2022 ASABE Robotics Competition

Robotics Written Report

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Division:	Beginner
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Catalog

1 Information About Team Members

Table 1-1 Profile of team members

Name	Assigned Tasks	Note
Xin Jiang	Manipulator Control	Undergraduate Junior
Yuliang Zhou	Mechanical Structure Design	Undergraduate Junior
Yilin Zhang	Overall Design and Debugging	Undergraduate Junior
Haozheng Zhang	Machine Vision	Undergraduate Junior
Xinyue Sun	Circuit Design	Undergraduate Junior
Jiaming Chen	Structure Design	Undergraduate Sophomore

2 Design Background

2.1 Meaning of Cotton

Cotton is one of the world's most important cash crops and plays an vital role in the development of the world economy. Cotton has become an indispensable item in daily life because of its relatively low production cost and large output, as well as its ability to be made into a variety of different garments that are soft and comfortable while solving the basic human problem of keeping warm and cold. In 2021, global cotton production was 24,339 kt, while according to the USDA's forecast data in March 2022, global cotton production will increase to 26,095 kt and global cotton consumption will reach 27,115 kt in 2022.

Figure2-1 cotton

2.2 Current Status of Hand-Picked Cotton

Due to the large global cotton production and extensive area, picking cotton in large quantities has become a major task. If we rely mainly on manpower to pick, it is a waste of time and requires a lot of manpower and resources, which is costly; in addition, manual picking is uncertain and easily affected by weather and environmental factors.

With the rapid development of science and technology, machinery is gradually replacing manpower, and the development of cotton-picking robots that can accurately locate, efficiently operate, and do as little damage to the cotton plant as possible has become a hot spot.

2.3 Challenges of Automated Cotton Picking

① The picking process of inaccurate machinery is easy to break the stalk. Especially for the serious lodging cotton fields, machine picking cotton loss rate of up to 10% or more.

②Difficult to achieve thorough harvesting, much residue of raw materials and a great waste of resources.

③The collected cotton contains a high rate of impurity, containing more cotton husks ; the pulling process makes the length of cotton short, and low fiber strength, resulting in unstable production quality.

3 Design Goals

In the design of robots, we are committed to making them have better performance, stronger environmental adaptability, and expandability with some development prospects.

The main design goal of our cotton-picking robot is to locate the cotton plant in the field, recognize the specific position of cotton, and pick the cotton with an end-effector. Now split the target as follows:

A. Realize the autonomous driving of the robot

B. Locate the cotton plant

C. Identify open and unopened cotton bolls

D. Picking cotton

3.1 Design Principle

Our design principle is to complete tasks efficiently in a simple, stable, and low-cost way.

(1) Simple, reliable, low-cost hardware

We want to make the identification device with as few gears and controls as possible. We believe that simple, reliable, and practical components can better adapt to the requirements of operation in the agricultural environment, and lower-cost design can meet the needs of farmers for cost control.

(2) Stable and efficient software

We are committed to designing stable, reliable, and efficient software to ensure our recognition efficiency and accuracy through the use of advanced algorithms.

(3) Efficient and stable mechanical structure

We designed a very clever mechanism, the end of the mechanism through a simple retractable device, can automatically adjust the opening size of the gripping device, to achieve adaptive picking of cotton size, the captured cotton will be transported to the robot with the synchronous belt, the whole process is very stable and efficient.

3.2 Design Innovation Points

3.2.1 Advanced Visual Recognition Algorithm

Using YOLOv5s, the fastest one-stage target detection algorithm currently, we compressed and converted the model, which saves a lot of memory overhead. It is easy to load on the 2GB version of Jetson Nano, dealing with cotton identification tasks efficiently.

3.2.2 Minimalist Mechanism Design

Agricultural production has a complex environment, that requires high stability of the equipment and low net profit, so we try our best to simplify our design to ensure the stability and reliability of our institutions and reduce the cost of the entire vehicle.

4 Mechanism Design

4.1 Overall Structure

In general, our robot consists of four main parts: motion mechanism, rotating lifting platform, extend structure, and Belt - clamp cotton picker. The overall appearance of the robot is shown in Figure 4-1.

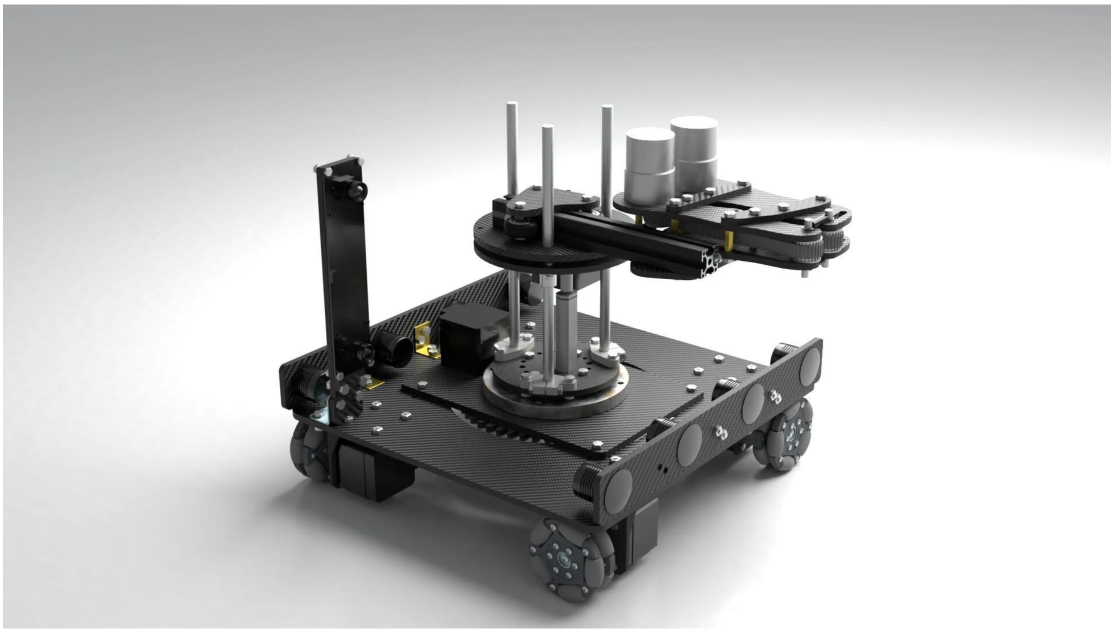

Figure 4-1 Overall structure

4.2 Extend Structure

To move the end-effector to the right position in the horizontal direction, we designed a device that can be extended in the horizontal direction, consisting of a stepper motor, synchronous belt, three rubber bearing pulleys, and an aluminum Extrusion Profile, as shown in Figure 4-2.

Figure 4-2 Extend Structure

4.3 Rotating Lifting Platform

On the steel rotating base with bearings, three steel rods are erected to move the end effector. The rotating part is driven by the stepper motor fixed on the rotating base. The small gear in the stepper motor drives the big gear, providing a small transmission ratio and improving control accuracy. Simultaneously, the linear actuators can drive the heavy upper structure.

The three vertical steel rods are connected with a liftable platform driven by an electric actuator, which provides sufficient force to lift the platform while maintaining a small volume.

Aimed at elevating control accuracy, we built a stretchable structure on the platform driven by a stepper motor.

Thus, the whole platform has three degrees of freedom. and the coordinates are determined by three parameters: height, rotation angle, and extension length, similar to cylindrical coordinates.

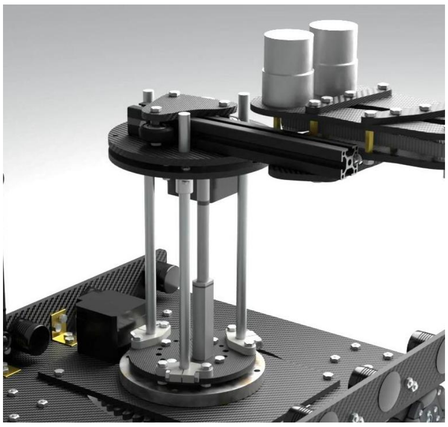

Figure 4-3

4.5 Belt – clamp Cotton Picker

In the process of designing the end picker, we want to simulate the action of picking cotton with two fingers, i.e., hold it first and then pull it back.

After a series of trials, we found the synchronous belt can meet our expectation of simulating finger movement. The teeth of the belt engage with each other, clamping the cotton, while the smooth surface avoids the circumstance in which cotton bolls are stuck on belts. Therefore, we designed the structure as follows.

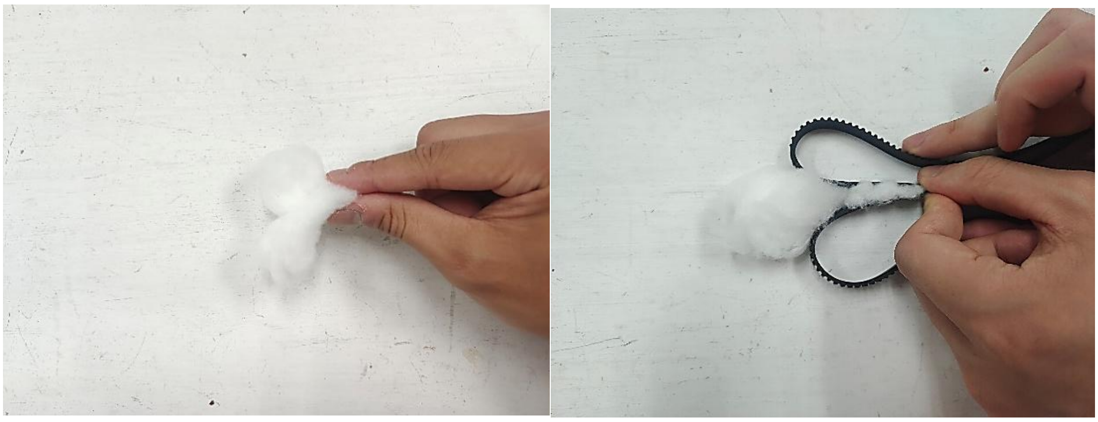

Figure 4-4 Manual harvesting and synchronous belt simulation

The cotton is harvested by two DC geared motors driving the synchronous belt to rotate inwards.

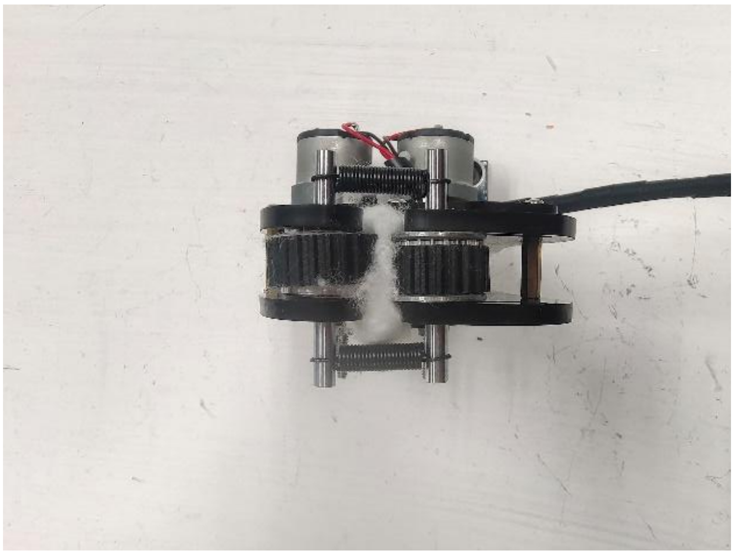

Figure 4-5 DC geared motors and the spring

To harvest different sizes of cotton balls, the entrance of the end effector design is a flexible opening, and the elastic force of the spring is constraining the size of the entrance. First, we utilized rubber bands to provide elastic force, whose gel-like surface tends to stick to the cotton and interfere with the collection, so we finally chose a spring with a smooth surface.

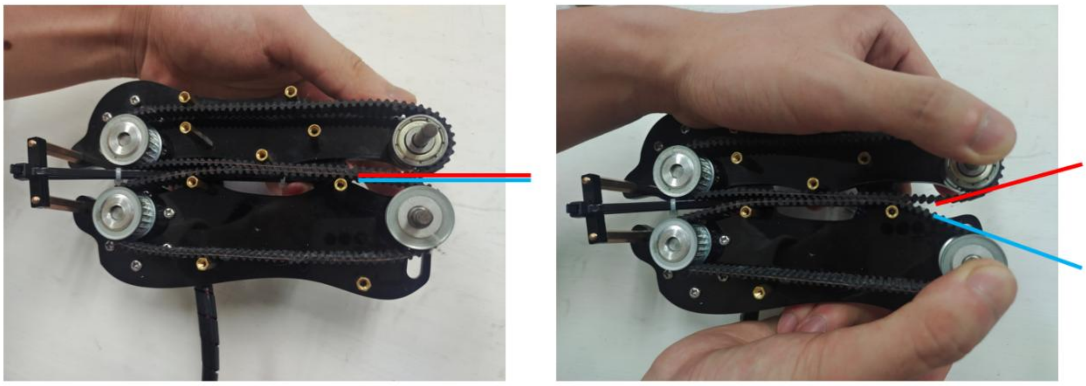

Figure 4-6 Flexible entrance

The two side plates of the collector are slotted in the middle, thus preventing the cotton from clogging.

Several copper pillars are set at certain intervals on two sides, ensuring the distance between two synchronous belts is close enough. Consequently, the cotton is provided with large enough friction force.

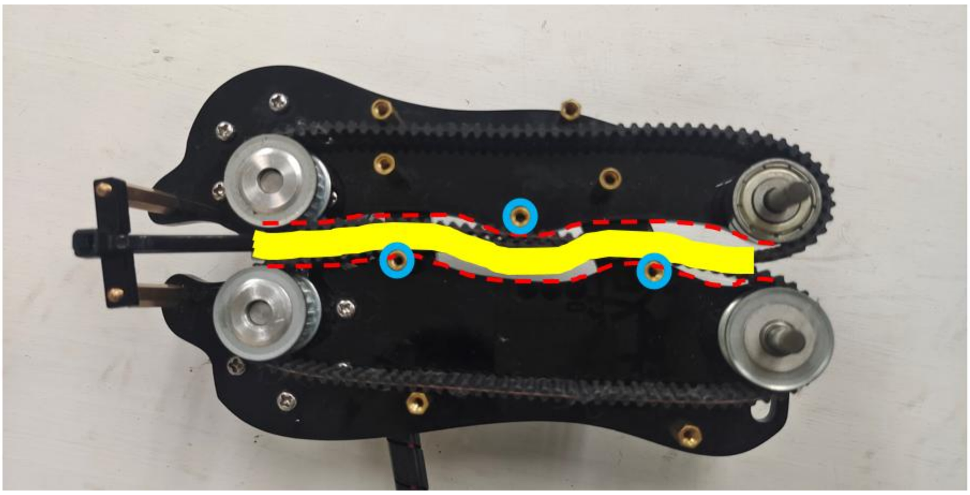

Figure 4-7 Cotton trail

5 Hardware Design

The hardware we used is shown in Table 5-1.

Table 5-1 Electronic component list

The name of the hardware	Type	Appearance	Number
Main control device Jetson Nano	Jetson Nano 2GB		1
Arduino	Mega2560 Pro		1
DC motor	JGB37-520		2
Stepper Motor	42HB34-401A 42HB60-403A		2 4

Binocular camera	HBV-1714-2 S2.0		1
Pusher	150N，4mm/s		1
Laser sensor	XKC-KL200-V		7

Considering that the amount required is within 200 USD and the basic performance requirements are guaranteed, we choose Jetson Nano to run the deep learning model image algorithm and Arduino mega 2560 Pro as the processor to control the whole robot work to meet the basic power supply requirements and sensor access.

6 Software design

6.1 Main program design

The logic flowchart of the robot working is shown in Figure 6-1. The robot performs initial positioning and mapping by laser sensors and plans a path as shown in Figure 6-2. When the robot runs along the planned path, if the robot detects a cotton stem, it stops moving forward and waits for the camera connected to the upper processor to identify the cotton and return the coordinate information of the cotton and the related kinematic solution information of the picking mechanism to the lower processor, which controls the mechanism to pick the cotton after receiving the signal from the upper processor. After the picking of a cotton plant is completely completed, the robot continues to move forward according to the predetermined route and picks another cotton.

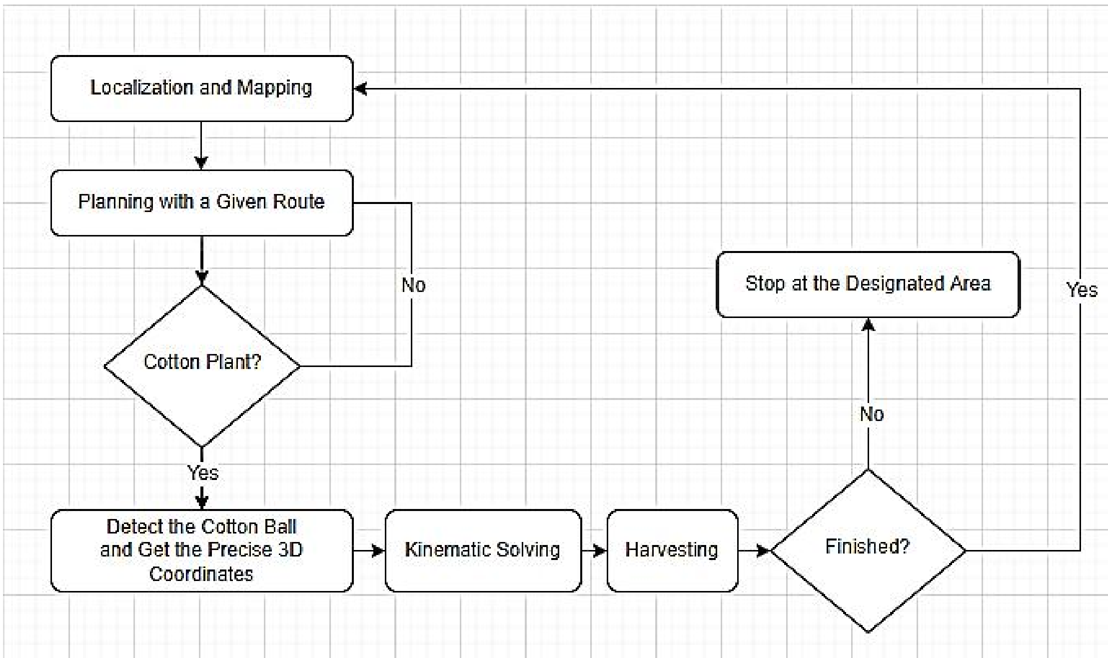

Figure 6-1 Logic flowchart of robot working

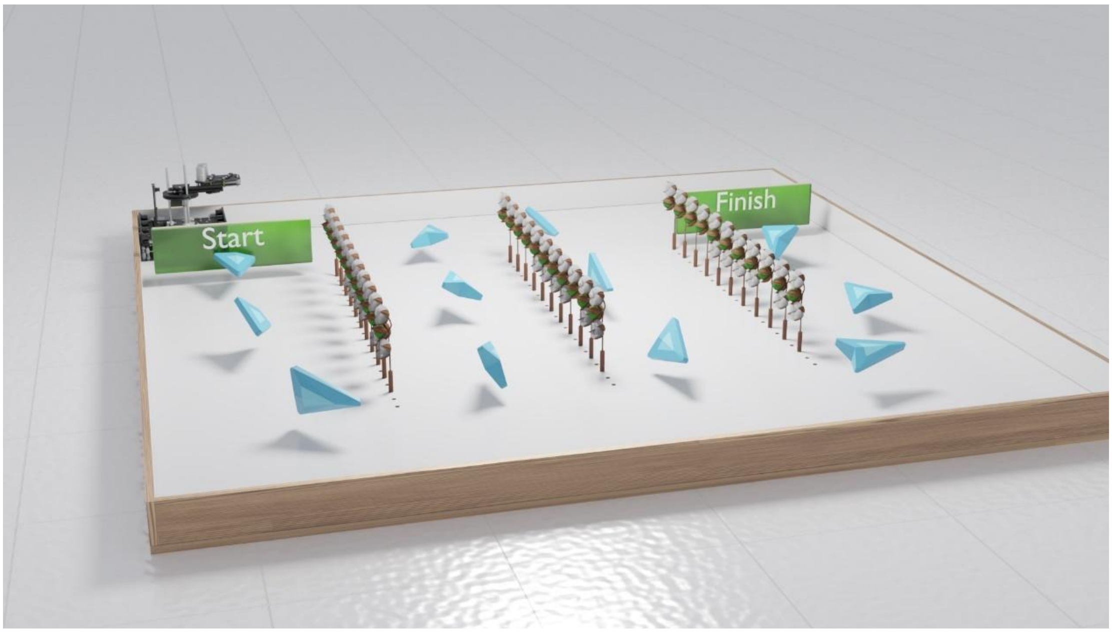

Figure 6-2 The route of the robot

6.2 Autonomous Navigation

The distance between the robot and the side board is measured by laser sensors installed on the robot to obtain the robot's position and attitude, and the robot's running direction and posture are continuously corrected accordingly.

The laser sensor on the other side of the robot is responsible for detecting the cotton plant. When the laser sensor emits a laser in a straight line with the cotton plant, the robot pauses and sends a message to the upper computer, waiting for the upper computer to perform further work.

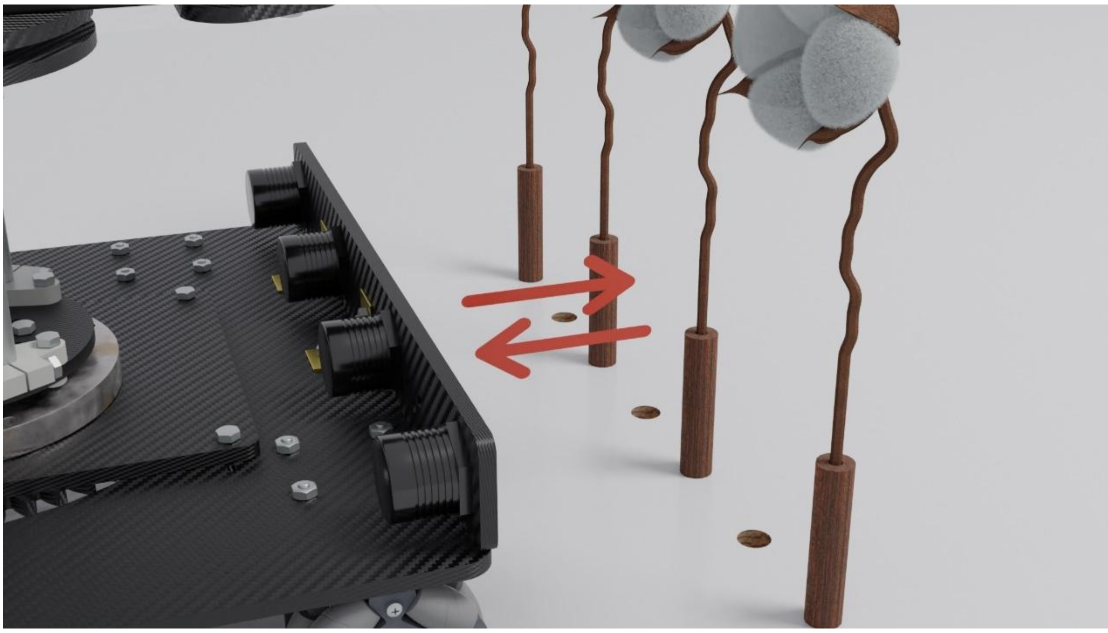

Figure 6-2 Principle of robot positioning

6.3 Machine Vision

Our machine vision system detects cotton bolls with binocular vision combined with the Yolov5 model. After framing cotton, we compare two images shot by the binocular camera and calculated the coordinates of the cotton. Subsequently, we send the location information to Arduino to implement harvesting.

6.3.1 YOLOv5s

In the process of image recognition, traditional image algorithms can't detect cotton bolls with color similar to the color of the background and cotton. Additionally, cotton has various poses and shapes, elevating the difficulty of the cotton detection task. Thus, we choose to use deep learning to solve the cotton detection problem. Among the commonly used object detection models, the Yolo series is one of the representatives of detection models. YOLOv5s, a derivative model of YOLOv5, is widely used for real-time object detection on edge computing devices for its easy deployment, training convenience, and small model size.

In the process of deploying YOLOv5 models, pre-training models need to be imported to help the models be trained, and the universally used YOLOv5 models are shown in the figure below. Among these models, the YOLOv5s model has the smallest size, reducing the time cost when training and usage of device GPU when running, while ensuring certain recognition accuracy, thus we choose YOLOv5s as our pre-training model.

Table 6-1 YOLOV5 Model Performance Comparison

Model	size(pixels)	mAP val 0.5:0.95	mAP test 0.5:0.95	mAP val 0.5	Speed 100(ms)
YOLOv5s	640	36.7	36.7	55.4	2
YOLOv5m	640	44.5	44.5	63.1	2.7
YOLOv5l	640	48.2	48.2	66.9	3.8
YOLOv5x	640	50.4	50.4	68.8	6.1
YOLOv5s6	1280	43.3	43.3	61.9	4.3
YOLOv5m6	1280	50.5	50.5	68.7	8.4
YOLOv5l6	1280	53.4	53.4	71.1	12.3
YOLOv5x6	1280	54.4	54.4	72	22.4
YOLOv5x6TTA	1280	55	55	72	70.8

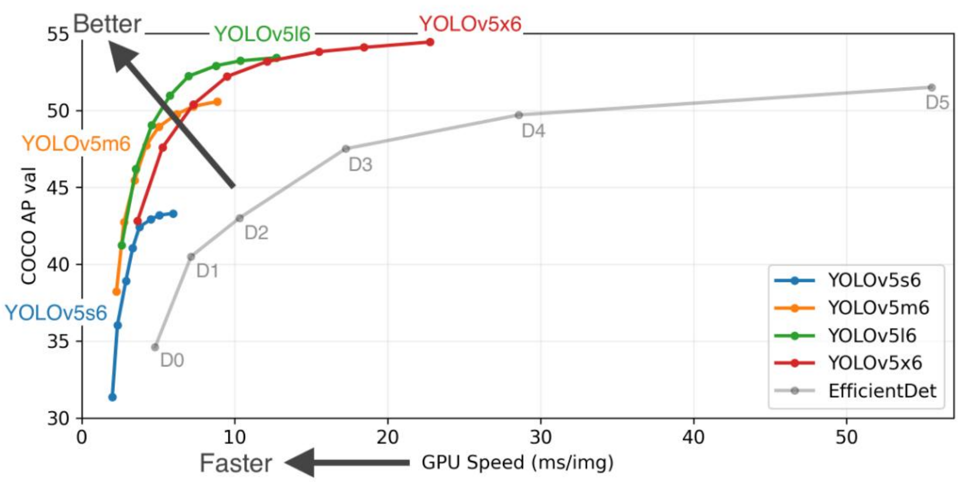

Figure 6-1 The YOLO v5s network architecture

The YOLOv5 network architecture has the following innovations.

Input: Use Mosaic data enhancement that takes 4 random samples, resizes them, stitches them together, and then takes a random cutout of the stitched images to get the final Mosaic image. This method enriches the dataset while enhancing the robustness and reducing the GPU requirements. It also uses adaptive anchor frame calculation, and adaptive image scaling to enhance features.

Backbone: It uses a focused structure that slices the feature map; uses CSP structure to reduce the redundant gradient information in network optimization to ensure accuracy while reducing the computational effort.

Neck: FPN+PAN structure

Prediction: GIOU_Loss loss function is used.

6.3.2 Label Data Sets

Before training the YOLOv5 model, we first need to label the images. We use the open-source labeling project to label the images with two classes, cotton, and ball, where cotton represents the open cotton bolls and balls represents the unopened cotton bolls.

Figure 6-2 Label data sets

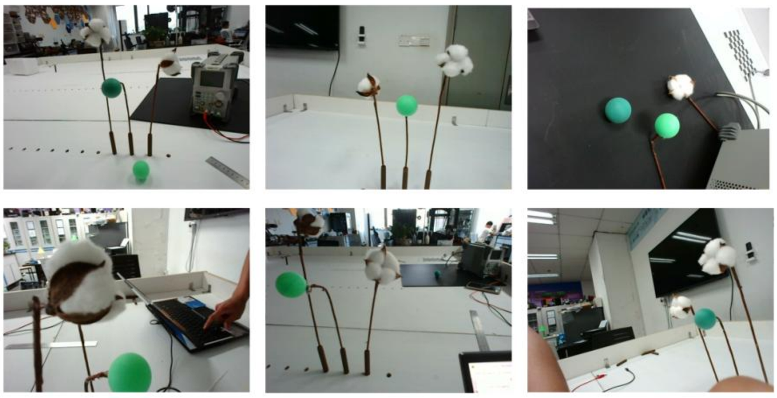

Figure 6-3 The raw images of the dataset

We collected 500 images with in total of 1131 cotton and 1077 ping pong balls unevenly distributed under different environments. This allows us to guarantee the recognition accuracy of the trained model.

Figure 6-4 The loss after 264 epochs

As is shown in the Figure 6-4 above, the loss after 264 epochs reaches a very low stage and the network starts to converge after around 15 epochs.

After labeling, we obtain a *txt* file and a *yaml* file for every sample, which contains the coordinates, size, and class of frames.

Figure 6-5 Model transformation process

6.3.3 Model Training

After setting the parameters and training the model after labeling, we can eventually get the *best.pt* model files in the weight folder, and import the *best.pt* into *detect.py* to achieve target detection on the Windows platform. Using only the pt model, we could not run the YOLOv5 model properly on our Jetson nano 2GB version, so we simplified and sped up the model. Therefore, we used *TensorRTx* for conversion, first converting the pt file to a *wts* file and then converting the *wts* file to a *trt.* file. After configuring the dependencies on our Jetson nano and calling the interface for YOLOv5 detection we can achieve real-time monitoring of cotton.

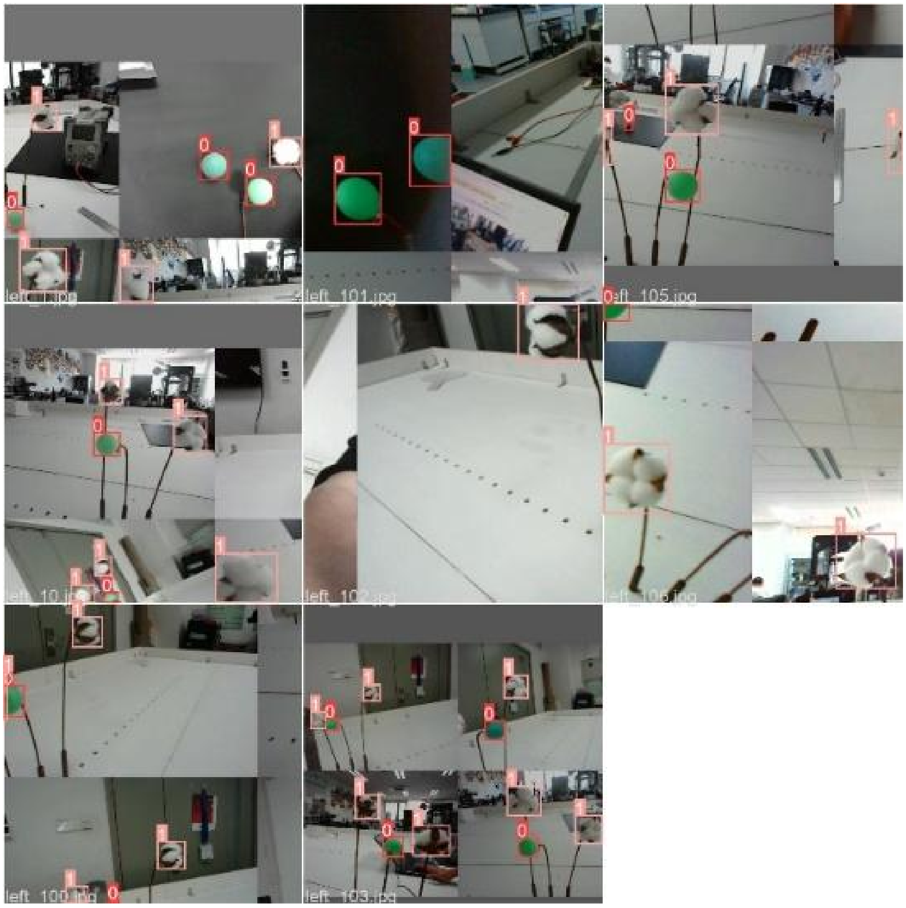

Figure 6-6 The detection results

The figure above shows the detecting results, which demonstrates the high accuracy of our model.

6.4 Mechanical Control

Our actuator is controlled using Arduino. Our actuator has a total of three degrees of freedom and can perform multi-position and multi-angle cotton grasping in space. When the upper computer gets the position information of the cotton, the upper computer transmits the position coordinates of the cotton to the lower computer, and Arduino analyzes the coordinate information and converts it into the control signal of the actuator to control the actuator movement. Among them, the circular table at the bottom of the machine can be rotated, the push rod can push the upper actuator upward, and the end actuator can be extended using the synchronous belt.

7 Parts List and Cost Analysis

As shown in Table 8-1, the total cost of our robot was $303.16. As shown in Table 8-2, the total cost of computational devices to be integrated with our robot was $67.36.

Table 7-1 Total cost

Material	Unit Price (USD)	Number	Total Price (USD)
Acrylic board	/	/	2.99
Circuit board	0.30	3	0.90
Jetson Nano 2GB	59.00	1	59.00
Arduino Mega 2560 pro	8.36	1	8.36
Stepper motor	4.48	6	26.87
Motor drive	7.46	6	44.78
DC Motor	5.22	2	10.45
Linear Actuator	22.09	1	22.09
Laser Sensor	10.15	8	81.19
Binocular camera	32.69	1	32.69
Aluminum rods	/	/	0.75
Screws	/	88	0.30
Nuts	/	80	0.30
Lock nuts of M4	/	8	0.22
Angle iron	0.04	8	0.36
Bearing	0.45	3	1.34
Bearing support	0.45	3	1.34
Motor support	0.37	4	1.49
Omnidirectional wheels	1.49	4	5.97
Switch and wires	/	/	1.79
Total			**303.16**

Table 7-2 Computational devices

Material	Unit Price (USD)	Number	Total Price (USD)
Jetson Nano 2GB	59	1	59
Arduino Mega 2560 pro	8.4	1	8.4

Total	**67.36**