DESIGN A MACHINE LEARNING MODEL FOR SEGMENTATION OF IRREGULAR SHAPE FRUIT IMAGE CAPTURED IN NATURAL LIGHT TO IDENTIFY ARTIFICIALLY RIPENED FRUIT

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Abstract : The segmentation of an image of an irregularly shaped fruit that was taken in natural light is a new way that visual recognition and machine learning can be used to find artificially ripened fruit. When eaten by people, ripe fruits can spread a wide range of infectious diseases. Several different classifiers were used to look at the fruits' colour (measured in the RGB colour space), shape, and texture in order to find out which one was the most accurate. After the first step of picture segmentation using the FCM Based Enhanced Technique, the suggested method uses a modified Convolutional Neural Network to sort the images into one of several groups. The study's authors suggest using a convolutional neural network (CNN) to make predictions about mangos that have been ripened in a lab. By doing this, they hope to cut down on the amount of money that will be wasted because of their work. Using this method, mango fruits that have been ripened in a lab can be put into the right category more accurately and with less waste. The artificially ripened mango fruit method of predicting the future shows that things are going to get better soon. Based on the results of our tests, the proposed method can help a lot with accurate identification and automatic classification of fruits with odd shapes in natural light images. This can be done to tell the difference between fruits that have ripened on their own and those that have been made to ripen. When figuring out what characteristics ripe fruit has, a grey-level co-occurrence matrix is used. The fruits that are being looked at right now are apples, oranges, grapes, pomegranates, and bananas.

Keywords: Irregular Shape Fruit Image, convolutional neural network, FCM.

Introduction

Historically, skilled experts' own eyes were used alongside conventional methods for detecting and identifying artificially ripened fruit. Getting expert help in some third world nations can be time consuming and costly due to constraints on the free mobility of the local population. To immediately recognise the markers of ripened fruit whenever they appear on the image of an irregularly shaped fruit being taken, the early ripening identification process must be automated. If the fruits aren't uniform in size and shape, the harvesting process could result in major losses in both output and quality. Gaining an understanding of the data collected is crucial for selecting the most appropriate control measures for the coming year. Apples sometimes develop scabs, which look like grey or brown corky spots. Sunken, spherical, brown or black patches, sometimes surrounded by a red halo, are the hallmark indication of an apple rot infestation. The dark, irregular, or lobed borders left by apple blotch, a fungal disease, are

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a telltale sign that the fruit was infected. In the company, machine vision technology is already in use for automated visual inspections of apples for size and colour. However, it is challenging to detect defects in product in a reliable manner due to the presence of a stem or calyx, as well as the broad diversity of different types of defects. Studies of fruits are important because the outward appearance of some fruits can be used to infer their overall health or to reveal the presence of disease within the fruit itself. Diseases can be prevented and eventually eradicated thanks to the use of pesticides, fungicides, and other chemical applications, in addition to other preventative measures undertaken by management. Techniques based on spectroscopic and imaging technology are among those that can be used to monitor and stop the spread of plant diseases. A fruit detection system is most often used in automated harvesting of fruit. With some tweaks, this technology could be useful in many different fields, such as illness diagnostics, maturity detection, yield monitoring in trees, and other closely connected endeavours. Several types of fruit have become more accessible for international trade as shipping and cold storage methods have advanced. Professional visual inspection is currently necessary to keep export quality at a high standard. This is a costly and time-consuming endeavour because farms are spread out. Helping farmers, precision agriculture provides them with ample and reasonably priced data and management tools. Recent discoveries and innovations in a number of disciplines have made this possible. The goals include increased profitability, less environmental impact, and uniformity in agricultural inputs. Consequently, this paper details a strategy for identifying and categorising fruit diseases, a strategy that is backed up by actual evidence. In order to determine if fruit is tainted with a disease, this method uses a photograph of the fruit as input. As part of this planned study, a method that will help farmers make precise disease identifications will be offered. It is common for picture segmentation algorithms to rely on either the consistency or the similarity of the pixel intensity levels. The first method makes use of the idea of segmenting the image into subparts, with each segment consisting of image pixels that are comparable to one another according to some preset set of standards. As opposed to the first group, the second analyses data primarily through the process of image partitioning based on sudden changes in intensity levels. Methods like edge detection, which are comparable to those used in border extraction, are covered in this category. Researchers have spent a great deal of time and energy investigating these two methods, during which time they have produced a diverse set of procedures while bearing in mind the aforementioned geographical peculiarities. In contrast, no single approach has yet become the de facto standard for image segmentation. There are many different approaches to segmentation, but they can be broken down into six categories according to the criteria of discontinuity or similarity they employ: (1) the histogram-based method; (2) edge detection; (3) neural network-based segmentation techniques; (4) the physical-model-based approach; and (5) region-based techniques (region splitting, region growing, and region merging) (Fuzzy C-means clustering and K- Means clustering). In this study, we introduce an improved method for colour feature-based FCM-based image segmentation. The process of defect segmentation happens in two stages. The pixels are put into groups based on the colours and sizes they have in common. This is the first step in the clustering process. The blocks are then put together into a certain number of regions. Using this two-step method, it is possible to speed up computations by not having to extract features from every single pixel in an image of fruits. The colour is rarely used to separate faults, but it gives the image a lot of power to tell things apart. We give an improved FCM-based method using M-CNN for segmenting natural-light images of odd-shaped fruits in order to figure out if the fruit has been ripened artificially. Here's how the rest of the paper is put together: In the second part, a short summary of relevant literature is given. In Section 3, a lot is said about K-means clustering. In Section 4, we show and explain the proposed method for FCM-based enhanced defect segmentation of fruits based on colour. In Section 5, the results of the apple tests are given and talked about. Some final points are made at the end of Section 6.

Related work

M. Shah and S. Naik[1]

The mango really does deserve to be called the "king of fruit." It is sweet and tasty in its own way, and it has a lot of good things in it. It is liked by people of all ages because of this. Mangoes are becoming more and more popular right now, so it's not surprising that some vendors are thinking about how to speed up the ripening process by using chemicals like calcium carbide that could be harmful. Several international groups have basically made calcium carbide illegal everywhere in the world. A number of reports show that calcium carbide is still being used, which is sad. People who go shopping today know not to buy mangoes that have been ripened in a lab, and they are able to do this because of better knowledge and inspection. On the other hand, it is hard for the human eye to tell the difference between a mango that has been ripened artificially and one that has ripened naturally. This is especially true for some mango species, such as the Kesar. The authors of this study show a non-destructive way to tell if a Kesar mango has been ripened by humans. First, photo features are used to train a decision tree, which is then used to figure out if a mango is ripe, not ripe, or only partly ripe. This step works about 93% of the time. In the next step, we get rid of any photos that show unripe mango and replace them with ones that use a GLSM-based image processor and a MQ3 fragrance sensor to tell if a mango has been ripened artificially or naturally.

M. S, et al[2] Advanced computer vision-based image processing systems are now used to do things like clearly identify, sort, and grade a wide range of fruit species. In the next few paragraphs, we'll look at some examples of what these systems can do. Because fruits are full of vitamins and minerals, it makes perfect sense to eat a lot of them. You will live a long and healthy life if you do this. The banana is a fruit that a lot of people like, so it makes sense that its price and nutritional value are good. On the other hand, the same variety is exposed to large amounts of heavy chemicals like calcium carbide, acetylene, and ethylene during the whole ripening process. Also, research is being done right now to find out when bananas are ripe by putting them into groups based on their size, colour, and shape. Because of these worries, the research in this paper uses a hybrid tool to look at the differences between banana varieties when it comes to how they ripen naturally and how they ripen in a lab. This tool uses sensor data and the histogram values from a raspberry pi, which is a type of single-board computer, to find a threshold value. The method that has been made has an accuracy of about 94% when it comes to testing for ripened bananas that have been ripened in a lab.

Laxmi, V., et al[3] Mangoes are grown and consumed at a high rate in India. Mangoes, being a tropical fruit, are typically ripened artificially with artificial ripening agents like calcium carbide due to the high demand during the season. Knowing whether or not the mango fruit was artificially ripened is vital because of the numerous health risks posed by artificial ripening chemicals. Contrarily, advances in computer-vision-based methods for assessing fruit quality have led to improvements in areas such as sorting, defect and disease detection. Therefore, detecting artificially ripened mango fruit aids consumers in making snap decisions as compared to manual identification. Convolutional neural network (CNN) is the most successful deep learning model, and it has achieved amazing success in the fields of fruit identification, defect detection, and classification.

Adikaram, N., et al[4] In June 2018, some ripe jack fruits from a 150-acre fruit field in Madatugama were found to have large, blackish spots on the syncarp, or outer peel. These spots were up to 15 centimetres in diameter. These wounds were separate from each other (off Dambulla, Central Province, Sri Lanka). Lasiodiplodia theobromae (Pat.) Griffon and Maubl., a black fungus, was found in PDA and was found to be the cause of the black spots seen on the syncarp tissues and the inner fruitlets underneath them. A fungus called Lasiodiplodia, which makes fruit rot, has been found to be the cause of the disease. Before the results of this study, Lasiodiplodia fruit disease had never been seen in jackfruit in Sri Lanka.

Xanthopoulou, A et al[5] We don't have enough genomic and transcriptome data on the common garden plant known as summer squash (Cucurbita pepo: Cucurbitaceae). Gene expression atlases are a must-have if you want to know which genes are active in which plant tissues and at what stages of development. This is the first gene expression atlas of a summer squash cultivar. It includes transcripts from all of the following tissues: seeds, shoots, leaf stems, immature and mature leaves, male and female flowers, fruits at seven different stages of development, primary and lateral roots.

Karagiannis, E., et al[6] In particular, we were able to find several layers of scald resistance responses and figure out what roles certain pathways, like the production of dehydroabietic acid and the control of UDP-D-glucose, play in the resistance mechanism. With this method, we were able to figure out the transcriptional, proteomic, and metabolic signs of scald and show how the shared and separate roles that DPA and 1-MCP played changed the pathways. There is also evidence that methylation of cytosine, which is a type of epigenetic regulation, plays a role in scald resistance. This evidence was already shown. The results show how scald resistance is controlled by metabolic pathways. These metabolic processes could depend on or not depend on ethylene.

Papavasileiou, A., et al[7] Brown rot, which is caused by Monilinia spp., can happen to peaches in every part of the world. In a series of experiments, the peach cultivars Royal Glory (RG) and Rich Lady (RL) were infected with either Monilinia fructicola or Monilinia laxa to see how they reacted to the pathogens. Artificial inoculations showed that 'RL' was moderately susceptible to Monilinia spp., but 'RG' was moderately resistant to the infection caused by this pathogen. Using proteomic comparisons, we were able to find out which proteins in the mesocarp of the two cultivars were changed when the two Monilinia species grew together. Most of the changes that pathogens made to proteins in Region G had to do with energy and metabolism, while most of the changes that pathogens made to proteins in Region L had to do with disease/defense and metabolism.

Methodology

Image segmentation of fruit with an irregular shape that is illuminated with natural light in order to determine whether or not the fruit has been artificially ripened is being proposed. CNNs are a type of Deep Learning algorithm that can take in an input image, assign meaning to the image in the form of learnable weights and biases, and then differentiate between various objects or characteristics that are contained within the input image. Another name for a CNN is a convolutional neural network. ConvNet requires a significantly smaller[8] amount of work for the pre-processing stage than do other classification algorithms when contrasted with those strategies. On the other hand, ConvNets may be trained to learn certain filters and attributes on their own, whereas in more fundamental systems, these things need to be manually engineered in order to function properly. A model for the building of ConvNets is provided by the structure of the Visual Cortex, which is analogous to the connecting network of neurons that can be found in the human brain. A neuron's receptive field is the region of the visual field in which it is most receptive to the stimulation that is being provided to it. Receptivity refers to the neuron's ability to respond to the stimulation[9]. When multiple of these fields overlap with one another, it is feasible to block off an entire field of view. The example provides a visual representation of an RGB image that has been separated into the red, green, and blue colour channels, respectively. Images are able to be represented in a wide range of colour spaces, including grayscale, RGB, high-saturation value (HSV), cyan, magenta, yellow, and many others. We can only imagine about how computationally hard things will get until the image size approaches something like 8K, but whenever it does, it will likely be significant (7680 x 4320). ConvNet[10] is responsible for transforming the input images into a form that can be processed more quickly and accurately, without losing any information that is essential to producing an accurate forecast. This transformation takes place without the loss of any information that is necessary to produce an accurate forecast. This can be done without compromising any of the information that is required to generate a reliable forecast. This is incredibly vital information for us to have as we work on establishing a framework that is not just effective in the process of acquiring new capabilities but also has the capability to accommodate applications[11] on a large scale. Having this information at our disposal is quite important. datasets.

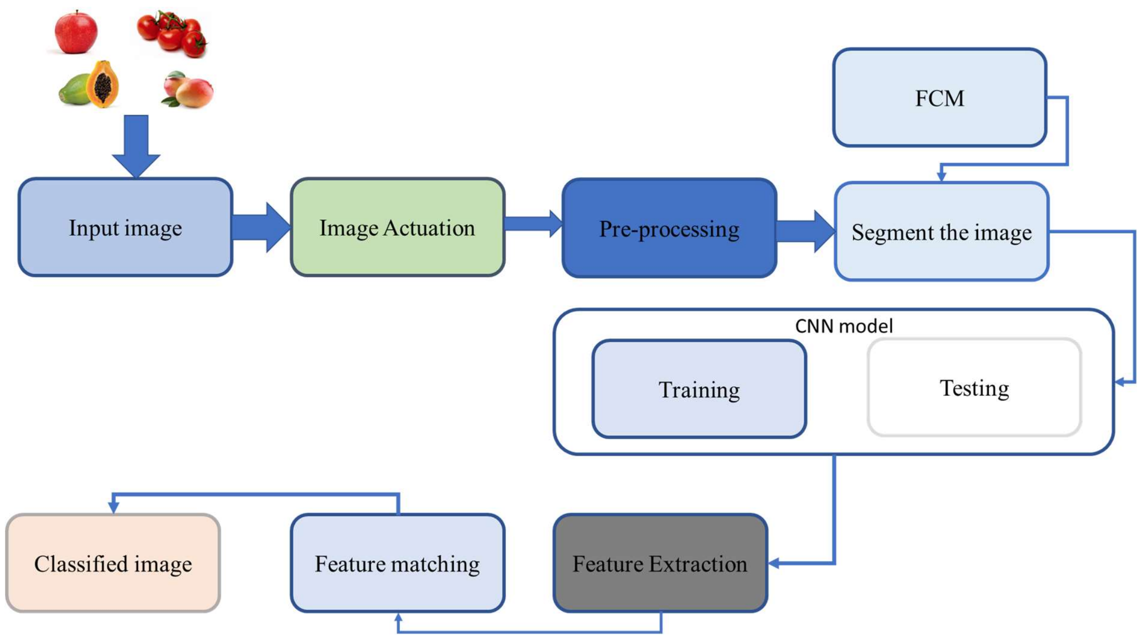

Figure 1: Proposed System architecture

When the Back Propagation (BP)[12] method is used, both the network weights and the bias weights need to be changed. The BP method makes small changes to the weights at regular intervals to keep the difference between the actual output vector and the target vector as small as possible. To do this, the real output vector is compared to the target vector. The sum-of-squares error is the error function that needs to be cut down as much as possible (SSE). During training, only regions that are in the same hidden class are allowed to use the same weights. In stochastic mode, you can change the weights between the hidden and output layers, as well as how important each interesting region is. For each training sample, the back-propagated error is used to get new information about each neuron, which is used right away to update the weights of each neuron.

A step in how convolutional neural networks[13] are made. In a convolutional neural network (CNN), the "backbone" of the network is the convolutional layer[14]. This is where most of the "heavy lifting" in terms of computation takes place. There is a chance that there will be another convolutional layer after the first one. During the convolution process, a kernel or filter in this layer will look at the receptive fields of the image to see if a certain feature is there or not.

As the kernel iterates over and over again[15], the picture is completely covered. At the end of each cycle, the dot product between the pixels that were sent in and the filter is calculated. A feature map or convolved feature is what you can call the conclusion you can draw from these places. During this last layer, the image is turned into numbers[16] that the CNN can use to figure out what it is and pull out the important parts.

A layer of water that isn't moving anymore. In a way similar to how the convolutional layer[17] works, the pooling layer applies a kernel or filter to the whole image. Unlike the convolutional layer, the pooling layer reduces the number of input parameters while also decreasing the amount of information that is kept. This layer makes CNN easier to use, which makes the network more efficient in general, so adding it is a win.

System of integrated and complete layering The CNN's FC layer is in charge of putting images into categories. It does this by using the information from the layers that came before it. "Fully linked" means that all of the inputs from one layer are connected to all of the activation units from the next layer.

The CNN's layers are not all connected to each other because that would make the network too big. It would be hard to do with computers, would cause more losses, and would lower the quality of the output.

Fuzzy-C-Means Clustering Algorithm

By putting the data into groups, you can look into the connections between the different pieces of information and draw conclusions about those connections. Using a process called "clustering," the feature vectors are put into N different groups. There, you can find the central node, or point N, of each of the n clusters. Fuzzy clustering can be used for a lot of different things, like recognising patterns and figuring out what is fuzzy. Even though fuzzy C-Mean clustering, also called FCM, is just one way to do fuzzy clustering, it is by far the most popular. Fuzzy cost modelling uses reciprocal distance to assign uncertain values. This method takes N as an input, which is the fixed size[18] of a cluster. It is possible to figure out where, on average, the people in a cluster live. The end result is a grouping of the class's items into N clusters. The goal of the FCM cluster is to get the weighted mean square error to be as low as possible (MSE). When the FCM is used, each feature vector can have more than one fuzzy membership value. The final segmentation uses the weight of the feature vector that gives the best optimization across all clusters. In the next few paragraphs, we'll talk in more detail about each step of the FCM algorithm.

Step 1: One way to get the needed total is to group the data points at random..

Assuming that the data will be split into two groups, a random starting point will be chosen for each cluster. Each piece of information is part of both clusters at the same time, and its membership values can be assumed from the beginning of the process.

Step 2: Locate the object's centre of gravity.

Applying the following formula will allow you to determine the centroid (V):

$$\mathrm{V}_{ij} = (\sum_{1}^{n}(\gamma_{ik}^{m} * x_k) / \sum_{1}^{n} \gamma_{ik}^{m}$$

The data point is denoted by xk, the fuzzy membership value of that point is denoted by, and the fuzziness parameter is denoted by m. (often assumed to be 2).
Step 3: Find out how far away each location is from the centroids of the map.
The two centres of the area being looked at are used to measure every other distance.
Step 4: Adjusting the totals of the members.

$$\gamma = \sum_{1}^{n} (d_{ki}^2 / d_{kj}^2)^{1/m-1}]^{-1}$$

$$\gamma_{12} = 1 - \gamma_{11} = 0.04$$

Step 5: It is necessary to keep doing the things listed above until either the membership values stay the same or the difference between them isn't as big as the tolerance value (a small value up to which the difference in values of two consequent updations is accepted).
Step 6: Defuzzification needs to be done on the values of membership that were acquired.

Results Analysis

Table 1 shows the Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) values that were used to measure how well the categorization techniques that are already in use and those that are being suggested work. Both of these metrics are used to measure different kinds of error when comparing image quality. The Mean Squared Error, or MSE for short, is the total number of squared differences between the first image and the final image. The peak signal-to-noise ratio is a way to figure out how much error there is at the peak (PSNR). When the number of errors is low, the MSE value is also usually low. On two different images, a measurement called the PSNR is used to figure out, in decibels, how much more signal there is than noise. This is the ratio that is used to measure the quality of both the image that goes into the device and the image that comes out of it. If the PSNR number is high enough, the image that comes out will be of better quality.

Table 1: Various Measures of Efficiency

S.n.	Parameter	FCM	CNN	Proposed (FCM+CNN)
1	MSE	0.564	0.234	0.17
2	PSNR	49.54	50.58	56.43
3	Loss percentage	17	16	7
4	Accuracy	89	95	98

Conclusion

In this research work, a method for finding fruit that has been ripened artificially is presented and tested. The method is based on processing images. For easier understanding, the proposed method can be broken down into three main steps. Applying an FCM Based Enhanced Method to a picture is the first step in the process of segmentation. The second step is to get traits out of the person. In the last phase, an M-CNN will be used both for training and for sorting. The most important goal of this work is to make it easier to divide up images of unevenly ripe fruit taken in natural light. This will be done through:

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