruits that are taken into account are those that are round. This picture was taken with both a digital camera with a high resolution and a smartphone. The size of sweet limes and how ripe they are can be figured out with the help of a MATLAB method. To figure out how much space the fruit takes up, we need to make an educated guess about how big it is around. The ratio of red to green (RG) colours on a plant can be used to estimate how mature it is. Vernier Calipers are used to measure the results of an experiment and figure out whether or not they are correct.

S. M. T. Islam, et al. [7]

The goal of this study is to come up with a way to accurately classify mangoes into the different stages of ripeness they can reach. To start, the RGB values of the pictures were changed to HSV values so that the results could be compared. After the image has been taken, its parts are separated using a thresholding method, with the "S" channel taken into account at every step. Fifteen important parts of the image have been taken out after it has been segmented.

Proposed methodology

When you segment an image, you put together groups of pixels that have similar qualities. Before a digital image can be analysed and given a grade, it needs to be broken down into its parts. At last, it separates the subject of interest from the rest of the digital image while also hiding the background. The results of image segmentation have a big effect on the next steps in analysing an image. By focusing on the area of interest, you can rest easy knowing that all of your research and analysis was done on the topic at hand. But the method for segmentation has been hard to figure out because the photos have complicated backgrounds and lighting that changes. So, it is very important to have a method of image segmentation that is both accurate and quick. This will make it possible to tell the difference between a picture's foreground and background even when the lighting is natural. [4] The first step in automated object analysis is to separate an image into its parts. It can be used in many different fields, such as agriculture, industry, health care, and figuring out patterns. Image segmentation has many uses in agriculture, such as finding contaminated parts of fruit, classifying fruits, managing fruit quality, finding fruit while it's still on the plant, estimating crops, and finding out when fruit is ready to be picked. Image segmentation is also used to figure out if a fruit is fully grown or not. When you segment an image, you separate one part of it from the pixels around it. Segmenting an image is one of the most difficult tasks in the field of image processing because it is the first step in image analysis, the basis of computer vision, a key part of learning about an image, and so on. Also, it is one of the most important things to do. When it comes to a grayscale image, the pixels inside the zone often have similar intensities, but the intensities at the zone's edges don't stay the same. Image segmentation processing can be done in many different ways, such as thresholding, region-based segmentation, edge detection-based techniques, and machine learning-based methods. Since the photos for this study were taken in natural light, they have a wide range of levels of brightness, just like real-world situations. Because of this, it's important to find a good threshold and clear, precise edges when you're trying to divide up the target. Since this is the case, the K-means algorithm is used to solve this problem. K-means uses the distance between two points as a way to figure out how similar they are. The most important thing to remember is to put the samples into different groups based on how far apart they are. The closer two places are, the more close they are to each other. The last step in the process is to put each piece of information in the cluster whose centre is closest to that piece of information. The goal of this step is to make sure that the sum of the squares of the distances between each location and its cluster centre is as small as possible. Before the K-means treatment, the photos were given a rank filter and a log transformation to reduce the amount of noise and increase the level of contrast. I.2. Feature Extraction shows the results of the segmentation of the sample. Images can be put into different groups based on their differences. There are many things in the physical world that can be directly felt, such as brightness, edges, texture, and colour. Before you can get things like moments, histograms, and main components, you have to change or process them. So that computers can better recognise photos, these properties will be retrieved as numbers or vectors.

The algorithm uses the distance between a data point and the centre of a cluster as one of the ways to decide if a data point belongs to a certain cluster or not. If a piece of data is closer to the centre of a cluster, it is more likely to be in that cluster. When all the information is added up, it makes sense to think that the total number of members will be one. After each iteration, the following algorithm is used to recalculate the centres of the clusters and who is in each one:

$$\mu_{ij} = 1 / \sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/m-1)}$$

$$v_j = (\sum_{i=1}^{n} (\mu_{ij})^m x_i) / (\sum_{i=1}^{n} (\mu_{ij})^m), \forall j = 1, 2, \ldots..c$$

where n represents the total number of data points. The "vj" denotes the cluster's epicentre. The "fuzziness index," denoted by the symbol "m," is defined as m € [1]. The cluster's central number, denoted by "c," identifies its geographical epicentre. The notation "ij" indicates that the ith set of data originates from the jth major cluster. The ith datapoint's "dij" represents its geometric distance from the centre of the jth cluster.

The primary objective of the fuzzy c-means algorithm is to:

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (\mu_{ij})^m \left\| x_i - v_j \right\|^2$$

where "||xi - vj||" indicates the Euclidean distance between the ith data point and the jth cluster midpoint and "||i" represents the ith data point.

Algorithmic steps for Fuzzy c-means clustering

Let X = {x_1, x_2, x_3 ..., x_n} be the set of data points and V = {v_1, v_2, v_3 ..., v_c} be the set of centers.

1) Randomly select *'c'* cluster centers.

2) Calculate the fuzzy membership *'μ_{ij}'* using:

$$\mu_{ij} = 1 / \sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/m-1)}$$

3) Compute the fuzzy centers *'v_j'* using:

$$v_j = (\sum_{i=1}^{n} (\mu_{ij})^m x_i) / (\sum_{i=1}^{n} (\mu_{ij})^m), \forall j = 1, 2, \ldots..c$$

4) Repeat steps 2) and 3) until ||U(k+1) - U(k)||, where 'k' is the iteration step, or until the minimum value for 'J' is reached, whichever comes first.

The character '' is the line that separates the ranges [0, 1], and it can show up anywhere in that range.

The fuzzy membership matrix can be shown by the formula U = (ij)n * c.

"J" stands for the number that needs to go up as much as possible.

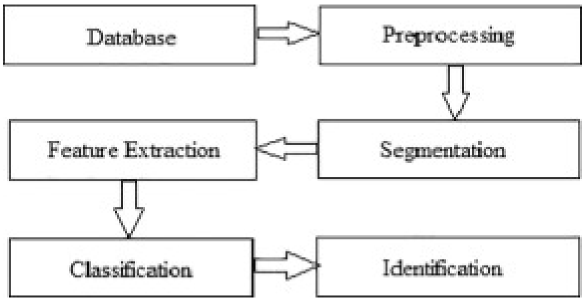

Figure 1: Process of Proposed Approach

Color, texture, shape, and where an object is in the picture are all common examples of picture properties. What makes each colour what it is. The colour of an object in an image is an example of a global feature that can be used to describe the surface qualities of the objects in the image. Each pixel in the same image or the same part of an image contributes to the overall colour based on its own properties. There are many different kinds of colour features that can be retrieved. Histograms, sets, moments, and coherence vectors are some examples. Because the different stages of ripeness are linked to different colours (green, yellow, and brown), one of the things used to train the classifier in this study was the colour feature. Also, the colour space distribution didn't need to be taken into account, which was one of the reasons why the colour feature was retrieved. Most digital image processing uses the RGB colour space, which stands for "Red, Green, and Blue." On the other hand, the HSV colour space is better for statistical research because it is closer to how people see colours. So, the HSV colour space was used to figure out the colours from the set of data that was given. Semantic segmentation of images can be seen as a matter of putting pixels into groups. For the pixel-level two-classification task, the proposed network RD-Net uses a loss function called BCE-DiceLoss. This loss function is a mix of the binary cross entropy (BCE) loss function [11], which is usually used for image classification, and the Dice coefficient loss function [10], which is usually used for image segmentation. The cross-entropy loss function is a way to measure how different the expected (P) distributions are from the trained distributions (Q). The binary cross entropy loss function should be used when there are only two possible values, such as 0 and 1. Here is the formula for the calculation: where iy is the label for the pixel and (w) ih x is the chance that the predicted pixel will be there.

$$J(w) = -\frac{1}{m}\sum_{i=1}^{m}\left[y_i \log h_w(x_i) + (1-y_i)\log(1-h_w(x_i))\right]$$

A lot of the time, the Dice coefficient loss function [10] is used to figure out how far apart two different sets of segmentation results and labels are. To find the Dice loss function, first find the sum of the lengths in set A, then find the sum of the lengths in set B, and then divide the sum of the lengths in set A by the sum of the lengths in set B, with the numerator being twice the intersection of sets A and B.2 $BCE\text{-}DiceLoss = J(w) + (1 - Dice)$

Both A and B are on the scale, which goes from 0 to 1.

Because of this, we can come up with the following BCE-DiceLoss loss function: (3). During the training phase, the loss function is changed so that it has the smallest value possible.

$$Dice = \frac{2|A \cap B|}{|A| + |B|}$$

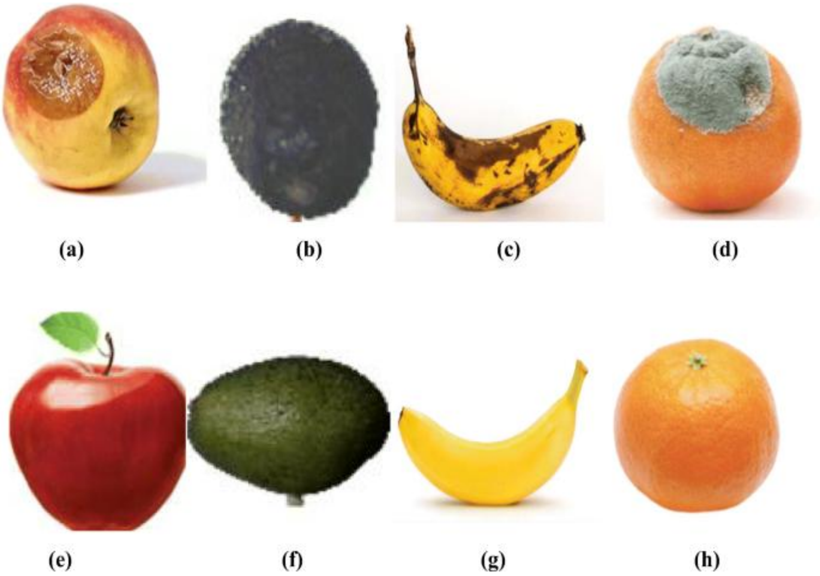

Figure 2: Using Deep Neural Networks, We Can Automatically Identify and Rate Several Types of Fruit [10]

Results analysis

The results of the first-layer classification are judged by accuracy, precision, and recall, which are all common ways of judging in statistics.

Intersection over Union (IoU) and recall are used on the expected positions of the target to find out more about how well the FCM with deep learning is doing (Mean Average Precision). The criteria for judging are explained in detail. The area of overlap is the area that is inside both the ground truth bounding box and the predicted bounding box. The area of union is the sum of the areas that are inside both the ground truth bounding box and thepredicted bounding box.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN},$$

$$Sensitivity/Recall = \frac{TP}{TP + FN},$$

$$Precision = \frac{TP}{TP + FP},$$

$$F1 - score = 2 \cdot \frac{Precision \cdot Reccall}{Precision + Reccall}.$$

$$TP = True\ positive, TN = True\ negative,$$
$$FP = False\ positive, FN = False\ negative.$$

Table 1: Comparison of the Results of different machine learning model

Model	Training Accuracy	Testing Accuracy	Computation time (MS)
Support Vector Machine (SVM)	79.43%	81.23%	250ms
K-Nearest Neighbour (KNN),	81.34%	83.35%	200ms
Decision Trees,	83.56%	86.67%	180ms
Artificial Neural Networks (ANN) and	85.67%	87.54%	150ms
Proposed FCM with Deep learning	91.34%	92.34%	101ms

Conclusion and future work

In this study, the task of separating parts of a fruit image is done in three different ways: grayscale segmentation, K-means adaptive segmentation, and black-and-white segmentation. Even though there are a lot of ways, like using oranges and lemons, to accurately segment photos of round fruits, these methods have not yet been used to successfully segment photos of fruits that don't have a round shape. When the photos were taken with natural light, the ones with odd shapes were the hardest to divide. Image segmentation is harder to do when natural light is used because the light intensity isn't always the same all over the surface of the fruit. Because of this, a k-means algorithm has been made that can better separate photos of fruit taken in natural light and with different shapes. Each method of segmentation, its corresponding segmentation strategy, and the amount of light available are all tailored to a specific fruit. Even though some updated and hybrid methods have been able to get around the illumination effect, there is still a lot of work to be done to come up with a method that can reliably segment photos of oddly shaped fruits that are lit by natural light.

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