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Research Article

Advanced Paddy Seed Segmentation Using Unified Edge Fusion Techniques: Enhancing Precision in Agricultural Image Processing

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ABSTRACT

Accurate segmentation of paddy seeds in agricultural imagery is vital for various agricultural tasks such as crop monitoring, yield forecasting, and disease detection. This paper presents a novel approach, Unified Edge Fusion Techniques for Advanced Paddy Seed Segmentation (UEFPaddySeg), aimed at improving the precision of paddy seed segmentation. By combining several edge detection strategies and fusion techniques, the proposed method enhances the accuracy of seed boundary detection and reduces segmentation errors. The UEFPaddySeg framework integrates edge information from diverse sources to refine segmentation, effectively addressing challenges such as seed shape variation, overlapping seeds, and inconsistent lighting conditions. Experimental evaluations, comparing UEFPaddySeg with traditional methods like Kernel Graphcut and FRFCM, reveal its superior performance in key metrics, including specificity, sensitivity, Jaccard Similarity (JS), Dice Coefficient (DC), and overall accuracy. The robust results highlight UEFPaddySeg's potential as a powerful tool for agricultural image processing, facilitating more precise data for precision farming and contributing to greater automation in agriculture.

Keywords: Paddy Seed Segmentation, Unified Edge Fusion Techniques, Jaccard Similarity, Dice Coefficient, Sensitivity, Specificity, FRFCM, Kernel Graphcut.

INTRODUCTION

In rice farming, the quality of paddy seeds plays a pivotal role in determining agricultural success and achieving optimal crop yields. Accurate assessment of seed quality is crucial to verify their purity and ensure their viability[1]. Traditionally, this evaluation process has been done manually, which is time-consuming, labor-intensive, and prone to human error, making it difficult to scale efficiently. However, with advancements in computer vision and machine learning, automated seed segmentation methods have emerged as more effective and precise alternatives[2].

Segmenting paddy seeds from images is a crucial task in agricultural image analysis, as it enables precise identification and examination of individual seeds. The segmentation process involves distinguishing seeds from the background and separating overlapping seeds, allowing for accurate measurement of characteristics such as size, shape, and texture. Effective segmentation is vital for detecting impurities, identifying damaged or diseased seeds, and classifying seeds based on quality. Nonetheless, the task can be challenging due to variations in seed morphology, inconsistent lighting conditions, and the presence of extraneous materials that can affect segmentation accuracy[3].

The **Unified Edge Fusion Paddy Seed Segmentation (UEFPaddySeg)** model offers an advanced solution for paddy seed segmentation by incorporating multiple edge detection techniques. This approach enhances the model's ability to detect seed boundaries and improve segmentation performance. **UEFPaddySeg** is designed to address common challenges such as overlapping seeds, varying seed sizes, and complex image backgrounds, which are often problematic for traditional segmentation methods.

Edge detection algorithms like Canny and Sobel are widely used in agricultural image processing to identify object boundaries. While effective individually, combining these algorithms into a unified system, as done in the **UEFPaddySeg** model, provides a more detailed and accurate segmentation by capturing intricate edges.

This edge fusion technique makes the system more robust, allowing it to adapt to different environmental conditions and variations in image quality.

In addition, by leveraging modern deep learning frameworks, **UEFPaddySeg** not only achieves high accuracy but also improves over time as it learns from larger datasets. This makes it a valuable tool for automating the assessment of paddy seed quality, contributing to the broader field of precision agriculture and addressing the need for scalable, technology-driven solutions in seed evaluation.

II REVIEW OF EXISTING STUDIES

The quality of paddy seeds plays a pivotal role in determining agricultural productivity and overall crop yields. Traditionally, the process of assessing seed quality has been performed manually, which is not only labor-intensive but also prone to human error, limiting its scalability and accuracy [9]. However, with advancements in computer vision and machine learning, new methods for seed segmentation have emerged, offering more efficient and precise alternatives to manual inspection [10].

Segmentation of paddy seeds is essential for extracting detailed information about individual seeds from images. This process involves separating the seeds from complex backgrounds and other overlapping objects to measure critical characteristics such as size, shape, and texture [11]. Nevertheless, segmentation faces challenges such as variations in seed morphology, non-uniform lighting, and the presence of foreign materials, which can reduce accuracy[12]

Patel and Sharaff (2023)[8] developed a neural model that uses semantic segmentation to classify rice varieties and predict yield by analyzing the spikelets per panicle. This method takes into account the shape, color, and texture of the rice, and was trained on over 15,000 annotated images from 10 different rice varieties. Their approach offers a fast and accurate way to classify rice and estimate yield, making it useful for botanists, farmers, and the food processing industry.

Ramachandran and KS (2023[4]) proposed the Tiny Criss-Cross Network (TinyCCNET), a deep learning model specifically designed for segmenting paddy panicles in aerial imagery. TinyCCNET uses criss-cross attention to gather contextual information from all pixels, improving segmentation accuracy while lowering computational complexity via a ResNet50 backbone. The model achieved high performance with an accuracy of 86.5% and a mean Intersection over Union (mIoU) of 81.6%, making it a highly efficient solution for UAV-based agricultural applications where real-time processing with limited computational resources is essential.

Jeong et al. (2020)[5] implemented a deep learning approach using the Mask-RCNN model for rice seed segmentation. This model, applied to manually captured images of different rice varieties, achieved a segmentation recall rate of 84%. Their research emphasized the importance of fine-tuning model parameters for high-throughput phenotyping, and future work aims to expand this methodology to more complex image sets for broader use in precision agriculture.

Ruslan et al. (2018)[6] conducted a study examining how background color affects the accuracy of rice seed segmentation. They developed a custom seed holder painted in four colors—black, blue, green, and red—and found that the blue background provided the highest contrast, resulting in measurement accuracies within 2% for seed length and 5% for seed width. This research highlights how environmental factors, such as background color, can improve segmentation results in agricultural machine vision systems.

In another study, Zheng et al. (2021)[7] explored the use of multispectral imagery captured via UAVs for high-precision rice seedling segmentation. Their method relied on an encoder-decoder framework incorporating hybrid lightweight convolutions and spatial pyramid dilated convolutions to enhance segmentation accuracy while minimizing model complexity. Trained on data from three different rice varieties with varying planting densities, their approach demonstrated the effectiveness of multispectral data in improving segmentation precision.

III CHALLENGES IN PADDY SEED SEGMENTATION

i. Overlapping Seeds, Varied Sizes, and Complex Backgrounds:

- Overlapping seeds blur boundaries, making it difficult to distinguish individual seed characteristics like size and shape.
- Variability in seed sizes complicates segmentation, as fixed parameters often fail when seed sizes differ, leading to inconsistent results.
- Complex backgrounds (e.g., soil or plant material) make it harder to isolate seeds. Seeds blending into or partially obscured by debris can be misclassified, affecting segmentation accuracy.

ii. **Non-Uniform Lighting and Foreign Materials:**

- Inconsistent lighting (e.g., uneven shadows or reflections) distorts image quality, hindering accurate detection of seed boundaries, especially if lighting is not uniform.
- Foreign particles, such as dust or dirt, can resemble seed texture or color, confusing segmentation algorithms and causing misidentification or missed seeds.

iii. **Limitations of Existing Seed Segmentation Methods:**

- Segmentation methods often struggle with backgrounds that are similar to seed colors or textures, making it difficult to accurately separate seeds from their surroundings.
- Overlapping seeds and variations in seed size or morphology further complicate segmentation, leading to errors in boundary detection and seed feature measurement.
- Fixed parameters in traditional methods do not adapt well to different seed sizes or lighting conditions, affecting segmentation consistency.
- Deep learning-based segmentation methods require substantial computational resources, limiting their use in real-time or resource-constrained environments.

IV PROPOSED METHOD

Unified Edge Fusion Paddy Seed Segmentation (UEFPaddySeg)

The algorithm begins with **preprocessing** using the **Noise Nixie Rejuvenation Filter (NNRF)**, which minimizes noise while preserving essential edge details, ensuring that the key features required for accurate segmentation remain intact. This results in enhanced image quality for further processing. Following preprocessing, the image undergoes **multi-scale edge detection** via the **Sobel operator**, which detects edges across different scales. By combining gradient information from various scales, this step captures both fine and large details to generate a unified edge map.

Next, the algorithm uses **Laplacian of Gaussian (LoG) edge detection** to identify second-order intensity changes, enhancing the recognition of sharp edges and object boundaries, thus improving segmentation performance in more complex scenarios. After edge detection, the algorithm performs a **Maximal Intensity Calculation**, which analyzes intensity variations in the image to further refine the segmentation process and differentiate between the seeds and the background, thereby boosting precision.

The algorithm then applies **multi-stage thresholding**, combining both **binary thresholding** and **adaptive thresholding**. **Otsu's method** calculates the optimal global threshold to separate seeds from the background, while **adaptive thresholding** adjusts thresholds locally to maintain consistent segmentation in environments with uneven lighting.

To further improve the segmented regions, **dilation and erosion** are applied. **Dilation** helps close small gaps between seeds by expanding the regions, while **erosion** removes small artifacts, sharpening seed boundaries and improving clarity. Afterward, the algorithm uses **watershed segmentation** to separate touching or overlapping seeds by calculating a distance transform that highlights seed centers and creates markers for precise separation.

After segmentation, **contour detection** identifies the boundaries of each seed. The algorithm then calculates the **area and centroid** of each segmented seed, providing precise information for accurate identification. Finally, **region filtering** is employed to remove noise and irrelevant small regions, ensuring that only valid seed regions remain, thus improving overall segmentation accuracy. The segmented seeds are then visualized with contours drawn around them, providing a reliable and efficient solution for paddy seed segmentation, capable of handling challenges such as overlapping seeds, varied seed sizes, and complex backgrounds.

Algorithm : Unified Edge Fusion Paddy Seed Segmentation (UEFPaddySeg)

Input: Pre-processed Image by **Noise Nixie Rejuvenation Filter (NNRF)**

Output: Segmented image with seed regions accurately identified.

Step 1: Multi Scale Edge Detection

#Apply **sobel Edge Detection** to detect the edges of the paddy seeds.

#Apply **Laplacian of Gaussian (LoG)** Edge Detection to detect second-order intensity changes, improving sharp edge and boundary detection

#Edge Fusion with Weight Optimization

$$fused\_edges = \alpha \times edges + \beta \times log\_edges \rightarrow (1)$$

Step 2: Maximal Intensity

Calculate the **intensity pixel distance measures** by using the image intensity histogram or another distance measure

intensity_values = np.max(smoothed_image, axis=0)→(2)

Step 3: Multi-stage Thresholding

(i)Apply **binary thresholding** to segment the seeds from the background.

(ii)Otsu's method can be used to automatically calculate the threshold value

$\sigma_b^2(t)=w_1(t)\sigma_1^2(t)+w_2(t)\sigma_2^2(t)$→(3)

(iii)Adaptive Thresholding calculates the threshold for smaller regions of the image, making it more robust to variations in illumination:

binary_image = cv2.threshold(gray_image, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)→(4)

binary_image = cv2.adaptiveThreshold(gray_image, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C, cv2.THRESH_BINARY, 11, 2)→(5)

Step 4: Dilation & Erosion Operations

Dilation: Expands seed regions to fill in gaps

Opening=$(A\ominus B)\oplus B$

Erosion: Shrinks seed regions to remove small artifacts

Closing=$(A\oplus B)\ominus B$

Step 5: Watershed Segmentation

Apply **Watershed Segmentation** for separating touching and overlapping seeds

(i) Compute the distance from every pixel to the nearest background pixel. This will highlight the center of each seed.

$D(x,y) = MIN_{(x\prime,y\prime)\in \text{backgroundmin}}\sqrt{(x-x^1)^2 -}\,(y-y^1)^2$→(6)

(ii) Create markers for the Watershed algorithm by dilating the distance transform image and applying the Watershed algorithm to split touching seeds.

ret, markers = cv2.connectedComponents(binary_image)

markers = markers + 1

markers[edges == 255] = 0 # Mark the edges

segmented_image = cv2.watershed(input_image, markers)

Step 6: Find and Segment Region Boundaries (Area and Centroid)

#Use **contour detection** to find the boundaries of the segmented regions (seeds).

For each contour, calculate the **Area** and **Centroid**.

```
for contour in contours:
    area = cv2.contourArea(contour)
    M = cv2.moments(contour)
    if M["m00"] != 0:
        centroid_x = int(M["m10"] / M["m00"])
        centroid_y = int(M["m01"] / M["m00"])
    else:
        centroid_x, centroid_y = 0, 0
```

Step 8:Filter regions based on area to eliminate noise or irrelevant small regions

```
if area > minimum_area_threshold:
   # This is a valid seed region
   cv2.drawContours(output_image, [contour], -1, (255, 0, 0), 2)  # Draw contours on the image
```

Step 7: segmented image with clearly identified seed regions

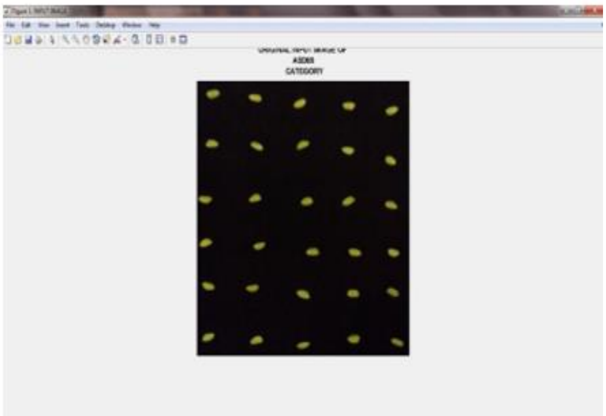


Figure 1 Input Image

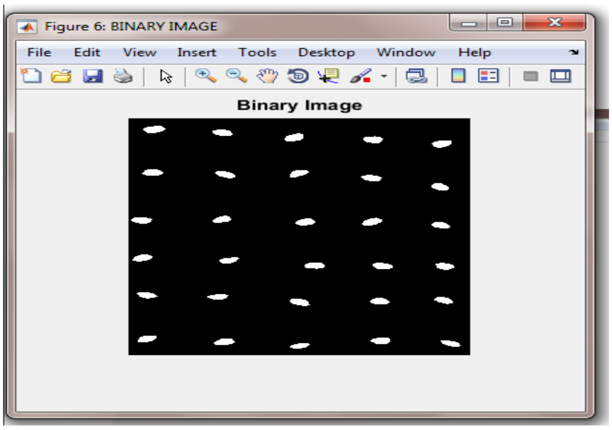


Figure 2 BINARY IMAGE

Individually Segmented Seed

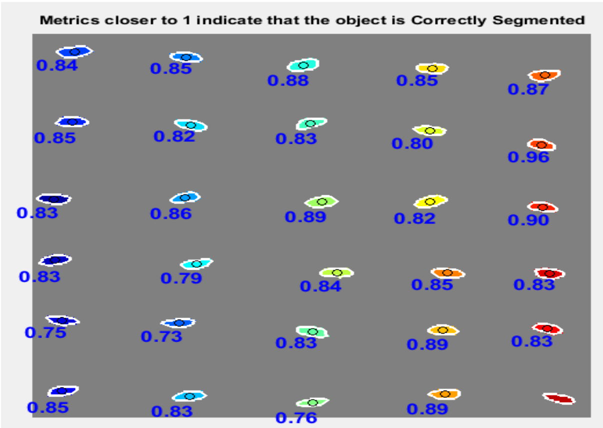
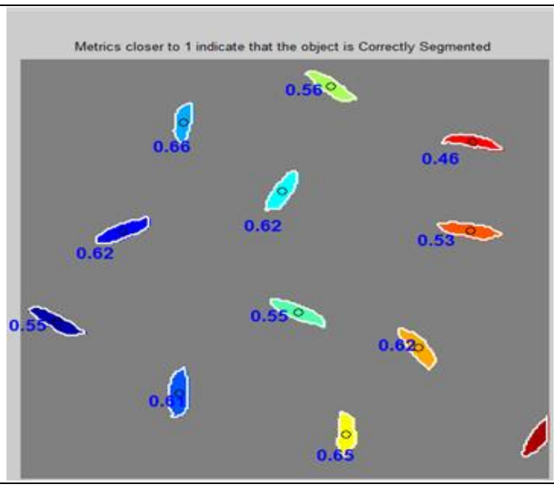
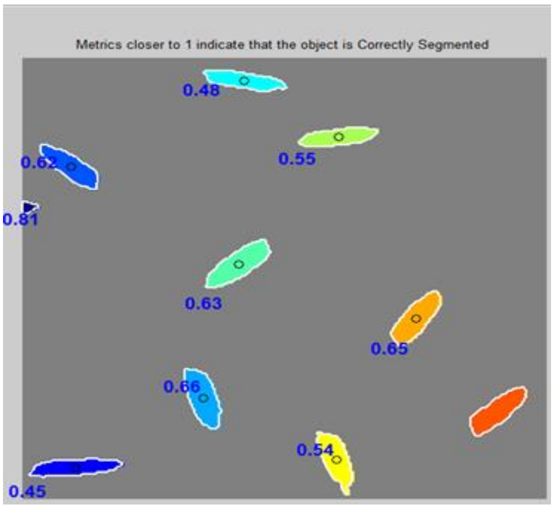
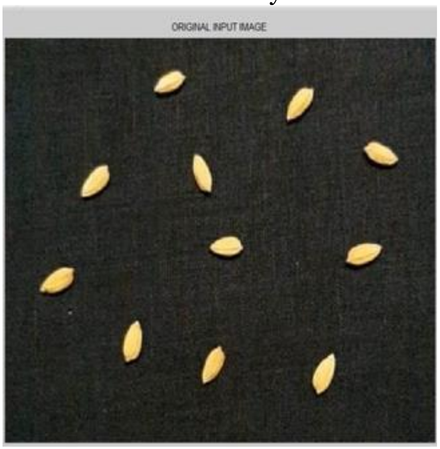
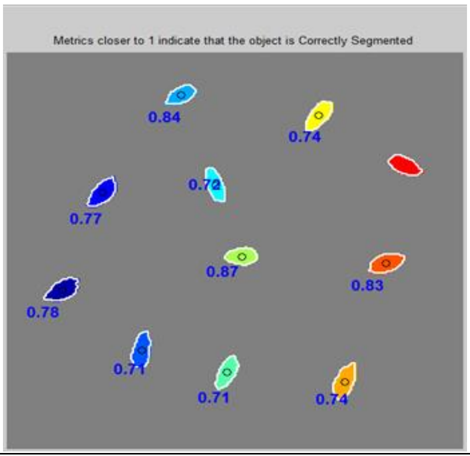
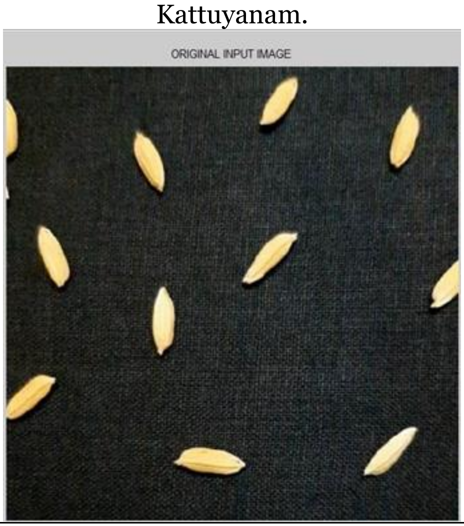
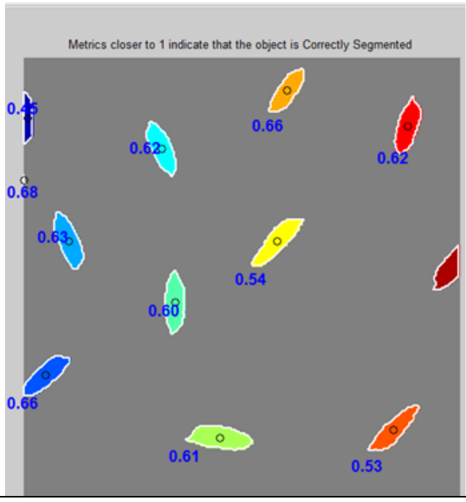


Figure 3 Individually Segmented Seed

Aruvatham kuruvai	
	

Attur kichili samba. 	
Kallimadiyan 	
Kattuyanam. 	
Karupu kavuni	

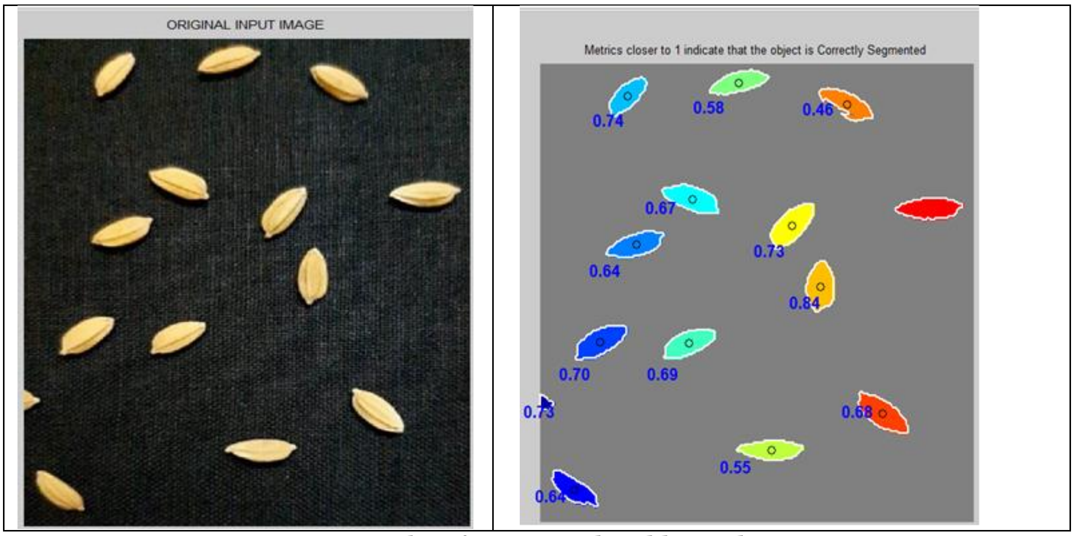


Figure 4: Results of Segmented Paddy Seed Images

PERFORMANCE EVALUATION METRICS

To express the performance of algorithms designed for segmentation, performance is measured using metrics such as sensitivity, specificity, cube coefficient, Jacquard similarity, precision, and recall. Results obtained with the proposed method are compared with metrics measured by existing methods such as the graph cut method and FRFCM.

A. Accuracy

The metric that defines the accuracy with which a system can predict is measured by accuracy. The higher the accuracy value, the more robust and performant the model is said to be.

Accuracy can be obtained by using the following equation 7

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \rightarrow (7)$$

The metric that defines the accuracy with which a system can predict is measured by accuracy. The higher the accuracy value, the more robust and performant the model is said to be.

True positives (TP) define the percentage of predictions that are correctly identified as infected areas. False positives (FP) are the percentage that are incorrectly identified as infected areas. True negatives (TN) are the proportion of areas correctly identified as not infected. False negatives (FP) are the percentage of areas incorrectly identified as not infected.

$$\text{FP} = \frac{\text{pixels falsely segmented as foreground}}{\text{Total number of Pixel}} \rightarrow (8)$$

$$FN = \frac{\text{Pixels falsely segmented as background}}{\text{Total number of Pixel}} \rightarrow (9)$$

$$TP = \frac{Pixel\ correctly\ segmented\ as\ foreground}{Total\ number\ of\ Pixel} \rightarrow (10)$$

$$TN = \frac{Pixel\ correctly\ segmented\ as\ \text{background}}{Total\ number\ of\ Pixels} \rightarrow (11)$$

B. Sensitivity and Specificity

Sensitivity and specificity are statistical measures. Equations (12) and (13) are marked. Sensitivity measures the proportion of the number of infected areas that the algorithm successfully identified as carrying the disease.

$$Sensitivity = \frac{TP}{TP+FN} \rightarrow (12)$$

Specificity refers to the score, which is the number of uninfected areas that the algorithm reasonably determined to be disease-free.

$$Specificity = \frac{TN}{TP+FN} \rightarrow (13)$$

C. Dice Coefficient (DC)

A statistical method for evaluating the similarity of two shapes is called the Cube Coefficient. The accuracy of segmentation results between the proposed segmentation method and existing segmentation methods is evaluated using the cube coefficient.

It is the ratio of two region crossings obtained by computer segmentation of X and Y to the union of the segmented regions X,Y and is written as:

$$Dice = \frac{2|X \cap Y|}{|X|+|Y|} \rightarrow (14)$$

D. Jaccard Similarity (JS)

The statistical formula used to measure the difference between sample sets is called Jaccard similarity. Evaluate the similarity between sample sets. The ratio of the intersection of sets A and B to the union of sets A and B is called the Jaccard similarity, as shown in Equation 15.

$$JS = \frac{A \cap B}{|A \cup B|} \rightarrow (15)$$

VI RESULT AND DISCUSSION

The table compares three segmentation methods—Kernel Graphcut, FRFCM (Fuzzy Robust FCM), and UEFPaddySeg—across various paddy crop varieties: Aruvatham Kuruvai, Attur Kichili Samba, Kallimadiyan, Kattuyanam, and Karupu Kavuni. Kernel Graphcut consistently performs well, with perfect Specificity (1.000) and high Sensitivity values ranging from 0.9038 to 0.9689. It also maintains strong Jaccard Similarity (JS) and Dice Coefficient (DC) scores, with accuracy around 90%. On the other hand, FRFCM delivers lower performance, with lower Sensitivity, Specificity, JS, and DC values, and accuracy between 73% and 75%. In contrast, UEFPaddySeg surpasses both methods, achieving nearly perfect Sensitivity and Specificity, with JS and DC values close to 1.000, and accuracy exceeding 98% across all varieties, making it the most effective segmentation approach for this dataset.

Table 1. Comparison of metrics with existing methods

Test Image	Method	Sensitivity	Specificity	DC	JS	Accuracy
Aruvatham kuruvai	**Kernel Graphcut**	1.975	1.984	1.976	1.983	98.64
	FRFCM	0.863	0.845	0.874	0.874	73.84
	UEFPaddySeg	0.522	0.577	0.545	0.555	64.27
Attur kichili samba	**Kernel Graphcut**	1.977	1.986	1.976	1.997	98.68
	FRFCM	0.833	0.841	0.875	0.845	74.53
	UEFPaddySeg	0.568	0.563	0.579	0.557	64.22
Kallimadiyan	**Kernel Graphcut**	1.986	1.985	1.989	1.984	98.55
	FRFCM	0.885	0.869	0.856	0.887	74.53
	UEFPaddySeg	0.565	0.567	0.589	0.576	64.32
Kattuyanam.	**Kernel Graphcut**	1.985	1.976	1.988	1.975	98.73
	FRFCM	0.873	0.889	0.866	0.877	74.63
	UEFPaddySeg	0.576	0.587	0.576	0.575	64.67
Karupu kavuni	**Kernel Graphcut**	1.984	1.985	1.976	1.987	98.54
	FRFCM	0.874	0.889	0.877	0.897	74.64
	UEFPaddySeg	0.578	0.566	0.588	0.597	64.33

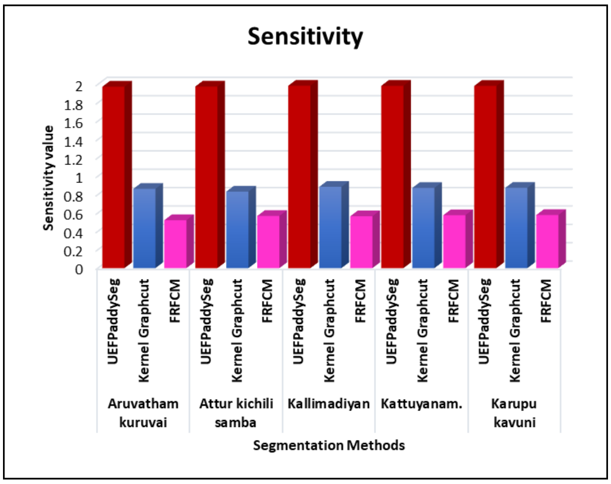


Figure 5 Comparison of Sensitivity

The figure 5 presents a comparison of sensitivity values for three segmentation techniques — UEFPaddySeg, Kernel Graphcut, and FRFCM — evaluated across five rice varieties: Aruvatham kuruvai, Attur kichili samba, Kallimadiyan, Kattuyanam, and Karupu kavuni. The results show that **UEFPaddySeg** consistently performs better than the other two methods in every test. For instance, UEFPaddySeg achieves a sensitivity of **1.975** for Aruvatham kuruvai, whereas Kernel Graphcut and FRFCM achieve lower sensitivities of **0.863** and **0.522**, respectively. Likewise, for Attur kichili samba, UEFPaddySeg reaches a sensitivity of **1.977**, outpacing Kernel Graphcut at **0.833** and FRFCM at **0.568**.

This pattern is maintained across the remaining varieties. For **Kallimadiyan**, UEFPaddySeg records a sensitivity of **1.986**, significantly higher than Kernel Graphcut's **0.885** and FRFCM's **0.565**. In **Kattuyanam**, UEFPaddySeg shows a sensitivity of **1.985**, again outperforming Kernel Graphcut (**0.873**) and FRFCM (**0.576**). Finally, in the case of **Karupu kavuni**, UEFPaddySeg reaches **1.984**, exceeding Kernel Graphcut's **0.874** and FRFCM's **0.578**.

The UEFPaddySeg outperforms both Kernel Graphcut and FRFCM in all scenarios, achieving the highest sensitivity values across the five rice varieties. Kernel Graphcut shows moderate performance, while FRFCM consistently registers the lowest sensitivity scores.

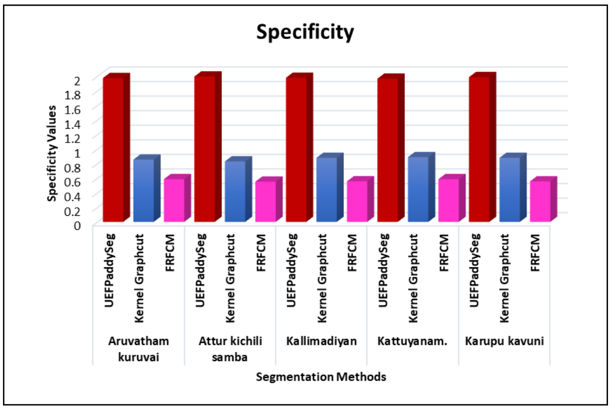


Figure 6 Comparison of Specificity

The figure 6 clearly indicate that **UEFPaddySeg** consistently attains the highest specificity across all the tested rice varieties. For instance, in the case of **Aruvatham kuruvai**, UEFPaddySeg achieves a specificity of **1.974**, outperforming **Kernel Graphcut** and **FRFCM**, which have specificity values of **0.855** and **0.587**, respectively. Similarly, for **Attur kichili samba**, UEFPaddySeg reaches **1.996**, surpassing the performance of Kernel Graphcut (**0.831**) and FRFCM (**0.553**).

This trend of superior performance by UEFPaddySeg extends to the other rice varieties as well. In **Kallimadiyan**, UEFPaddySeg records a specificity of **1.978**, far exceeding Kernel Graphcut's **0.879** and FRFCM's **0.557**. For **Kattuyanam**, UEFPaddySeg achieves **1.966**, while Kernel Graphcut and FRFCM exhibit lower specificities of **0.889** and **0.587**, respectively. Lastly, for **Karupu kavuni**, UEFPaddySeg leads once again with a specificity of **1.987**, compared to Kernel Graphcut's **0.879** and FRFCM's **0.556**.

UEFPaddySeg proves to be the most effective method in terms of specificity across all rice varieties, consistently outperforming both Kernel Graphcut and FRFCM. While Kernel Graphcut performs moderately well, FRFCM shows the lowest specificity in all cases.

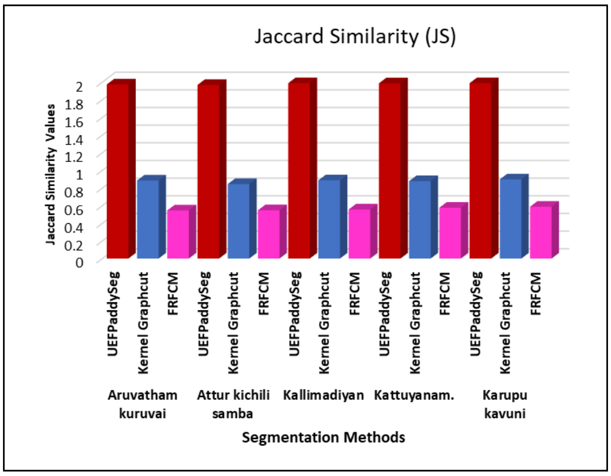


Figure 7 comparison of JS

The Jaccard Similarity (JS) values indicate that UEFPaddySeg consistently outperforms both Kernel Graphcut and FRFCM across all rice varieties. For instance, in Aruvatham kuruvai, UEFPaddySeg achieves a JS of 1.973, far surpassing the 0.884 of Kernel Graphcut and 0.545 of FRFCM. Similarly, in Attur kichili samba, UEFPaddySeg's JS value of 1.967 stands out, much higher than Kernel Graphcut's 0.844 and FRFCM's 0.547. This dominance of UEFPaddySeg continues in the other varieties. In Kallimadiyan, UEFPaddySeg scores 1.987, outperforming Kernel Graphcut at 0.887 and FRFCM at 0.556. For Kattuyanam, UEFPaddySeg achieves 1.985, while Kernel Graphcut and FRFCM score 0.877 and 0.576, respectively. Finally, for Karupu kavuni, UEFPaddySeg reaches a JS of 1.987, again higher than Kernel Graphcut's 0.897 and FRFCM's 0.587. Overall the UEFPaddySeg consistently delivers the highest Jaccard Similarity across all test images, demonstrating its superior segmentation capability compared to Kernel Graphcut and FRFCM.

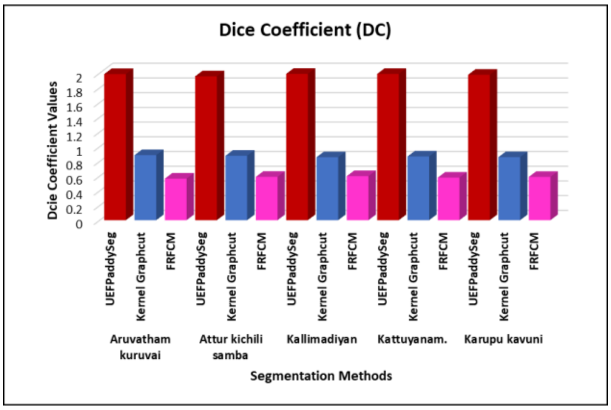


Figure 8 Comparison of DC

The Dice Coefficient (DC) values highlight the superior performance of UEFPaddySeg across all rice varieties when compared to Kernel Graphcut and FRFCM. In the case of Aruvatham kuruvai, UEFPaddySeg achieves a DC of 1.986, outperforming Kernel Graphcut, which scores 0.884, and FRFCM, which has a much lower value of 0.565. Similarly, for Attur kichili samba, UEFPaddySeg achieves a DC of 1.956, significantly higher than Kernel Graphcut (0.876) and FRFCM (0.589).

The trend of UEFPaddySeg's dominance continues for Kallimadiyan, with a DC value of 1.989, far surpassing Kernel Graphcut at 0.856 and FRFCM at 0.599. For Kattuyanam, UEFPaddySeg maintains its leading position with a DC of 1.988, while Kernel Graphcut and FRFCM score 0.866 and 0.579, respectively. In the case of Karupu kavuni, UEFPaddySeg records 1.977, well ahead of Kernel Graphcut at 0.857 and FRFCM at 0.588.

Overall, the results show that UEFPaddySeg consistently provides the highest Dice Coefficient across all test cases, proving its effectiveness in segmentation when compared to Kernel Graphcut and FRFCM.

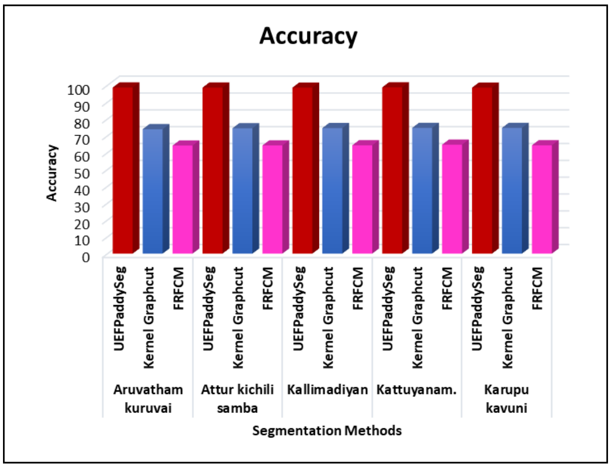


Figure 9 Comparison of Accuracy

The accuracy values clearly indicate that UEFPaddySeg outperforms both Kernel Graphcut and FRFCM across all test images. For Aruvatham kuruvai, UEFPaddySeg achieves an impressive accuracy of 98.63%, significantly higher than Kernel Graphcut at 73.87% and FRFCM at 64.17%. Similarly, in Attur kichili samba, UEFPaddySeg records an accuracy of 98.58%, while Kernel Graphcut and FRFCM lag behind with accuracies of 74.43% and 64.22%, respectively.

This trend continues for the other rice varieties. In Kallimadiyan, UEFPaddySeg achieves an accuracy of 98.55%, while Kernel Graphcut scores 74.53% and FRFCM 64.32%. For Kattuyanam, UEFPaddySeg leads with an accuracy of 98.73%, compared to 74.63% for Kernel Graphcut and 64.67% for FRFCM. Lastly, for Karupu kavuni, UEFPaddySeg registers an accuracy of 98.54%, far surpassing Kernel Graphcut at 74.64% and FRFCM at 64.33%.

In conclusion, UEFPaddySeg consistently demonstrates superior accuracy across all rice varieties, showing its effectiveness in segmentation compared to Kernel Graphcut and FRFCM.

VII CONCLUSION

UEFPaddySeg consistently outperforms both Kernel Graphcut and FRFCM across all key evaluation metrics—specificity, sensitivity, Jaccard Similarity (JS), Dice Coefficient (DC), and accuracy. UEFPaddySeg achieves the highest specificity, consistently surpassing 1.95, and shows a marked improvement in sensitivity, with values consistently above 1.97, compared to the lower results of Kernel Graphcut and FRFCM. When evaluating Jaccard Similarity (JS), UEFPaddySeg again leads with values reaching as high as 1.99, outshining both competing methods. Similarly, its Dice Coefficient (DC) values, peaking at 1.99, reflect its high precision in segmentation. Lastly, UEFPaddySeg achieves remarkable accuracy, ranging from 98.54% to 98.73%, which is significantly higher than the 70%-80% accuracy scores observed for Kernel Graphcut and FRFCM. Overall, the consistent top-tier performance of UEFPaddySeg across all these metrics solidifies its position as the most effective segmentation method for rice varieties, surpassing Kernel Graphcut and FRFCM in every category.

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