A

Capstone Project Report

On

“ Automatic Sugarcane Bud Detection Mechanism”

Submitted

in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

Electronics and Telecommunication Engineering

By

1.Mr. Aniket Sanjay Patil (1805011)

2.Mr. Shreyash Shankar Jondhale (1905007)

3.Mr. Parth Shriniwas Jadhav (1905008)

4.Mr. Prasanna Harish Joshi (1909021)

Under the Guidance of

Prof. R.J.Patil

Electronics and Telecommunication Engineering Department

K. E. Society’s

Rajarambapu Institute of Technology, Rajaramnagar

(An autonomous Institute, Affiliated to Shivaji University)

2022-2023

DECLARATION BY STUDENTS

We, undersigned, declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

1) Aniket Sanjay Patil (1805011) ( )
2) Shreyash Shankar Jondhale (1905007) ( )
3) Parth Shriniwas Jadhav (1905008) ( )
4) Prasanna Harish Joshi (1909021) ( )

DECLARATION BY GUIDE

It is certified that the work contained in the project report titled "**Automatic Sugarcane Bud Detection Mechanism**" By above mentioned students, has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

Guide

Prof. R.J.Patil

Dept of E & TC

ACKNOWLEDGEMENT

It is our foremost duty to express our deep sense of gratitude and respect to the guide **Prof. R.J.Patil** for his uplifting tendency and inspiring us for taking up this project work successful.
We are also grateful to **Dr. M. S. Patil (**Head of Department of Electronics & Telecommunication Engineering) for providing all necessary facilities to carry out the project work and whose encouraging part has been a perpetual source of information.

We are highly indebted to **Dr. Mrs. S. S. Kulkarni** for their guidance and constant supervision as well as for providing necessary information regarding the project & also for their support in completing the project.

We also thank all staff members of our department for their timely help and encouragement, which help us in completing of our project work.

We are indebted to the library personnel's for offering all the help in completing the project work. Last but not only the least we are thankful to our colleagues and those helped us directly or indirectly throughout this project work.

ABSTRACT

Sugar cane is one of the most important crops in India and many countries. The sugarcane bud cutting machine is designed to cut buds from sugar cane. But, using the old system of sugarcane bud cutting machine, it takes more time to cut the buds. In this project a machine is designed that cuts sugarcane buds using image processing technology. It helps to increase overall efficiency of the process. It provide additional safety and eliminates the risk of accidents.

An image processing-based sugarcane cutting system is developed to achieve damage-proof sugarcane buds and automatic cutting of sugarcane in a single bud element. The sugarcane bud cutting system includes mechanical, electrical and visual processing modules. The core of the system uses image processing to identify parts of the sugar cane bud. The feasibility and discriminative effect of the system can be confirmed by designing a bud detecting prototype. As a result of offline identification of sugar cane bud, the detection rate was 93%. Online tests showed that the integrity of the crossing point location could meet the husbandry needs, with zero bud injury rate.

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CHAPTER 1

1.1 INTRODUCTION

Sugarcane bud detection refers to the process of identifying and detecting the buds on sugarcane plants. An image processing-based sugarcane bud cutting system is developed to achieve buds with damage protection and automatic cutting in single bud segments of sugarcane. The bud cutting system includes mechanical, electrical and visual processing modules. The core of the system uses image processing to identify sugar cane bud segments. The feasibility and discrimination effect of the system can be better verified by building a bud-cutting prototype. Results of offline identification of sugarcane bud segments show a detection rate of 93% with an average time of 0.539 seconds.

There are several approaches that can be used for detecting sugarcane buds, including:

1. Manual inspection:

This includes physically inspecting plants and visually identifying buds. This can be time consuming and may not be suitable for large fields or crops with dense foliage.

2. Machine vision:

This involves using cameras and computer vision algorithms to automatically detect buds in plant images and videos. Vision systems are more efficient and accurate than manual inspection, but may require specialized hardware and software.

3. Neural networks:

A neural network is a type of machine learning algorithm that can be trained to recognize patterns in data. These can be used to detect sugar cane shoots by training a model on the dataset with annotated images of the plants.

1.2 Project Motivation:

- Sugarcane is one of the most important cash crops in the world and sugarcane cultivation and mechanization are the developing trends of the industry.

- However, most of the sugarcane bud cutting machines do not have the bud protection function for automatic cutting of sugar cane buds.

- Real-time automatic sugarcane bud cutting usually have a fixed cutting length and are more efficient than artificial sugarcane bud cutting.

- However, the bud damage rate is very high. Automatic sugarcane bud cutting avoid damaging buds and are more efficient than real-time cutting machines.

- However, real-time cutting machines cannot automatically find sugarcane buds. Cutting performance is not high.

1.3 Project Scope:

To meet farmers' demands, our system helps increase accuracy of bud detection. With increased accuracy and speed, our systems produce more product and provide nurseries with more input into production.

Due to our product's high accuracy, less sugar cane buds are wasted compared to traditional systems. The system is fully automated and can take full advantage of technology to do everything intelligently and efficiently, reducing both energy and time consumption. It has a wide range of applications in various industries as it can save time and effort.

Also, the mechanical structure is designed so that it can be attached to a tractor and planted directly in the field.

1.4 Relevance:

- This system has great potential to significantly reduce pipe stem, boron, and other input costs.
- The effects of relevant parameters on sugar cane seed production were investigated for high shoot pruning efficiency, throughput, and low power consumption.
- The signal is collected using both the acceleration sensor and the piezoelectric film sensor The weighted average algorithm is utilized to detect nodes and calculate error.
- This approach optimizes the mathematical model of the sugarcane node, increases program robustness and accuracy, and allows the system to finish local optimization and reach global optimization.

- Experimental results show that the new improved algorithm improves the solution quality and convergence speed during testing.

CHAPTER 2

LITERATURE SURVEY

This chapter deals with the literature survey of Sugarcane Bud Detection.

2.1 AUTOMATIC SUGARCANE NODE CUTTING MACHINE:

[1] International Journal of Innovative Research in Science and Engineering
Author: Pravin Chavan, Dr. Vithoba Tale, Ganesh Chavan, Swapnil Gadilkar, Atul Kote

[2] Sugar cane (Saccharum sp.) is a clonally propagated grass of the grass family characterized by a high degree of polyploidy and is a major crop providing about 65% of the world's sugar. Reproductive tissue is harvested as an economical product in almost all crops, but not sugarcane. In sugarcane, the culm is the harvested tissue, and culm size has a large impact on yield. In fact, there are some research reports that the size of individual stem internodes changes with the position of the stem and the growth of the plant. Cutting sugarcane bud using traditional methods is costly and time consuming, and because in sugarcane bud cutting, the required bud compaction in the field is not easily achieved. Traditional planting methods require a great deal of human effort and many cane stalks per hectare. To solve this problem and the mechanization of sugarcane cultivation, we propose the application of vision systems and vision methods to identify and plant sugarcane buds.

[3] Required human efforts for cutting buds will be reduced.

- Less time will be taken.
- Skilled person not required for cutting buds.
- Maximum nodes will be cut at minimum time so efficiency will be increased
- More Profit
- Reduce manpower
- Mass production
- Farmer can overcome the labour crises problem

2.2 A NEW DESIGN OF SUGARCANE SEED CUTTING SYSTEMS BASED ON MACHINE VISION:

[1] School of Mechanical Engineering, Jiangnan University, Wuxi 214122, China

Author: Deqiang Zhou, Yunlei Fan, Ganran Deng, Fengguang He, Meili Wang

[2] A machine vision-based sugarcane cutting system is developed to achieve buds with damage protection and automatic cutting in single bud segments of sugarcane. The bud cutting system includes mechanical, electrical, and visual processing modules. The core of the system uses computer vision to identify sugar cane stem segments. The feasibility and discrimination effect of the system can be better verified by building a seed-cutting prototype. Results of offline identification of cane stem segments show a detection rate of 93% with an average time of 0.539 seconds. The throughput of the developed system with a single cutter is up to 2400 buds/hour. Online tests show that the cutting point location accuracy can meet the needs of agriculture, and the bud damage rate is zero.

[3] Given the obvious leaf-marking features of sugarcane nodes, leaf-marking features have been used to identify sugarcane nodes. By constructing a feature description vector to describe the features of the cane image and defining the values of the vector elements at the cane nodes and the distances between the cane nodes, the positions of all root nodes in the cane image searched. The method in this study was validated experimentally, with a detection rate of 93% and an average time of 0.539 s. A prototype was designed and evaluated. The sugarcane conveying speed has no effect on the qualified cutting rate of seeds and the average positional error of cutting, and the stability of the system is good. The throughput of the developed system with a single cutter is up to 2400 buds/hour. Cutting equipment can meet the agricultural needs of sugar cane seed production. In summary, the main contribution of this paper is to develop a new system for cutting sugarcane seeds based on machine vision. This saves time, reduces labour intensity, and is safe and stable. It will be a reference for developing a sugarcane germination prevention system.

2.3AUTOMATIC SUGARCANE BUD DETECTION AND CUTTING MECHANISM:

[1] International Research Journal of Engineering and Technology (IRJET)

Author: Pragati V. Jadhav, Sonali S. Surwase, Smita S. Lad, S.S.Sankpal.

[2] In today's world, all needs are met by automated systems. A desire to reduce wastage of sugar cane. The search for automated systems is completed by this project. An alternative to reduce sugarcane seed mass and improve quality is to plant excised axillary buds of sugarcane stems, commonly known as bud detectors. This bud detector can be incorporated into a bud chip to detect buds. These bud detectors are less bulky, easier to carry and made from more economical materials. Bud detection technology holds promise for rapid diffusion of new sugarcane varieties. Establishment and early growth issues can be addressed by applying appropriate plant growth regulators and essential nutrients.

[3] In today's world, sugar cane automation has become important in the agricultural sector. In most countries where agriculture is the main occupation, automatic pruning of sugar cane buds has played a very important role. I chose this project because it solves the problems of farmers. Reduce manpower and make work easier by developing new designs to reduce labour. Our project develops devices with user interfaces and great look and feel. Automating sugar cane sprout detection improves simplicity and user satisfaction. This project has helped us provide a large amount of sugar cane shoots in a short time with less staff. In today's world, our sugar cane plantation projects will be in the agricultural sector.

2.4SUGARCANE BUD DETECTION METHOD BASED ONYOLOV3-CSE NETWORK:

[1] College of Mechanical and Control Engineering, Guilin University of Technology, Guilin, Guangxi, 541000, China

Author: Jiaodi Liu, Jie He, Hongzhen Xu, Manlin Shen, and Yulong Duan

[2] It is specified in agronomic requirements of sugarcane sowing that sugarcane buds should be placed toward the walls on both sides of the sowing ditch, while the traditional detection model of small sugarcane bud targets cannot meet the requirements of intelligent directional seeding machine

for sugarcane bud identification due to such shortcomings as low accuracy, low recognition speed, and low training speed. To this end, a network model targeting sugarcane buds, called YOLOv3-CSE was proposed in this paper. Based on analyzing the advantages and disadvantages of the YOLOv3 network, the original YOLOv3 network was improved to achieve accurate and rapid identification of small and medium-sized targets in sugarcane buds. Besides, to further enhance the detection ability of the model for small object regions such as sugarcane buds, the original DarkNet-53 network structure and the complete intersection over union (CIoU) bounding box regression loss function were improved to make the real box regression more stable, thus avoiding IoU divergence in the training process and ameliorating the regression effect on sugarcane bud identification. Mosaic data augmentation method was applied to enrich the data diversity,

to solve the inadequate generalization ability during small dataset training. Finally, the SE-ResNet module was incorporated to improve the network model's ability to identify sugar cane sprout features. Test results of the YOLOv3-CSE network and the original YOLOv3 network show that the accuracy and average accuracy (mAP) of the YOLOv3-CSE network are 96.93% and 95.87%, which are 5.66% and 4.95% higher than the original YOLOv3-CSE network. YOLOv3 network.

Compared with other object detection models using the same dataset, the YOLO v3 CSE network proposed in this article shows robustness, rapidity, accuracy, and accuracy in identifying small objects in sugar cane buds. Detection speed is improved. In addition, it can quickly identify sugarcane buds and provide technical assurance for the application of intelligent sugarcane seed directional seeders.

[3] A YoloV3-CSE-based sugarcane bud identification method was proposed in the study. Before the training of the network model, data augmentation was conducted to enhance the diversity of data. The inadequate generalization ability in training small datasets was further strengthened. Then, the feature layer of the network and the bounding-box regression loss function were improved. Finally, the SE-Reset module was embedded to reduce the parameters and computation, increase the identification velocity, and decrease the size of network models. Great improvements were made in identification velocity and precision, and the performance and identification effect of each network model were compared. The research results are as follows:

- The improvements reduced the parameters and computation of the network model. For YOLOv3, the size of weight files was decreased by 50.89% from 240.7 MB to 118.2 MB. In addition, the improvement method was verified according to the evaluation criteria of network model performance. The results showed that the values of mAP and precision of the network model reached 95.87% and 96.93%, respectively, after the improvement, and the identification time was 0.15 s. Compared with the original YOLOv3 network, the values of mAP and precision rose by 4.95% and 5.66%, respectively.

- When the IoU threshold was higher than 0.5, the values of mAP, precision, recall, and F1 decreased
- as the IoU threshold increased. For a given IoU threshold, mAP and F1 values decreased as the confidence threshold increased. The results showed that with an IoU threshold of 0.5 and a confidence threshold of 0.01, the network model produced the best prediction results.
- The YOLOv3-CSE network used solved the difficulty of dynamically identifying small targets in sugarcane buds, boasting the advantages of strong robustness, good real-time performance, high accuracy and fast detection speed. provided technical assurance for the application. of intelligent directional cutting for sugarcane bud.

CHAPTER 3

PROBLEM STATEMENTS AND OBJECTIVES

3.1 Problem Statement:

Sugarcane bud cutting using traditional methods is costly and time consuming, requiring a great deal of human effort, security issues and a large amount of wastage of sugarcane buds. Also, existing (traditional) tools used to cut sugarcane buds are unsafe, and require skill and training. The risk of injury is too high. Thus, requires the development of an image processing-based sugarcane bud cutting system to achieve damage-proof sugarcane buds. Automatic sugarcane bud cutting machines is used to reduce human effort and time. The buds may be cut, the buds may not germinate, and the seeds may be lost, thus requires the properly controlled bud cutting. Unfortunately, traditional sugar cane planters do not have such facilities. In this project, we explore solutions to overcome these problems and describe how to use image processing techniques for bud detection.

3.2 Project Objective:

• To design and fabricate an automatic sugarcane bud cutting machine.

• To design and develop a neural network model for the detection of sugarcane buds

• To use Python and Google-Colab as an effective tool for the development of neural network algorithms for the detection of buds

• To work faster and more efficiently in order to reduce human effort.

• To reduce the human effort required for sugarcane planting by developing automated sugarcane node cutting machine.

• To develop machine which have proper control on cutting location so cut cannot appear on bud.

• To cut maximum buds at minimum time so efficiency will be increased.

CHAPTER 4

METHODOLOGY

4.1 Block Diagram:

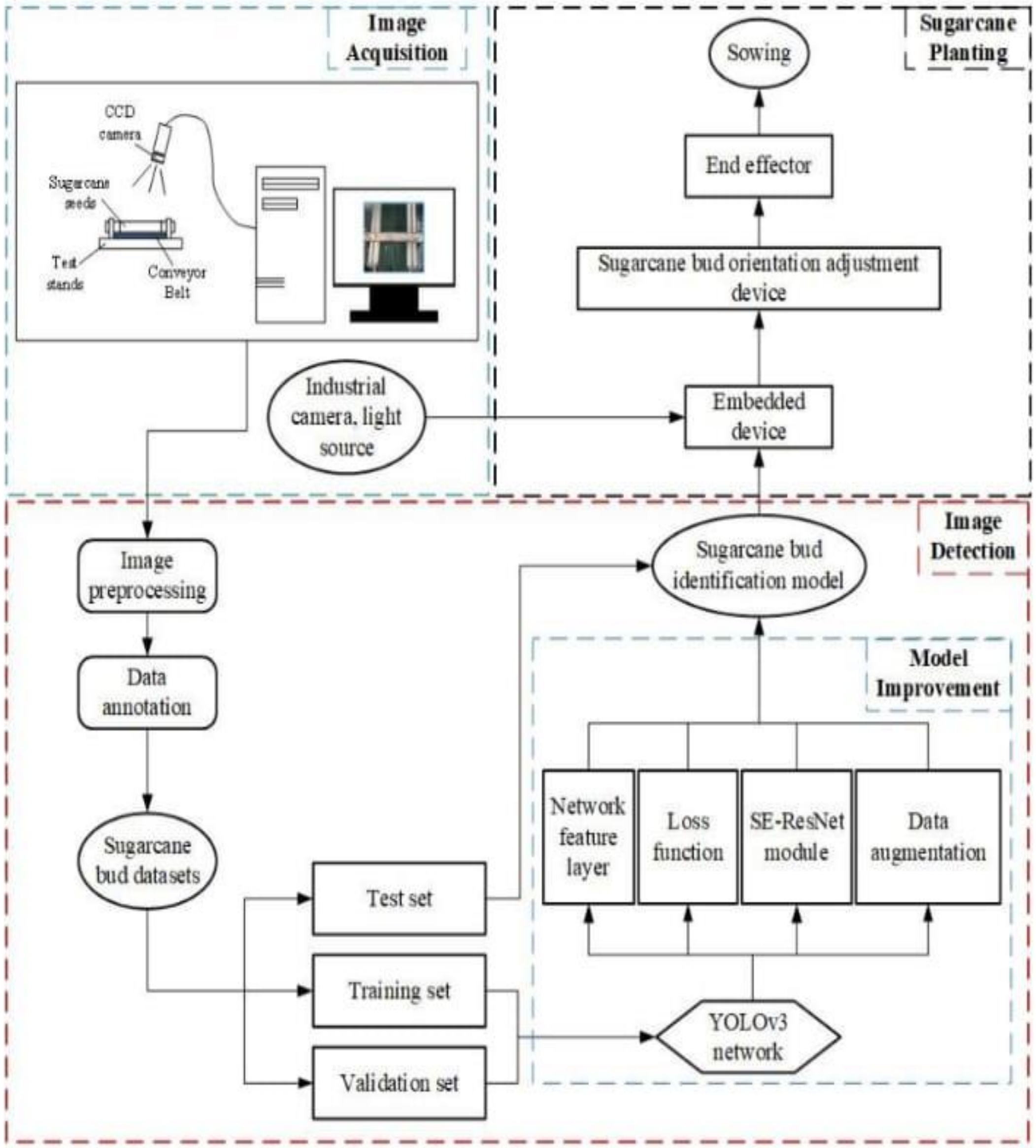


Fig1: Block Diagram

The 4 Phases:

To create Bud Detection, we must work on 4 very distinct phases:

I. Data Gathering

II. Labelling the Data

III. Model Training

IV. Bud Detection

I. Data Gathering

Collecting data to train a deep learning model is an essential step in the machine learning process. The predictions made by DL systems can only be as good as the data they are trained on. Below are some of the problems that may arise during data collection:

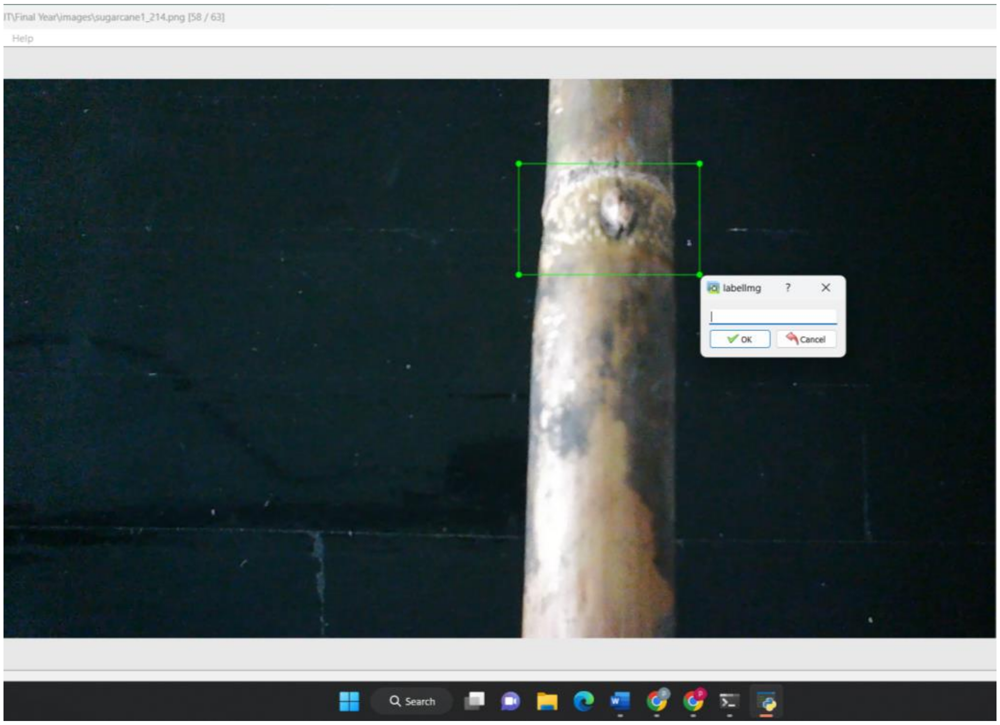
- Inaccurate data. The data collected may not be related to the problem statement.
- Missing data. Partial data may be missing. This could take the form of empty column values or missing images for a particular prediction class.
- Data imbalance. Some classes or categories in the data may have a disproportionately high or low number of matching samples. As a result, they risk being underrepresented in the model.
- Data distortion. Depending on how the data itself, the subjects, and the labels are chosen, the model could promote innate biases regarding, for example, gender, politics, age, or region. Data distortion is difficult to detect and remove.

Fig 2: Data Gathering

II. Data Labelling

Labelling image is the first and most significant part of object detection. Labelling is indeed a very time-consuming process, but the more dedication you will give in labelling images, the more accurate your model can be

LabelImg is a graphical image annotation tool that allows you to draw visual frames around your objects in each image and also automatically saves XML files of your labeled images.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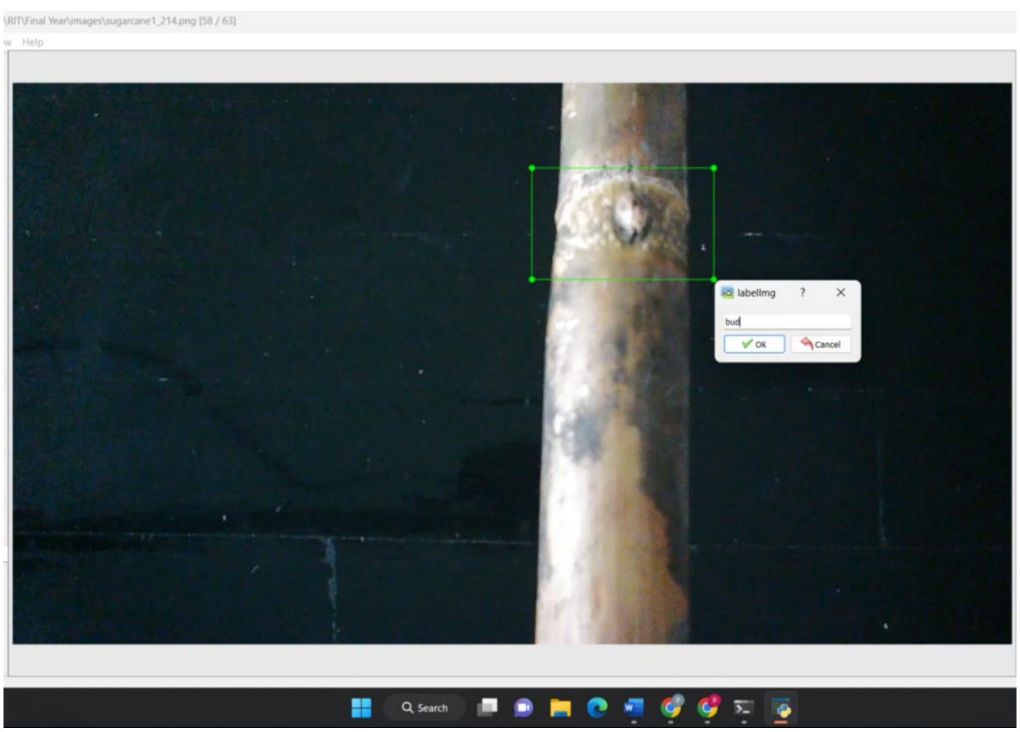
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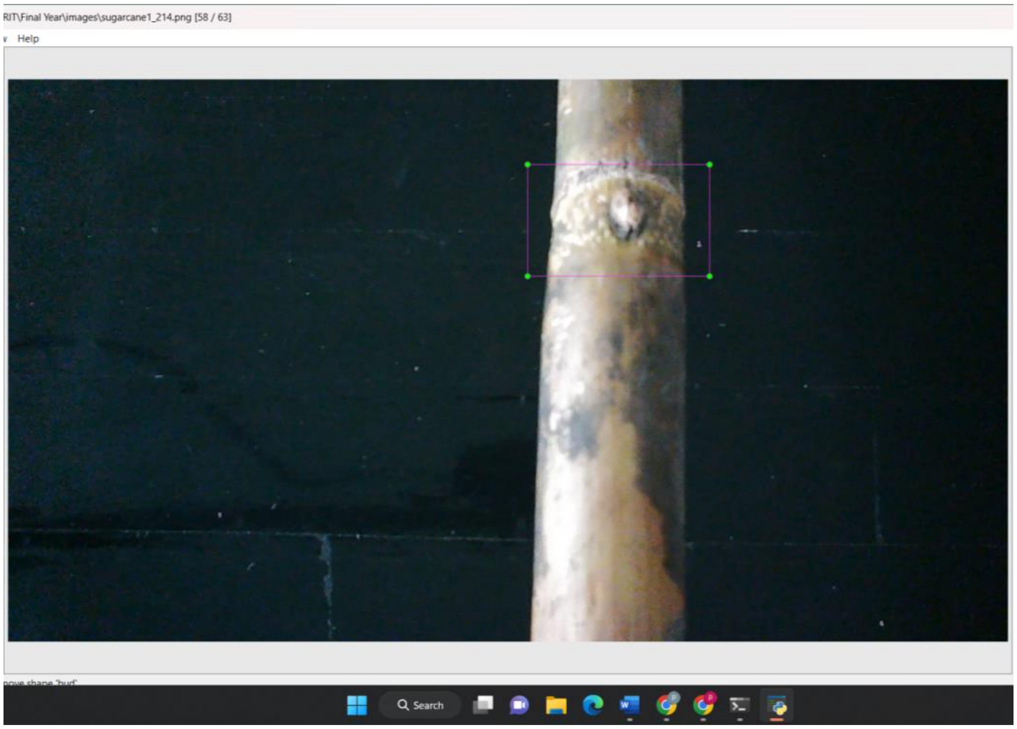


III. Model Training

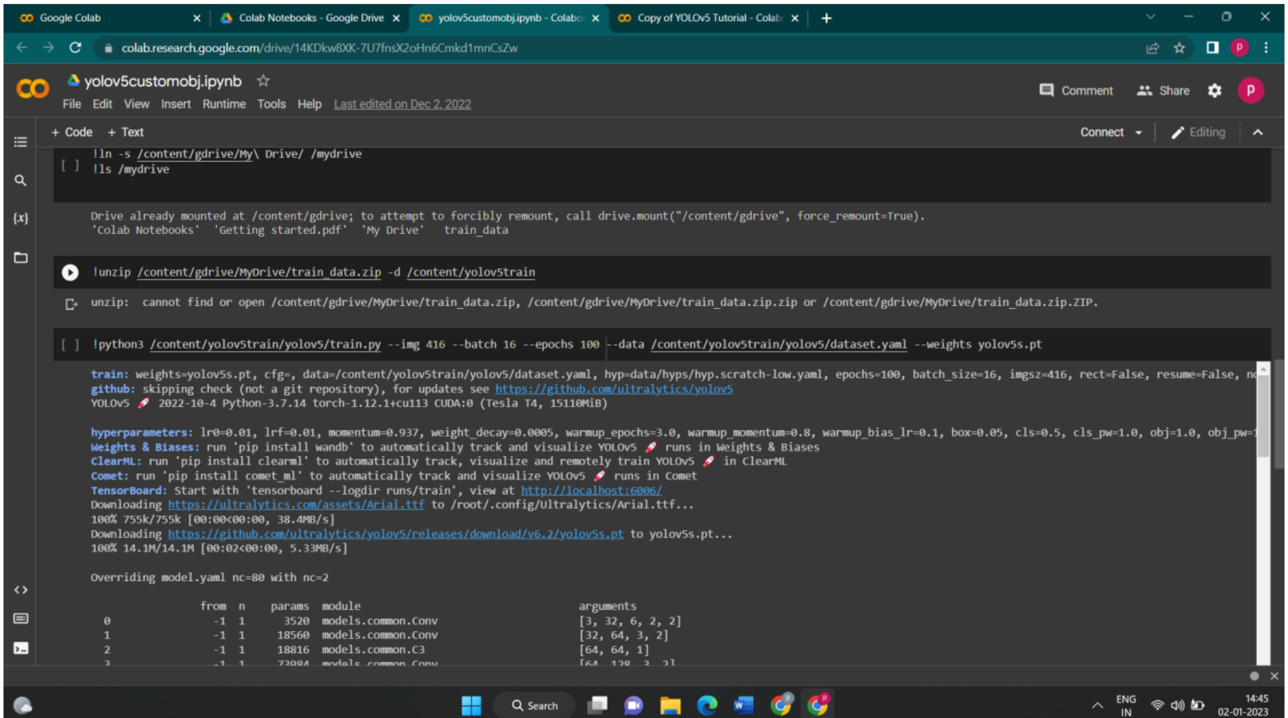
Some parameters of the YOLOv5 network could be determined through repeated testing. In order to select the optimal parameter values, the mode was tested repeatedly, and it was found that the accuracy of the model was relatively high when the learning rate was equal to 0.001. As a result, the initial learning rate was set to 0.001, which was decreased gradually with the increased number of training iterations. The final learning rate, IoU threshold, batch size, confidence and number of iterations were set as

0.0001, 0.5, 12, 0.01 and 100, respectively. The settings of model parameters are listed in Table. During training, small-batch training was conducted with 12 pieces of images as a batch, and the weights were updated once after the training of each batch of images. After training, 100 weights were screened to generate 10 weight files with relatively small test loss for inspection, from which the one with the highest mAP was selected as the weight file. Finally, the test set and the validation set were tested, and the test results were saved.

Parameter name	Parameter Value
Batch Size	16
Training Size	416 X 416
Numbers of iterations	100
IoU threshold	0.5
Initial learning rate	0.001
Final learning rate	0.0001
Confidence	0.01

Table No: 01

The change curves of loss value of five different network models for sugarcane bud training are shown in Figure. In the initial training stage, the sugarcane bud detection model manifested high learning efficiency and fast training convergence. As the number of iterations increased, however, the slope of the training curve was gradually decreased. When the number of training iterations reached 50, the changes in loss value tend to be stable after obvious fluctuations in convergence, and the loss value was converged slowly, uniformly and finally stably after 100 rounds of training. Additionally, the loss value rose slightly beyond 100 rounds, indicating overfitting of training set of the model. Hence, 100 rounds was determined as the termination condition of model training in comprehensive consideration of the accuracy of training the network model, so as to avoid the overfitting of the model due to excessive training times. According to the change curves of loss value of the five different network models, the YOLOv3-CSE network displayed prominently faster training convergence and milder fluctuations in convergence, as well as slightly lower loss value after training than the other four network models.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github: skipping check (not a git repository), for updates see https://github.com/ultralytics/yolov5
YOLOv5 2022-10-4 Python-3.7.14 torch-1.12.1+cu113 CUDA:0 (Tesla T4, 15110MiB)
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Weights & Biases: run 'pip install wandb' to automatically track and visualize YOLOv5 runs in Weights & Biases
ClearML: run 'pip install clearml' to automatically track, visualize and remotely train YOLOv5 in ClearML
Comet: run 'pip install comet_ml' to automatically track and visualize YOLOv5 runs in Comet
TensorBoard: Start with 'tensorboard --logdir runs/train', view at http://localhost:6006/
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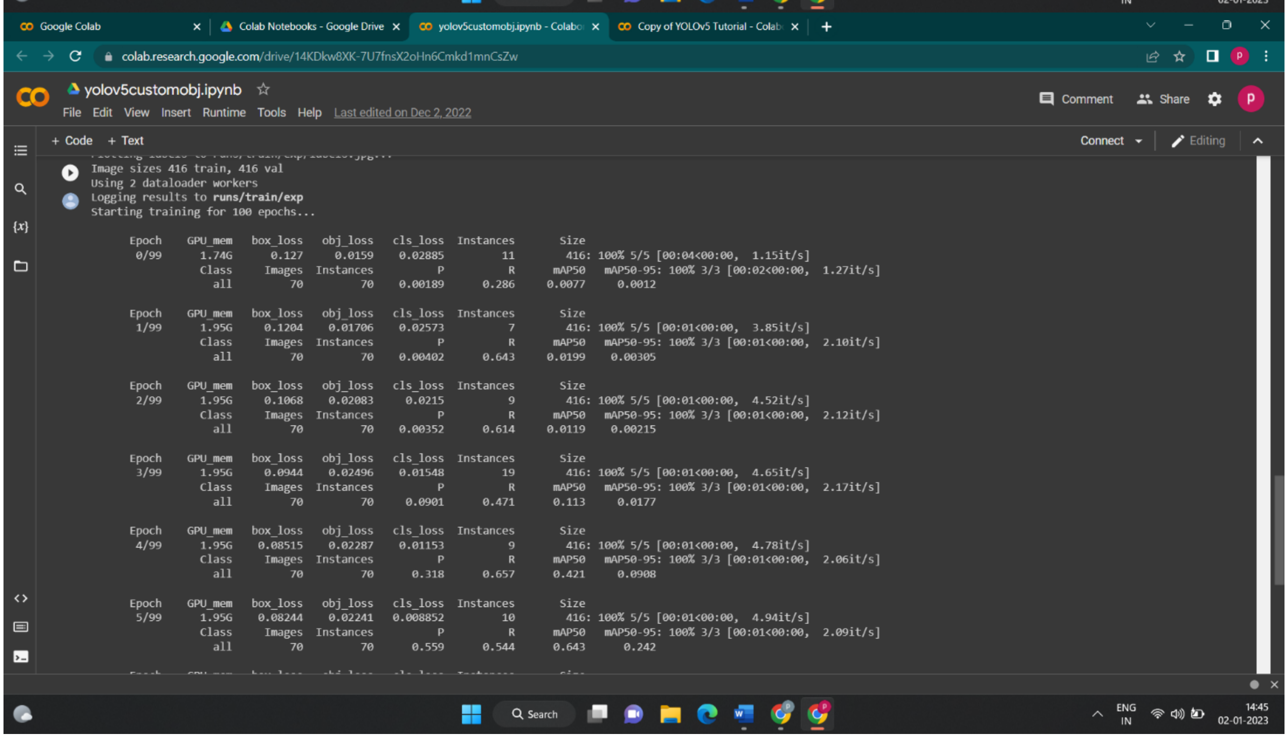
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Comment Share
+ Code + Text
Connect Editing
Image sizes 416 train, 416 val
Using 2 dataloader workers
Logging results to runs/train/exp
Starting training for 100 epochs...
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
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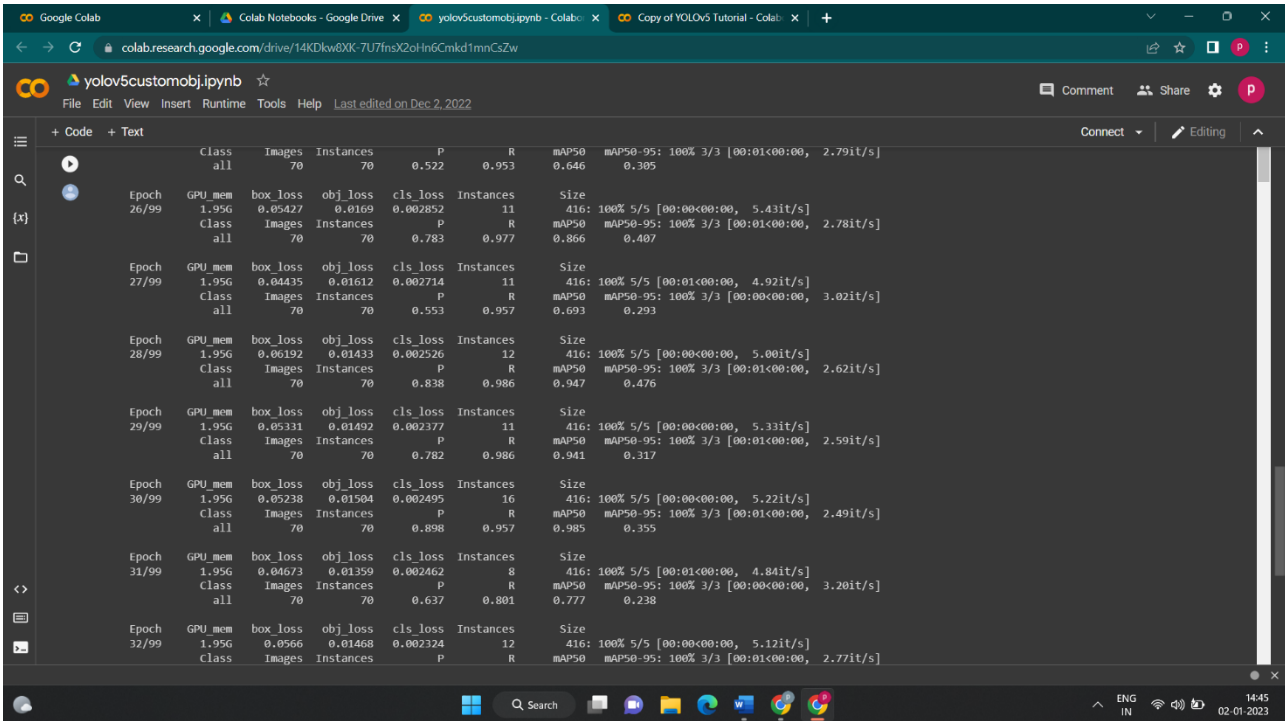

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Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:00<00:00, 3.02it/s]
all 70 70 0.553 0.957 0.693 0.293
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
28/99 1.95G 0.06192 0.01433 0.002526 12 416: 100% 5/5 [00:00<00:00, 5.00it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.62it/s]
all 70 70 0.838 0.986 0.947 0.476
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
29/99 1.95G 0.05331 0.01492 0.002377 11 416: 100% 5/5 [00:00<00:00, 5.33it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.59it/s]
all 70 70 0.782 0.986 0.941 0.317
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
30/99 1.95G 0.05238 0.01504 0.002495 16 416: 100% 5/5 [00:00<00:00, 5.22it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.49it/s]
all 70 70 0.898 0.957 0.985 0.355
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
31/99 1.95G 0.04673 0.01359 0.002462 8 416: 100% 5/5 [00:01<00:00, 4.84it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:00<00:00, 3.20it/s]
all 70 70 0.637 0.801 0.777 0.238
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
32/99 1.95G 0.0566 0.01468 0.002324 12 416: 100% 5/5 [00:00<00:00, 5.12it/s]
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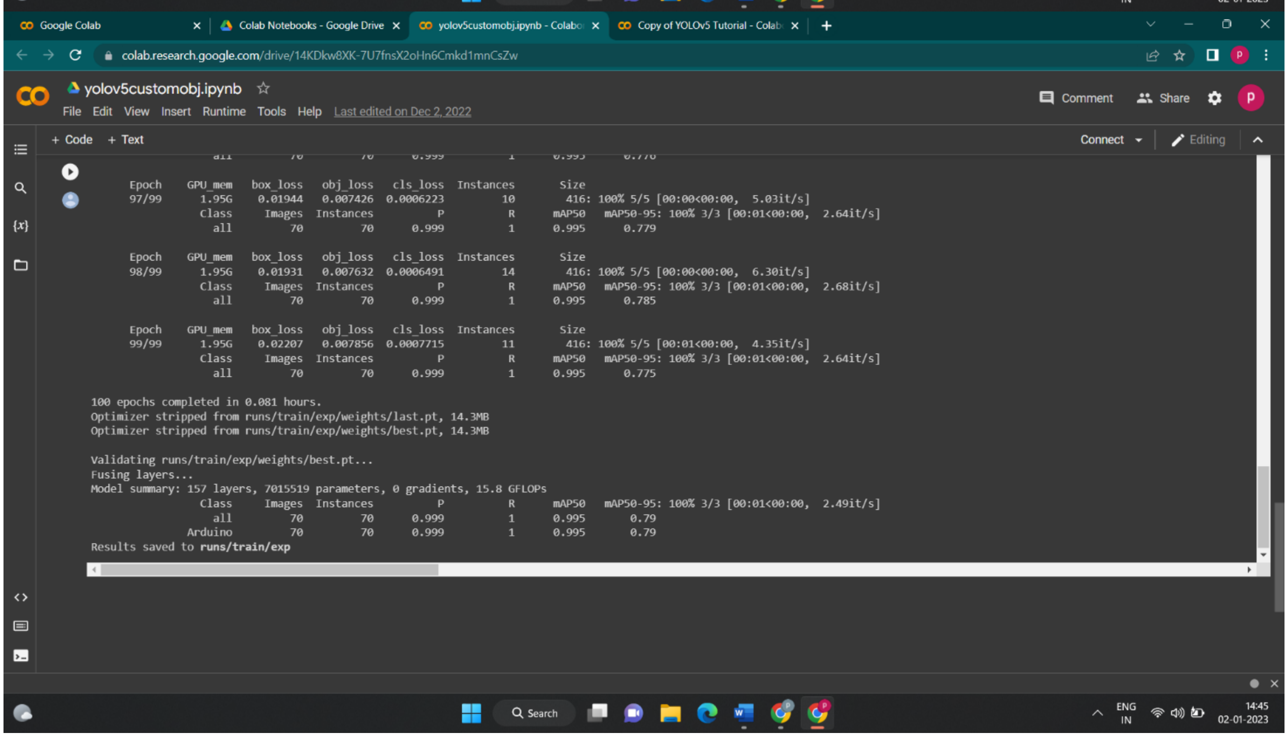
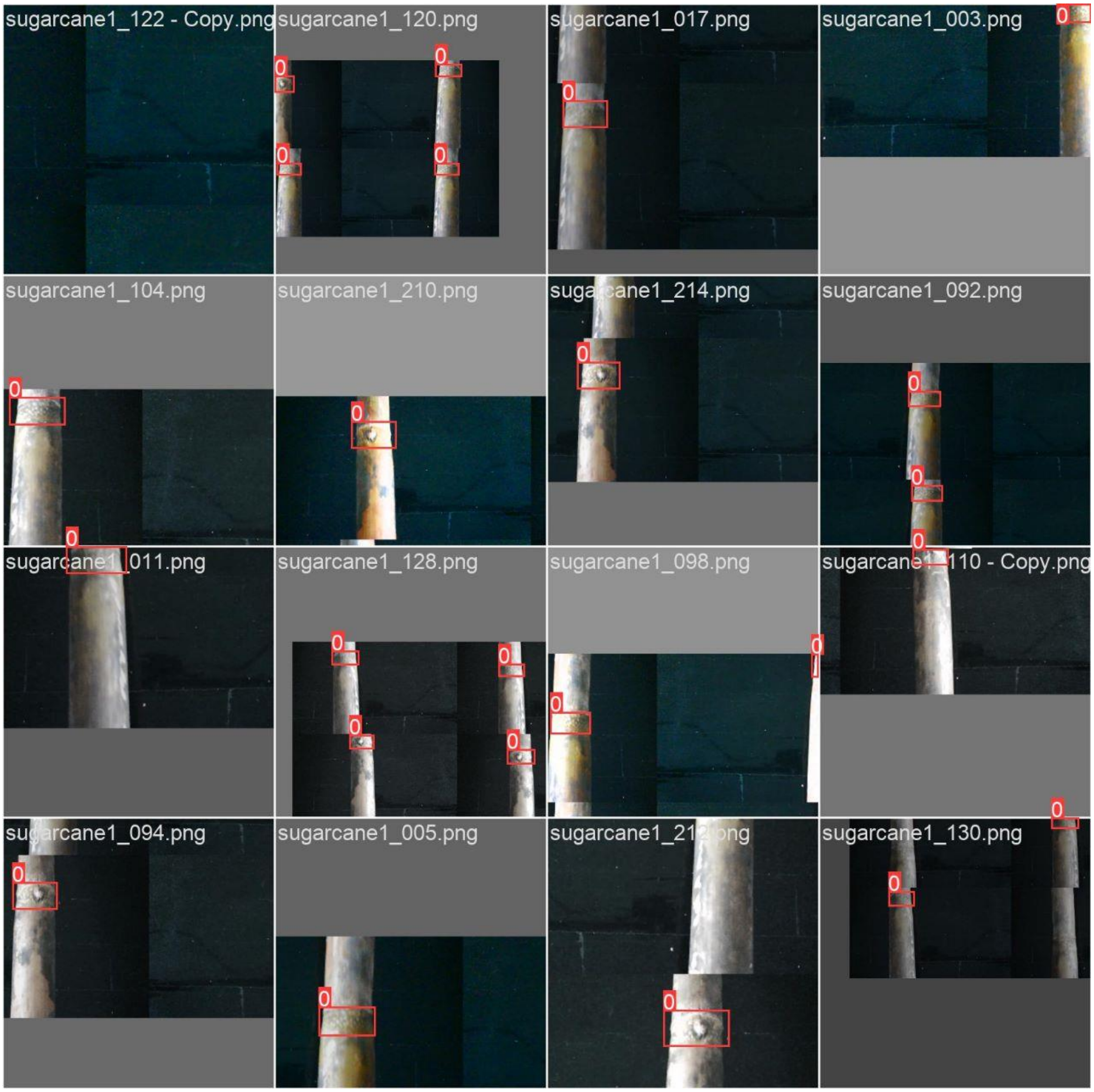


colab.research.google.com/drive/14KDkw8XK-7U7fnsX2oHn6Cmkd1mnCsZw
yolov5customobj.ipynb
File Edit View Insert Runtime Tools Help Last edited on Dec 2, 2022
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
97/99 1.95G 0.01944 0.007426 0.0006223 10 416: 100% 5/5 [00:00<00:00, 5.03it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.64it/s]
all 70 70 0.999 1 0.995 0.779
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
98/99 1.95G 0.01931 0.007632 0.0006491 14 416: 100% 5/5 [00:00<00:00, 6.30it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.68it/s]
all 70 70 0.999 1 0.995 0.785
Epoch GPU_mem box_loss obj_loss cls_loss Instances Size
99/99 1.95G 0.02207 0.007856 0.0007715 11 416: 100% 5/5 [00:01<00:00, 4.35it/s]
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.64it/s]
all 70 70 0.999 1 0.995 0.775
100 epochs completed in 0.081 hours.
Optimizer stripped from runs/train/exp/weights/last.pt, 14.3MB
Optimizer stripped from runs/train/exp/weights/best.pt, 14.3MB
Validating runs/train/exp/weights/best.pt...
Fusing layers...
Model summary: 157 layers, 7015519 parameters, 0 gradients, 15.8 GFLOPs
Class Images Instances P R mAP50 mAP50-95: 100% 3/3 [00:01<00:00, 2.49it/s]
all 70 70 0.999 1 0.995 0.79
Arduino 70 70 0.999 1 0.995 0.79
Results saved to runs/train/exp

IV. Bud Detection:

Now, we reached the final phase of our project. Here, we detect a Bud on our camera and if this Sugarcane had his bud captured and trained before, our detector will make a "prediction" returning its id and an index, shown how confident the detector with this match.
will take as a parameter a captured portion of the bud to be analysed.

Img - 1



Img - 2

Fig 3: Bud Detection

A bud detection system is used to identify and verify a bud from an image or video source. A Bud detection software differentiates a bud from rest of the background in the image. The software first detect the bud then measures different bud features.

4.2 Flow Chart

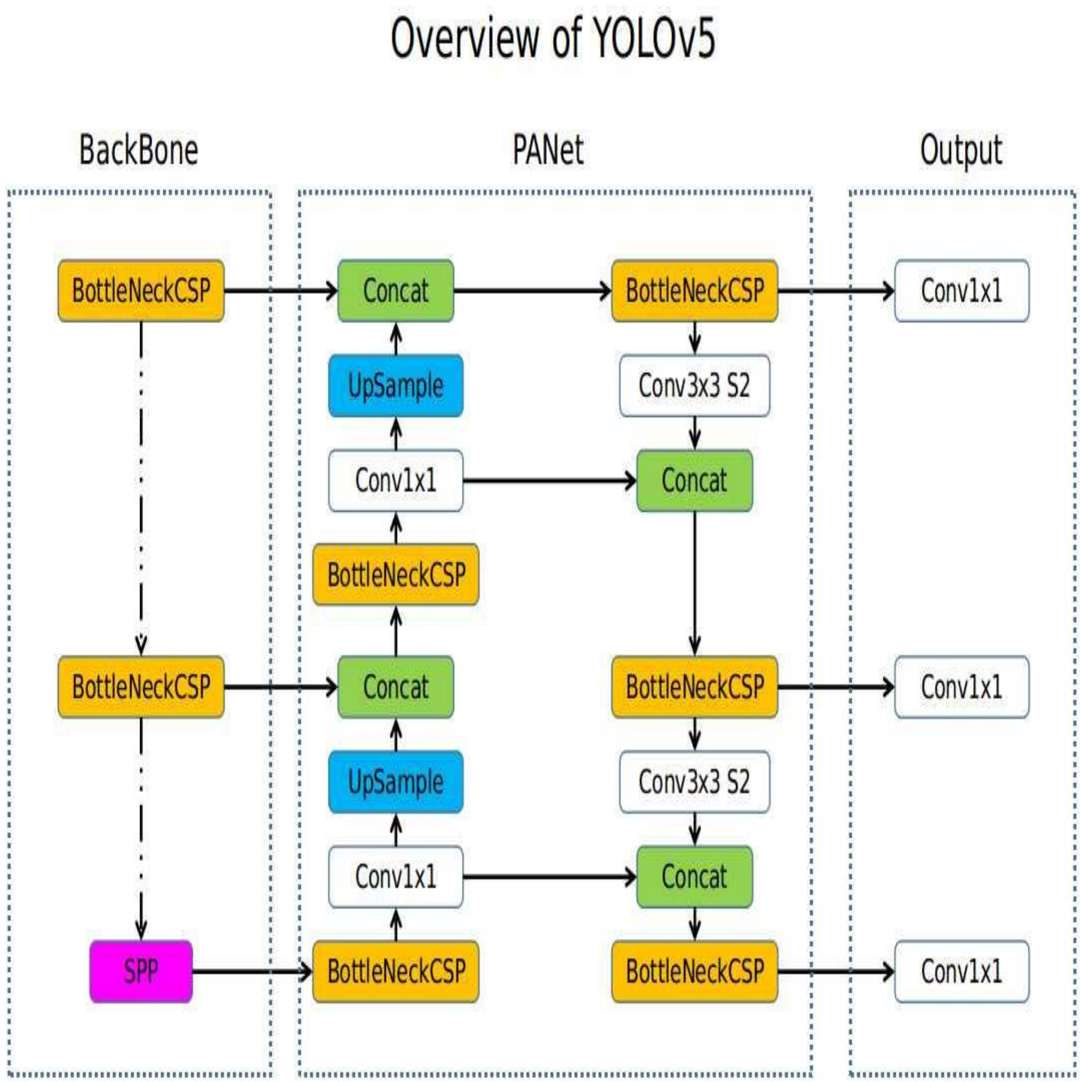


Fig 4: Flow Chart

4.2.1 Features of project:

- User friendly.
- It is speedy and saves time.
- Sugarcane buds detection and cutting will be automatically separated.
- To reduce the damage to sugarcane buds.
- The width of the sugarcane bud can be adjusted as per your requirement

4.2.2 Methodology:

- Identifying the Issue, A particular problem is taken into consideration, and a problem definition is prepared. Other parameters, such as the scope of work and the work objectives, are also defined.
- Selection of Mechanisms The combination of force and movement defines power, and a mechanism manages power to achieve a desired set of forces and movement.
- Material selection is an ordered process by which we can systematically and rapidly eliminate unsuitable materials and identify the one or a small number of materials that are the most suitable for selection.
- Using python and google collab as an effective tool, develop a neural network algorithm for detecting sugarcane buds.
- Manufacturing After finalising the design and material, the model is fabricated and various finishing operations are performed.
- Check for Testing whether the machine is working properly and also test the functioning of all the components.

4.3 Activity Chart

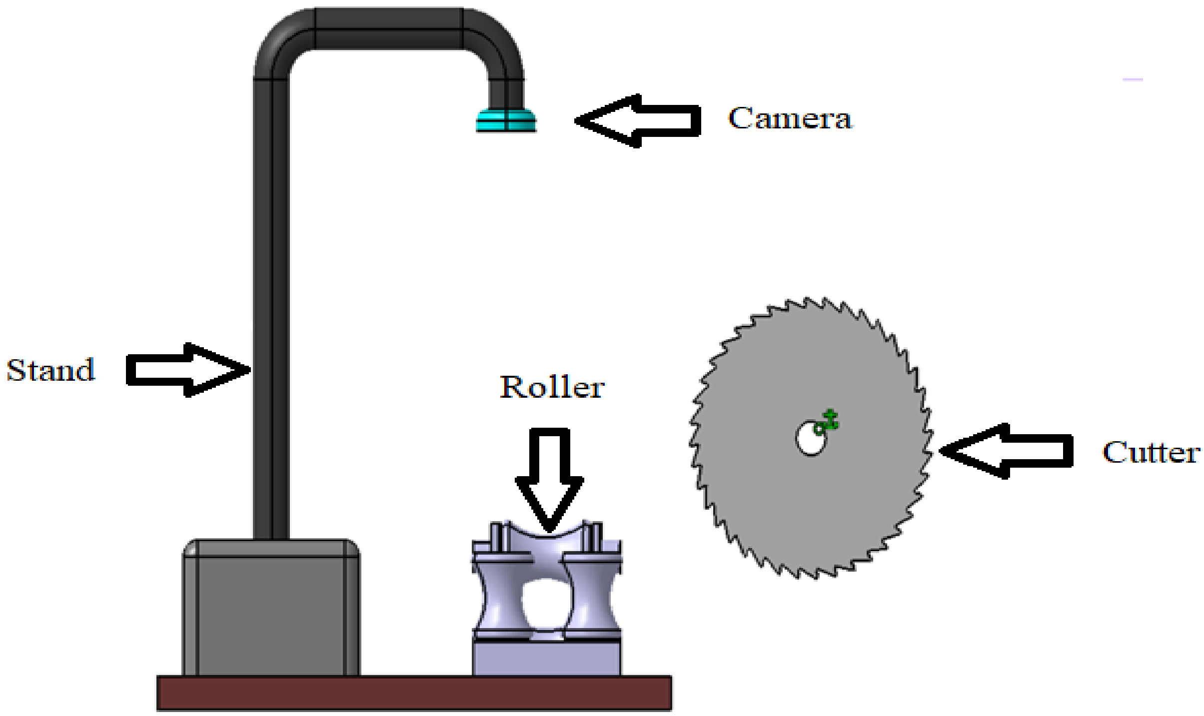
Sr. No.	Activity Details	Months											
		1	2	3	4	5	6	7	8	9	10	11	12
1	Learning Deep Learning Method												
2	MATLAB implementation												
3	Literature Review												
4	Collection and Formation of Dataset												
5	Training System												
6	Testing System												
7	Field Testing												

Table No: 02

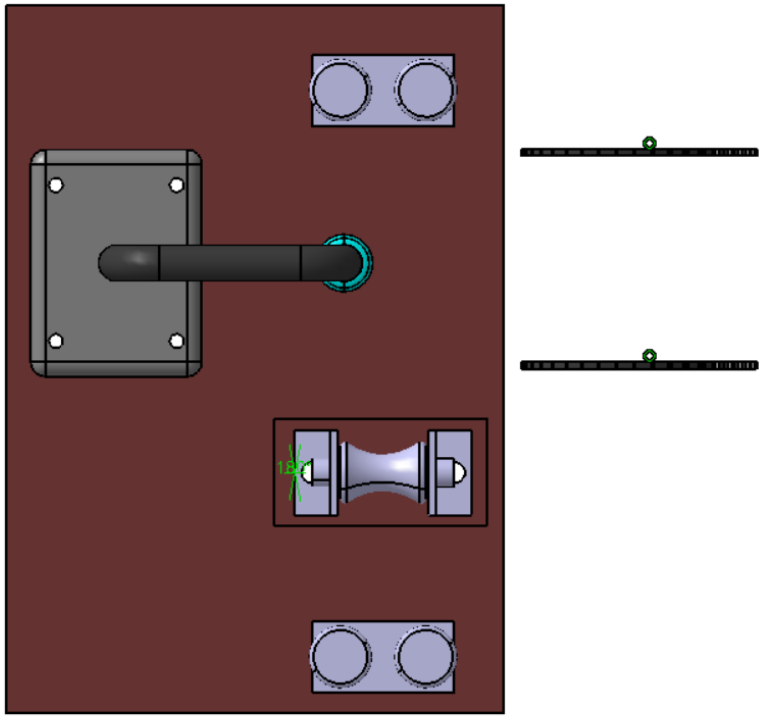
4.4 Expenditure

Product	**cost**
Camera (for image processing)	3000 Rs
Roller	900 Rs
DC Motors	600 Rs
Wooden Board	500 Rs

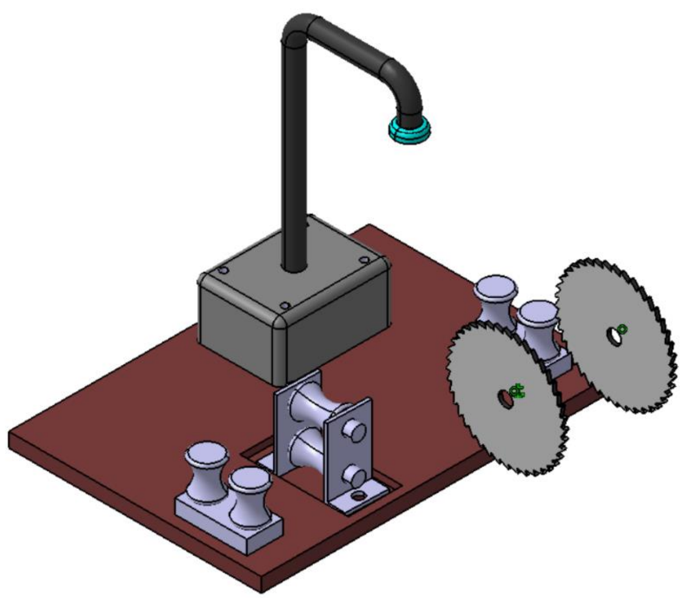
Cad Model Design:



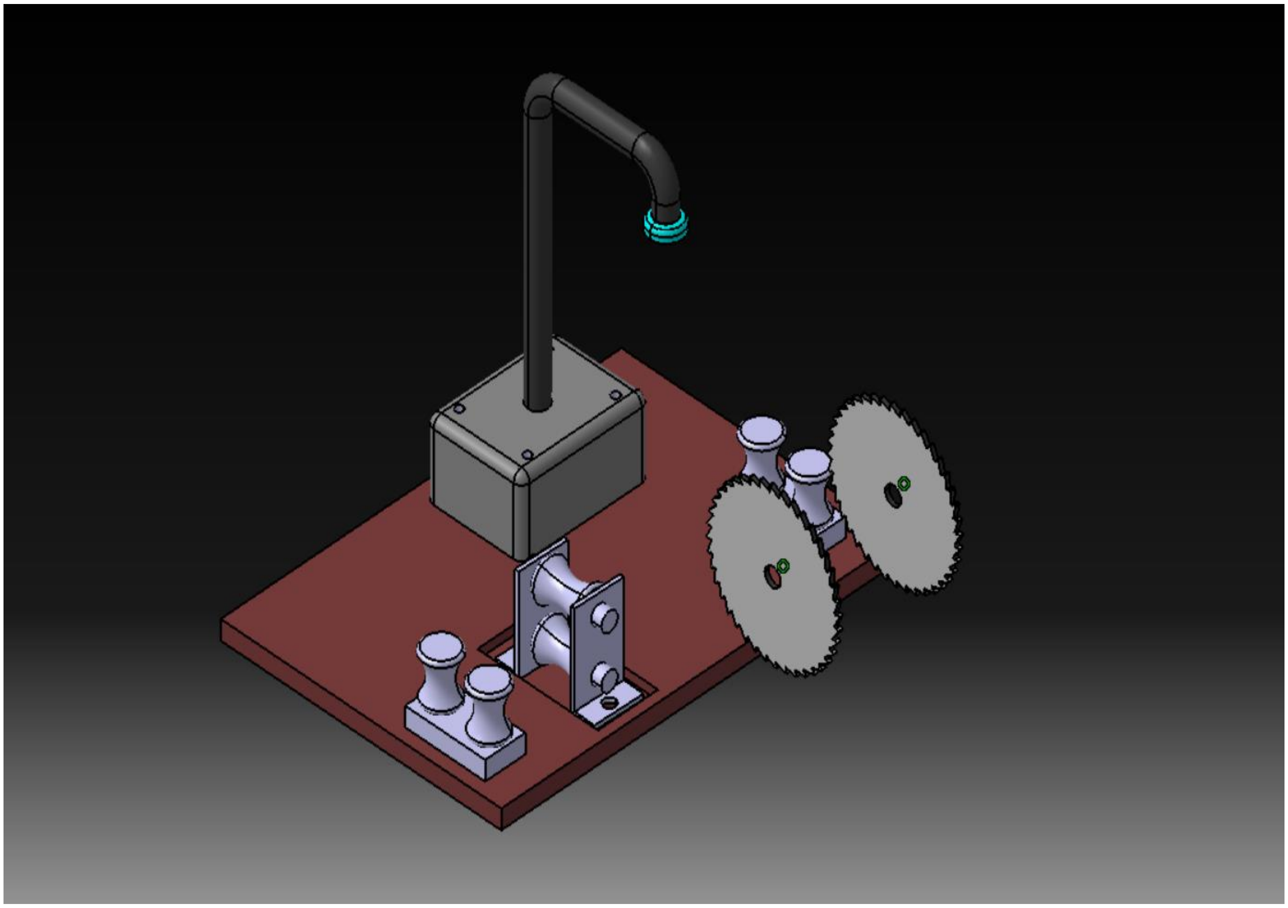
3D model Side View



3D model Top View



3D model Front View



Complete 3D model view

CHAPTER 5

SOFTWARE & HARDWARE REQUIREMENT

5.1 Software Tools:

1. PYTHON and Google Collab:

The Basics. Collaborator, or “Collab” for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education.

5.2 Catia Software Tool: -

Catia supports multiple phases of product development from conceptualization, design and engineering to manufacturing, is considered CAx-software and is sometimes referred to as a 3D Product Lifecycle Management software package. Like most of the competition, it enables collaborative engineering through an integrated cloud service and has support for use across disciplines, including surface and shape design, electrical, fluid and electronic systems design, mechanical engineering and systems engineering.

In addition to being used in a wide range of industries from aerospace and defence to packaging design, CATIA was used by architect Frank Gehry to design some of his signature curvilinear buildings and his company Gehry Technologies developed CATIA-based Digital Project software.

The software was merged with the company's other software suite, 3D XML Player, to create the Solid works Composer Player combo.

5.3 LabelImg Tool: -

LabelImg is a lightweight and easy-to-use image annotation tool to mark the bounding boxes of objects in images. This article provides an overview of LabelImg, when to use it and how to easily annotate images. Choosing the right image annotation software is critical to the long-term success of computer vision applications. Therefore, this guide aims to support your evaluation in finding the best image annotation software for your current and future projects.

In machine learning (ML) and deep learning (DL), image annotation is the technique of labeling or categorizing an image using annotation text, software tools, or both to display data features to be independently identified by your ML/DL model. When you annotate an image, you are essentially adding metadata to the dataset to specify the ground truth. Simply put, image annotation is a type of data labelling that is often called tagging, processing, or transcription. The image annotation method applies to both image and video annotation. As with a set of images, videos can also be annotated on-the-fly, such as image feed or frame by frame.

5.4 Hardware Tools:

1. Camera (web Cam)
2. Raspberry pi
3. DC motor
4. SanDisk Ultra microSD UHS-I Card 64GB,120 MB/s R
5. Roller

1.Camera (web Cam):

Fig 6: Webcam

Focus Type	• Fixed
Pan Angle	• 90 degrees
Connectivity	• USB
Has Tilt	• Yes
Sales Package	• 1 Webcam, USB 2.0 Type-A Connector
Tilt Angle	• 45 degrees
Model Id	• W200
Built In Microphone	• Yes
Usb Cable Length	• 1 m
Has Night Vision	• Yes
Compatible Devices	• PC
Colour	• Black
Brand	• HP

2.Raspberry Pi

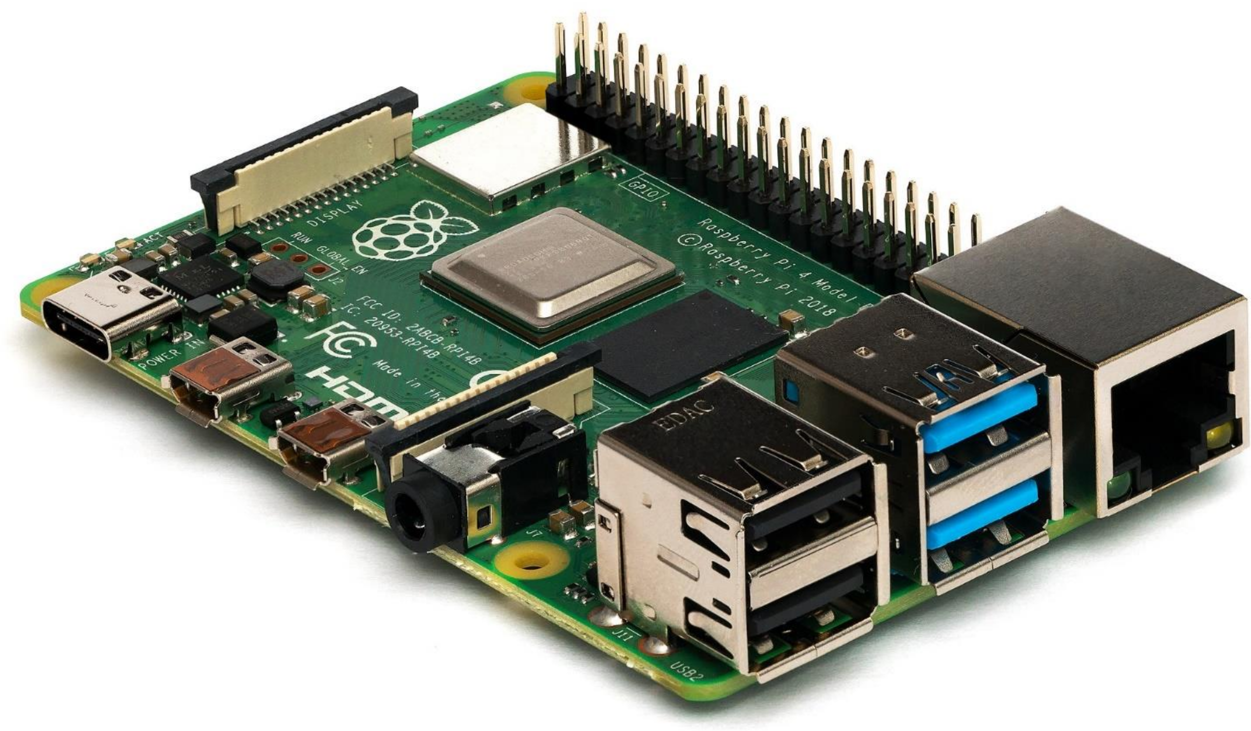


Fig 7: Raspberry Pi

The Raspberry Pi 4 Model B is a powerful single-board computer (SBC) that can be used for a variety of applications. It is capable of running a desktop operating system, such as Linux or Windows, and can be used for tasks such as home media centers, home automation, and even as a low-power desktop computer.

Some of the key features of the Raspberry Pi 4 Model B include:

- A 64-bit quad-core processor, which provides fast and efficient performance.
- Dual-display support, allowing you to connect two monitors to the Raspberry Pi 4 using micro-HDMI ports.
- Hardware video decoding, which allows the Raspberry Pi 4 to play back high-definition video at up to 4K resolution.
- Up to 4GB of RAM, which allows you to run multiple programs at the same time and improve the performance of the system.
- Dual-band wireless LAN and Bluetooth 5.0, which provide fast and reliable wireless connectivity.
- Gigabit Ethernet, which allows you to connect the Raspberry Pi 4 to a wired network for fast and stable internet access.
- USB 3.0 ports, which allow you to connect high-speed devices, such as external hard drives and USB sticks.
- PoE capability (via a separate PoE HAT add-on), which allows you to power the Raspberry Pi 4 using a Power over Ethernet (PoE) setup.

Overall, the Raspberry Pi 4 Model B is a powerful and versatile single-board computer that can be used for a wide range of projects. Whether you are a beginner or an experienced developer, the Raspberry Pi 4 Model B offers a range of features and capabilities that make it an excellent choice for many different applications.

3.DC Motor

Fig 8: DC Motor

A DC motor is defined as a class of electrical motors that convert direct current electrical energy into mechanical energy.

Working of DC Motor:

A magnetic field arises in the air gap when the field coil of the DC motor is energised. The created magnetic field is in the direction of the radii of the armature. The magnetic field enters the armature from the North pole side of the field coil and “exits” the armature from the field coil’s South pole side. The conductors located on the other pole are subjected to a force of the same intensity but in the opposite direction. These two opposing forces create a torque that causes the motor armature to rotate.

4.SanDisk Ultra microSD UHS-I Card 64GB,120 MB/s R

Fig 9: Memory Card

Brand	SanDisk
Model Name	SanDisk Ultra® microSD™ card
Flash Memory Type	Micro SDHC, SDXC
Memory Storage Capacity	64 GB
Read Speed	120 Megabytes Per Second
Write Speed	56x

CHAPTER 6

RESULTS AND DISCUSSION

Result: -


sugarcane1_001.pn
bud
sugarcane1_120 - C
png
bud
sugarcane1_124 - C
png
bud
sugarcane1_128 - C
png
bud
sugarcane1_116.pn
bud
sugarcane1_120.pn
bud
sugarcane1_124.pn
bud
sugarcane1_128.pn
bud
sugarcane1_118 - C
png
bud
sugarcane1_122 - C
png
bud
sugarcane1_126 - C
png
bud
sugarcane1_116 - C
png
bud
sugarcane1_118.pn
bud
sugarcane1_122.pn
bud
sugarcane1_126.pn
bud
sugarcane1_130.pn
bud


sugarcane1_001.pn
bud
sugarcane1_120 - C
png
bud
sugarcane1_124 - C
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sugarcane1_128 - C
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sugarcane1_120.pn
bud
sugarcane1_124.pn
bud
sugarcane1_128.pn
bud
sugarcane1_118 - C
png
bud
sugarcane1_122 - C
png
bud
sugarcane1_126 - C
png
bud
sugarcane1_116 - C
png
bud
sugarcane1_118.pn
bud
sugarcane1_122.pn
bud
sugarcane1_126.pn
bud
sugarcane1_130.pn
bud

Fig 10: Detection of Bud

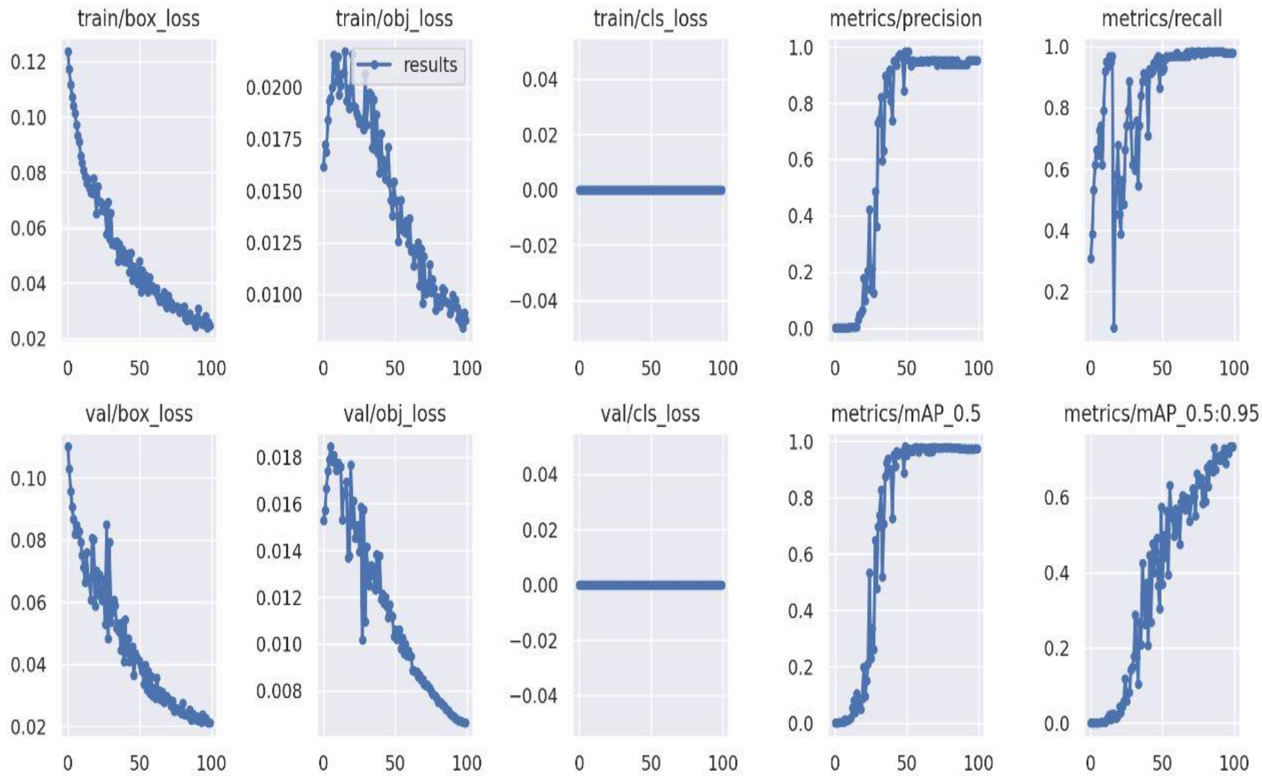

Fig 11.1: Graph of Training and validation after model is train for bud detection

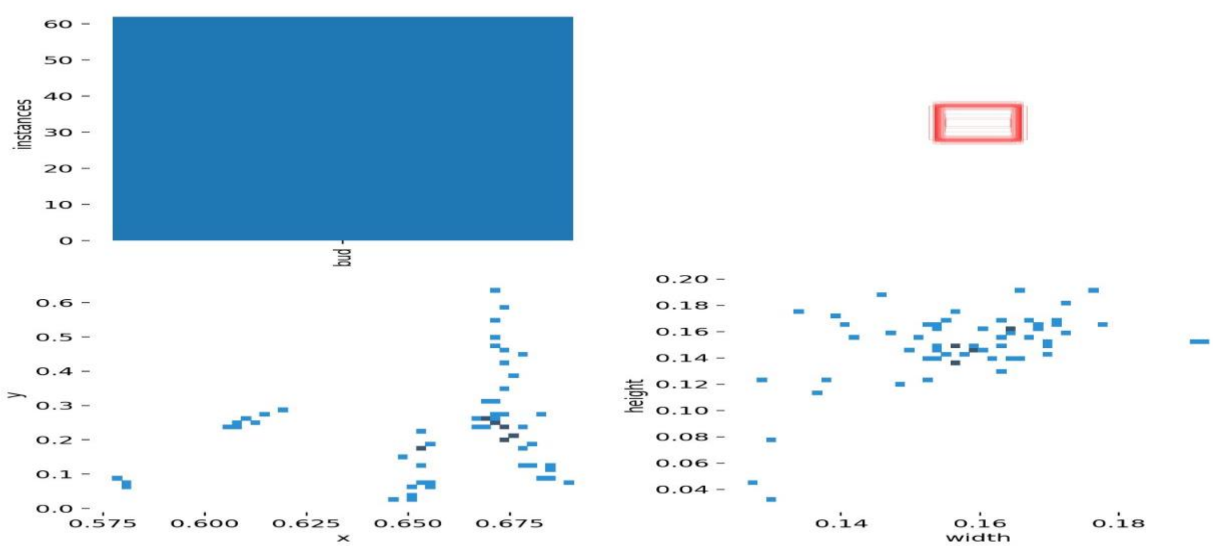

Fig 11.1: Graph of co-ordinate of bud detected

Fig 11: Graph

Discussion:

1.Images of Model

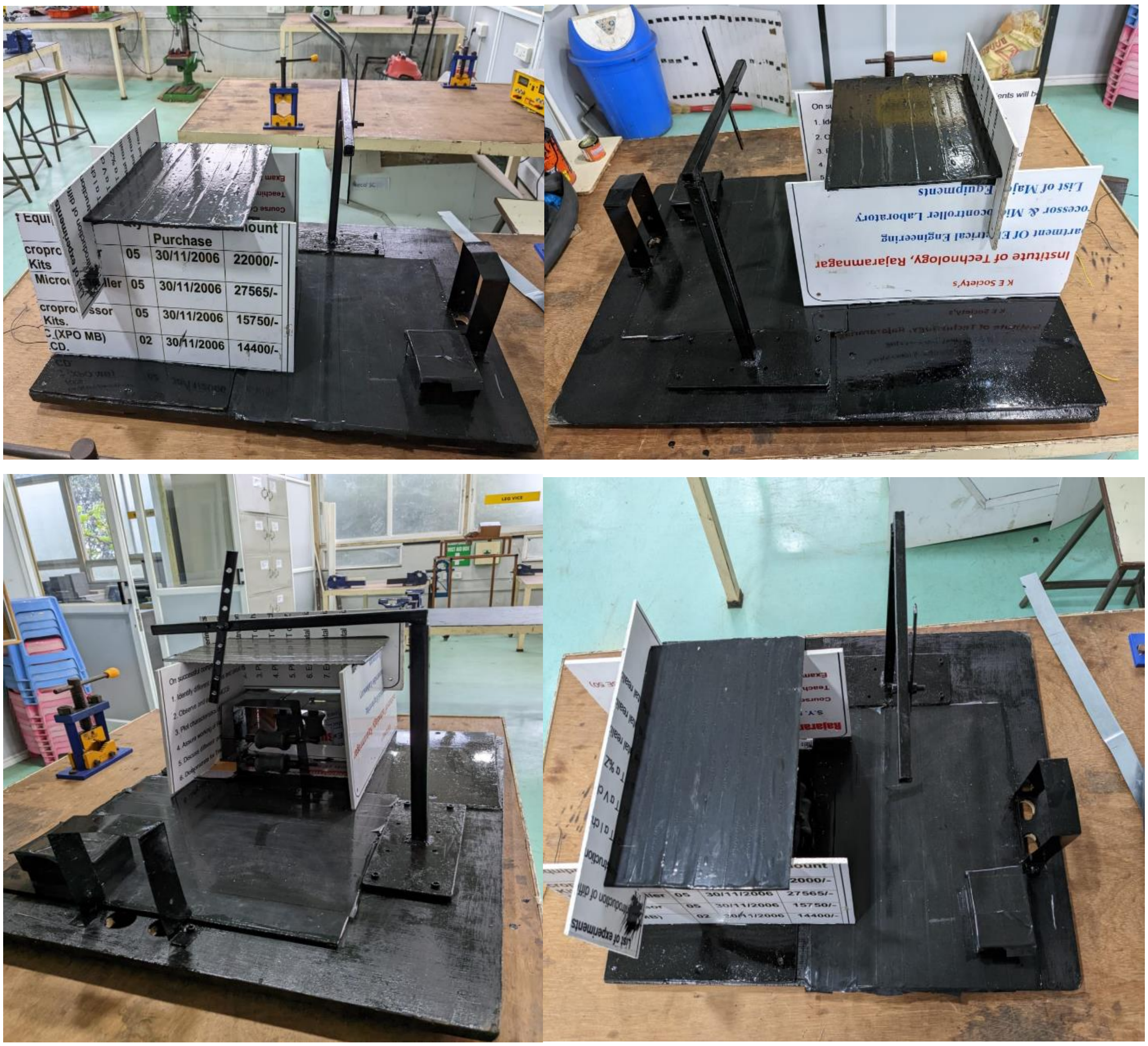

Fig 12: Prototype Model

2.Images of Buds:

Fig 13: Sugarcane Bud

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion:

The design of sugarcane bud cutting machine which can allow the farmer to cut the sugarcane bud in a form which can be utilized as a planting for agricultural of sugarcane. It reduces the manual work of farmer and increases the production. Hence, the project objective of to reduce the human effort to cut the buds from the sugarcane for sowing purpose, taking safety as prime consideration this device is safer in all respects, to build a device which cuts the buds without applying greater force is get satisfied by such a design of bud cutting machine. The sugarcane node cutting machine is very useful to small scale farmers to planting sugarcane node.

During testing of project, following conclusions were made, i.e, the automated sugarcane bud cutting machine is fabricated and assembled as per the proposed design. This machine detects the bud automatically so the newly developed machine is more effective for sugarcane bud detecting.

7.2 Future Scope:

The existing sugarcane bud cutting machine machines do not have control on cutting location. To achieve such accuracy by providing control on cutting location it is simple and effective to use of image processing method. So there is vast scope to increase the accuracy and effectiveness of machine by providing control on cutting location by image processing and deep learning system.

CHAPTER 8

REFRENCES

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[3] A new design of sugarcane seed cutting systems based on machine vision

[4] https://www.researchsquare.com/article/rs-1298165/v1.pdf

[5] https://www.irjet.net/archives/V7/i6/IRJET-V7I6178.pdf

Videos and Photos

Video :- 3Dprinting of the Rollers

Complete Code