

COT-AD: Cotton Analysis Dataset

I. KEY CONTRIBUTIONS

The key points and problems addressed in this work:

- Dataset Documentation
- Need of Cotton data
- Methodology
- Object Segmentation and Restoration
- Data Acquisition
- hardware specificaiton
- Insights from fields
- Dataset for Disease detection in crop
- Dataset Access and storage
- Dataset Organization
- Acknowledgements

II. DATASET DOCUMENTATION

Description

This dataset comprises high-quality aerial and DSLR images designed for advanced agricultural applications, particularly targeting cotton crops. The aerial images offer extensive coverage suitable for detection and segmentation tasks, aiding in the analysis of crop growth and land use efficiency. The DSLR images are specifically curated for detailed classification of crop diseases, promoting early detection and management.

Dataset Link

<https://kaggle.com/datasets/fd33db9983dd2b32d1b2f7dec30f26882265a34e6b4bef16ff1756a5c7137da6>

Data Subject(s)

Detection, Segmentation, Disease Detection, Restoration, Synthesis

Data Type

Dataset consists of Aerial and DSLR Images along with videos of Cotton crops in two farms for the entire life cycle.

Volume

Approximately 330 GB.

Total Number of Images

The dataset comprises more than 25,000 images.

Total Number of Videos

The dataset comprises more than 140 videos.

Image Format

The images are in JPG and JPEG formats.

Time Frame of Data Collection

Collected over a full harvest cycle of cotton crops across two farms.

Data Source

Aerial images captured through drones with an altitude of [10,15,115] Meters.

DSLR images taken in zoomed in mode.

Label Details for Aerial Images

Separate folders containing the images; **segmentation masks**, that is, the binary masks for crop segmentation in *JPG* format; **segmentation labels** for crop segmentation in YOLO standard *.txt* format; and **detection labels** for crop detection in YOLO standard *.txt* format.

Label Details for DSLR Images

Each disease type is organized into distinct folders containing the corresponding *JPG* images.

Annotation Details

Each image underwent meticulous manual annotation followed by several rigorous rounds of quality checks to ensure high accuracy and reliability.

Version Details

Current Version is 1.0

Maintenance Status

Limited Maintenance - The data will not be updated, but any technical issues will be addressed.

Sample of Data

Provided in **Figure 2** and **Figure 3** of main paper.

Dataset Organization

The dataset organization is provided in Section X

Training and Validation Codes

Click here to access the training and validation codes.

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DOI

10.34740/kaggle/dsv/10654288 AND 10.34740/kaggle/dsv/10654658

Author statement

We state that we bear all responsibility in case of violation of rights, etc.

III. NEED OF COTTON DATA

Agriculture and food management are critical challenges that the world will face in the near future. Advancements in crop management and sustainable practices will be essential to ensure adequate food supplies. Utilizing aerial vehicles and cameras combined with advanced computer vision techniques can address various aspects of crop management, such as disease detection, weed density analysis, and harvesting information, enabling farmers to make timely and informed decisions. This paper presents two comprehensive datasets focused on cotton crops: an aerial dataset capturing the crop's entire life cycle and a dataset of up-close DSLR images detailing various diseases affecting cotton crops at different stages. The aerial dataset is meticulously annotated for cotton crop detection and segmentation, offering valuable insights into vegetation and weed competition in specific farm areas. The DSLR dataset includes images of leaf diseases, cotton boll rot, and red cotton bugs, facilitating the classification and early management of cotton diseases. Our dataset fills a crucial gap in the current agricultural repositories by providing detailed segmentation data tailored for cotton crops, enhancing its utility for both plant-level and field-level detection and segmentation tasks. With more than 5000 manually annotated images, captured weekly over a complete harvest cycle, it is one of the most comprehensive datasets available. These datasets can serve as benchmarks for developing advanced technical solutions to improve agricultural practices, paving the way for more efficient and sustainable farming. Agriculture and food management are critical challenges that the world will face in the near future. Advancements in crop management and sustainable practices will be essential to ensure adequate food supplies. Utilizing aerial vehicles and cameras combined with advanced computer vision techniques can address various aspects of crop

management, such as disease detection, weed density analysis, and harvesting information, enabling farmers to make timely and informed decisions regarding crop management. This paper presents an aerial dataset of cotton fields captured throughout the crop's life cycle and a dataset with up-close DSLR images of various diseases affecting cotton crops at different life cycle stages.

IV. METHODOLOGY

Harnessing Crops Detection in Modern Farming. In smart farming, accurately detecting crops is essential for enhancing agricultural productivity and sustainability. Our dataset facilitates precise crop detection and is foundational for numerous smart farming applications. This technology enables effective crop health and growth monitoring using drones equipped with object detection capabilities. Timely identification helps in applying targeted interventions, ultimately supporting healthier crop yields. Accurate crop detection is vital for optimizing the use of agricultural inputs such as water, fertilizers, and pesticides. By precisely identifying crop locations and conditions, farmers can apply these resources more judiciously, reducing waste and environmental impact. This targeted approach not only conserves resources but also enhances crop health by ensuring that interventions are applied exactly where and when they are needed. Crop detection plays a significant role in automating and refining the harvesting processes of cotton buds. By accurately identifying mature crops and buds, automated systems can efficiently harvest them at the peak of ripeness, reducing labour costs and minimizing damage to crops and soil.

Harnessing Crops Segmentation in Modern Farming. Detection in agricultural imagery identifies the presence or absence of specific objects such as weeds, diseased plants, or different crop types. This process is typically quick and efficient, providing a useful method for initial assessments over large areas. While detection helps identify problems, it does not offer detailed insights into the extent or severity of these issues. Segmentation, on the other hand, is more detailed and involves dividing an image into distinct segments or regions based on pixel characteristics like colour, texture, or shape. This approach allows for the precise identification and isolation of specific objects or areas within the image, such as individual plants or different types of weeds.

The primary benefit of crop segmentation is the accurate identification and delineation of individual plants within larger fields. This precision is crucial for effective crop yield estimation. By understanding the specific characteristics of each plant, such as size, density, and overall health, farmers can make accurate predictions about yield. This information helps in planning resource allocation and scheduling harvest operations more efficiently. Another critical application of crop segmentation is in the management of weeds. The ability to differentiate between crops and weeds within imagery enables targeted interventions. Farmers can apply herbicides or perform weed removal precisely where needed, significantly reducing the amount of chemicals used and minimizing their impact on the crops and environment. Disease and pest management also benefits greatly from accurate crop segmentation. Early detection of affected areas allows for targeted treatment, preventing disease spread and minimising crop yield damage. By isolating and treating only the affected areas, farmers can use pesticides more sparingly and effectively.

V. OBJECT SEGMENTATION AND RESTORATION

We performed object segmentation in both supervised and unsupervised settings. In the supervised setting, we used Segment Anything Model (SAM) [2], and in unsupervised setting, we used the Deep Spectral method [3]. DSM extracts features from a self-supervised pre-trained network and uses spectral graph theory on feature correlations to obtain eigenvectors. These eigensegments correspond to semantically meaningful regions with well-defined boundaries. Qualitative outputs on proposed dataset are shown in Fig(3, 1).

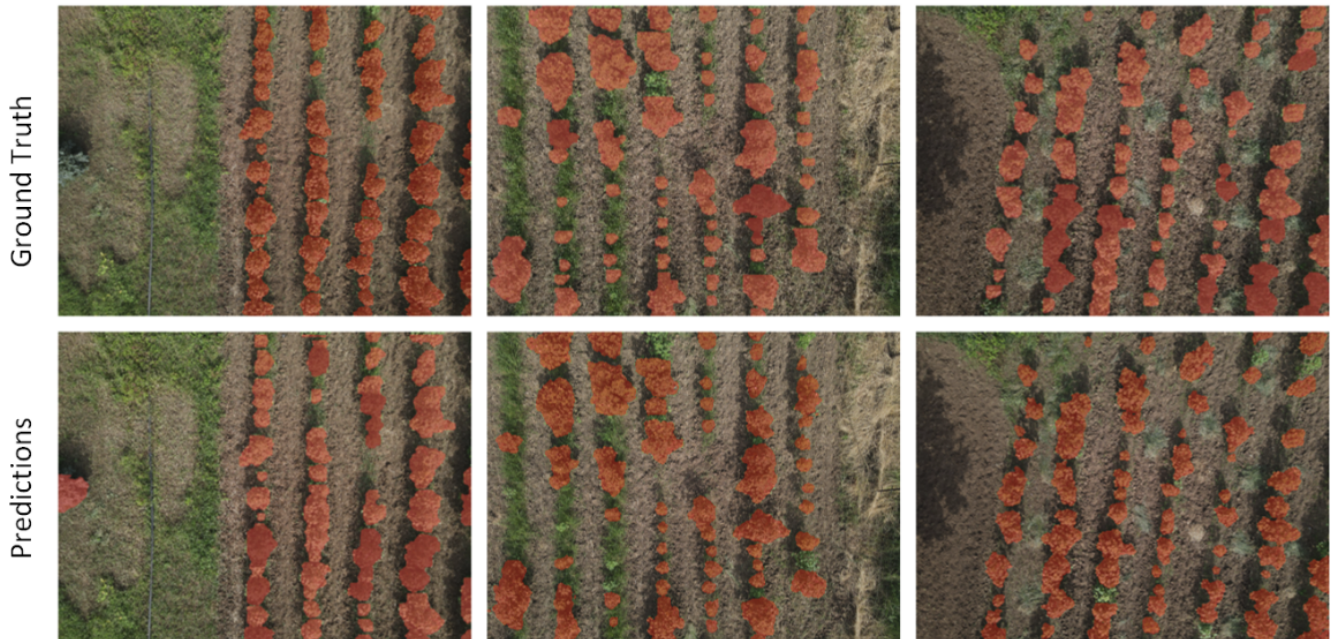


Fig. 1: Comparison of segmentation results for YOLOv11 against the ground truth. The top row displays the ground truth annotations, and the bottom row illustrates predictions by YOLOv11.

Image restoration is essential for addressing noise, artefacts, low resolution, and missing data in computer vision. We explored a robust unsupervised restoration [1] framework using a StyleGAN-based architecture and the Bilateral Graph Regularization Model (BGRM) for improved restoration across degradation scenarios. Evaluated on denoising, deartifacting, upsampling, and inpainting tasks with drone and DSLR image datasets, the results show significant quality improvements and state-of-the-art performance(see Fig.(2).

A. Data Acquisition

The acquisition of data for our crop detection and segmentation dataset was meticulously planned to capture the detailed growth cycles of cotton crops. Using drone technology, we conducted aerial surveys of two cotton fields throughout their life cycle. The drones operated at altitudes ranging from 10 to 15 meters, providing a balanced perspective for capturing high-resolution images without compromising the detail necessary for precise segmentation and detection tasks. The drone flights were scheduled at regular intervals to ensure that each phase of the crop growth was adequately documented. This systematic capture process allowed us to monitor the developmental stages of the cotton plants. Also, it enabled the identification of various agricultural phenomena, such as weed proliferation, pest infestations, and disease outbreaks. The hardware specification of the drone is provided in Appendix VI.

Addressing Variable Conditions. During data collection, we faced a range of lighting and weather conditions, which could potentially impact the quality of the imagery. To mitigate these effects, we utilized drones equipped with sensors capable of adjusting exposure and focus dynamically. This adaptability was crucial for maintaining image quality during early morning, late evening, or cloudy conditions. Moreover, we programmed flight paths to avoid adverse weather conditions like heavy winds or rain, which could disrupt the clarity of the images.

Quality Control Measures. To ensure the reliability and accuracy of our dataset, we implemented several quality control measures. Each batch of images was initially reviewed for clarity and coverage by a team that could flag any issues with image quality due to drone stability or sensor performance. Images not meeting our high standards were rescheduled for recapture during the next appropriate flight window. Additionally, the manual annotation process was cross-verified in multiple stages to prevent mislabeling and ensure that the data accurately represented the observed agricultural conditions.

VI. HARDWARE SPECIFICATION FOR DATA COLLECTION

RGB Drone (DJI MAVIC Air 2s) — DJI Mavic Air 2s capture Red, Green, and Blue- visible spectra, creating humanly recognizable coloured images with a maximum flight distance of up to 18.5 km and with a maximum flight time of around 30 minutes (under no wind conditions). It has GNSSconnectivity of GPS + GLONASS + Galileo constellations. A camera with 20 MP is integrated with the drone on a 3-axis Gimbal. Figure 4 shows the DJI Mavic Air 2s flying for the survey.

DSLR Camera (Canon EOS 80D (W)) — Canon EOS 80D (W) is a versatile and high-performance digital single-lense reflex camera with a CMOS sensor with approximately 24.2 megapixels and DIGIC 6 image processor. The 45-point all-cross-type autofocus system allows high precision and high-speed performance with a maximum of approximately 7.0 fps continuous shooting and wireless functions. Figure 4 shows the Canon EOS 80D (W) used in capturing cotton disease images.

VII. INSIGHTS FROM THE FIELDS

Table II provides a detailed month-by-month analysis of cotton farms using aerial imagery. This analysis helps understand the dataset in greater depth as it curates the crops across its growth stages throughout the season.

Table III provides a detailed month-by-month analysis of diseases seen in the cotton crops. This analysis helps identify disease occurrence and progression patterns, denoting timely and effective data collection and stats throughout the growing season.

VIII. DATASET FOR DISEASE DETECTION IN CROPS

Cotton Crops are susceptible to pests, diseases, climate changes and weed competition. Primarily, the types of insects found during cultivation include Jassids/Aphids, Thrips, Whiteflies, and bollworms, and the diseases include bacterial blight, fungal leafspots, root rot, leaf curling, leaf reddening, etc. To support the management of diseases and pests, high-resolution images of the diseased part of the cotton plants were systematically captured from the cotton farm. Leaf diseases such as bacterial blight, leaf spots and leaf reddening, and pink boll rotting were prominently present towards the end of the crop's lifecycle. Pesticides were intentionally avoided on the farm to allow diseases to spread naturally. Experts meticulously captured the abnormalities present in the plants to develop a comprehensive dataset. Red Cotton Bugs and Mealy Bugs were notably present in certain farm sections during their maturity period.

The diseases and bug infestations were the primary reason to capture images with a high-resolution DSLR camera. Collection of the *High-Resolution DSLR Images of Cotton Crop Insights* aims to provide a benchmark for classifying cotton diseases. It can be used to get information about the diseases present on the farm, such as their names, causes, measures to be taken, and pesticide information to decrease their effect.

A. Data Annotation and Organization

Once the imagery was collected, the annotation process began. Each image was manually annotated, labelling the cotton crops within the images. Manual annotation ensures high data accuracy, crucial for training effective machine learning models.

The folder structure for the annotated data is organized under the *Detection and Segmentation Task* directory, which is divided into four main parts: Part A (data from the first two months), Part B (data from the third month), Part C (data from the fourth month), and Part D (data from the fifth and sixth months). A comprehensive specification of the dataset structure is included in the supplementary materials.

IX. DATASET ACCESS AND STORAGE

We have shared the COT-AD dataset on Kaggle [4], which comprises approximately 330 GB of data. The training and validation codes are included in the supplementary material. Researchers and practitioners interested in accessing the dataset can visit the following link — <https://kaggle.com/datasets/fd33db9983dd2b32d1b2f7dec30f26882265a34e6b4bef16ff1756a5c7137da6>. The dataset is intended for non-commercial use.

X. DATASET ORGANIZATION

Aerial Images for Detection and Segmentation: The data for detection and segmentation tasks is organized under the directory named *Aerial Images for Detection and Segmentation*, which is segmented into four main parts:

- **Part A:** Data from the first two months.
- **Part B:** Data from the third month.
- **Part C:** Data from the fourth month.
- **Part D:** Data from the fifth and sixth months.

Each part includes four subfolders:

- **Images:** Holds *JPG* aerial images of cotton crops.
- **Detection Labels:** Stores YOLO-formatted *.txt* files for single-class detection tasks.
- **Segmentation Masks:** Holds *JPG* binary masks for cotton crop segmentation.
- **Segmentation Labels:** Contains YOLO-formatted *.txt* files tailored for segmentation tasks.

Dataset for Disease Classification: Organized under the directory *High-Resolution DSLR Images for Cotton Crop Insights*, the classification of images is based on three categories – Leaf Disease, Cotton Boll and Bugs.

- The **Leaf** folder contains the four subdirectories – Yellowish Leaf, Leaf Spot Bacterial Blight, Leaf Reddening, and Fresh Leaf.
- The **Cotton Boll** folder contains the three subdirectories – Boll Rot, Damaged Cotton Boll, and Healthy Cotton Boll.
- The **Bugs** folder contains two subdirectories – Mealy Bug and Red Cotton Bug.

This organization enhances the accessibility and efficiency of data processing for various model training purposes related to detection, segmentation and disease classification tasks. This organization of the dataset is pictorially depicted in Figure 6.

ACKNOWLEDGMENTS

This research and data collection is funded by L&T Technology Services Limited, Vadodara, India, in collaboration with the Indian Institute of Technology, Gandhinagar, India. We thank the research group of L&T Technology Services, specifically Mr Ashokkumar Jain, Mr Pushkar Shaktawat, and Mr Nikhil Dev. Additionally, we would like to acknowledge the efforts of Mr Prakram Singh Rathore, Mr Medhansh Singh, Mr Pavidhar Jain, Mr Yash Khandelwal, and Mr Harshvardhan Vala at the Indian Institute of Technology Gandhinagar for help with annotating the aerial images.

REFERENCES

- [1] Yohan Poirier-Ginter and Jean-François Lalonde, “Robust unsupervised stylegan image restoration,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 22292–22301.
- [2] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al., “Segment anything,” in *iccv*, 2023.
- [3] Luke Melas-Kyriazi, Christian Rupprecht, Iro Laina, and Andrea Vedaldi, “Deep spectral methods: A surprisingly strong baseline for unsupervised semantic segmentation and localization,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 8364–8375.
- [4] “Kaggle: Your Machine Learning and Data Science Community — kaggle.com,” <https://www.kaggle.com/>, [Accessed 06-06-2024].

Method	DSLR Cotton Crop Data			Drone Cotton Crop Data		
	LPIPS↓	LPIPS- vgg↓	PFID↓	LPIPS↓	LPIPS- vgg↓	PFID↓
Deartifacting (JPEG Compression)						
L	0.584	0.619	121.419	0.598	0.588	120.462
M	0.576	0.613	115.922	0.583	0.580	112.291
S	0.573	0.611	114.228	0.579	0.576	113.928
XL	0.6	0.633	118.723	0.615	0.601	157.034
XS	0.571	0.609	115.213	0.577	0.575	113.201
Denoising (Clamped Poisson and Bernoulli Mixture)						
L	0.58	0.628	116.625	0.576	0.583	130.393
M	0.573	0.62	113.264	0.570	0.579	115.636
S	0.567	0.613	109.726	0.568	0.575	114.738
XL	0.592	0.64	115.037	0.591	0.591	146.684
XS	0.56	0.607	113.883	0.562	0.571	107.531
Inpainting (Random Strokes)						
L	0.553	0.596	126.934	0.527	0.553	112.856
M	0.548	0.59	121.841	0.528	0.552	106.999
S	0.542	0.585	114.523	0.524	0.549	104.970
XL	0.558	0.602	133.558	0.533	0.557	109.472
XS	0.551	0.59	114.447	0.543	0.556	96.843
Upsampling (Bilinear, Bicubic or Lanczos)						
L	0.619	0.642	129.074	0.604	0.599	154.395
M	0.598	0.632	126.482	0.606	0.598	140.140
S	0.581	0.619	119.499	0.592	0.587	103.984
XL	0.628	0.651	130	0.620	0.609	161.933
XS	0.566	0.605	116.894	0.578	0.577	102.341
2 Degradations						
AP	0.57	0.61	121.229	0.542	0.569	112.517
NA	0.584	0.627	114.7	0.584	0.589	136.752
NP	0.57	0.615	122.015	0.538	0.566	118.027
UA	0.639	0.673	127.588	0.636	0.617	163.628
UN	0.623	0.66	116.295	0.604	0.605	140.503
UP	0.588	0.626	120.72	0.573	0.583	139.341
3 Degradations						
NAP	0.578	0.621	122.239	0.542	0.569	123.345
UAP	0.617	0.66	124.197	0.592	0.596	119.654
UNA	0.644	0.68	119.279	0.614	0.612	138.181
UNP	0.624	0.654	124.385	0.557	0.578	108.822
4 Degradations						
UNAP	0.638	0.67	120.707	0.598	0.591	107.681

TABLE I: Performance matrices of the RUSIR [1] for image restoration on cotton crop data from DSLR and Drone cameras, evaluated across five levels (S, M, L, XL, XS) for single degradation types (deartifacting, denoising, inpainting, and upsampling), we also used multiple degradations. The RUSIR method uses a consistent set of hyperparameters across all levels, while baselines are optimized for accuracy at each individual level. The reported metrics include Accuracy (LPIPS), Fidelity (LPIPS-vgg), and Realism (PFID), with lower values indicating better performance.

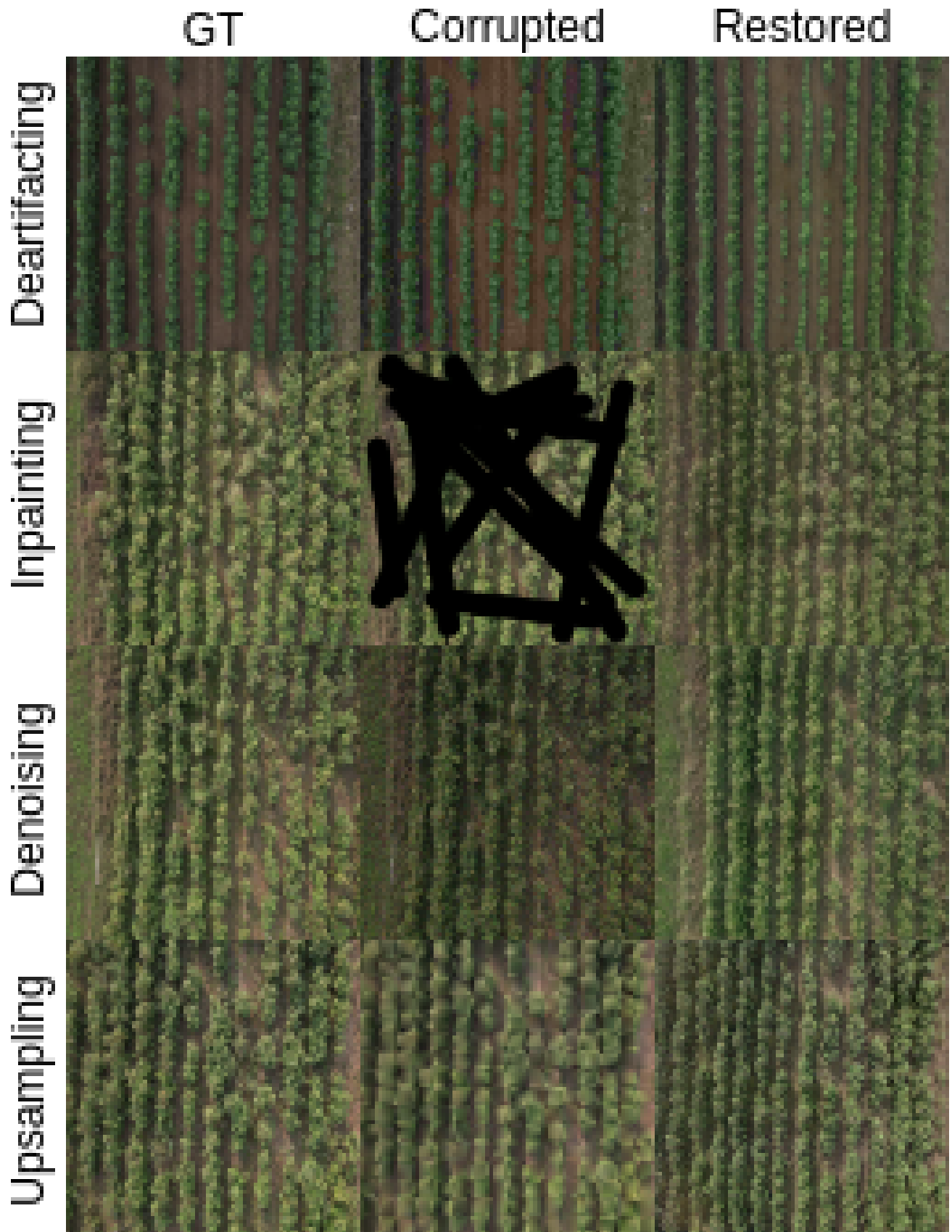


Fig. 2: Image Restoration Results .

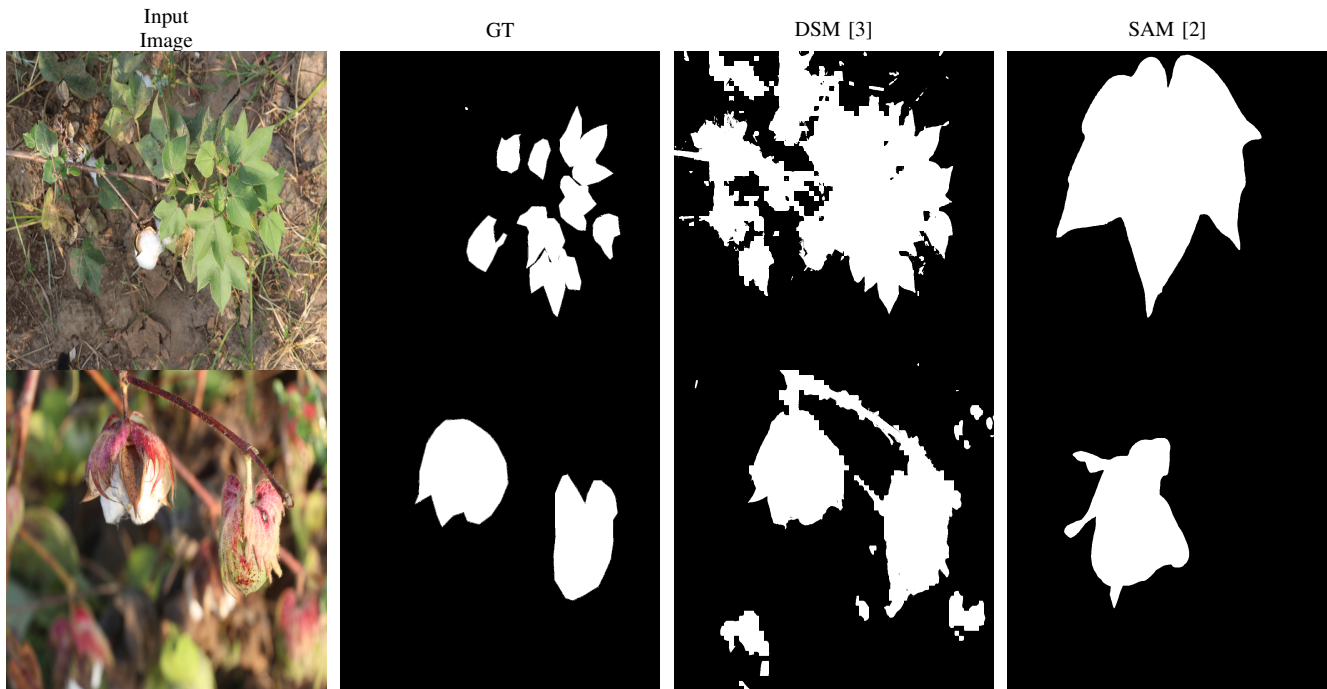


Fig. 3: Object Segmentation with supervised (SAM [2]) and unsupervised [3] methods.



(a)



(b)

Fig. 4: Data Acquisition Equipment: (a) DJI MAVIC Air 2s (b) DSLR Camera Canon 80D (w) *Image Source: Canon Asia*)

TABLE II: Month-wise interpretation of cotton farms for aerial imagery

Month #	Stage of Cotton	Interpretation
Month 0	Root establishment	Plantation and cotton plants started growing.
Month 1	Leaf Area Expansion and Flowering	Plants were growing and leaf area increased. In the last week, flowering started in some plants.
Month 2	Flowering + cotton boll development	Flower development in good amount. Cotton boll development. Very few cotton bolls started opening.
Month 3	Flowering + cotton boll development + cotton boll opening	Flowering and cotton boll development increased.
Month 4	Flowering + cotton boll development + cotton boll opening and harvesting	Flowering and cotton boll development seen across the farm. In some farm areas, plants were seen moving towards the end of the life cycle.
Month 5	Flowering + cotton boll development + cotton boll opening and harvesting	Cotton bolls are harvested in between. Many plants move toward the end of their life cycles.
Month 6	Cotton Boll opening and harvesting	New cotton flowering stops. The rest of the bolls are developing and opening, and many plants are in the final stages of their life cycle.

TABLE III: Month-wise interpretation of cotton farm for disease classification

Month	Stage of Cotton	Diseases Seen	Interpretation
Month 2	Flowering + cotton boll development	Mealy Bug development	The plants are growing. Mealy bug infestation started on some leaf and branches. Towards the end of the month, yellowish-ness was visible in plants.
Month 3	Flowering + cotton boll development + cotton boll opening	Mealy Bug + Leaf Disease symptoms + some cotton bolls started having pink spots	Mealy bug infestation found in both the farms. The leaf diseases started growing. Spots started developing in some leaves. Some cotton bolls started having pinkish spots.
Month 4	Flowering + cotton boll development + cotton boll opening and harvesting	Leaf Disease + Pink Cotton Boll Rot + Red Cotton Bug	Leaf disease and infection increased with time. Cotton Boll pink spot increased. Mealy Bug numbers dropped. Red Cotton Bugs presence developed.
Month 5	Flowering + cotton boll development + cotton boll opening and harvesting	Leaf Disease + Pink Cotton Boll Rot + Red Cotton Bug + Leaf Reddening	Same as above. Additionally, Leaf reddening symptoms started to increase. Red cotton Bugs infestation decreased with time.
Month 6	Cotton Boll opening and harvesting	Leaf Disease + Pink Cotton Boll Rot + Leaf Reddening	Leaf disease, leaf reddening and cotton boll rotting increased, many cotton bolls were dropped before maturity. Till the end, all the plants were infected.

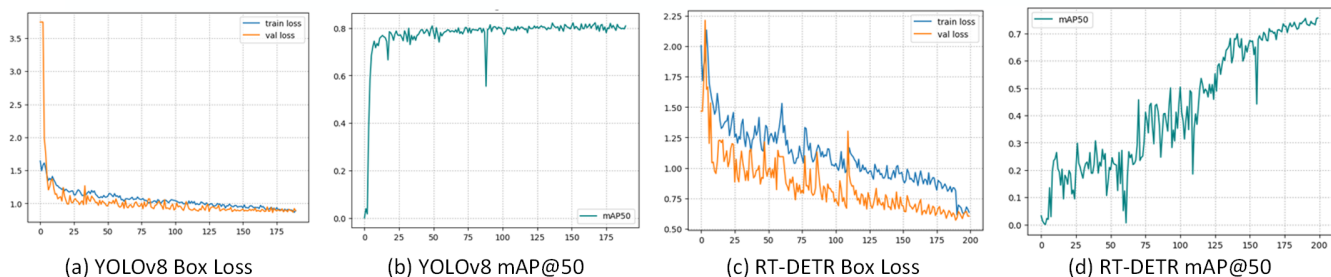


Fig. 5: Graphical representation of training performance metrics for detection models YOLOv8 and DETR: (a) Curve showing the box loss of YOLOv8 over training epochs. (b) A curve showing mAP@50 (mean Average Precision at 50% IoU threshold) for YOLOv8. (c) A curve showing the box loss of DETR through the training epochs. (d) Curve showing mAP@50 for DETR

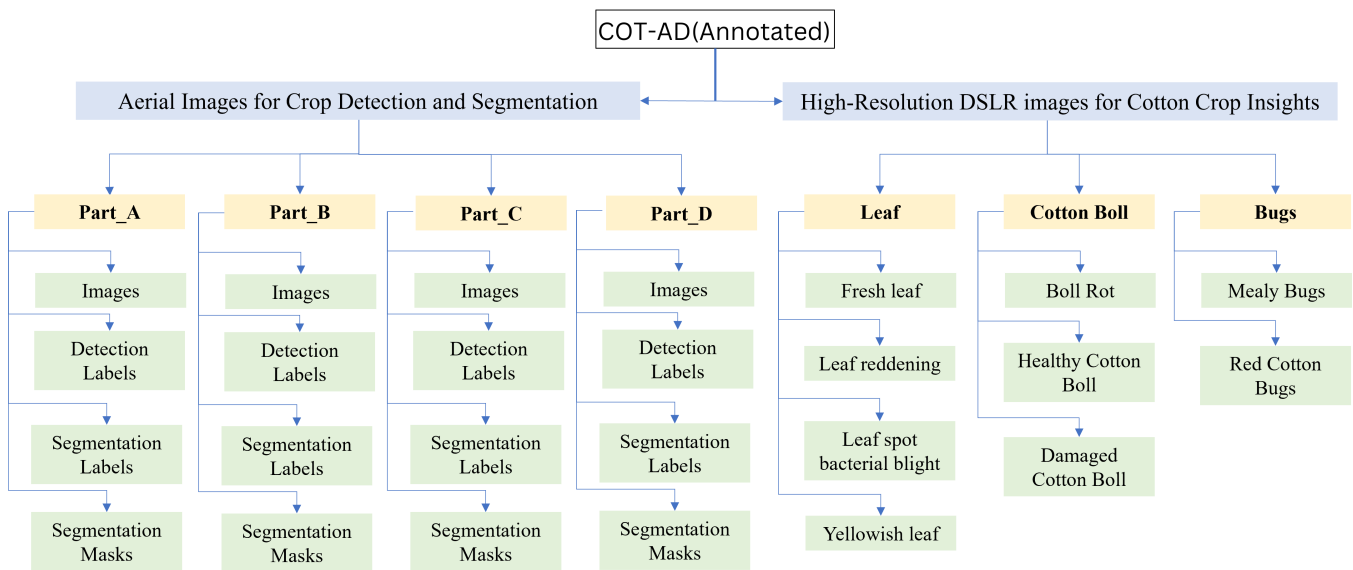


Fig. 6: Folder structure of the COT-AD Dataset Annotated. The directory, *Aerial Images for Detection and Segmentation*, is divided into four parts over six months, each containing subfolders for images, detection labels, segmentation masks, and segmentation labels. The *High-Resolution DSLR Images for Cotton Crop Insights* directory is organized into categories of Leaf disease, Cotton Boll, and Bugs, each with specific subdirectories for detailed analysis.