Crop fields segmentation Using K-Means and Color Thresholding

Group 11

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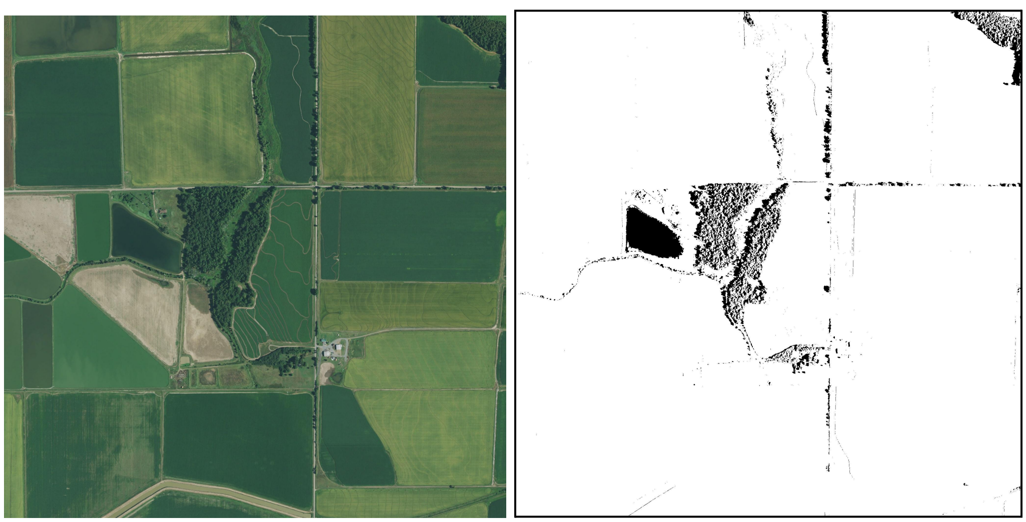
1. Introduction

Our project is about image segmentation. We have developed a method that can successfully segment crop fields from the satellite images. The effectiveness of our method will be evaluated on the nine ground truth images. Using K-means clustering and color threshold, we were able to achieve satisfactory performance in the segmentation task. We considered accuracy, precision, recall and F1 score as our evaluation metric. The average accuracy, recall, precision, and F1-score were 83.11%, 99.17%, 82.30%, and 89.95% respectively.

An example of our final result is shown in Figure 1. In the final result image, crop fields are white areas and non-crop fields, which include other objects in the image, such as wood, house/storage, and roads are in different shades black/gray (Figure 1b).



(a) (b)

Figure 1: Original satellite image (a) and segmented processed image (b).

2. Dataset

We used nine satellite JPG format images that have a 1-meter ground sample distance and dimensions of 2048x2048.

Subject	Feature	Solution
Woods	Higher green intensity than other subjects with adjacent shadow to the left (all images were taken at the same time range).	Contrast enhancement.
House / storage	Similar color intensity with road and unused crops.	Ignored since they don't appear a lot in the images.
Roads	Small, straight lines, something occluded by trees' shadow.	histogram stretching and histogram equalization.
Crop field	Various of green intensity, artifacts made.	K-means and color thresholding.
Unused crop field	Closest to white.	Color thresholding with different thresholds for each channel of the colorspace.

3. Methodology

We developed a method that can successfully segment crop fields from the satellite images. The effectiveness of our method will be evaluated on different ground truth images. We implemented different phases to ensure the progress towards our final goal. Figure 2 represents the workflow of our implementation.

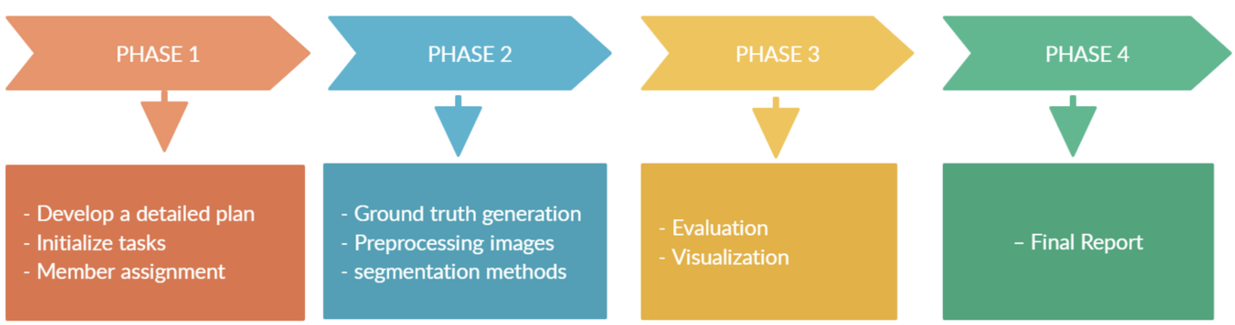


Figure 2: Workflow of our implementation.

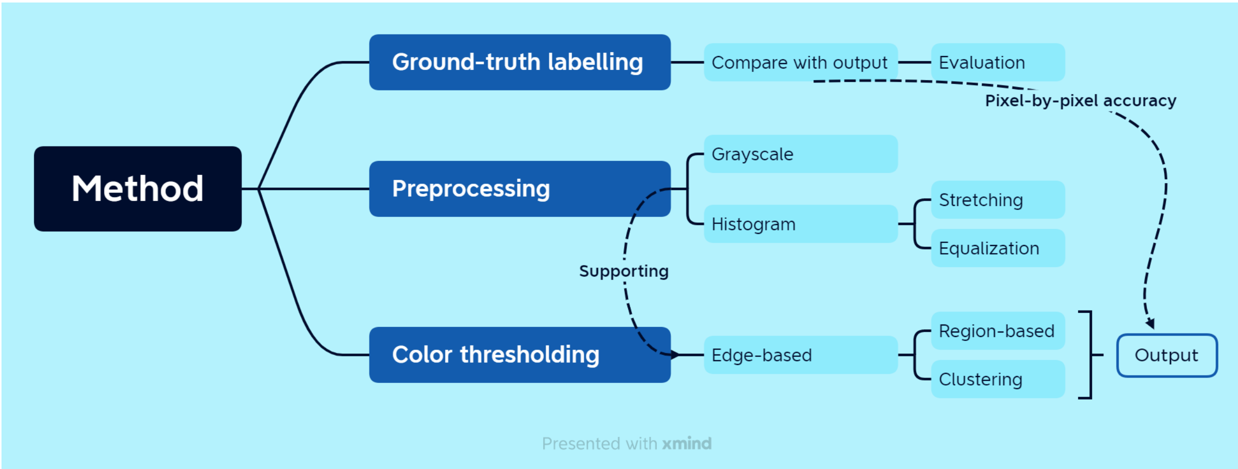


Figure 3: Overview of methodology.

3.1. Ground truth generation:

Figure 3 shows the overview of the methodology. We manually annotated the images to create ground truth for evaluation. Ideally, two members split the dataset and created the ground truth images. Their annotations were combined to eliminate subjective biases.

We used Kleki ("Kleki - Paint Tool" n.d.), an online tool for painting and editing, to create labels for the ground truth images. We have two classes of label:

- Crop fields - represented in white color.
- Non crop fields – other objects in the image, which are not crop fields, are grouped together in this class.

We have manually applied these two classes of label to all nine ground truth images. Figure 4 is an example of our outputs.

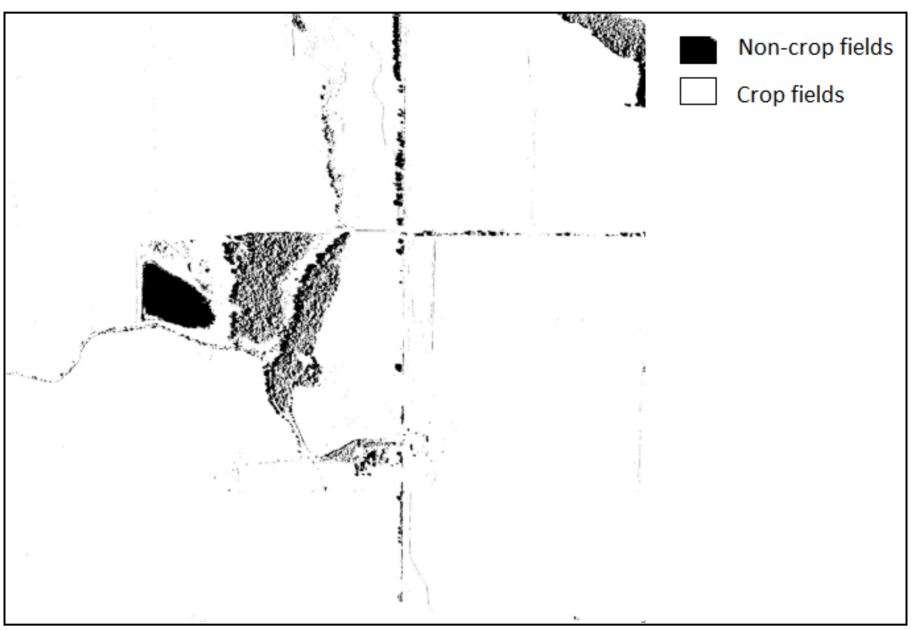


Figure 4: Labeled ground truth image.

3.2. Preprocessing images

Since some algorithms can only function with binary images, this step is necessary to enable the ones that follow, such as grayscale images, where contrasted parts of images could aid in identifying details, patterns, and classes.

After converting color images into grayscale for edge detection, we applied histogram stretching and histogram equalization to enhance image contrast (Figure 5).

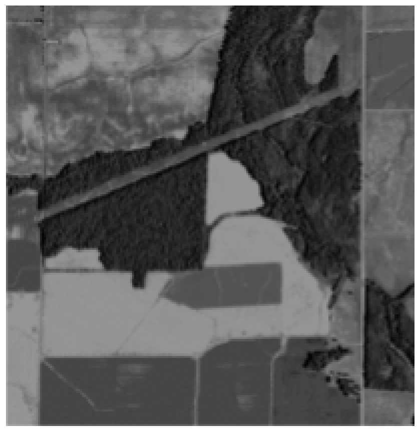


Figure 5: Preprocessed image.

3.3. Techniques for segmentation

- *Thresholding*: Our first approach was implementing a threshold method to see how it separates the crop fields from the image. Based on the intensity, the pixels in an image get divided by comparing the pixel's intensity with a threshold value.

  This step was optional since we wanted to test how much color thresholding could distinguish the classes in the dataset because it was predicted to have comparable variations of green. Additionally, some crops were immature and had a noticeably whiter tint than others.

- *Clustering*: A group of pixels that can belong to more than one cluster or group but they can have varying levels of associativity per group. As the dataset's images had variants of green intensity, choosing a good k, the number of clusters can help in segmentation. Some choices include k-means, spatial k-means, mean shift, and spatial mean shift. To distinguish crops from the rest, multiple algorithms can be run simultaneously with various parameter combinations.

  We chose K-means because it is the mostly used method to classify the pixels of an image. Compared to other hierarchical clustering methods, K-means is simple and less computationally expensive (Dhanachandra, Manglem, and Chanu 2015). Figure 4 is the result obtained after 6 peaks.

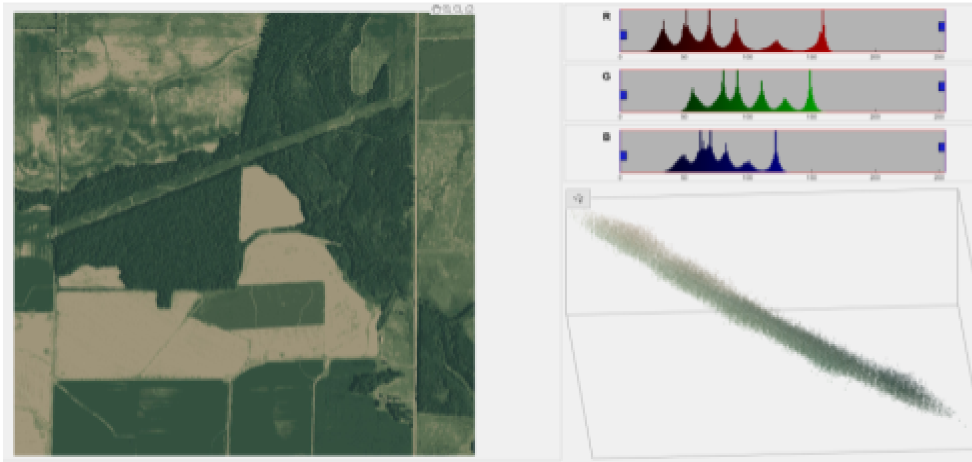


Figure 6: K-means Thresholding after 6 peaks.

- *Color thresholding*: We applied color thresholding to outputs from K-means. The three thresholds for each channel of the colorspace were set based on histogram settings. Figure 7 shows our results after applying a different threshold method.

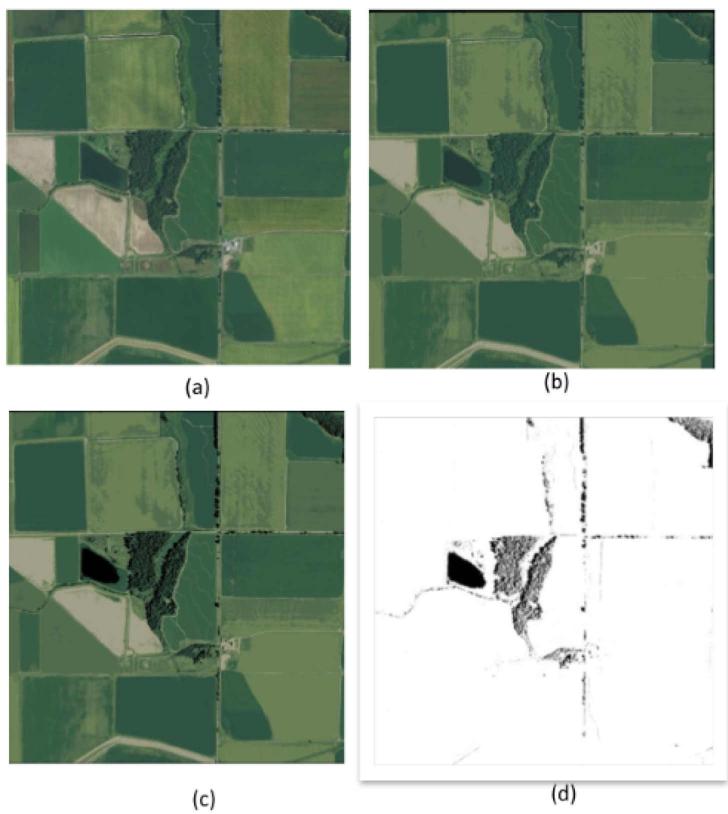


Figure 7: Final result. (a) original image; (b) K-means; (c) color thresholding and (d) binary image.

3.4. Evaluation and visualization

- Evaluation method: Processed and ground-truth images will be compared pixel-by-pixel (Soomro et al. 2022).
- Visualization: Segmented areas should be of a different color from those in the original image (in our case, different shades black/gray) to avoid confusion.

4. Experimental Results

We used accuracy, precision, recall and F1 score as the evaluation metrics. Table 1 shows the evaluation results for each segmented image. The formulas for calculation are given below:

Accuracy = (TP+TN) / (FN+FP+TP+TN)
Recall = TP / (TP+FN)
Precision = TP / (TP+FP)
F1 score = (2 x Precision x Recall) / (Precision+Recall)

where, TP represents true positive which is correctly segmented crop fields in our case;
FP represents false positive: incorrectly segmented as crop fields, actually non-crop-fields;
TN defines true negative: Correctly segmented as non-crop-fields;
FN represents false negative: Incorrectly segmented as non-crop-fields, actually crop fields.

Table 1: Accuracy, precision, recall and F1 score for each segmented satellite image

Image title	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
field	85.68	98.52	86.24	91.97
L88a	81.77	98.47	79.67	88.08
L88b	85.55	98.45	84.84	91.14
L96a	**78.53**	97.05	72.42	82.94
L96b	**92.74**	99.26	93.13	96.09
L97a	**80.27**	87.78	87.67	87.72
L97b	83.05	95.38	81.44	87.86
W107a	**90.44**	97.45	91.87	94.58
Average	**83.11**	**99.17**	**82.3**	**89.95**

In our evaluation, we got 78.53% and 80.27% accuracy for the two images “L96a” and “L97a” respectively and these segmentation accuracies were the lowest among all the images (Figure 8 and Figure 9). On the other hand, the images, “W107a” and “L96b” obtained the highest accuracy which is 92.74% and 90.44% respectively (Figure 10 and Figure 11).

(a) (b) (c)

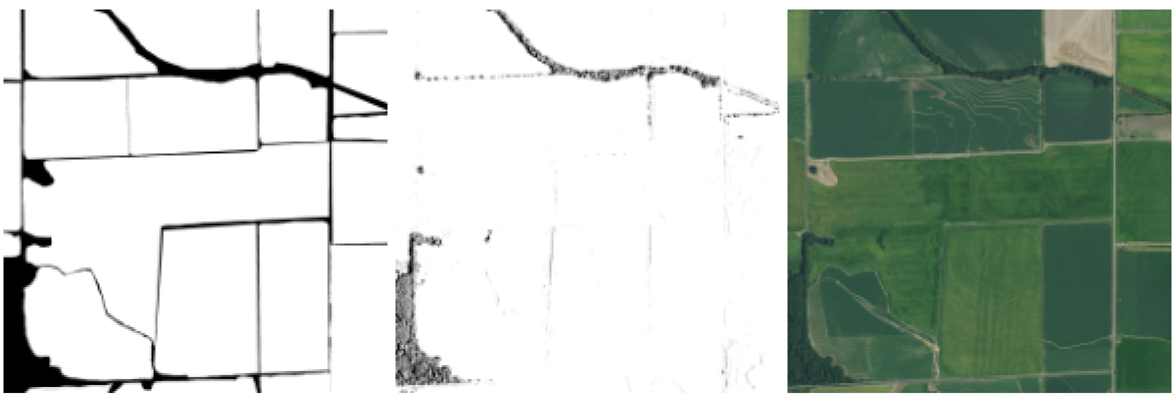
Figure 8: Image L96a, accuracy 78.53%. (a) ground truth image; (b) processed image; (c) original image.

(a) (b) (c)

Figure 9: Image L97a, accuracy 80.27%. (a) ground truth image; (b) processed image; (c) original image.

(a) (b) (c)

Figure 10: Image W107a, accuracy 90.44%. (a) ground truth image; (b) processed image and (c) original image.



(a) (b) (c)

Figure 11: Image L96b, accuracy 92.74%. (a) ground truth image; (b) processed image and (c) original image.

5. Discussion

During the course of the project, we faced a number of obstacles in order to reach our goal, one of them was how water ponds and forests are frequently used as farming fields. The effectiveness of our strategy also is impacted by changes in the hue of various crop fields. Our approach to overcome these obstacles was converting the original images into grayscale, then applying histogram stretching and histogram equalization to enhance image contrast. Using K-means threshold and color threshold to perform segmentation, we were able to achieve high accuracy, recall, precision, and F1-score.

6. Conclusion

In this project, we developed a segmentation method to extract crop fields from the satellite images. We used accuracy, precision, recall and F1 score as evaluation metrics to perform pixel-by-pixel comparison between the ground truth and the result.processed images. In addition, we achieved average accuracy of 83.11%, recall of 99.17%, precision of 82.30% and F1 score of 89.95% in our evaluation. Recently, machine learning and deep learning techniques have become popular and shown significant improvement in the field of image processing. In future, we are planning to apply such methods to this segmentation task.

References

Dhanachandra, Nameirakpam, Khumanthem Manglem, and Yambem Jina Chanu. 2015. “Image Segmentation Using K -Means Clustering Algorithm and Subtractive Clustering Algorithm.” *Procedia Computer Science* 54 (January): 764–71.

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