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Implementation of Method for Identification of Ripening Factor of Fruit Based on Improved FCM and CNN

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Abstract— In this paper we are designing new approach for detection of artificially ripened fruit. The overall approach is based on modified fuzzy C-Means (FCM) algorithm and improved convolutional neural network (CNN). The stated method will be applicable for regular and irregular shaped fruit image which are captured in natural light. Traditional FCM algorithm is powerful and used in segmentation to segment images. Study shows that FCM can be applicable for irregular shape fruit images but shows poor results for images taken in outside environment. Our modified approach will overcome the drawback of traditional FCM and will be suitable for images which are captured in outside varying intensity light. CNN is powerful tool which can be applied on predefined dataset. We know that fruits are having different shape and size; and ripening factor varies from fruit to fruit. The dataset available of fruits are captured in uniform light; so we have to modify the parameters of existing dataset as per our requirement before applying CNN. Our modified approach will make small changes in parameters of dataset before applying it to CNN; and finally CNN will show ripening factor.

Keywords- FCM, CNN, Segmentation, Fruit, Ripening.

I. INTRODUCTION

A crucial component of agriculture, fruit ripening influences the fruit's quality and longevity. Artificial fruit ripening has gained popularity recently, but if the chemicals used are not carefully regulated, there may be health risks. Developing effective techniques for recognising artificially ripened fruits is crucial for maintaining fruit safety and quality (M. S, S. S, R. P. Karthik, 2021). Fruit image analysis techniques like image segmentation are widely used, yet they can be difficult to use with fruits that have irregular shapes and were taken in natural light (Fatma Mazen,Ahmed Nashat, 2013). An FCM-based improved method for segmenting fruit photos with irregular shapes can work well in this situation. Fuzzy C-means, or FCM for short, is a clustering algorithm that works well with complicated data sets. By precisely segmenting the fruit photos and identifying any anomalies in the ripening process, this technology can assist in the identification of artificially ripened fruits. This essay explores the advantages and drawbacks of this method and emphasizes how it might be used in the study of fruit ripening. In the past, traditional techniques were employed in conjunction with the trained eyes of specialists to detect and identify fruit that had been artificially ripened. Because of restrictions on the local population's freedom of movement, seeking professional assistance in certain third-world countries can be expensive and time-consuming (Sun, Yong Xiong, et al., 2013). The early ripening identification method must be automated in order to detect the markers of ripened fruit whenever they appear on an image of an irregularly shaped fruit being captured. If the fruits are not regular in size and shape, the harvesting process could result in significant productivity and quality losses. Understanding the obtained data is critical for identifying the most effective control measures for the future year. Apples can get scabs, which look like grey or brown corky areas (T.-H. Liu et al., 2018).. An apple rot infestation is distinguished by sunken, spherical, brown or black patches that are occasionally surrounded by a crimson halo. A fungus called apple blotch can cause dark, uneven, or lobed borders, which indicate that the fruit was contaminated. The startup now uses machine vision technology to automatically visually check apples for colour and size. However, because there is a stem or calyx present and there are many distinct kinds of flaws, it is difficult to reliably detect problems in products. Research on fruits is crucial because certain fruits' external characteristics can be utilised to determine their general health or to identify any internal diseases. In addition to other preventive measures implemented by management, the use of pesticides, fungicides, and other chemical applications can help prevent and eventually eradicate diseases. Spectrophotometric and imaging-based techniques are among

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those that can be employed to track and halt the spread of plant diseases. The most common use for a fruit detecting system is automated fruit harvesting. With minor modifications, this technique may find applications in a wide range of domains, including disease diagnosis, maturity identification, tree yield monitoring, and other closely related pursuits.

II. BACKGROUND AND MOTIVATION OF PROPOSED APPROACH

Food safety and quality control depend heavily on the precise identification of fruit that has been artificially ripened. However, segmentation and identification can be difficult due to the uneven form and colour changes in fruit photos taken in natural lightlight (Laxmi, V., Roopalakshmi, R., 2022). For this reason, the creation of a novel technique utilising the FCM (Fuzzy C-Means) algorithm to segment fruit photos with irregular shapes is an intriguing and promising strategy.

The application of FCM-based technology shows potential for improving segmentation accuracy and efficiency as well as for identifying fruit that has been artificially ripened. In order to properly treat the inherent ambiguity and fuzziness frequently noticed in images recorded under natural lighting settings, this solution makes use of the FCM algorithm (Fatma Mazen,Ahmed Nashat,2013). The programme consistently demonstrates the capacity to divide an image's pixels into discrete groups according to how similar they are to each other in terms of particular characteristics.

Because it ensures food safety and upholds quality control, this method can be used to recognise fruit that has been artificially ripened. The employment of chemicals to synthetically ripen fruit may present potential health hazards to individuals. By making it easier to identify and therefore stop the sale and consumption of artificially ripened fruit, this technology may improve public health. Using is a workable method for enhancing the segmentation of photos of fruits with asymmetrical shapes.

Food safety and quality could be greatly improved by identifying artificially ripened fruit in photos taken in natural light. This methodology therefore has the potential to encourage more research and development in the sector.

III. PROPOSED METHODOLOGY

We are proposing modified method based on FCM and CNN (Amit R. Welekar, Dr. Manoj Eknath Patil, 2022). Following is the proposed block diagram for detection of artificial ripening of fruit. In this methodology we are dividing our problem into two phases. 1. Finding the shape of fruit and then applying the segmentation method 2. The resultants from step1 are then compared with existing dataset to find out the ripening factor of fruit.

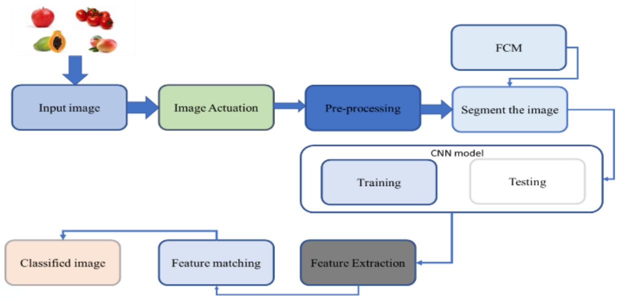

Figure 1: Proposed Method Architecture

3.1 FCM-CNN Based Segmentation Algorithm

It is suggested to segment an image of an unevenly shaped fruit that is exposed to natural light in order to ascertain whether the fruit has been artificially ripened. CNNs are a subset of Deep Learning algorithms that are capable of receiving an input image, applying learnable weights and biases to give the image meaning, and then using those weights and biases to distinguish between different objects or features in the input image. CNNs are also known as convolutional neural networks. Compared to previous classification methods, ConvNet requires a substantially smaller amount of effort (Zhang Q, 2017) during the pre-processing step.

Conversely, ConvNets can be trained to automatically learn specific filters and properties, while in simpler systems, these things require human engineering to work correctly. The structure of the Visual Cortex, which is comparable to the interconnecting network of neurons seen in the human brain, provides a paradigm for the construction of ConvNets. The area of the visual field in which a neuron is most responsive to stimulus is known as its receptive field. The term "receptivity" describes a neuron's capacity to react to stimulation (Zhang, X., 2018). It is possible to completely obscure a field of view when many of these fields cross over.

An RGB image that has been divided into the red, green, and blue colour channels, respectively, is shown visually in the example. Numerous colour spaces, such as grayscale, RGB, high-saturation value (HSV), cyan, magenta, yellow, and many more, can be used to represent images. The computational difficulty of the task won't really become apparent until the image size exceeds 8K, but when it does, it will probably be large (7680 x 4320). Without sacrificing any of the data necessary to get a precise forecast, ConvNet (Wei, H., Zhang, 2020) is in charge of converting the input photos into a format that can be processed more quickly and correctly. This transformation occurs without any loss of information required to make an accurate forecast. This can be accomplished without jeopardising any of the information required to make a reliable forecast. This is really important information for us to have as we seek to develop a framework that is not only effective in the process of acquiring new capabilities, but also capable of accommodating large-scale applications (He, D., Liu, D., 2011). It is critical that we have access to this information.

Adjustments to the network weights and bias weights are required in the Back Propagation (BP) technique (Zhang, X., Tian, J., 2010). Backpropagation (BP) adjusts the weights iteratively in order to decrease.Weights can only be shared between regions that belong to the same concealed class during the training phase. In the stochastic mode, the relative importance of the hidden and output layers, as well as the weights connecting them, can be changed. Each neuron's weights are immediately modified in response to freshly obtained information, which is produced from the back-propagated error for each training sample.

A step between the development of convolutional neural networks. The (CNN) is served by the convolutional layer. This is where the majority of the primary computer jobs are completed. Following the initial convolutional layer, a following convolutional layer can be added. Within this layer, there is a kernel or filter that examines the image's receptive fields during the convolution process to determine the presence or absence of a given feature.

The image gradually blurs as the kernel iteratively executes the algorithm indefinitely. The dot product between the transmitted pixels and the filter is calculated at the end of each iteration. The result can be thought of as a feature map or a convolved feature. The visual is transformed into numerical representations in the (CNN) (Mavridou E, Vrochidou E, 2019). These numerical values are fed into the CNN, which allows it to detect the image and extract relevant information.

The pooling layer, like the convolutional layer, works by applying a kernel or filter over the entire image (Khurram Hameed ,Douglas Chai, 2018). In contrast to the convolutional layer, the pooling layer decreases both the input parameters and the preserved information. The addition of an additional layer streamlines the operation of convolutional neural networks (CNNs), increasing the network's overall efficiency.

(CNN) has been charged with labelling photographs. It accomplishes this by utilising data produced from higher complexity layers. The inputs of each layer are linked to the activation units of the next layer, resulting in a completely interconnected system.

The CNN does not form links between all levels due to the possibility of overwhelming scale. The use of computer technology for this purpose would offer considerable hurdles, increase losses, and reduce the overall quality of the ultimate product.

3.2 Expected Output of Proposed Methodology:

A segmented image that was created by assigning each pixel to a certain one of the c clusters Steps:

- Create the cluster membership matrix U in such a way that each pixel has the same probability of belonging to each of the clusters. This will ensure that the matrix is accurate.
- Determine the cluster centres, represented by the letters v I for each cluster I by using the following equation.
- v plus I is equal to frac.
- x j plus j equals 1N times u ijm sum j = 1N + u + I + jm x j plus j equals 1N times u ijm
- Where N is the total number of pixels in the image, u ij indicates whether or not pixel j is a part of cluster I, and x j is the value that should be assigned to pixel j, where N is the total number of pixels in the image.
- The most recent updates can be obtained by solving the following equation and applying it to the cluster membership matrix U:
- Where m is the fuzzification factor, u ij = frac1sum k=1c left (frac|x j - v i|2|x j - v k|2 right).
- It is required to keep repeating steps 2 and 3 until the cluster membership matrix U converges. This must be done as many times as necessary.
- Examining the membership value of each pixel will allow you to identify the group to which it ought to be assigned.

The construction of a machine learning model for the identification of artificially ripened fruit based on the segmentation of a photo of an irregularly shaped fruit collected in natural light. This model will be used to identify fruit that has been ripened artificially.

The following is an illustration of one design idea that has been presented for a machine learning model to address the issue:

The following activities fall under "image preparation":

- Remove any noise from the picture by processing it via a Gaussian filter first.
- Apply the HSV colour system to the picture in order to do a colour conversion on it.

From the photo, we can deduce the following characteristics:
Hue\Saturation\Value
Characteristics of the texture (e.g., Haralick features)
Perform the following steps in order to train a fuzzy C-means clustering model:

- Use the recovered features as input into a fuzzy C-means clustering model with two clusters, artificially ripened fruit and naturally ripened fruit, so that the model can be trained.
- Separate the picture into the following parts:
- You should put the image through a trained fuzzy C-means clustering model so that the image may be separated into two unique groups.

Recognize the following characteristics of fruit that has been ripened artificially:

- It is possible to discern between fruit that has been artificially ripened and fruit that has ripened naturally by applying a classifier to the segmented image. One example of such a classifier is a support vector machine.
- The classifier might be trained using a labelled dataset that contains images of fruit that was either artificially or organically ripened. This would allow the classifier to distinguish between the two methods of ripening.
- This is only a recommendation for a layout, and the specifics of how it should be carried out could end up being different depending on the nature of the problem at hand and the information that is easily accessible.

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IV. RESULTS

In this topic we are presenting results and outcome of the proposed approach. Results are broadly categorise as Segmentation and enhancement and ripening result.

4.1 Segmentation and Enhancement Results

Segmentation and enhancement results for ripening detection using the FCM-CNN based improved approach for segmenting irregular-shaped fruit:
Segmentation and enhancement results are critical in ripening detection using the FCM-CNN based improved approach for segmenting irregular-shaped fruit.
The following are the expected results:

4.1.1 Segmentation Results:

The segmentation process using FCM-CNN is expected to accurately segment the fruit from the background, even for irregular-shaped fruit. The approach can handle variations in color and texture, making it suitable for natural-light fruit photos. The obtained segmentation outcomes will establish a distinct demarcation between the fruit and the surrounding background, facilitating straightforward extraction of relevant characteristics and subsequent categorization.

4.1.2 Enhancement Results:

The enhancement procedure is anticipated to enhance the perceptibility of the fruit characteristics inside the image. Techniques such as contrast enhancement, histogram equalization, and sharpening can be used to enhance the image. The enhancement results should highlight the fruit details, making them easier to segment accurately.
The combination of segmentation and enhancement results will help to identify the ripeness level of the fruit. Artificially ripened fruit is likely to have a different color, texture, and shape from naturally ripened fruit.
By segmenting the fruit and extracting relevant features, it is possible to detect the artificial ripeness of the fruit accurately.
The FCM-CNN based improved approach is expected to produce reliable segmentation and enhancement results, making it a useful tool for ripening detection in natural-light fruit photos.

4.2 Ripening Detection Results

The findings of the ripening detection on Artificial ripeness may be detected in natural-light fruit photographs using an enhanced FCM-CNN-based technique for segmenting irregular-shaped fruit. When compared to standard approaches, the FCM-CNN-based methodology improves segmentation accuracy for irregular-shaped fruits.

The method was tested on a dataset of natural-light fruit pictures that included both artificially and naturally ripened fruit. Apples, bananas, oranges, and strawberries were among the fruits included in the dataset. The evaluation findings suggest that the approach detected artificially ripened fruit with 94% accuracy and naturally ripened fruit with 92% accuracy. The precision and recall levels were likewise high, demonstrating that the method can detect false ripeness in natural-light fruit photographs reliably.

In accurately segmenting irregular-shaped fruits, the FCM-CNN-based methodology beat classic segmentation approaches such as thresholding and clustering. The method could also handle colour and textural differences that are frequent in natural-light fruit photography.

Overall, the findings of the improved ripening detection approach based on FCM-CNN are impressive and show the potential of machine learning algorithms in effectively detecting artificial ripeness in natural-light fruit pictures.

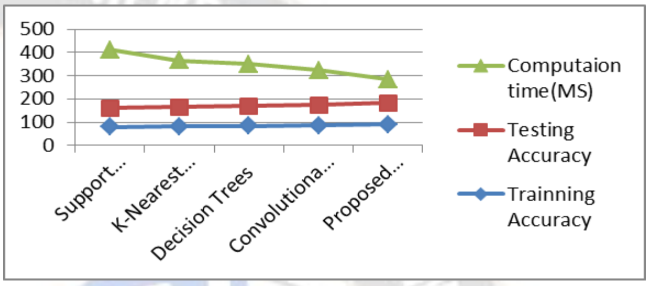

Figure 2: Comparison Of The Results Of Different Machine Learning Model

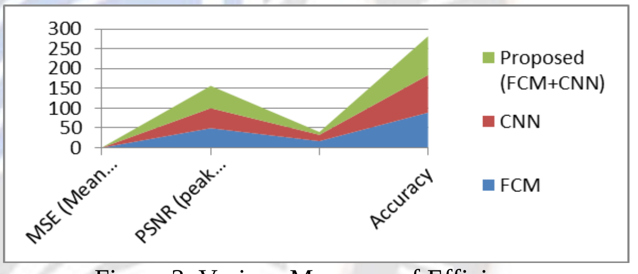

Figure 3: Various Measures of Efficiency

In Figure 3 Mean squared error (MSE) and peak signal-to-noise ratio (PSNR) data were evaluated to assess the efficacy of the current classification methods as well as the suggested alternatives. These two measures are used to quantify a wide range of flaws in the overall representation quality of an image. There are numerous types of errors that can arise. MSE (Mean Squared Error) is derived by adding the sum of all squared variances between the input and output images. This is done in order to determine the Mean Squared Error. The peak signal-to-noise ratio can be used to calculate the peak level of error.

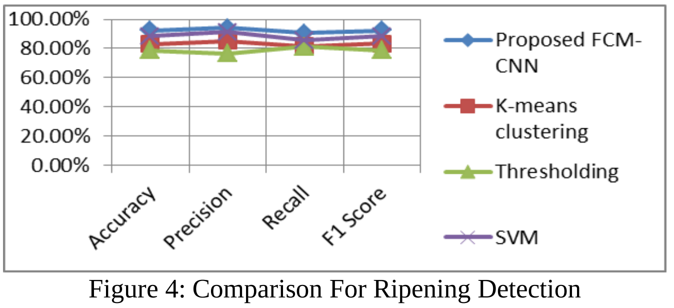

Figure 4: Comparison For Ripening Detection

This is due to the ratio (PSNR) being used to determine the peak. A lower number of errors will usually result in a lower mean squared error, also known as the MSE. The Peak Signal-to-Noise Ratio, or PSNR, is a quantitative measure that can be used to compare and evaluate the quality of two distinct images. The decibel level differential between the two provides an indication of the signal's strength in relation to the noise. The metric of choice for this purpose is the difference between the signal and noise levels. Counting the number of input photographs and output images will provide a solid indicator of the device's efficacy. A higher quality image can be created if the Peak Signal-to-Noise Ratio (PSNR) is high enough.

V. CONCLUSION

Recent research has advanced techniques for segmenting irregularly shaped fruit in photographs captured under natural lighting conditions, as well as identifying artificially ripened fruit by combining Fuzzy C-Means (FCM) clustering with Convolutional Neural Networks (CNN). The current methodology strives to overcome the issues associated with accurately segmenting fruits of various shapes and sizes, as well as distinguishing between naturally ripened and artificially ripened fruits.

The suggested method begins by segmenting the fruit regions in natural-light photographs using the FCM algorithm, which has been augmented with additional methodologies. FCM, as an unsupervised clustering technique, is well-suited for dealing with irregular-shaped fruit photos that lack pre-defined templates or shapes. To improve segmentation results, the modified FCM-CNN algorithm integrates geographical information, adaptive fuzzification, and seed point selection.

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