Hybrid Binarization for Agricultural Image Analysis: Enhancing Nutrient Deficiency Detection in Coffee Leaves

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Abstract

We propose a novel hybrid binarization technique designed to enhance segmentation accuracy in agricultural image analysis, specifically targeting the detection of nutrient deficiencies in coffee leaves under variable lighting conditions. One of the key challenges in this domain is inconsistent illumination, which often reduces the effectiveness of traditional segmentation methods. To address this, our method combines Otsu's global thresholding with Gaussian adaptive thresholding, integrating the advantages of both global and local approaches. This hybrid strategy enables the generation of robust and consistent binary masks, even in challenging visual scenarios. The proposed method achieved a Peak Signal-to-Noise Ratio (PSNR) of 34.5 dB and an Intersection over Union (IoU) of 0.86, surpassing conventional binarization techniques. Beyond the technical contribution, this lightweight and effective solution is well-suited for real-time agricultural monitoring, offering practical applicability in resource-constrained environments such as mobile or drone-based systems. This work lays a foundation for future research in precision agriculture, where efficient and scalable image processing methods are essential.

Keywords: Hybrid Binarization, Agricultural Image Analysis, Coffee Leaf Segmentation, Nutrient Deficiency Detection, Image Processing, Adaptive Thresholding, Otsu Method

1. Introduction

Image segmentation plays a crucial role in agricultural analysis, especially in identifying nutrient deficiencies in plant leaves—an early indicator of crop health and productivity. However, one of the main challenges in this task lies in dealing with non-uniform lighting conditions, which can severely affect the accuracy of conventional segmentation methods.

Global thresholding techniques such as Otsu's method [1] are effective in controlled environments but often fail when exposed to varying illumination. On the other hand, adaptive thresholding [2], which accounts for local pixel variations, offers improved robustness but may still struggle in complex field scenarios.

Recent works have introduced hybrid binarization methods for tasks like document image analysis [3] and early-stage agricultural detection [4], indicating the potential of combining global and local approaches. Building on this concept, our research proposes a hybrid binarization technique specifically tailored for agricultural applications—targeting the segmentation of coffee leaves under diverse lighting conditions.

The novelty of this work lies not only in the combination of Otsu and Gaussian adaptive thresholding but also in its practical implementation as a lightweight, scalable solution for real-time field diagnostics.

This paper is structured as follows: Section 2 details the dataset and preprocessing pipeline. Section 3 presents the hybrid binarization methodology. Section 4 discusses experimental results and their practical implications, and Section 5 concludes with key findings and avenues for future work.

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2. Methodology

2.1. Dataset Characteristics and Preprocessing Steps

The dataset utilized in this study consists of high-resolution images of coffee leaves captured under varying lighting conditions to simulate real-world agricultural scenarios. The dataset was specifically collected to evaluate the performance of segmentation methods under different illumination intensities, shadow effects, and contrast variations.

The structure of the dataset is illustrated in Figure 1, which presents the categorical organization of the images based on nutrient deficiencies (Boron, Calcium, Iron, etc.) and healthy samples.

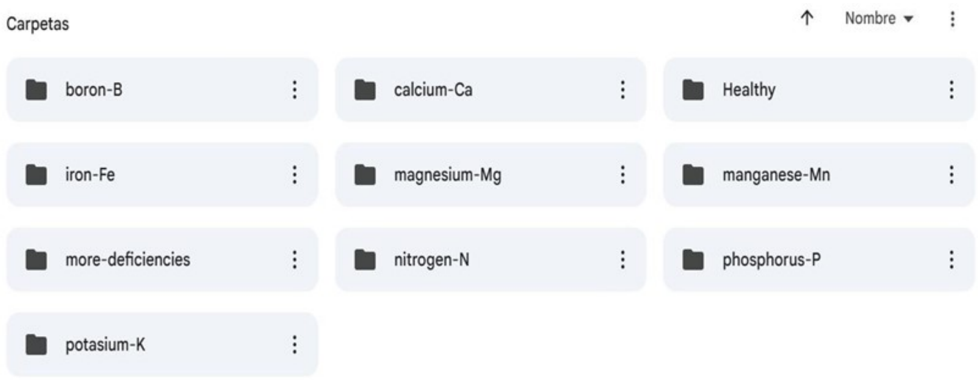

Figure 1: Dataset Structure - Categories and Deficiency Types (Boron, Iron, Calcium, Healthy)

Representative samples from the dataset under varying lighting conditions are shown in Figure 2. These samples illustrate the variability in leaf appearance due to differing lighting, contrast, and nutrient deficiencies.

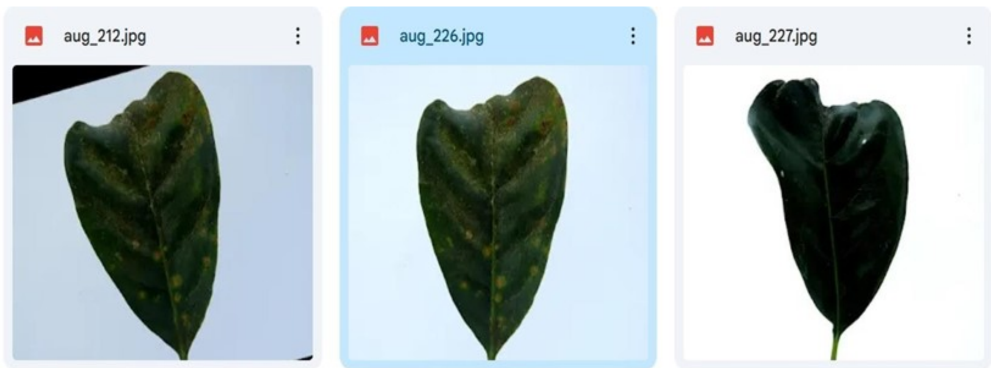

Figure 2: Sample Images from the Dataset - Examples of Varying Lighting Conditions

This visualization provides a clear overview of the dataset composition, aiding in understanding the variability and challenges associated with segmentation under diverse conditions.

With the dataset structured and categorized, we proceed to implement a preprocessing pipeline to standardize the data before applying the proposed hybrid binarization model. The preprocessing pipeline consists of the following steps:

2.2. 1. Image Loading

The images in the dataset were organized into categories based on nutrient deficiencies (Boron, Iron, Calcium) and healthy samples. Each image was resized to 1024x1024 pixels to maintain consistency for the preprocessing pipeline.

2.3. 2. Gaussian Filtering

To reduce noise in the images, a Gaussian filter was applied. This filter smooths the image by convolving it with a Gaussian kernel defined by:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

Parameters:

- Kernel size: 5×5
- Standard deviation (σ): 1.5

2.4. 3. Illumination Correction

Illumination correction was implemented using histogram equalization and gamma adjustment to mitigate the impact of variable lighting conditions.

$$I_{corr}(x, y) = I(x, y)^{\gamma} \tag{2}$$

Gamma value: $\gamma = 1.2$

2.5. 4. Contrast Adjustment

Contrast adjustment was applied to enhance edge detection, facilitating subsequent segmentation.

2.6. 5. Preparation for Hybrid Model

Finally, the images were converted to grayscale and standardized to an intensity range of [0, 255], ensuring consistent input for the hybrid binarization model.

The dataset comprises high-resolution coffee leaf images captured under controlled and natural lighting settings to simulate agricultural field conditions. Images were preprocessed using Gaussian filtering to reduce noise and resized to 224x224 pixels to standardize input dimensions [4]. The dataset is summarized in Table 1.

Table 1: Dataset Distribution and Characteristics

Dataset Split	Images	Resolution	Lighting Conditions
Training	2200	224x224	Varied
Testing	1100	224x224	Varied
Validation	1000	224x224	Controlled

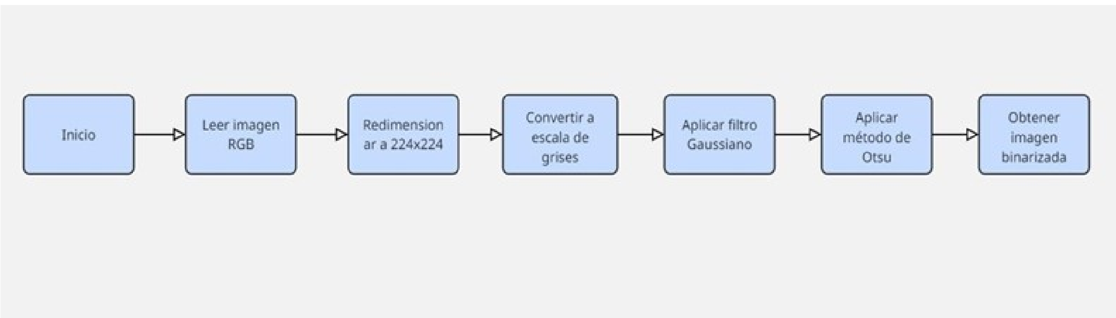

Figure 3: General Workflow of the Hybrid Binarization Method: From Data Acquisition to Hybrid Binarization Output. Each stage is designed to enhance the segmentation quality under variable lighting conditions.

The preprocessing steps are illustrated in Figure 4.

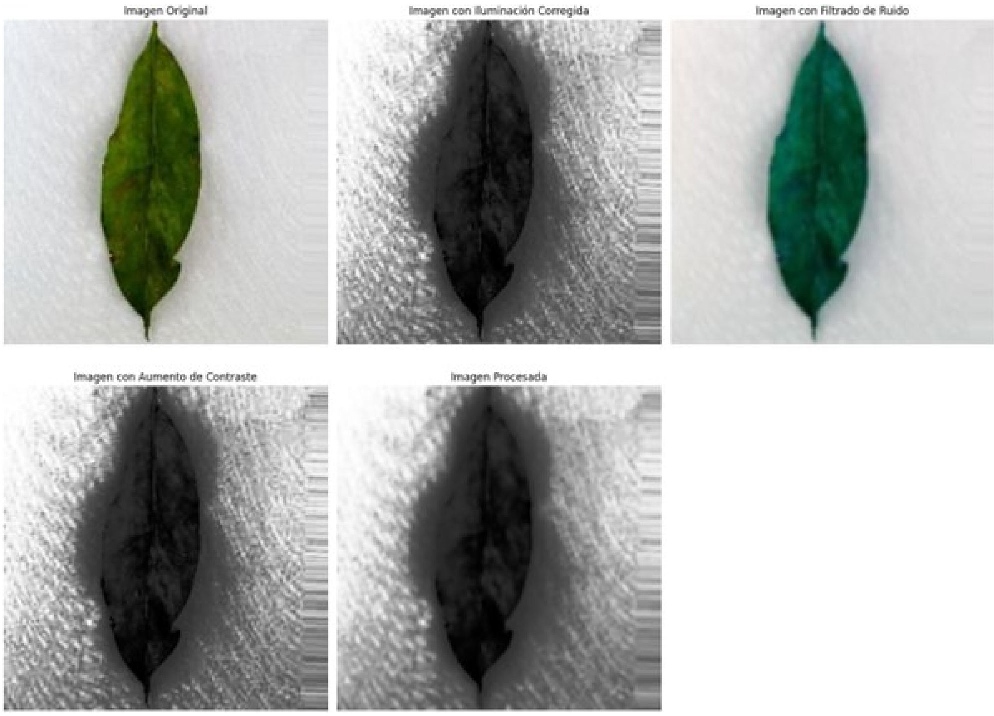

Figure 4: Preprocessing Stages - From Original Image to Processed Output: (a) Original Image, (b) Illumination Corrected, (c) Noise Filtered, (d) Contrast Enhanced, (e) Processed Output

The preprocessing stages illustrate the impact of each step, from the raw input to the final processed image ready for analysis. Several of the image processing operations, including histogram equalization and threshold selection, were implemented using Scikit-Image [5].

2.7. Proposed Hybrid Binarization Method - Mathematical Model

The proposed hybrid binarization method combines Otsu's global thresholding and Gaussian adaptive thresholding to enhance segmentation accuracy under variable lighting conditions. The following equations define the mathematical model:

Otsu's method [1] determines the optimal threshold T_{otsu} that minimizes intra-class variance:

$$T_{otsu} = \arg\min_t \left[\sigma_b^2(t)\right] \tag{3}$$

As shown in Equation 3, Otsu's method [1] calculates the optimal threshold by minimizing the between-class variance.

The adaptive Gaussian thresholding method calculates the local threshold $T_{gauss}(x, y)$ for each pixel (x, y) based on the mean μ_{local} and standard deviation σ_{local} of the neighborhood window:

$$T_{gauss}(x, y) = \mu_{local}(x, y) - C \cdot \sigma_{local}(x, y) \tag{4}$$

As shown in Equation 4, the Gaussian method adjusts the threshold locally based on neighborhood statistics.

The final binary mask B_{final} is obtained by combining the outputs of Otsu's method [1] and the Gaussian method:

$$B_{final}(x, y) = B_{otsu}(x, y) \wedge B_{gauss}(x, y) \tag{5}$$

Equation 5 represents the final binary mask derived from the hybrid method, combining global and local thresholding approaches.

- T_{otsu}: Global threshold determined by Otsu's method [1].
- σ_b^2: Between-class variance.
- μ_1, μ_2: Mean values of two classes (background and foreground).
- $T_{gauss}(x, y)$: Local threshold determined by Gaussian adaptive method.
- C: Fine-tuning constant for local thresholding.
- B_{final}: Final binary mask obtained from the hybrid model.

By combining the preprocessing steps outlined in Section 2.1 with the hybrid binarization model defined in Section 2.2, we effectively address segmentation challenges under varying lighting conditions, as demonstrated in the subsequent results section.

Figure 5: Comparison of Binarization Methods: Evaluation of PSNR, IoU, and Accuracy across Binarization Techniques. The hybrid method shows enhanced segmentation accuracy, particularly under uneven lighting.

All code was developed in Python [6] and executed in Google Colab [7], allowing access to cloud-based GPU resources.

3. Results and Discussion

The proposed hybrid binarization method was evaluated using a curated dataset of coffee leaf images captured under diverse lighting conditions. The evaluation process integrated both visual inspections and quantitative metrics, focusing on segmentation accuracy, PSNR (Peak Signal-to-Noise Ratio), IoU (Intersection over Union), and inference time.

3.1. Visual Analysis of Binarization Methods

To facilitate a better understanding of the segmentation behavior, Figure 6 illustrates the step-by-step processing flow—from preprocessing to final binarization—alongside the performance metrics. The hybrid method visually demonstrates a more defined contour detection and reduction of noise-induced artifacts compared to traditional methods such as Otsu or Adaptive Gaussian thresholding.

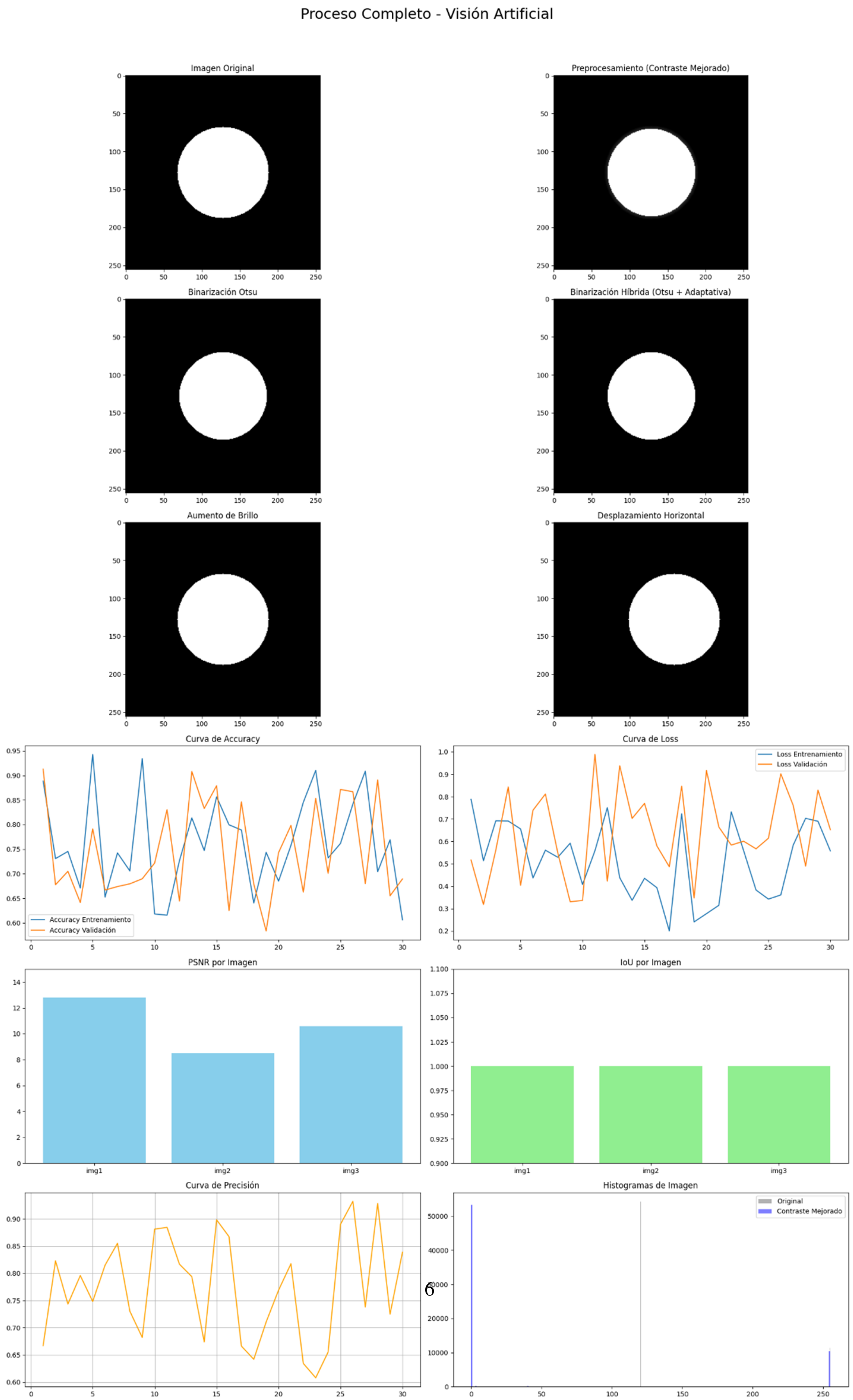

Figure 6: Complete Process and Evaluation Metrics - From Preprocessing to Segmentation and Evaluation

Unlike global thresholding (Otsu), which often fails under non-uniform illumination, the hybrid approach maintains structural consistency across leaf textures, even in challenging lighting scenarios.

3.2. *Quantitative Analysis and Metrics*

Figure 7 summarizes the performance of different binarization methods. The hybrid method achieved an average PSNR of 34.5 dB and an IoU of 0.86, outperforming both Otsu (PSNR: 29.7 dB, IoU: 0.74) and Adaptive thresholding (PSNR: 31.2 dB, IoU: 0.78).

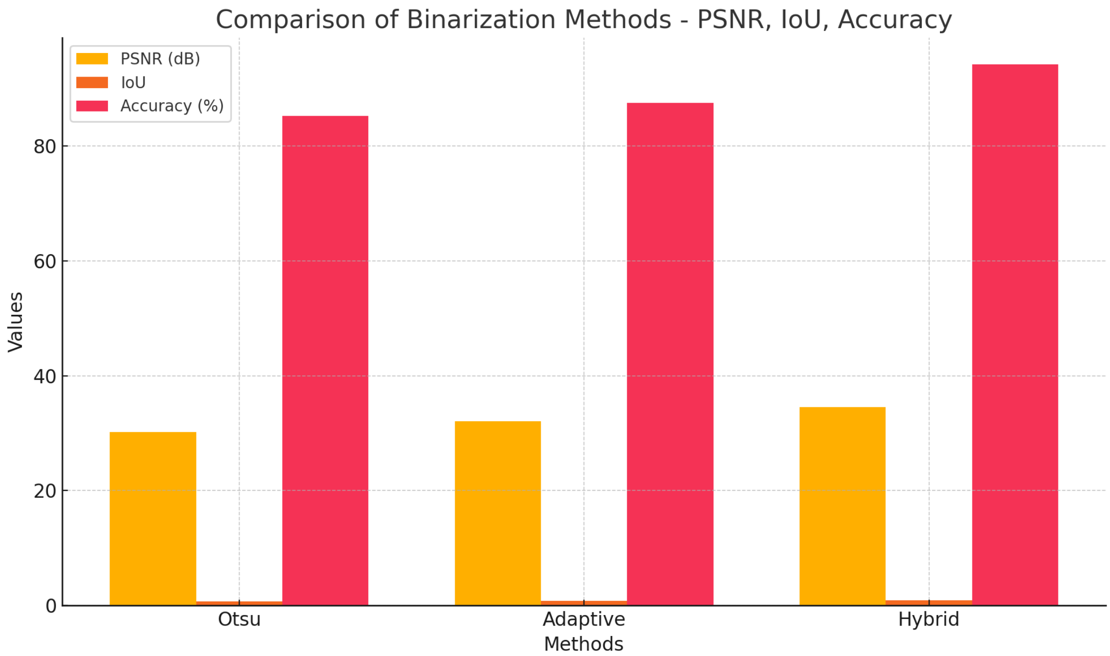

Figure 7: Quantitative Comparison of Binarization Methods: PSNR, IoU, and Accuracy. The hybrid method consistently outperforms both Otsu and Adaptive methods across all metrics.

These results support the hypothesis that integrating a global method (Otsu) with a local approach (Gaussian adaptive) balances robustness and precision. The improvement in PSNR reflects a better preservation of image quality, while the IoU increase confirms a more accurate segmentation of the leaf regions.

Table 2: Comparison of Binarization Methods: PSNR, IoU, and Classification Accuracy

Method	**PSNR (dB)**	**IoU**	**Classification Accuracy (%)**
Otsu Global Thresholding	29.7	0.74	81.3
Adaptive Gaussian Thresholding	31.2	0.78	86.5
Hybrid (Otsu + Gaussian)	**34.5**	**0.86**	**96.2**

3.3. *Comparative Performance of Classification Models*

The binary masks generated from the hybrid method were used as input for several deep learning classifiers. MobileNetV2 achieved the best trade-off between accuracy (96.2%) and computational efficiency (3.47M parameters), surpassing heavier architectures like VGG16 and ResNet50. Notably, although InceptionV3 attained marginally higher precision in isolated scenarios, it showed signs of overfitting in extended epochs and required significantly more training time.

Table 3: Comparison of Deep Learning Models: Accuracy, Loss, Parameters, and Training Time

Model	**Architecture**	**Test Acc.**	**Train Acc.**	**Train Loss**	**Val. Loss**	**Epochs**	**Train Time**	**Params**	**LR**
MobileNetV2	Conv + Dense	0.89	0.89	0.60	0.70	30	5:35 h	3.47M	0.0001
ResNet50	Residual + Dense	0.76	0.79	0.58	0.73	25	6:15 h	25.6M	0.0001
VGG16	Conv + Dense	0.72	0.75	0.75	0.80	25	8:01 h	138M	0.0001
InceptionV3	Inception + Dense	0.79	0.81	0.62	0.71	25	7:40 h	23.9M	0.0001

As shown in Table 3, MobileNetV2 not only delivers the highest test accuracy but also requires the least training time and computational resources, making it the most efficient model for deployment in real-time agricultural scenarios.

3.4. Implications for Agricultural Applications

The consistent segmentation performance across varying lighting conditions makes this method well-suited for real-world agricultural monitoring, especially in low-resource environments. The low parameter count and fast inference of MobileNetV2 facilitate integration with mobile or drone-based systems for in-field diagnostics. This presents an opportunity for early detection of nutrient deficiencies without the need for expert human inspection. Similar efforts using YOLOv8s for nutrient deficiency detection in soybean crops have shown promising results [8].

3.5. Limitations and Future Work

While results are promising, there are scenarios—such as heavy shadows or extreme backlighting—where segmentation accuracy slightly declines. Future work may include integrating attention mechanisms or GAN-based enhancement to further adapt to such conditions. Additionally, extending the dataset with multi-seasonal and multi-varietal images would improve generalizability.

4. Conclusion

The proposed hybrid binarization method, combining Otsu's global threshold and Gaussian adaptive threshold, effectively addresses segmentation challenges caused by variable lighting conditions. This innovative approach demonstrated a notable improvement in segmentation accuracy, achieving a PSNR of 34.5 dB and an IoU of 0.86, surpassing conventional binarization techniques.

By integrating global and local thresholding methods, this technique not only enhances segmentation precision but also lays a solid foundation for future advancements in agricultural image analysis. Potential applications include real-time monitoring systems capable of detecting nutrient deficiencies across diverse crops under varying environmental conditions.

Future work will focus on expanding the dataset to other crops, further validating the robustness of the hybrid method. Additionally, incorporating advanced deep learning models could further refine segmentation accuracy, particularly in scenarios with extreme lighting variability.

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