Cotton Detection Using YOLOv5

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Article Info

Article history: Using recent deep learning techniques for object detection and a discussion of alternatives to conventional methods, a review paper investigates the application of computer vision technology in the Cotton Harvesting Rover to automate cotton blossom identification and harvesting.

Keywords:

Cotton Picking
Computer vision
Deep learning
Object detection
YOLOv5.

ABSTRACT

Cotton harvesting has long been a labor- and time-intensive process with several difficulties. Yield and quality were inconsistent when harvested by hand. In conventional techniques, obstructions from leaves or the inaccuracy of identifying the sky over the cotton based on characteristics like color prevented the proper detection of cotton blossoms. To solve this problem, Cotton Harvesting Rover uses computer vision technology to deploy a robotic system that can precisely identify cotton blossoms. Using specific features, the system automatically locates the cotton flowers in the fields and then uses a robotic arm to harvest them. The most recent deep-learning techniques for object detection are reviewed in this paper.

This review paper will offer a thorough analysis of numerous deep learning techniques that can be helpful for different image processing approaches and automatic detection. It also provides performance metrics, such as F-1 score, accuracy, and precision, for each technique utilized. There has been discussion of the climate requirements for cotton productivity in different areas. This study reviews alternatives to conventional approaches that require previous knowledge, handle vast amounts of data, and lessen issues brought on by computer technology.

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1. INTRODUCTION

Cotton was traditionally picked by hand, with the use of mechanical stripping, chemical defoliation, manual picking equipment, etc. The notion goal of the project is to create a sophisticated cotton-picking robot that uses computer vision to improve cotton harvesting's accuracy and efficiency [8].

Computers can now extract information from photos and other visual inputs thanks to the science of computer vision. It makes the required decisions based on this information. It teaches the machines to operate by the functionality that needs to be carried out. Applications for computer vision include tracking moving objects, detecting faces, and collecting videos. The robotic arm seeks to pick and store the cotton bolls in a container by using image processing and computer vision to identify them based on their attributes. Real-time cotton blossom recognition is achieved through the use of a deep-learning object detection model known as YOLOv5 (You Only Look Once version 5). Data collecting, labeling, model version selection, training the model with the annotated dataset, fine-tuning, and finally assessing the outcomes using test datasets are the steps involved in successfully detecting cotton bolls [17].

Farmers in India and other developing countries have a productive way of gathering cotton. Even with these recent and significant advancements, adoption in India continues to face obstacles. All cotton picking is done by machinery in wealthy countries. A lack of workers and growing labor expenses have led to a mechanization of the Indian agriculture sector [1]. According to Haolu Li, cotton crops were accurately identified through the use of remote sensing imagery. DenseNet is a multidimensional densely connected convolutional network that was employed as a deep learning model. Applications of remote sensing techniques include disease detection, area estimation, growth tracking, and several parameters. SVM is capable of classifying agricultural data even when there are few support vectors available and a smaller training dataset without compromising classification accuracy. Unmanned aerial vehicles, unmanned ground vehicles, and satellites are the sources of remote sensing imagery [2].

Has explained how to use a fuzzy reasoning-based method in conjunction with RGB and HSV channels of color for cotton recognition to modify image color pixel values and establish upper/lower bounds for white cotton bolls [6]. An improved version of YOLOv5, which included DenseNet, an attention mechanism, and bi-frequency frequency prediction to accurately and economically identify closed cotton bolls in the field, was reportedly presented by Zhang, Yan, and Yang, among others. The experiment findings show that the proposed method performs better than the original YOLOv5 model and other methods such as YOLOv3, SSD, and FasterRCNN when the simultaneous factors of detection precision, computational cost, model size, and speed are considered [10].

Amey Nimkar Sanjay concluded that the project's objective is to locate, gather, and store cotton utilizing a cotton harvester that leverages powerful IP, robotics, and digital analytics to establish effective and sustainable agriculture. To pick a variety of crops, the system would make use of multiple robotic arms built in the harvest zone. Because it is electrically and remotely operated, this machine is perfect for ladies because it does not require a driver [12]. The different types of AI algorithms and sensors used in these systems are also covered in the review. The primary goal of this effort is to develop an improved YOLOv5 for damage identification based only on cotton seed appearance [16]. A massive fusion-based cotton boll localization method together with point annotation was employed in this work [19].

By considering all the above literature, it has been seen that there is scope to make the system more optimized. After a thorough DL evaluation of various cotton-picking methods, we identified the following holes that needed to be filled.

The literature review identifies the following gaps:
Obstacles such as branches, leaves, or other objects may prolong the picking time. Implementation costs related to hardware, software, and maintenance. Reduced maintenance time is necessary for autonomous systems. solely identifies specific cotton blooming patterns; it does not provide a list of further application cases. Some cotton bolls were left behind because the bolls were hidden beneath branches that could not be identified.

A multidisciplinary approach is needed to solve the limits in object detection approaches for agricultural applications that have been discovered. First and foremost, more machine learning research and development is required to automate the extraction of features and hyperparameter tuning and lessen the need for human intervention. Furthermore, for wider applicability, detection models must be modified to account for different crop varieties and environmental circumstances. Implementation costs can be reduced by making investments in the creation of affordable hardware options and combining them with reliable software frameworks. Furthermore, emphasizing practical application and real-world deployment in agricultural contexts will increase the significance and effect of research findings. It will be easier to compare and evaluate results across research if evaluation standards, data sets, and algorithm performances are standardized through cooperative efforts. Ultimately, the development of robustness testing, improved algorithms, and sensor technologies are essential for raising the accuracy and dependability of object identification systems in changing agricultural settings.

2. PROPOSED METHOD

2.1 DETECTION USING YoloV5

This paper describes how YOLOv5, a deep learning-based pre-trained model, can be explicitly trained for a cotton dataset and, once installed, be able to recognize cotton in any surroundings. The specific goals at hand and the availability of data for the model's training are the determining factors when choosing YOLOv5 or any other machine-learning model. To achieve high-performance object identification, YOLO models are used. YOLO divides an image into grid systems, and each grid system is aware of its contents.

Table 1 Comparison of YOLO versions

Parameter	**YOLOv4**	**YOLOv5**	**YOLOv7**
Speed	Varies based on the model selected	Has good balance	Fastest
Accuracy	varies accordingto the selected mode	Offers good balance	Highest
Open-source	No	Yes	No
Trainingdata	COCO dataset	Diverse D5 dataset	COCO dataset
Computation power	Higher generally	Low than v4	Lowest

In Table 1, various YOLO versions are compared. Since v5 is open source, lighter than v7, and more accurate than v4, it is the most appropriate of them for our application in cotton detection. Version 5 uses a variety of D5 datasets for data training, whereas versions 4 and 7 only use the COCO dataset, as shown in the table below. The cotton detection research uses this model

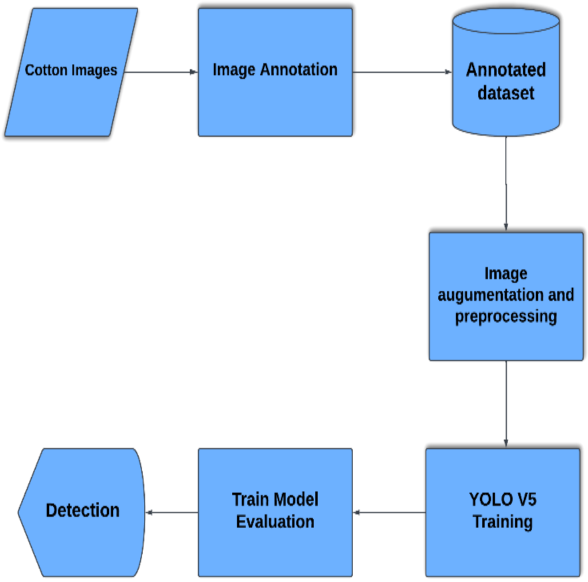

Figure 1 Generalized flow of YOLOv5 cotton detection model.

The explanation of the YOLO cotton detecting model is provided in Figure 1:

Cotton Image: The initial stage of model training is data collection. This information was obtained from several sources, including cotton grown in a greenhouse or a laboratory, among others. The Roboflow dataset is used for training.

Image Annotation: Machine learning and artificial intelligence techniques are used to annotate images. Often, image annotation is carried out by human annotators who use an image annotation tool to label photos or tag pertinent information, such as assigning the proper classifications to different objects in an image. We created two classes for our model, as mentioned in the section on picture datasets. For simple tasks like classification and segmentation, pre-trained models are usually available. These models can be tailored to specific use cases with the help of Transfer Learning and little data. The comprehensive description of the Roboflow platform, where the annotation was finished, may be found in the data preprocessing section.

Annotated Dataset: The data is sent to the Colab for model training after going through the platform's annotation process. It is separated into three sections: test, validation, and training.

Image augmentation and preprocessing: Before exporting the dataset to Colab, it is first made larger using the augmentation technique, which is covered in detail in the data pretreatment section.

YOLOv5 training: To train our v5 model on our custom dataset, we first export our previously processed data from the Roboflow platform in a format that is compatible with Python. After everything is finished, a repository code is produced. We set the parameters to start training after importing the dataset into Colab using the code. Initially, we adjusted the image size to match the export size. The epochs for this model are then set. To train our model, we tried training it with epochs ranging from 50 to 200; however, the best results were obtained with a batch size of 32 and 150 epochs. We obtained an accuracy of 0.83 by using this input value [16] [17].

Train Model Evaluation: We use the trained model to perform object detection in test set photos after testing it on unseen data. After an object has been detected, the performance is evaluated, and metrics including precision, mAP, and the accuracy and effectiveness of the model in object detection are examined [10].

Detection: After cotton is detected, a box enclosing the cotton emerges, which appears to represent the degree of confidence. This level only expresses the degree of confidence that the object being recognized is cotton or not (for instance, a level of 0.8 would indicate an 80% confidence level on cotton detection).

Table 2 Configuration details of Yolo

Parameter	**Details**
Batch Size	32
Model	YOLOv5s
Loss function	Returns class loss, box loss, object loss
Convolutional network	Backbone-Darknet, Neck-PANet [28]
Epochs	150
Resolution	640 x 640
Activation function	SiLU and Sigmoid activation function.

2.2 YOLOv5 ARCHITECTURE

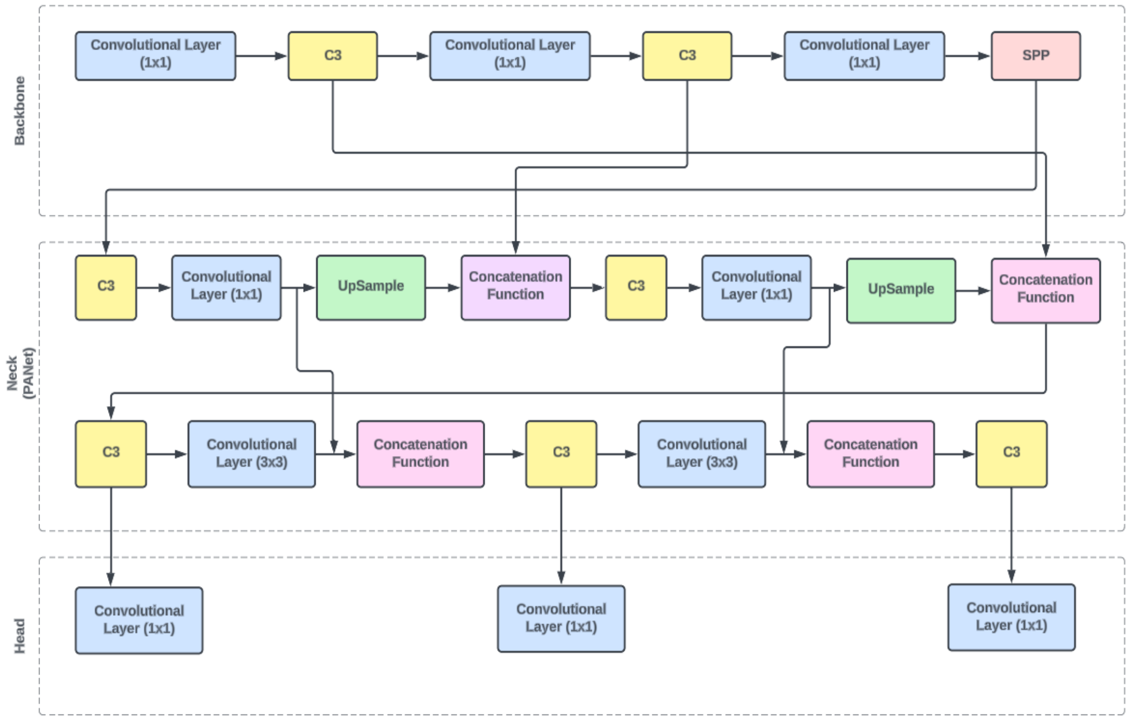

Figure 2 YOLOv5-s architecture

The Yolov5 architecture consists of three parts:

1. **Backbone**: The task of extracting features from the input image falls to the backbone network. The backbone of YOLOv5 usually consists of a sequence of convolutional layers that increase the number of channels to record hierarchical information while gradually downsampling the input image's spatial dimensions.
   Convolutional layer: This layer is responsible for extracting features from the input image by convolving with the kernels.
   C3: Convolutional 3x3 is a specific type of convolutional layer in which 3x3 filters are applied to the input image.
   After a set of Convolution layer and C3 the output goes through SPP.
   SPP: Spatial Pyramid Pooling is done which divides the feature maps into sub-regions of various sizes and the pooling operation is done without the need for resizing the image.

2. **Neck**: The YOLOv5 architecture's neck functions as a transitional element between the head and the backbone. It is in charge of performing further processing on the characteristics that the backbone has retrieved to improve its representational ability. To enhance the network's capacity to identify objects of different sizes, YOLOv5's neck usually consists of extra convolutional layers, feature pyramid networks (FPNs), or other architectural components that merge features from several scales.
   In this layer Convolution and C3 are done along with Upsampling and application of concatenation function.
   Concatenation function: The resultant feature maps from various sub-regions are concatenated together along the depth dimension after applying SPP. Concatenation retains spatial information across many scales by combining the data from these sub-regions into a single feature vector.
   Upsample: Feature maps can have their spatial resolution increased through the technique of upsampling. It means increasing the size of feature maps through the use of interpolation methods like bilinear or nearest-neighbor interpolation, or by adding empty rows and columns (zero-padding). Spatial features lost during downsampling processes, such as max pooling or convolution with stride, can be recovered with the aid of upsampling.
3. **Head:** The YOLOv5 architecture's head is in charge of producing object detection predictions using the features of the neck and backbone supply. The final output layer, which predicts boundaries, objectness scores, and probabilities of classes for the objects in the input image, usually comes after a series of convolutional layers. Depending on which version of YOLOv5 is being used, the head of the algorithm may incorporate methods like anchor box clustering, sigmoid activation, or softmax for classifying object classes, and prediction of objectness scores.

2.3 DATASET COLLECTION AND PREPROCESSING

The picture dataset was created in June and July of 2023 using data acquired from the internet and photos taken from nearby farmers' farms in Marathwada. The online dataset was collected from two different websites, Roboflow and figshare. We utilized every bit of data from the over 1421 photos in the Roboflow dataset. Similarly to this, a dataset comprising over 6000 images was taken down from the figshare website because the model's training accuracy was less than 0.60. Information about the five classes—that is, the five categories into which the Roboflow dataset is split—that comprise the dataset is included in the preprocessing section. Comprehensive information about augmentation can be found in the preparation section. The process of creating the model was facilitated by the pre-labeled and annotated internet dataset that we gathered. The second dataset, collected from neighboring farms, was used just to test the model. To make sure that the model's testing would be adequate for a range of contexts, the photographs were taken from different viewpoints, postures, and backgrounds.

Figure 3 Samples of Cotton Dataset from fields

The actual images from our collection, which totals 614 pictures, are shown in Figure 3. The number of photos increased to 1421 following the augmentation process, which is discussed in the preprocessing section. Before preprocessing, the dataset's image resolution was 640x640 pixels. 15% is used for validation, 5% is for testing, and 85% of the data set is used for training[27]. The dataset contains images of individual cotton bolls on the plant to help the model recognize cotton bolls up close, and images of multiple cotton bolls on a single plant to help the model detect cotton bolls at a distance.

Data preprocessing converts raw data into a format that computers and machine learning can comprehend and analyze as part of the data analysis process. We annotated the photographs by putting an anchor box around the area of interest that has to be detected to obtain raw data for our investigation. The cotton boll in this case is growing in several stages, including split, maturity, early, and flower. By first specifying all classes for each growth stage and then selecting a particular class each time a bounding box is created during the annotation process, this can be split into five categories. The next stage is data augmentation after each image has been annotated. During this procedure, the photographs are rotated 90 degrees in both clockwise and counterclockwise directions, flipped vertically and horizontally, and their exposure is adjusted between -12% and +12% to increase the size of the data. The platform used for data augmentation and annotation is depicted in Figure 4, and the dataset was exported in a format compatible with PyTorch version 5 [27].

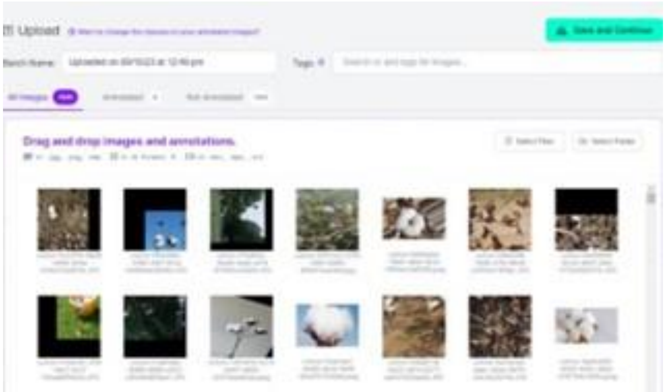

Figure 4 Annotated Dataset

2.3 DESIGN AND MODELLING OF SYSTEM

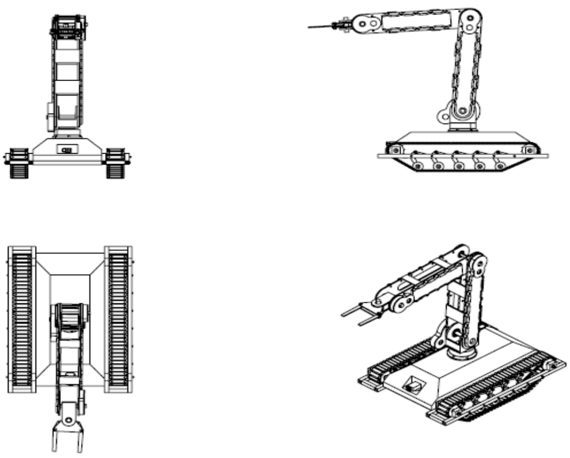

Figure 5 Schematic diagram

Figure 5 illustrates the design for the robot arm and the rover. The self-navigating cotton-picking rover is made up of a wheeled platform for moving through cotton fields. The rover has a hand extension installed that can reach mature cotton bolls on plants and delicately harvest them. The rover's sensors and cameras enable it to capture in-depth images of the cotton plants. These photos are processed in real-time using computer vision algorithms, which allow mature cotton bolls to be distinguished from other plant components including leaves and stems. The computer vision system uses a variety of visual signals, including size, texture, and color, to accurately identify mature cotton bolls.
Once a mature cotton boll is discovered, the rover's control system decides the optimal route and position for the hand attachment to reach and pick it. The hand extension's actuators allow for the exact and cautious removal. It is set up with defined pathways and obstacle elimination algorithms for efficient field coverage while avoiding collisions with impediments.

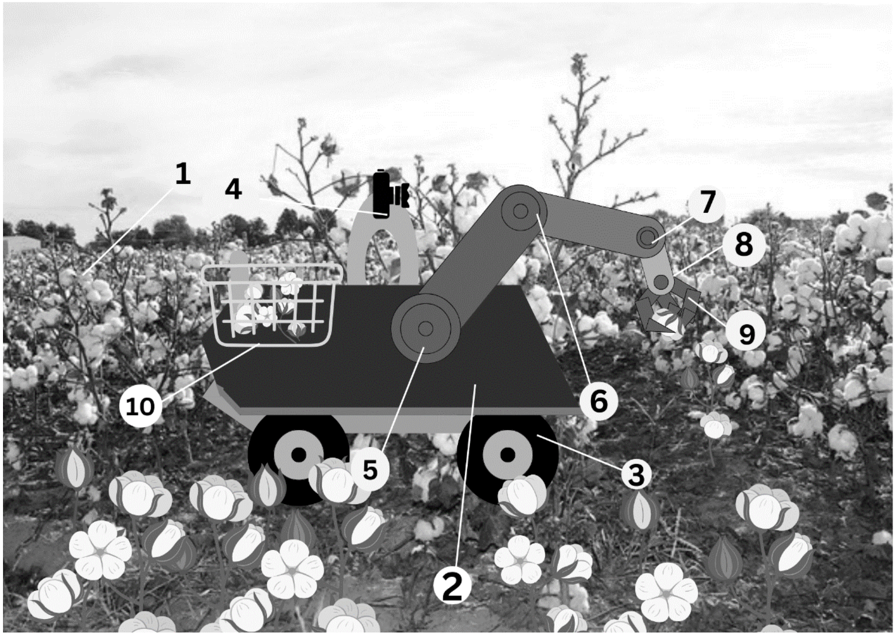

Figure 6 Working of prototype

Figure 6 shows rows of fully grown cotton plants extending into the distance on a cotton field. An automatic cotton picking rover is situated among the cotton plants in the image's foreground. The rover is a small, three-wheeled vehicle with a robust structure made for challenging outdoor conditions.

3. RESULTS AND DISCUSSION

4.1 Software Results

The confusion matrix of our model is specified in Figure 7. A confusion matrix, also called an error matrix, is a specific table arrangement used in the field of machine learning, specifically for statistical classification problems. It makes the performance of an algorithm easier to visualize. Typically, this algorithm is supervised learning; in unsupervised learning, it is commonly referred to as a matching matrix.

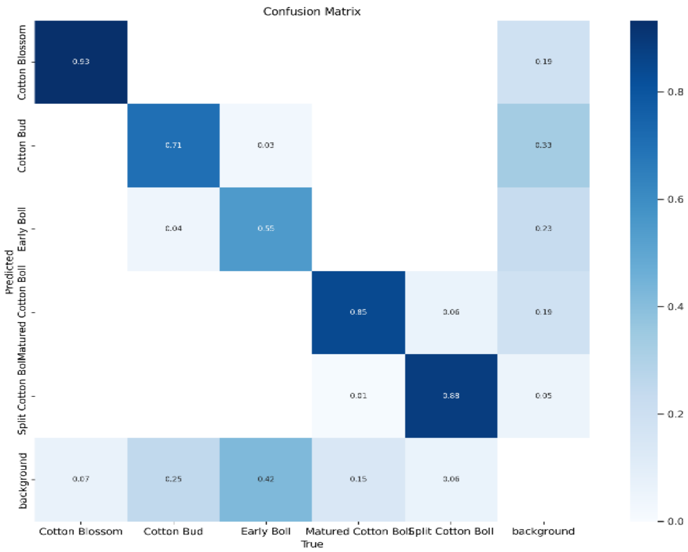

Figure 7 Confusion matrix

From Figure 8 we can see from the confusion matrix that the true value for the cotton blossom matches the projected values by 0.93 times, the true value for the bud matches by 0.71 times, and the true value for the early boll matches by 0.55 times. Both the split cotton forecast and the matured boll prediction match the true value by 0.88 times and 0.85, respectively. The background influences the values of the cotton buds and the early boll.

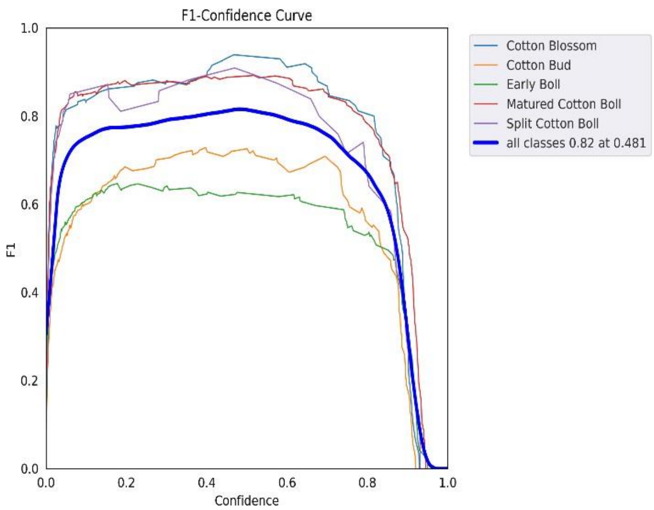

Figure 8 F1 confidence curve

In Figure 9, the F1 curve as a reference for all classes, the confidence value of 0.481 maximizes both precision and recall. A greater confidence value is preferred in many situations. This model's confidence value must be 0.8, which isn't far from its highest confidence of 0.82.

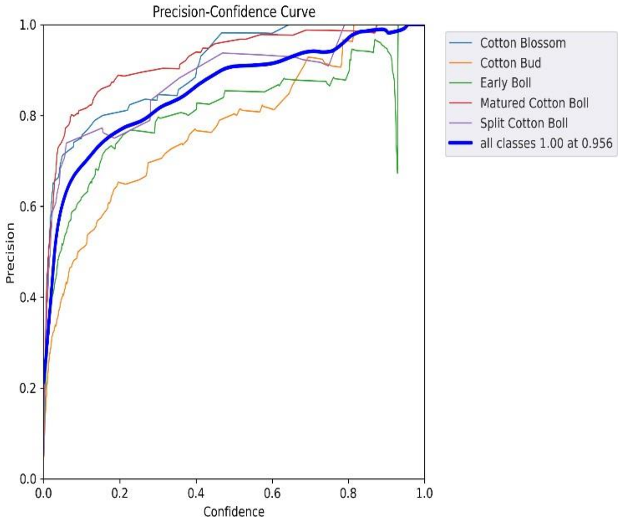

Figure 9 Precision confidence curve

Figure 10 illustrates the relationship between the model's confidence and precision.

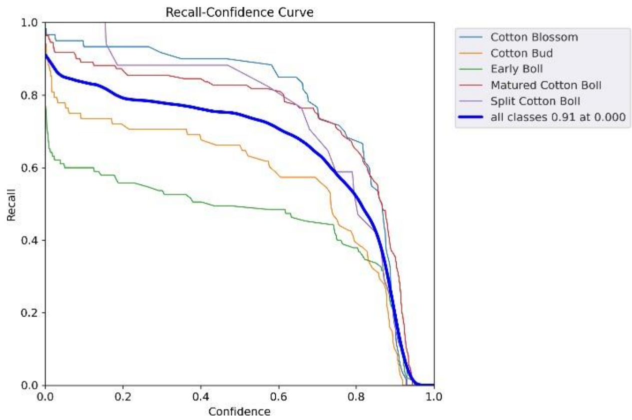

Figure 10 Recall confidence curve

Figure 11 shows the relationship between the trained model's recall and confidence.

$$\mathrm{F1} = 2 * \left(\frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}\right) \qquad (1)$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad (2)$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (3)$$

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \qquad (4)$$

Figure 11 Evaluation metrics

The summary of performance metrics is given in the following table which gives information of precision, recall and F1 score of multiple classes.

Table 3 Performance Metrics

Classes	**Precision**	**Recall**	**F-1 score**
Cotton Blossom	0.83	0.93	0.87
Cotton Bud	0.66	0.71	0.68
Early Boll	0.67	0.55	0.60
Matured Cotton	0.77	0.84	0.80
Split Cotton	0.91	0.87	0.88

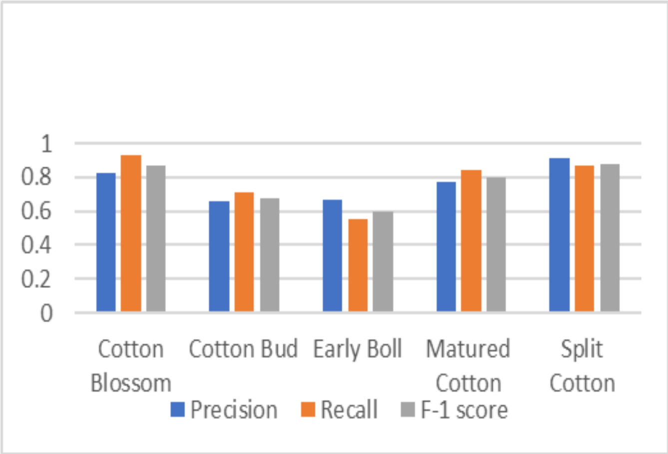

Figure 12 Performance metrics

4.2 Hardware Results

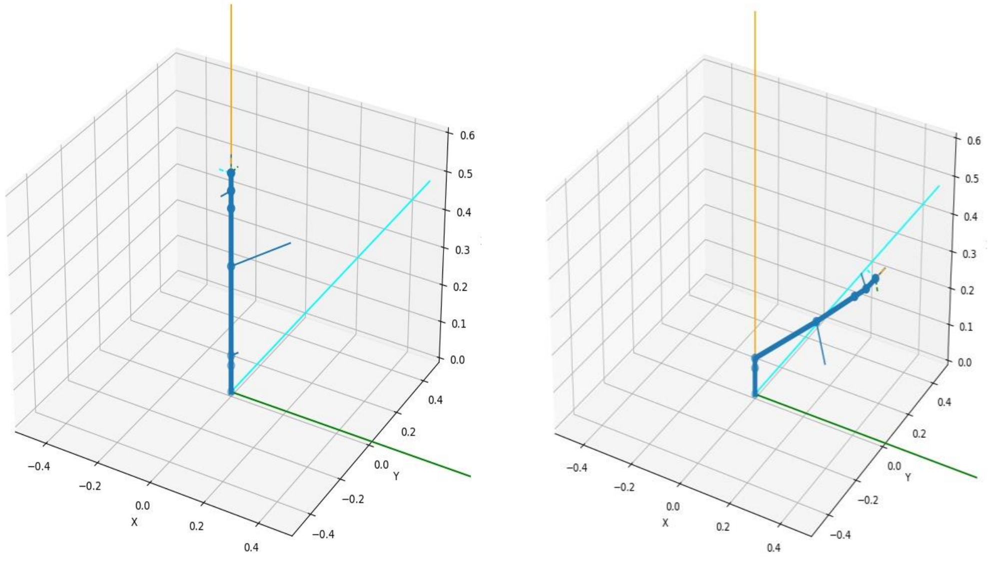

Figure 13 Simulation results for the position of the robotic arm

Concerning Figure 13, the simulation results were obtained by running a Python program on Jupyter Notebook which depicted the position of the robotic arm. To get the position and the required angles required for the movement of the arm, the 3d coordinates were provided to the program which then calculates the angles for each joint resulting in the positioning of the end effector at the mentioned 3d coordinates to the program.

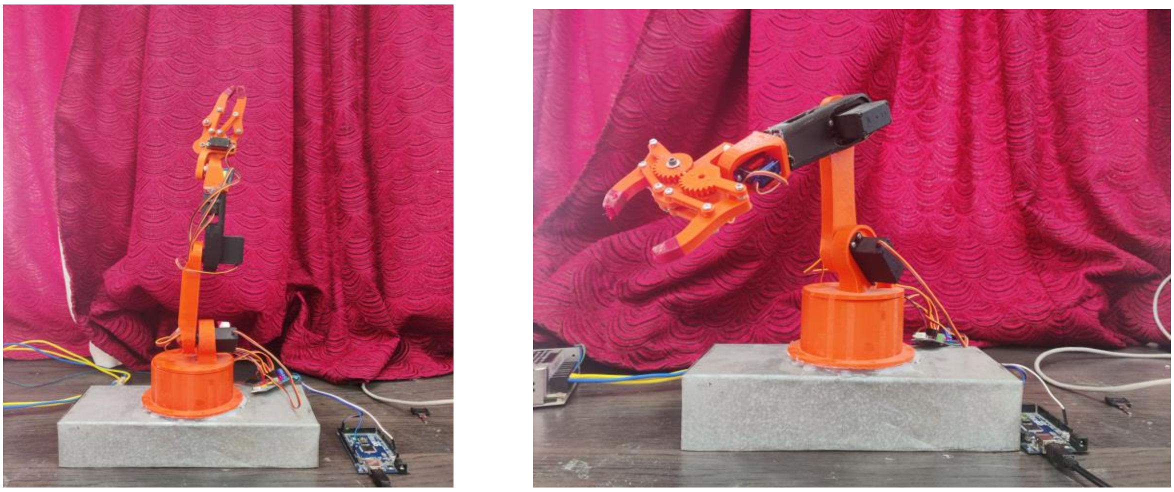

Figure 14 Results of working of the robotic arm

The Python code that developed the simulation results was modified into Embedded C for real-time servos control and uploaded on Arduino Mega. The microcontroller was able to actuate the servos according to the coordinates provided, based on the calculation of the angles for each joint the simulation results and the real-time working of the arm had similar results. The model is shown in Figure 14.

5 CONCLUSION

This paper presented the idea of creating a model for cotton detection using Yolov5. Using the PyTorch compatible dataset and YOLOv5, we were able to successfully build a cotton detection model using the Google Colab platform. The model was able to predict the existence of the cotton boll after completing its training. It was achievable to properly detect 5 different classes of cotton. As for the working of the robotic arm, for given coordinates, the arm could extend to those particular coordinates and do the picking action based on the calculated angles. The outcomes of the simulation and the arm's actual operation were similar and true to the requirement.

6 FUTURE SCOPE

- Real-time detection and robotic arm integration: Using sensors and actuators, the robotic arm can employ real-time detection from the video feed to pluck the cotton boll.
- Personalized Route Planning and Self-governing Navigation: Develop intricate algorithms for dynamic path planning and autonomous navigation to increase the robot's agility in the field.

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