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Article

Advancements in nutty quality: Segmentation for enhanced monitoring and determination

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Abstract: Segmentation of nut images plays a vital role in computer vision and agricultural applications. Precise segmentation enables the extraction and analysis of essential information about the nuts, supporting quality evaluation, yield estimation, and automated sorting processes. This study explores nuts image segmentation utilizing the cuckoo search algorithm. The cuckoo search algorithm, a nature-inspired optimization technique, is introduced to enhance the segmentation process, potentially optimizing parameters or guiding the segmentation algorithms. Performance evaluation emphasizes metrics such as MSE, IoU, and dice coefficient. CSA (cuckoo search algorithm) demonstrates superior results, showcasing its effectiveness in automated nuts segmentation. This research contributes to the advancement of nut image analysis, providing insights into segmentation methodologies that can enhance automated processes in agriculture and food industry applications. The findings underscore the significance of employing advanced algorithms like CSA for accurate and efficient segmentation of nuts in images.

Keywords: nut segmentation; image analysis; region growing; k-means clustering; cuckoo search algorithm (CSA); mean squared error (MSE); intersection over union (IoU); dice coefficient (DC); computer vision; agricultural applications

1. Introduction

Nuts are a vital component of a balanced diet because of their numerous health advantages [1]. Unusual camera angles and perspectives, camera matrix thermal noise and lens characteristics, atmospheric distortions, picture digitization, and compression defects are some examples of the distortions that appear in the photographs [2]. A better ability to distinguish between different features in nuts is also facilitated by effective noise removal. Noise reduction is important in businesses where nut quality is mostly determined by appearance. Noise reduction increases the robustness of nut categorization systems in real-world settings [3].

Significance of image processing in nuts segmentation

Image processing is an effective tool that is frequently used to identify agricultural items. Images are frequently analyzed for quality using criteria related to color, geometry, and texture [4]. The method is automatic since IP algorithms effectively partition rice grains and extract features. These features are then supplied to ML (machine learning) algorithms for automatic classification [5]. One of the most important methods for precisely assessing each seed's quality during the rice evaluation procedure is the segmentation and extraction of grain pixels [1]. Assessing the quality of the seed is crucial before planting to guarantee the intended number of seedlings. High-quality seed identification by hand is inaccurate and takes time. One fundamental method for guaranteeing a stable food supply is the screening of healthy seeds [6].

The entire article has been divided into following sections. Section 2 deals with latest research survey, Section 3 deals with proposed methodology, Section 4 deals with results and discussion and finally Section 5 deals with conclusion and future work.

2. Literature review

According to Ajit et al. [7], the YCBCR image is effectively segmented into areca nuts using three-sigma control limits. Three sigma control limits are used to model the areca nut color space, which encompasses the majority of the color elements' variance. The successful segmentation of the areca nut is achieved by utilizing the upper and lower boundaries of the color elements. The red and green pigments of the areca nut's categorized parts are used to classify the nuts. The effectiveness of the suggested strategy is demonstrated by the study's outcome.

Sudip et al. [8], say that grain size, density, stiffness, friction, dissipation, and adhesion are some of the characteristics. The range of granular substances that can be sorted can be greatly expanded by using this behavior-based categorization approach. It can also be used to improve other small particle sorting in microfluidic systems, such as cells and droplets.

In the food sector, DIP (digital image processing) can be used to grade and assess the quality of crop products. Grading grains is a crucial step in determining the quality of the grain, this can be done manually or with the use of pricey technological equipment. A straightforward technique utilizing ANN Artificial.

Neural network is presented by Shivpriya et al. [9] for rice granule grading. In this case, the major axis length, minor axis length, area, eccentricity, and perimeter of the rice seed will be calculated for grading. The outcome will be shown on the LCD, and the notification will also be audible. They offer a method for classifying and analyzing rice grains based on their size and form by utilizing ANN (artificial neural network) and IP techniques. This approach is inexpensive and takes the least amount of time.

Using IP techniques, Nikita et al. [10] describe a method for grading and evaluating rice grains according to their size and shape. Particularly, the borders of each grain are identified by use of an edge detection technique. Using a caliper, measure the length and width of the rice after determining the endpoints of each grain using this method. This approach is inexpensive and takes the least amount of time.

According to Amin et al. [11], the improved DL (deep learning) model demonstrated a median precision in the classification of over 94% in identifying various chickpea seed kinds. Additionally, regardless of the image capture device, lighting conditions, or imaging environments, the suggested vision-based approach demonstrated exceptional robustness in identifying seed varieties. This makes it possible to expand into new applications that use mobile phones to gather and interpret data on an immediate basis. The suggested process generates opportunities for mobile apps and the seed business to implement quick and reliable computerized seed recognition methods.

Ye et al. [12] proposed a rice seed instance segmentation method based on a six-layer feature fusion network and a parallel prediction head structure where the rice segmentation results are quite interesting.

Huang [13] uses neural networks and image processing techniques to classify and detect areca nut quality. To distinguish areca nut flaws linked to diseases or insects, a DL (detection line) technique was employed.

In order to swiftly and precisely distinguish between good and bad walnut nuts across a range of targets, Zhan et al. [14] introduced an enhanced version of the YOLOv5s model.

Around the world, walnuts are grown in temperate climates, and producers must keep up with the growing demand. Anthony Bernard et colleagues. developed a method for measuring numerous morphological traits on several walnuts at once [15].

Many grain characteristics are difficult to identify on-site, which significantly lowers sorting efficiency. In order to infer difference in a range of grain properties, Sudip et al. [16] show how a simple neural network (NN) can find patterns in the apparent kinematics of grains.

3. Proposed system

The proposed model consists of two phases that are image segmentation by region growing, k-means clustering, and CSA algorithms. Then the methods are assessed based on various metrics such as IoU, MSE, and DC. The following **Figure 1** represents the proposed model framework.

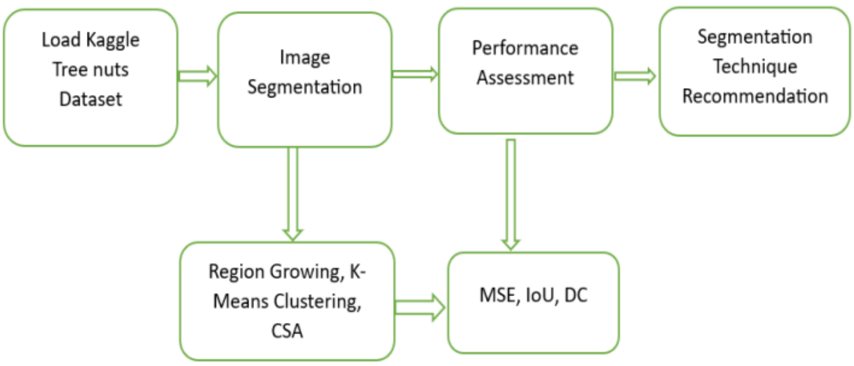

Figure 1. Proposed model framework.

3.1. Load dataset

A critical stage in training and assessing the effectiveness of a CSA is loading a dataset into the system. A good dataset should be chosen for noise removal from nuts. The Kaggle Tree Nuts Dataset is used in this study. **Figure 1** shows the overall architecture of the proposed system.

3.2. Image segmentation

A computer vision problem called "seed image segmentation" involves dividing photographs of seeds into meaningful and distinguishable sections. For use in agricultural analysis, quality evaluation, and yield estimation, among other uses, the objective is to precisely detect and isolate particular seeds within the image.

3.3. Region growing segmentation

A pixel-based method for segmenting images called "region growing" aggregates nearby pixels with comparable characteristics into regions. Choosing seed pixels, which act as the segmentation's beginning points, is the first step. A pixel similarity criterion, which specifies the characteristics, such as intensity or color values, that adjacent pixels must share to be taken into consideration for inclusion in the growing region, is the key to the segmentation process. Region growing is a local technique, meaning it only considers pixel-to-pixel similarities and grows regions based on local intensity or color values.

After the seed is chosen, the pixels to be processed in the region-expanding method are managed by a dynamic data structure called a pixel queue, which is initialized. The iterative algorithm is the essential component of the region growth process. One by one, each pixel in the dequeue is unloaded, and its surrounding pixels are inspected. A neighbor is added to the growing region and enqueued if it satisfies the predetermined similarity criterion. This process keeps going until all of the pixels are in the queue.

The ED (Euclidean Distance) in the color space is calculated using the following formula, which measures the similarity between pixels:

$$Similarity(p_i, p_j) = \sqrt{\sum_{k=1}^{n} \left(p_i^k - p_j^k\right)^2} \tag{1}$$

- p_i: This often represents a pixel in an image, typically denoted by its intensity or color value. In grayscale images, p_i would be a single value representing the pixel's intensity (brightness). In color images, p_i could be a vector representing color components (e.g., red, green, blue values for an RGB image).
- p_j: This usually represents the mean value of a region or cluster that includes pixel j, or the mean of the neighboring pixels around p_i.

This formula evaluates pixel similarity based on color attributes to determine if pixels are sufficiently similar to be included in the growing region during the region-growing algorithm.

3.4. K-means clustering

A flexible technique used in seed image segmentation, k-means clustering makes it easier to organize pixels into discrete groups. The procedure starts with the initial k cluster centroids being chosen at random, k is the number of clusters that will be included in the segmentation. Every pixel in the seed image corresponds to the closest cluster centroid. The centroids are updated by recalculating them using the mean of all pixels given to each cluster after the assignment phase. Up until convergence, where the clusters settle, or until a predefined number of iterations have occurred, the centroid update and assignment processes are carried out iteratively. K-means is sensitive to the initial choice of cluster centroids (initialization). If the centroids are poorly chosen, the algorithm may converge to suboptimal solutions (local minima).

The following expression can be used to allocate a pixel x_i to the closest cluster centroid c_j:

$$argmin_j(\sum_{i=1}^{n}\|x_i - c_j\|^2) \quad (2)$$

From the above equation:

- n denotes the quantity of the clusters.
- x_i represents the pixel value.
- c_j denotes the j^{th} cluster centroid value.
- $\|x_i - c_j\|$ illustrates the ED among the cluster and the pixel value.

3.5. CSA

The CSA is utilized in seed picture segmentation to improve the process, drawing inspiration from the brood parasitism of cuckoo birds. The following **Figure 2** represents the working of CSA.

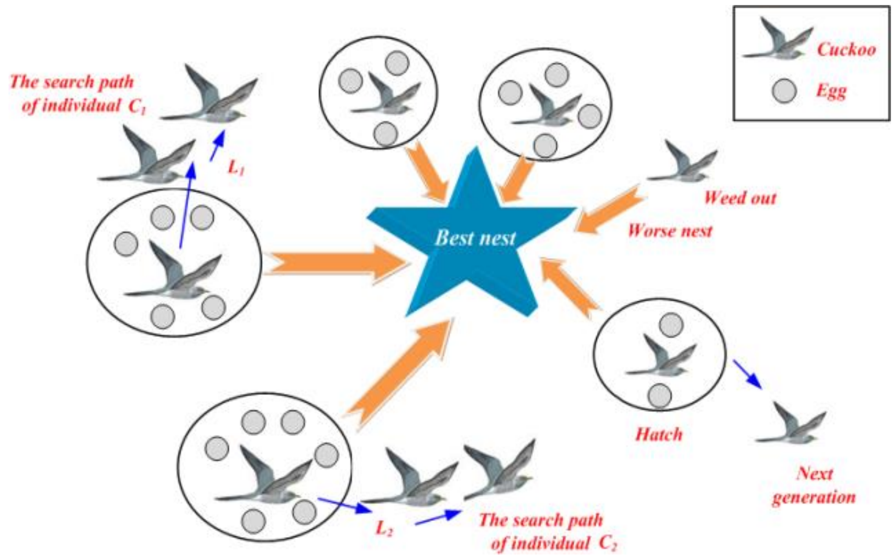

Figure 2. Working of CSA.

The fundamental principle of CSA is to update cuckoos' positions according to their fitness and the fitness of fresh solutions (eggs). The following is a simplified method for updating a cuckoo's position:

$$x_{i+1} = x_i + \alpha.LevyFlight.\left(Fitness(x_i) - Fitness(x_{best})\right) \quad (3)$$

- x_i and x_{i+1} denote the present and renewed cuckoo location.
- α indicates the parameter used for step size indication.
- $LevyFlight$ describes the Levy flight, a kind of random-based walk used in most of the nature-based techniques.
- $Fitness(x_i)$ denotes the current location fitness value.
- $Fitness(x_{best})$ illustrates the best final solution from the entire population.

This formula shows how a cuckoo's location is changed based on how fit it is right now and how fit the optimal solution is, allowing an exploration-exploitation balance to be achieved during the optimization process.

4. Result and analysis

4.1. Kaggle tree nuts dataset information

Dataset of 10 types of tree nuts, 1163 train, 50 test, 50 validation files 224 × 224 × 3 jpg format. Also includes a tensor flow trained model nuts 100.0. hs that achieved an *F*1 score of 100%. A CSV file tree nuts.csv is also provided [17].

4.2. Output metrics evaluation

The following **Figure 3** represents loading of dataset, **Figure 4** represents noise removal process and **Figure 5** represents segmentation process.

Figure 3. Load sample dataset.

Figure 4. Noise removal process.

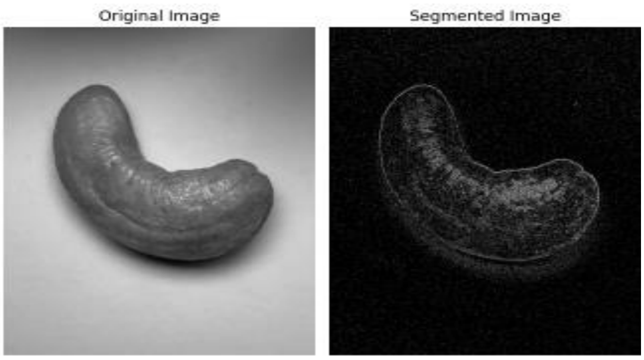

Figure 5. Segmentation process.

To evaluate a segmentation algorithm's performance and quality, segmentation output parameters must be evaluated. The accuracy and efficacy of segmentation findings are frequently measured using several measures. The following are important assessment criteria.

4.2.1. Dice coefficient analysis

The more the similarity, the higher the dice coefficient and the greater the segmentation outcome. The dice coefficient measures the similarity between the predicted and true segmentation. A typical statistical metric for measuring the geographical overlap or similarity between two sets is the dice coefficient, also called the dice similarity coefficient. The DC is commonly used in image segmentation to evaluate the degree of agreement between the initial reality mask and the expected segmentation mask.

$$Dice\ Coefficient(DC) = \frac{2 \times (S \cap P)}{(S + P)} \tag{4}$$

The upcoming **Table 1** indicates the DC value gained from region growing, CSA, and k-means clustering separation method using the Tree Nuts Dataset.

Table 1. Dice coefficient (DC) of CSA, region growing, and k-means clustering segmentation models.

No of Images	Region Growing	K Means	CSA
1	0.786	0.890	0.994
2	0.756	0.986	0.995
3	0.78	0.891	0.991
4	0.821	0.899	0.995

The **Table 1** and **Figure 6** represents the dice coefficient (DC) of CSA, region growing and k-means clustering segmentation models. From the results its proved that DC of proposed CSA is high and ranges between 0.991 to 0.995. Whereas region growing ranges between 0.756 to 0.821 and k means ranges between 0.890 to 0.986 respectively.

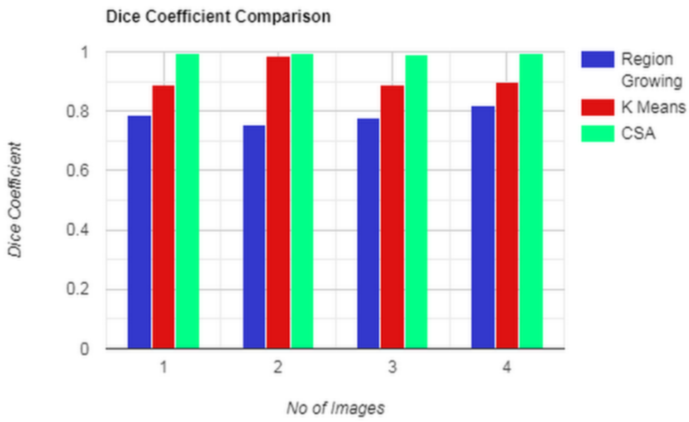

Figure 6. Dice coefficient (DC) of CSA, region growing and k-means clustering segmentation models.

4.2.2. IoU analysis

Under the assumption that an estimate of separation accuracy exists, IoU estimates the spatial overlap between the projected separation and the ground truth. The segmentation between the expected and ground truth overlaps correctly when the

IoU is sorted from 0 to 1. The ratio between the model's segmented output and the union and intersection of the expected standard are described. It provides an assessment of the predictable standard and the segmented output of the suggested approach. As the coincidence grows, so does the IoU, and segmentation accuracy gets better.

$$IoU = \frac{S \cap P}{S \cup P} \tag{5}$$

where P represents the segmented tumor area the model produced, S stands for the expected standard and indicates the area where the output of the proposed model and the expected standard overlap.

The upcoming **Table 2** indicates the IoU value gained from region growing, CSA, and k-means clustering separation methods using the Tree Nuts Dataset.

Table 2. IoU of CSA, region growing and k-means clustering segmentation models.

No of Images	Region Growing	K Means	CSA
1	0.771	0.891	0.991
2	0.761	0.989	0.990
3	0.779	0.896	0.992
4	0.816	0.902	0.993

The above **Table 2** and **Figure 7** represents the IoU of CSA, region growing and k-means clustering segmentation models. From the results its proved that IoU of proposed CSA is high and ranges between 0.991 to 0.993. Whereas region growing ranges between 0.771 to 0.816 and k means ranges between 0.891 to 0.902 respectively.

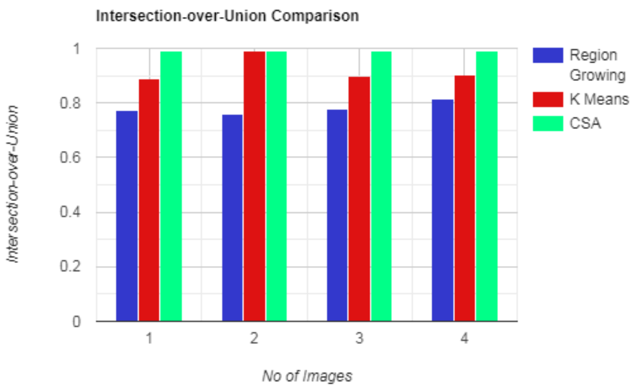

Figure 7. IoU of CSA, region growing and k-means clustering segmentation models.

4.2.3. MSE analysis

MSE measures the average squared difference between the pixel values of the predicted and true segmentation.

MSE is used to quantify the difference between the segmented image data and the original image data, the better the segmentation ability, the lower the rate of MSE.

$$MSE = \frac{1}{n} \sum (source - segmented)^2 \tag{6}$$

The upcoming **Table 3** indicates the IoU value gained from region growing, CSA, and k-means clustering separation method using the Tree Nuts Dataset.

Table 3. MSE of CSA, region growing, and k-means clustering segmentation models.

No of Images	Region Growing	K Means	CSA
1	0.000146	0.000136	0.0001191
2	0.000436	0.000368	0.0000975
3	0.000578	0.000446	0.0001063
4	0.000143	0.000122	0.0001079

The above **Table 3** and **Figure 8** represents the MSE of CSA, region growing and k-means clustering segmentation models. From the results its proved that MSE of proposed CSA is low and ranges between 0.0000975 to 0.0001191. Whereas region growing ranges between 0.000143 to 0.000578 and k means ranges between 0.000122 to 0.000446 respectively.

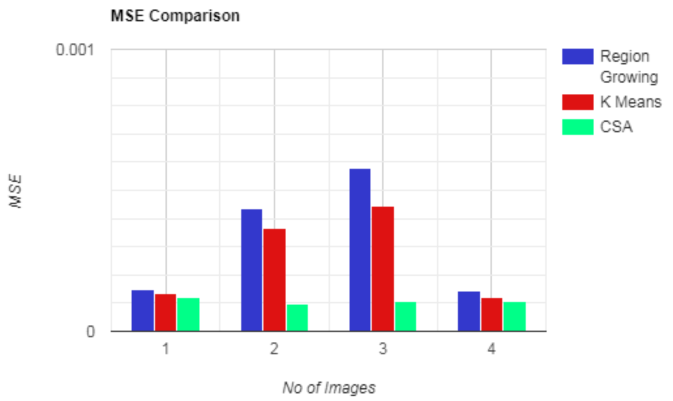

Figure 8. MSE of CSA, region growing and k-means clustering segmentation models.

To evaluate the precision, overlap, and similarity of the segmentation results, the MSE, DC, and IoU analyses in nuts image segmentation are essential. Better pixel-wise accuracy is indicated by a lower MSE value, which shows that the segmented areas closely match the real data. Better spatial overlap between the segmented regions and the reality is indicated by a higher DC. In particular, it tackles the problem of false positives and false negatives, offering information on how closely the segmentation matches the real nuts in space. As with DC, a better spatial agreement between the segmented regions and the actual value is indicated by a larger IoU. It is also helpful in determining how well the segmentation captures the actual scope of nut areas overall.

5. Conclusion and future work

The performance of the three algorithms used to evaluate the segmentation of nuts—region expanding, k-means clustering, and the cuckoo search algorithm (CSA) is carefully evaluated using MSE, IoU, and DC. The results show that CSA fared better than the other algorithms on all three metrics. While higher IoU and DC values imply better overlap and similarity segmentations, lower MSE values suggest improved accuracy. CSA's optimization capabilities demonstrated its effectiveness in enhancing the segmentation process for nut images. The adaptive nature of CSA contributed to more accurate pixel grouping and region identification compared to traditional methods. The study establishes CSA as a promising algorithm for nuts segmentation, exceeding traditional methods in terms of MSE, IoU, and DC. Future enhancements can further refine segmentation accuracy and applicability in various real-world problems. Subsequent research in the segmentation of nuts may investigate the integration of sophisticated machine learning algorithms, with a particular emphasis on DL (deep learning) approaches. Future work could also focus on nut classification by expanding the segmentation challenge to semantic segmentation. This would need labeling distinct kinds of nuts within the segmented sections with particular semantic labels in addition to separating the nuts from the background.

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