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# Cotton Boll Segmentation, Detection and Counting Using a Thresholding - HSV Algorithm

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**Abstract -** In contemporary cotton farming and agriculture, where accurate yield estimation is essential for maximizing resource allocation and crop management, comprehensive cotton boll recognition and counting technology has significant applications. Enhancing agricultural production, cutting waste, and addressing labor shortages are critical in order to support cotton farming operations' sustainability and profitability. Accurate cotton boll yield estimation is highly valued in agriculture since it influences decisions about crop management and resource allocation. The S channel of the HSV (Hue, Saturation, Value) color scheme has been used for effective boll recognition. It employs clever thresholding and contour detection technology for extremely precise boll counting. To begin the inquiry, high-resolution images of cotton fields must be obtained. Then, through a laborious thresholding process, the cotton bolls are successfully separated from their background to create binary images. This binary encoding holds the key to accurate boll detection. The maximum level of accuracy in boll counting is achieved using OpenCV's find contours These images undergo laborious pre-processing to extract the S channel, which preserves the essential color and texture details unique to cotton bolls. A powerful contour detection technique is then applied to identify individual bolls within the binary images. The architecture of the algorithm accounts for variations in boll size, shape, and orientation, ensuring the robustness of the solution across a wide range of cotton field conditions. The model, with an impressive 95% accuracy rate, highlights the efficacy and relevance of the proposed methodology. This advancement holds the potential to revolutionize the calculation of cotton output in agriculture.

***Keywords***- *Saturation, HSV algorithm, cotton boll detection, cotton boll counting, histogram S channel.*

## I. Introduction

Cotton, the "white gold,", is a vital global necessity or substance with significant economic value. Millions of employment in the textile and agricultural industries are supported globally by the cotton industry. To optimize the benefits of cotton production, a precise understanding of cotton boll yield is essential [1]. This benefits downstream industries such as textile and apparel manufacturing as well as farmers. Human enumeration has historically been the primary method of cotton boll counting, although it is labor-intensive and prone to error. The lengthy and often error-prone nature of the traditional methods affects market forecasts and profitability across the cotton supply chain.

The rapid advancement of image processing and computer vision technologies has spurred agricultural innovation and created new avenues for automating the recognition and counting of cotton boll output. In order to offer an automated approach to this research domain, the guided, semi-supervised, and unsupervised ML approaches, such as DL algorithms as well as variations of YOLO (You Only Look Once), have been decoded in recent years [2]. These advancements herald a new era of revolutionary advances in cotton farming practices, with increased efficiency, accuracy, and consistency in yield estimation.

This study allows us to implement the phase and develop this project to the next level. Using HSV (Hue, Saturation, Value) [3] color space as a tool for imaging analysis, the distinctions in this space are utilized innovatively in this work. Photo images of field-collected bolls have to be accurately identified and the number of bolls should be counted by adapting this color space for segmentation purpose along with caution. The rationale of the research study is premised on the fluctuating environment of 21st century agriculture. Another objective of the mentioned approach is to achieve balance between the innovative solutions to meet those needs and the old approaches to yield calculation. The aim is to develop a standardised tool for the determination and counting of the cotton bolls, in other words, to change the approach to the cotton cultivation in order to increase its productivity. Actionable data from the research help farmers, agronomists, and other interested parties allocate resources more wisely, make decisions faster, and eventually produce more productive and sustainable cotton. Figure 1 displays the Original Image (1(a)), Masked Image (1(b)), and Segmented Image (1(c)) on which the HSV algorithm is applied.

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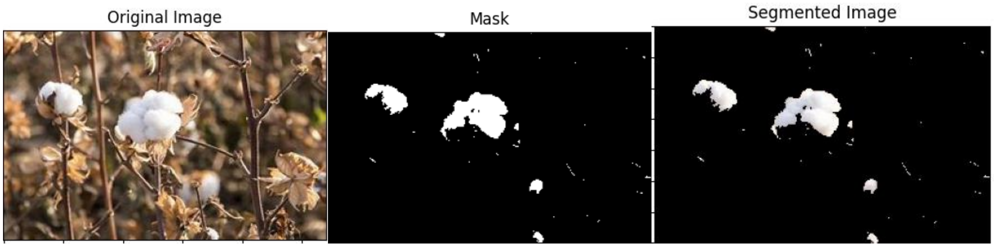


1(a) Original Image 1(b) Masked Image 1(c) Segmented Image

**Fig 1:** HSV segmentation of an image

This study's simple and effective method makes it easier to recognize and count cotton bolls, which is a significant improvement over current method. Unlike many other complex and computationally intensive methods, the methodology prioritizes efficiency without compromising precision. The utilization of the inherent color and texture data that are exclusive to cotton bolls in the HSV color space is able to achieve accurate segmentation and make it easier to distinguish individual bolls from background noise. Using find contours in OpenCV, cotton bolls from individual image frames are separated.

Because of its simplicity of usage, this method is economical, efficient, and adaptable to a range of agricultural situations [4]. This methodology achieves a 95% threshold accuracy on test data, reducing the need for substantial data labelling and training.

To the best of our knowledge, all the earlier research projects used heavily weighted models that required a lot of processing power to train. For retraining, weighted GPUs are necessary for reinforcement learning models [5]. This unique lightweight concept works well with large-scale photographs and improves accuracy and efficiency in the cotton boll segmentation and counting process. The objectives of this study are -

1. To combine subtle color and texture data and take advantage of the potential of the HSV color space, a resource that has yet to be extensively studied in the field of cotton yield estimation.

2. To improve the efficiency of agricultural data analysis by introducing a lightweight model for object segmentation and counting techniques.

3. To offer innovative and reliable methods that demand minimal processing power to operate on massive data clusters.

4. To provide a faster and more accurate alternative to manual counting by automating the labor-intensive and time-consuming process of counting cotton bolls.

## II. Background Work

An overview of earlier literary works in the field of cotton boll counting and segmentation is provided in this section.

### *a) Cotton Boll Detection*

Using coarse-to-fine maps and the "UP" algorithm for interference reduction, Li, Yanan, et al. [6] was able to create a revolutionary deep learning method that surpassed conventional techniques for in-field cotton boll segmentation (IoU: 8.1% improvement). Researchers published a dependable method for in-field cotton detection. In this study Li, Yanan, et al. [7], outperforming previous methods by combining supervised semantic labeling with unsupervised region formation.

Using point clouds generated from multi-view photographs, Sun Shangpeng et al. [8] developed a 3D cotton boll mapping technique that enables precise counting and geographic dispersion assessments with up to 90% counting accuracy. By employing a Fisher discrimination vector and optimizing color space selection, Liu JinShuai et al. [9] successfully distinguished cotton images with 90.44% accuracy. This significantly decreased segmentation noise.

By presenting a top-down partitioning technique for high-resolution plant mesh segmentation, Paproki Anthony et al. [10] showed that an automated system for plant analysis and phenotyping could be achieved. A semantic segmentation model with an attention mechanism was proposed by Kang Jia, et al. [11] for accurate segmentation of the cotton root system in complex soil backgrounds. The model demonstrated precision and recall values of 0.9971 and 0.9984, respectively.

Yu Qiushi et al. [12] created an inexpensive, edge device-based technique that reduced time consumption (22.71%) and improved accuracy (93.11%) for in-situ root extraction and segmentation. The research using a hybrid DL model for cotton leaf edge segmentation in real-world conditions performed better than earlier models in terms of accuracy and processing time Jian-hua et al. [13].

Hauser, Marc D et al. [14] found that humans and cotton-top tamarins can differentiate between syllable sequences based on statistical features, suggesting that primates and apes share a mechanism for sequential learning.

The Singh, Naseeb et al. [15] employed convolutional neural networks to separate cotton berries from sky pixels in order to obtain threshold IoU scores; the InceptionV3 model performed the best. Table I presents the assessment measure scores, picture features picked, techniques utilized, contribution, and limitations of the aforementioned works.

**Table I:** An overview of earlier studies in the field of image-based cotton boll segmentation.

| Paper | Contribution | Limitation | Algorithms Used | Feature Considered | Evaluation Metric Score/ Conclusion |
|---|---|---|---|---|---|
| [6] | Cotton boll segmentation using deep learning and interference removal using the UP algorithm | No use of feature extraction techniques | UP algorithm, deep learning | Cotton bolls against the backdrop | 8.1% improvement in IoU |
| [7] | Cotton detection in the field using supervised semantic labelling and unsupervised region creation | Insufficient scope of restrictions understood | Random Forest, DBSCAN, and SLIC | Cotton bolls against the backdrop | Maximum average values, minimum standard deviations |
| [8] | Using point clouds for 3D mapping of cotton balls | Segments of the mapping not covered | Motion-based structure and density-based clustering | Cotton blossoms in close proximity | 90% precision in counting |
| [9] | Precise segmentation of cotton images in the YCbCr colour space | Colour space dependency in YCbCr | YCbCr colour space and self-adjusting noise reduction | Background vs. cotton | 90.44% segmentation accuracy |
| [10] | Pipeline for top-down partitioning in plant mesh segmentation | Only partitioning is used; feature selection is not used | Top-down division | Veg mesh against backdrop | Individual algorithms perform worse than hybrid models. |
| [11] | Cotton Root System Semantic Segmentation Model with Attention Mechanism | Inadequate examination of the used algorithms | With an attention mechanism, DeepLabv3+ | Complex soil versus cotton root | Recall 0.9984, Precision 0.9971 |
| [12] | An inexpensive approach for in-situ root | Inadequate examination of | Enhanced DeeplabV3+ with care | Root in-situ versus backdrop | A 93.01% segmentation accuracy |

| | | | | | |
|---|---|---|---|---|---|
| | extraction and segmentation using edge devices | the used algorithms | | | |
| [13] | Model for segmenting the edges of cotton leaves under natural circumstances | Absence of segmentation technique analysis | Heaviside function and composite function | Cotton leaves against intricate backdrops | High precision in segmenting |
| [14] | Cotton-top tamarins cognitive capacities for sequential learning | Restricted to cognitive capacities of primates | Analytical statistics | Mental faculties | Comparison of cognitive capacities |
| [15] | Using convolutional neural networks (CNN) to segment cotton bolls | ResNet34, InceptionV3, VGG16 | Inadequate examination of the used algorithms | Sky vs. cotton blossoms | Elevated IoU ratings, with InceptionV3 surpassing |

*b) Cotton Boll Counting*

In order to count plants Oh,Sungchan, et al. [16] provides a deep learning-based method using data from unmanned aircraft systems (UAS). However, there are disadvantages when cotton is in a different stage of development. The program uses measures such as RMSE and R2 to assess how well it applies YOLOv3 and photogrammetry to UAS data. The Huang,Yuhan et al. [17] suggest a density-guided optimal transport strategy for cotton boll counting and localization at the same time. The technique maximizes counting and localization accuracy as measured by metrics like MAE, RMSE, Precision, and Recall based on optimum transport theory and VGG19.

Oh Fleming, Daniel et al. [18] discusses how well Bt cotton works to control lepidopteran pests, particularly Helicoverpa zea and Heliothis virescent. It suggests that although Bt cotton increased yields and reduced the need for pesticides, some Bt cotton cultivars eventually showed declining performance, most likely due to pest resistance. Sun.Shangpeng, et al. [19] describe image processing methods that use ambient light to count and identify cotton bolls in the field automatically. Although boll recognition accuracy has reached a high level, the research indicates that boll counting accuracy can still be further enhanced.

Lin, Zhe et al. [20], deep learning models—specifically, MobileNet and CenterNet—are used to identify and count cotton plants in the seedling stage based on UAS photographs. The models show good accuracy, although they require more training data when applied to photographs of different sizes. Among them are the assessment measures mAP, AR, MAPE, R2, and RMSE. With a focus on seedling detection, Yang Hao, et al. [21] offers a multi-object tracking technique that is accurate and yields good F1 scores for autonomously counting cotton seedlings.

Lin,Qianhui et al. [22] presents method featured with machine vision and SVM-base classifiers for automated cotton boll candidate recognition and counting. This remark is valid as the algorithm is known for incredible precision and an extremely direct connection with the real world which are two of its advantages, however, its accuracy level is affected by the environment. Bourland, F. M, et al. [23] utilized the number of main-stem nodes above the sympodial branch bearing the first white flower from the main axis (NAWF) as marker for the continuous plant growth. An easy-to-comprehend and functional index which virtually coincides with the daytime canopy photosynthesis is the net assimilation process (NAWF).

By contrasting supervised and poorly supervised deep learning models, Adke, Shrinidhi et al. [24] highlights the benefits of weakly supervised techniques with regard to annotation costs. The weakly supervised models attain competitive accuracy with lower annotation costs. Using high-resolution UAV photographs, Bawa, Arun et al. [25] proposes to combine spectral-spatial, supervised machine learning, and counting algorithms for cotton boll candidates. Because of its strong classification accuracy and consistency with ground reality, it is a promising method for forecasting the number of cotton bolls over large areas with various backgrounds. As previously noted, Table II shows the studies' contributions, limitations, algorithms, picture feature selections, and assessment metric scores.

**Table II:** An overview of earlier studies in the field of image-based counting of cotton bolls.

| **Reference Paper** | **Contribution** | **Limitation** | **Algorithms Used** | **Feature Considered** | **Evaluation Metric Score/ Conclusion** |
|---|---|---|---|---|---|
| [16] | UAS-driven plant enumeration | Variations in developmental stages | Photogrammetry - YOLOv3 | UAS data differences | 0.60 (RMSE) |
| [17] | Density-based cotton localization and counting | An uneven dispersion and occlusion | VGG19, ideal conveyance | Conditions in the cotton field | 10.54 (MAE) |
| [18] | Evaluation of Bt cotton's efficacy | Resistance to pests | Profound Learning | Background vs cotton | Clustering algorithms are less effective than deep learning |
| [19] | Image processing to identify cotton balls | Enhanced precision in counting | Algorithms for image processing | Natural lighting | 0.94 (F1 Score) |
| [20] | Deep learning for the identification and counting of cotton plants | Variations in dimensions | CenterNet and MobileNet | UAS images | 0.38 (RMSE) |
| [21] | Multiple-object tracking for counting cotton seedlings | Confined to young plants | Tracking and detecting objects | Videos with seedlings above | 0.8998 (RMSE) |
| [22] | Recognition and tally of cotton boll candidates | Sensitivity to the environment | SVM, or machine vision | UAV photos featuring backgrounds | 89.4% (Classification accuracy) |
| [23] | Observing the growth of cotton plants | Restricted growth phases | Plant Features | Background versus cotton | Survey Established |
| [24] | Evaluation of models with and without supervision | Thorough data annotation | Weakly supervised and supervised deep learning | RGB images | 0.5 (RMSE) |

| | | | | | |
|---|---|---|---|---|---|
| [25] | Using supervised and spectral-spatial learning for cotton boll counting | High-quality UAV photos | SVM, or machine vision | UAV images | Classification accuracy (>90%) |

## III. METHODOLOGY

The thorough process of this implementation, as shown in Figure 2, and presented as follows

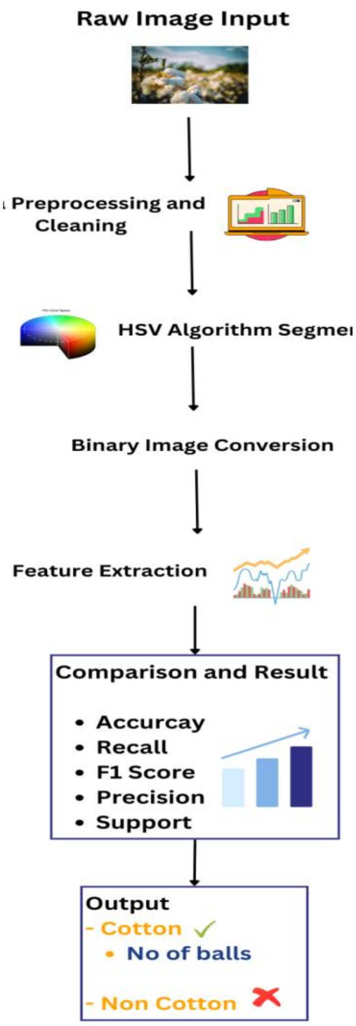


**Fig 2:** Detailed schematic representation of the proposed methodology

### 1. *Data Preparation*

Data collection followed a strict plan in order to create comprehensive data for cotton boll analysis. A great care is taken to collect a wide range of samples to ensure the representativeness of the images, and Google is used for high-quality images of cotton bolls. Ensuring data integrity and copyright compliance, images were selected with care from publicly accessible sources and attributed to the appropriate authors when necessary. The resilience and value of the images selected were increased by these images, which captured cotton bolls at different phases of growth, under varied lighting conditions, and against varied backgrounds. Before being used in the study, every photo was subjected to a thorough quality assessment, which eliminated any low-resolution or unnecessary samples.

### 2. *Data Preprocessing*

A preprocessing step is performed on the images to ensure data quality and relevance, aligning with the research objectives and setting the stage for in-depth analysis and accurate model training. The images underwent numerous important processing steps. It consisted of raw photos of cotton fields. Among these was image scaling on the 0.2-scale, which maximizes computer efficiency without sacrificing significant information. Boll recognition required distinguishing cotton bolls from the chaotic background, whereas boll counting required finding individual bolls and figuring out their total number. The color-based feature extraction made these tasks easier. The final image, or post-preprocessing, served as the main foundation for the study because it offered a clear, helpful, and organized framework for additional analysis and model creation.

*3. Segmentation using the HSV algorithm*

Cotton balls are segmented using the HSV algorithm. It is used to extract cotton bolls from photos and offers a helpful method for identifying things with particular color features. This method depends on the HSV color system's Saturation (S) channel. Because cotton bolls frequently have higher saturation values than the background, they can typically be differentiated from it . The algorithm uses this feature to differentiate cotton bolls from surrounding items such as leaves and branches. The operation of the HSV method in this implementation is demonstrated in Algorithm 1.

**Algorithm 1:** HSV algorithm

---

**Declare** pix, sat, thres

**for** pix **in** img:

Convert pix to HSV space

Store the sat (S) value

**if** S > thres **then**

pix = 1 (cotton boll)

**else**:

pix = 0 (background space)

**end if**

**end for**

---

The hue (Hue), in degrees, the saturation (Sat) and the value (Val) calculated on the RGB format formulated as -

$$Hue = \tan^{-1} (\sqrt{3} * (G - B), 2 * R - G - B)^2$$

$$Sat = 1 - 3 * (\min(R, G, B) / (R + G + B))$$

$$Val = \max(R, G, B)$$

Considering an example with RGB values of R = 100, G = 200, and B = 50. Using these data, HSV components can be calculated using the above example. The Hue (H), which represents the color's tint, is calculated using the arctangent function and the RGB components. The saturation (S), which represents the color intensity, is calculated by dividing the minimum of the RGB components by the sum of all RGB components. Finally, the maximum value from the RGB components is used to calculate the Value (V), which represents the color's brightness. Applying these formulae to the above RGB values gets the following HSV values: H = 98.13°, S = 0.5, and V = 200.

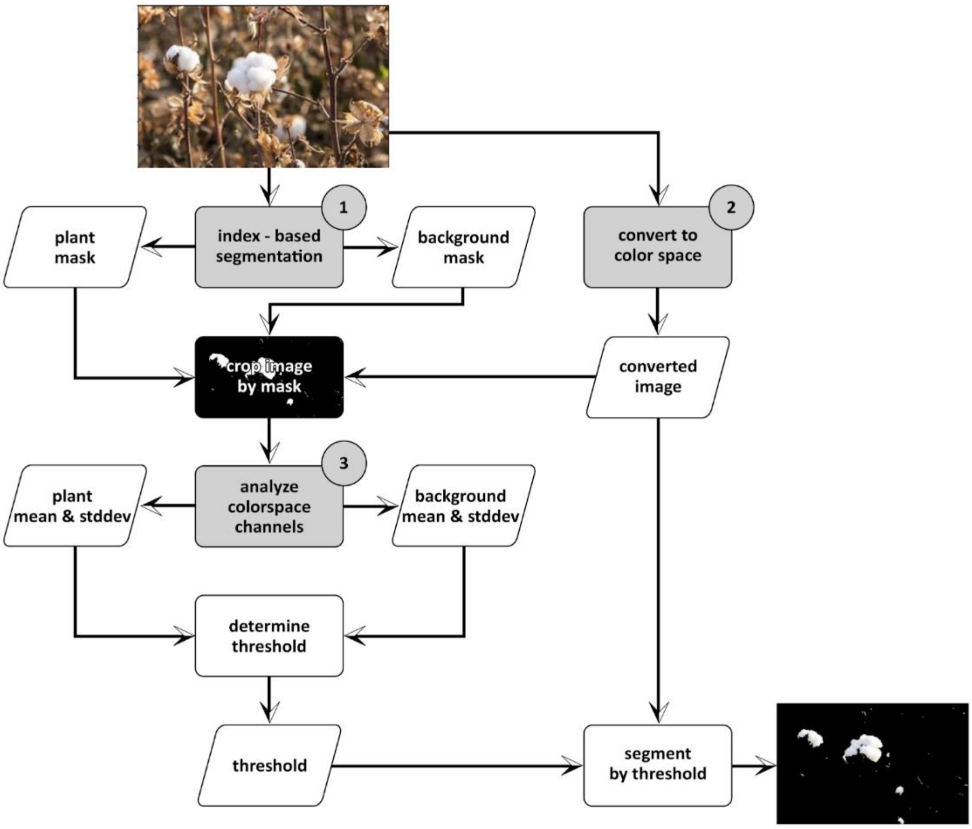


**Fig 3:** Infographic demonstrating the HSV segmentation of an image using color space channels and index segmentation

The Saturation channel is used to identify cotton boll pixels from background pixels because they have higher saturation values. Thresholding the S channel allows pixels to be classified into backgrounds and cotton bolls, enabling accurate segmentation. Figure 3 presents an illustration demonstrating the HSV segmentation of an image utilizing color space channels and index segmentation. The multi-step procedure shown in Figure 4 begins with the acquisition of the inputted image in order to isolate the region of interest. Next, index-based segmentation is used to separate the cotton bolls from the backdrop. An unneeded element is eliminated by creating a backdrop mask. The HSV color space is applied to the image in order to improve color-based analysis. The next step is to convert the image to the HSV color space in order to improve color-based analysis. Specific features are located by analyzing distinct color channels. The regions of interest are distinguished using suitable criteria. The lower threshold has been set at [0, 0, 200], and the upper threshold at [180, 30, 225].

*4. Binary Image Conversion Using Thresholding*

Binary classification tasks allow one to discriminate between pixels representing cotton bolls and background features such as vegetation, trees, and the topography of the field. The spatial and color-based data that were gathered during segmentation are combined to create a binary image. The cotton bolls are shown as white (pixel intensity one) in this binary representation, with black serving as the background. Thresholding is used to perform binary picture classification. Pixels are categorized into Cotton Bolls or Background classes based on whether their saturation value surpasses a predefined threshold, as shown in Algorithm 1.

*5. Feature Selection and Extraction:*

By carefully extracting essential features from images and identifying them, this approach ensures accurate counting and recognition of cotton bolls while minimizing noise and unwanted fluctuations in the data. Geometric features, including line features, position attributes, shape aspects, and size metrics, are obtained from each split region of interest. The selection and examination of these features play a crucial role in distinguishing cotton bolls from potential misleading elements such as small debris or artifacts. The meticulous choice of characteristics enhances the overall quality and effectiveness of the implementation in agricultural research and yield estimation. Moreover, it significantly improves the precision and accuracy of the algorithm in counting cotton bolls.

*6. Boll Detection and Counting*

After binary image classification and HSV-based segmentation, the cotton bolls are carefully segregated and isolated from their surroundings. Following that, data preparation is used to refine the segmented images. To recognize and count individual cotton bolls, geometric information such as position, shape, and size measurements are extracted from segmented binary images. To improve the segmentation process, a neighbor-based reassignment technique is used, which uses the S channel in the HSV colour space. Algorithm 2 describes how to extract cotton bolls from a picture and create binary masks for both the backdrop (R2) and cotton bolls (R1).

**Algorithm 2:** Cotton Boll Segmentation and Detection

---

**Input:** img

hsv_img = cv2.cvtColor(raw_image, cv2.COLOR_BGR2HSV) *Convert Image to HSV Space*

s_channel = hsv_img[:, :, 1] *Extract the Saturation (S) channel*R1 = s_channel < x1 *Initialize binary masks for region R1*

R2 = s_channel >= x2 *Initialize binary masks for region R2*

neig_ker = np.array([[0, 1, 0], [1, 0, 1], [0, 1, 0]], dtype=np.uint8) *Create a binary kernel*

Iterate until convergence

R3 = np.logical and(s_channel > x2, s_channel < x1) *Calculate R3 as the x1  x2*

R3_neig_R1 = cv2.filter2D(R3.astype(np.uint8), -1, neig_ker) > 0 *Find pixels in R3 that have neighboring pixels in R1*

assigned = np.logical_and(R3, R3_neighbors_R1 *Reassign pixels from R3 to R1 based on neighbor criteria*

R1 = np.logical_or(R1,assigned) *Update R1 based on pixel reassignments*

R3 = np.logical_and(R3, np.logical_not(assigned)) *Update R3 based on pixel reassignments*

Check for convergence else exit  loop

R2 = np.logical_or(R2, R3)

**Display:** R2 (background), R1 (cotton bolls)

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**Algorithm 3:** Cotton Boll Count

---

**Input:** img (Algorithm 2 Output)

img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

thres = cv2.thres(img, 200, 255, cv2.THRESH_BINARY) *Apply a binary threshold*

contours = cv2.findContours(thresholded,cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE) *Find contours*

bound_rect = [] *Initialize an empty list to store bounding rectangles*

Initialize count as 0

**for** cont **in** list_of_cont:

  area = cv2.contourArea(cont) *Calculate the area*

    **if** area > area_thres **then**

    x, y, w, h = cv2.boundingRect(cont) *Obtain the bounding rectangle*

  **end if**

  bound_rect.append((x, y, w, h)) *Append the coordinates of the bounding rectangle to the list of bounding_rectangles*

  img_with_rect = cv2.cvtColor(image,cv2.COLOR_GRAY2BGR) *Create an image_with_rectangles by converting the original grayscale image to RGB*

  **for** bound_rect in list_of_bound_rect:

    cv2.rectangle(img_with_rect, (x, y), (x + w, y + h), (0, 255, 0), 2) \\. *Draw a green rectangle around the cotton boll on image_with_rectangles*

    Increment count by 1

  **end for**

**end for**

**Display:** img_with_rect.

A 250 threshold size has been contemplated. More than 250 cotton bolls have been counted.

$$Cotton\ Bolls\ Count = \sum(Size\_of\_i > 250)$$

Where, Size_of_i: Size of each segmented cotton boll.

In general, contours with an area of less than 250 may be false positives; thus, this threshold helps to verify that the cotton bolls tallied are clearly defined. The bounding boxes (green) around the cotton bolls were created with OpenCV's find Contours tool. This thorough approach ensured that the entire pipeline was adapted to match the specific needs of agricultural research, making accurate counting easier while also providing informative data for measuring crop health and cotton output. The program shows how to count cotton bolls in a binarized image by recognizing contours, applying an area-based filter, and enclosing them with green bounding rectangles. The recovered cotton bolls are then counted

and visualized for further analysis.

*7. Evaluation Metrics*

Accuracy is the ratio of accurately predicted instances to the total number of cases, including True Positives and True Negatives.

$$Accuracy = \frac{TN + TP + FN + FP}{\mathrm{TN} + \mathrm{TP}}$$

Precision determines the accuracy of positive predictions by dividing the percentage of correctly predicted positive instances (Cotton) by the total number of anticipated positive instances.

$$Precision = \frac{TP}{FP + TP} .$$

An impartial assessment of a model's performance is offered by the F1-Score, which is the harmonic mean of recall and precision. It provides beneficial information in cases where there is an uneven distribution of courses or data points.

$$F1\ Score = \frac{2. Recall. Precision}{Recall + Precision}$$

Recall quantifies the model's ability to identify every instance of a positive class. It is the percentage of all positively impacted occurrences (cotton bolls detected) that were correctly predicted to happen.

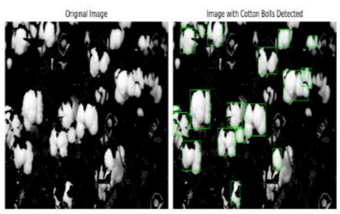
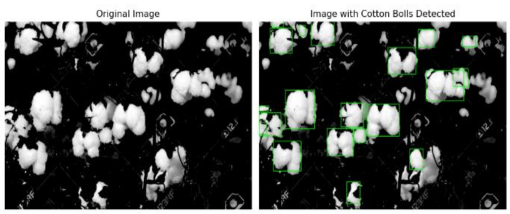
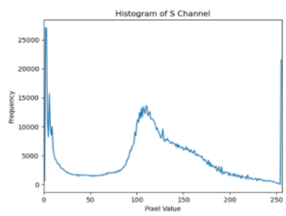
$$Recall = \frac{TP}{TP+FN} .$$

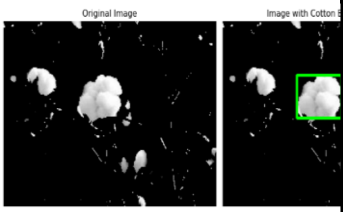
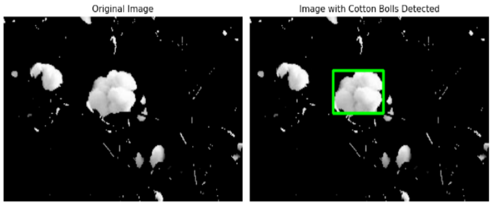
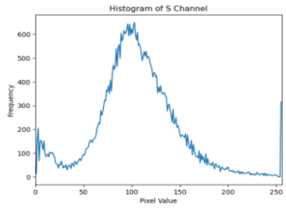
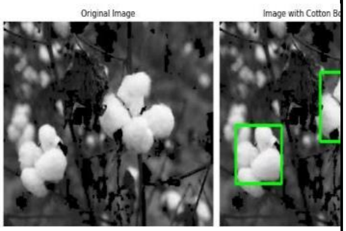
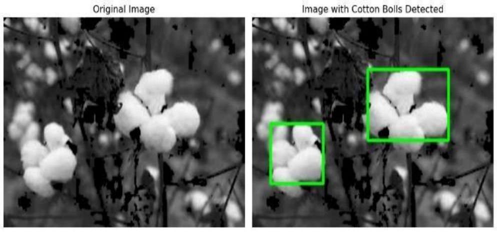
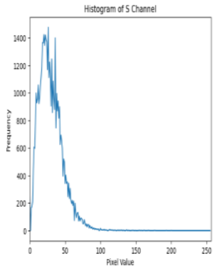
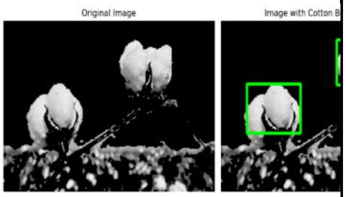
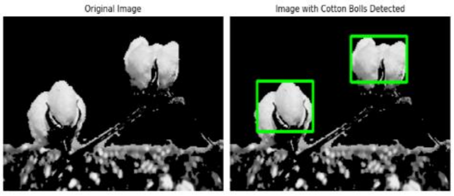
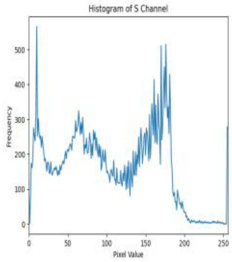
Support metric demonstrates the number of examples in the images for each class. Here it indicates the amount of each type (cotton and non-cotton).

## IV. EXPERIMENTAL RESULTS

Here is an example of what was found during the experiment. Table III displays four input images: the number of cotton bolls detected, the saturated image with recognized delimited segments, and the matching inputted image's histogram S channel. The cotton boll count, which provides quantitative data and indicates the total number of bolls visible in the photos, is one of the most significant indicators for yield estimation. The S channel histograms showed the color features of the segmented cotton bolls, which may have implications for figuring out the age and condition of the bolls.

**Table III:** Result images, cotton boll count, and histograms of the S (Saturation) channel

| Inputted Mask Image | Segmented Image | Histogram S channel | Bolls Counted |
|---|---|---|---|
|  |  |  | Number of cotton bolls detected are: 20 |

| | | | |
|---|---|---|---|
|  |  |  | Number of cotton bolls detected are: 1 |
|  |  |  | Number of cotton bolls detected are: 2 |
|  |  |  | Number of cotton bolls detected are: 2 |

The confusion matrix shows the level of accuracy achieved by the model. The data confusion matrix, shown in Figure 4, not only summarizes the performance results of our cotton boll recognition model but also gives a more detailed view of the model's inner process. It has two main components - PC (Cotton) and NPC (Non-Cotton) - which show the number of true positives (TP) and true negatives (TN) that correctly identify cotton bolls and non-cotton areas, respectively.

There is a controversy when authentic cotton bolls, which are recognized as other non-cotton materials, are identified as false negatives (FN). Firstly, the true positives (TP) are instances where the model correctly identifies regions that aren't of cotton as cotton bolls. The categorization of objects during agricultural analysis can be widely effective through the use of metrics such as precision, recall, and accuracy, which are absolutely obligatory. This study also aims at the precise identification and differentiation of cotton bolls from their surroundings, forming one part of this inspection.

The confusion matrix in Figure 4 has four values:

- 4 denotes the number of cases that were correctly categorized as non-cotton bolls (true negatives),
- 0 represents cases that were classified as cotton bolls but were wrongly regarded as non-cotton bolls (false negatives),
- 1 classifies cases that were not cotton bolls yet were considered as cotton bolls (false positives), and
- 16 shows the cases that were correctly grouped as cotton bolls (true positives).

Finally, the model was able to differentiate cotton bolls from non-cotton bolls effectively, avoiding mistakes, but also sometimes did not detect some cotton bolls at all.

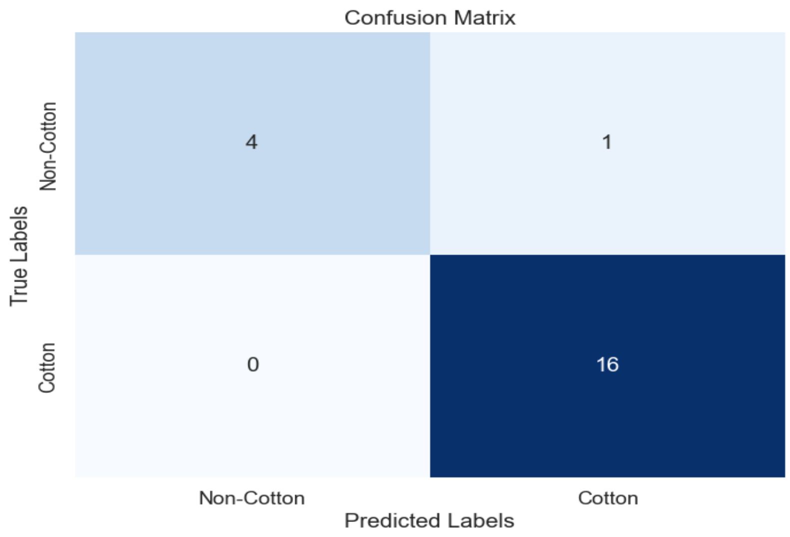



**Fig 4:** Confusion Matrix

The model's performance is detailed in Table IV, presenting crucial metric scores in the classification report that offer insights into its effectiveness in identifying cotton bolls. The precision score for the "Cotton" class is notably high at 0.94, indicating the model's accuracy in correctly labeling cotton bolls as positive predictions. Impressively, the model minimizes false positives to just 6%, showcasing its proficiency in reducing incorrect classifications.

For the "Non-Cotton" class, the model achieves a precision score of 1.00, underscoring its exceptional capability to distinguish non-cotton objects while maintaining an exceedingly low rate of false positives. This distinction is crucial for accurately identifying cotton bolls amidst other field components. Demonstrating its effectiveness, the model attains a recall score of 1.00 for the "Cotton" class, highlighting its ability to identify each actual cotton boll in the images. The high recall score indicates the model's success in minimizing false negatives, ensuring a minimal loss (if any) of cotton bolls during classification.

Additionally, the model achieves a recall score of 0.80 for the "Non-Cotton" class, signifying its accurate classification of most non-cotton objects with only a small fraction (20%) of false negatives. This performance further emphasizes the model's overall effectiveness in distinguishing between cotton and non-cotton elements in the images.

**Table IV:** Evaluation Metrics Score - Classification Report

| | Recall | Precision | Support | F1-Score |
|---|---|---|---|---|
| Cotton | 1.00 | 0.94 | 16 | 0.97 |
| Non-Cotton | 0.80 | 1.00 | 5 | 0.89 |
| Weighted average | 0.95 | 0.96 | 21 | 0.95 |
| Macro average | 0.90 | 0.97 | 21 | 0.93 |

The support score achieved is 21 and overall test accuracy achieved is 95%.

## V. Future Scope

The importance of future initiatives which will improve this area of research are also included in this section. Among the supervised machine learning and deep learning algorithms implemented in this field of study, CNN and its variants have been employed as the primary means of developing an automatic solution. As these architectures can identify complex spatial and color-sensitive features without manually requiring feature engineering, feature engineering might no longer be a priority. An integrative system that is capable of capturing different cotton varieties and field situations has been created to respond to the call for the research field particularly in regards to cotton boll identification and counting. Cotton fields found outdoors instead are often sufficiently dissimilar in area lighting, plant diversity, and boll dimensions. It is very important to delve into the progression of diverse algorithms which can handle many variations. The involvement in multi-parametric data collection, by using the thermal imaging or hyperspectral imaging, for example, have a great potential of providing comprehensive information on cotton boll development and health status. Enlarging the research to represent cotton pest detection or crop disease monitoring is another potential extension which can be done based on the foundation of image processing and computer vision established in the hot boll analysis project. Adopting this method can remarkably enhance the crop management techniques, and consequently, the food security of the world will be ensured.

## VI. Conclusion

The aim of this study is to design a simple algorithm which can differentiate and assess the cotton bolls in an innovative way. A system that can deliver accurate cotton boll segmentation and counting without complex deep learning models, using simple image processing techniques, has been developed." This approach makes the process simpler in the application and can be applied in resource-limited areas and agriculture. This low-weight technique can be taken as a very important application in the agricultural sector which often lacks computational resources or money. Hence, this study warrants the adoption of practical, easy to implement strategies that respond effectively to real-world problems to bring about efficient and sustainable farming practices.

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