“TEABOT” - TEA PLANTATION PRESERVATION USING AN INTELLIGENT ROBOT : A RESEARCH

TMP-2023-044

Project Proposal Report

Perera P.V.Y

B.Sc. (Hons) Degree in Information Technology
Specialized in Data Science

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DECLARATION

We declare that this is our own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

_______________ 23/04/2023

Signature of the supervisor Date

ABSTRACT

In large-scale tea estates precisely liquid fertilizing the tea plantations is a vital task. It helps to preserve the tea plantations effectively. Large-scale tea estates have been using various techniques and methodologies to liquid fertilize the plantations. By acquiring a large workforce, liquid fertilizing and liquid fertilizing plantations punctually is not feasible with manual labor, and irresponsible tasks done by the laborers have led to poor preservation of the plantations. Automatic liquid fertilizing systems, for example, drip irrigation systems need a large amount of capital to implement the pipes, which will not be suitable for a large-scale estate.

The research proposed through TeaBot is an intelligent robot for tea plantation preservation supporting optimizing the liquid fertilizing process of large-scale tea estates. The automatic navigation of the robot provides the opportunity to reach each and every plant even in various environmental conditions without human interference. The liquid fertilization will be done precisely reducing resource wastage since the stem of the plantations will be identified precisely by the robot. After the liquid fertilization process is done, it will be analyzed to identify the accuracy of the process by the robot. A manual robot controller will be developed to control the navigation of the robot since the stakeholders can control the robot in necessary conditions. TeaBot will be developed to optimize the liquid fertilizing, and the liquid fertilizing process by acquiring a low capital. The proposed intelligent robot and functions will be tested in a large-scale tea estate.

Keywords – drip irrigation, automatic navigation, robot controller

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Network
GPS	Global Positioning System
LKR	Lankan Rupees

1 INTRODUCTION

1.1 Background and Literature Survey

The agricultural industry is one of the key areas which directly influence the global economy, health, and society of humans. Urbanization has reduced the areas for cultivation, and the rising population has remarkably influenced to increase in the demand for large-scale agriculture fields[1]. The tea industry acts as a crucial part of the Sri Lankan agriculture field, and it is one of the major revenue sources in terms of foreign exchange earnings [2]. Maintaining the tea plantations in large-scale agricultural fields has been a huge challenge. Recent statistics have identified that the contribution of the tea industry to the economy is decreasing[2]. Several major problems have been identified, inefficient resource usage, high labor salaries, labor shortage, high resource wastage, and failures in liquid fertilizing the plantations punctually [2][3] are some of them. Several approaches have been made to automate liquid fertilizing tea plantations. Such as Center pivot irrigation[4], drip irrigation[5], and using intelligent robots. In center pivot irrigation large wheels are implemented in the field and sprinkles and nozzles are used to water the plants[4]. This involves a large initial cost to implement the system, and it is hard to water the plantations precisely using this method. Moreover, some plantations which are planted near the wheels will be sufficiently watered but the other plantations do not receive the required amount of water[4]. In drip irrigation systems implementing the pipes requires huge initial capital and the maintenance cost will be high too[5]. To maintain the preservation of tea plantations these approaches should be replaced by innovative sensor driven methodologies improved using information technology[6]. This has led to get the usage of intelligent robots for the preservation of tea plantations[7]. Robots have been developed for liquid fertilizing, and fertilizing [8] processes in large-scale agriculture fields. Navigating the robot precisely to the desired plantations in a large-scale field is a challenge in implementing the robot. The robot [8] is developed using Lora (Long Range) the stakeholders can instruct the robot and then the robot will perform the relevant task[8]. Implementing the robot using Lora acquires a high cost and providing manual instruction in a large-scale agriculture field is complicated[9].

In designing the robot for liquid fertilizing the tea plantations is a complex task since navigating the robot accurately in various environmental conditions, and weather conditions present difficulties [10]. Using computer vision to navigate the robot may be the best approach to bridge the gap discussed in the above problems [7],[10],[11],[12],[13],[14]. Vast development of artificial intelligence have been able to reduce the resource wastage in large scale agricultural fields[15]. The task of autonomous navigation using computer vision is capable of navigating the robot accurately by identifying the crop rows in various environmental, weather conditions[16]. Intelligent robots who detect the crop rows using computer vision have been successfully operating in crops harvesting[17], monitoring crop growth[18], disease prevention[19], plant irrigation and plant management[20] processes. This intelligent robot can be used to water and fertilize the tea plantations. Due to the automatic navigation of the robot it does not acquire manual labor to control the robot[12], since machine learning techniques are using to implement the crop rows it can be implemented using a small capital[8], and the processing accuracy will be high[14]. Tea plantation path detection help the robot in following ways to maintain the agri-field, as summarized from prior studies.

1. Low human interaction : Path detection help to navigate throughout the agriculture field and water, fertilizer the plantations[12] . which reduce labor cost and resource wastage[3].
2. Detecting the end of the tea plantation row : Robot will detect the end of the tea plantation rows and automatically identifies the next row which should be watered, so stakeholders do not need to monitor the robot constantly[21].
3. High accuracy in various condition: Tea plantation path detection algorithm provide a high accuracy even in various environmental conditions(ex: high altitudes, in slopes) and in various weather conditions (ex: sunny, raining weather conditions)[22].
4. Navigating the robot in the most accurate path: Computer vision algorithm will identify the middle of the tea plantation path and guide to navigate according to it. Moreover, it will help to water two tea plants (tea plants are situated in the left and the right side of the path) simultaneously [12],[21].

Navigating the robot is a challenging task. For better outcomes requirements, environmental conditions, limitations of the system should be identified[13]. In 2013, N. Shalal categorize path detection for automatic navigation of agriculture robots into main three categories[23].

i. Robot navigation sensors : Navigation sensors describes how the images will be taken by describes the vehicle status (ex: position of the vehicle, orientation) and the background surroundings [23]. Mainly vision sensors, laser scanners, global positioning sensors(GPS) have been have been proposed[23]. Several global positioning sensors systems have been implemented for automatic navigation but there are many limitations when using GPS. It acts as a single position sensors so to navigate automatically other sensors should be implemented which requires a high cost[24]. Also, it provides a low accuracy, when the robot is moving under the tree canopy it can block the satellite signal to the GPS receiver. Researchers have been using vision sensors and it is cost effective and provide a high accuracy[23].

ii. Computational methods : Machine learning algorithms are used to extract the features of input images. And hough transforms, image segmentation are widely used in this category[23],[25].

iii. Navigation control strategies[23] : Steering control design is discussed in this category[23] for autonomous navigation steering controller should be capable of providing the necessary commands in response to the variations[23],[25].

It has been proposed that for computation methods, detecting the tea plantation rows using computer vision and machine learning techniques are more suitable, and accurate[18],[23],[25]. In 2010 Rovira-Más[26] has analyzed various environmental conditions and proposed suitable sensors systems to navigate the robot accurately[26]. Cost effectiveness is one of the main reasons using computer vision in path detection in agricultural robots[23]. Detecting tea plantation rows in various environmental conditions(ex: in sunny conditions, high altitude areas, when having weeds in the agri-field) is challenging[23]. To detect the crop rows in agriculture fields which has many weed Schoenfisch [27] in 1997 has implemented an approach[27]. Image segmentation is used to overcome the problem of the noise added to the images, and it has provided a good accuracy[27].

Detection of the tea plantation rows by TeaBot is a great benefit in approaching autonomous navigation. It helps to water and fertilize all the target crops in the designated area. In 2018 Stavros G. Vougioukas proposed four main operations in order to fulfill the autonomous navigation purpose in large scale agriculture fields[25].

a) Field layout planning [25]: It discuss about various agriculture fields and there geographical surfaces can have complex, nonconvex shapes, and uncultivated areas [25] of land automatic navigation in this scenarios may cause less efficiency due to exclusive turns[25]. Crop row planting mechanisms are discussed by Galceran E in 2013[28] and accordingly the proposed TeaBot will be used in a large scale tea cultivation field and the plantations are planted in linear blocks, where the robot can be moved[28].

b) Compute row travel sequence and cooperation logistics [25]: Robot route planning suggest the optimum travel sequence where the robot can reach every plantation in the agri-field utilizing the resources[29],[30]. For the research TeaBot will be navigating row by row covering every tea plantation.

c) Computing path and motion profile[25] : Robot route planning has generated way point sequences for robot to navigate. In motion profile it will compute the path to navigate in between the tea plantation crops[25]. Most of the research work has focused on detection the tea plantation rows using computer vision[25]. Monocular cameras have been used in visible spectrum[31],[32] to segment crop rows from soil based color transforms[25],[33] and green indexes [34] which increases the feature extraction of received input and provide more accurate results in predicting the tea plantation rows[25] it has been proposed that Unet machine learning models [35] are capable of segmenting crop rows in real time[36].

d) Robot auto guidance[25] : According to the motion plan suggested the robot will be automatically navigated by the robot controller.

Accordingly, many studies from several angles have identified the high usage of detecting the navigation path automatically for large scale agriculture robots[11],[12],[22],[23],[25],[37],[38].

Autonomous navigation of agricultural robots has been useful in fulfilling various tasks, as illustrated in Table 1.2.

Table 1.1:Automatic navigation-supported activities

Activities	Viewed Studies
Liquid fertilizing the crops	8
Fertilizing	3
Harvesting	3
Crops management and disease identification	2

Moreover, computer vision based automatic path detection has been used in various scenarios in vehicle movement in agricultural fields. It has been a good approach in implementing a low cost, low computational, and more accurate model. In some scenarios, when direct sunlight is facing the vision sensors it may provide a lower accuracy[40], but using an advanced CNN model will help to increase the accuracy[22],[39]. Studies have suggested using ultrasonic devices in large scale agriculture fields[41]. Mainly ultrasonic devices are used to detect weed[42]. Due to low accuracy only a few approaches done to detect the navigation path using these devices[41].

Identifying the end of tea plantation rows accurately and turning at the end of the plantation row automatically has not been addressed yet[25],[41]. A successful automatic navigation at the end of plantation rows involve detecting the end of the path accurately, indicating the turn, and identifying the entrance to the new path[25]. Approach has been suggested to identify the end of the path using artificial landmarks[42]. Landmarks will create a map and detect the end of the current path and enter to the new path this requires a 2-D lidar, a camera but the accuracy of predicting the end of the path, successfully turning and entering to a new path is very low[25]. The TeaBot research suggest an approach to detect the end of plantations using the extinct environmental conditions using artificial intelligence.

1.2 Research Gap

As mentioned earlier, there are many methodologies suggested for autonomous navigation in large scale agricultural fields[25],[43]. Most of them depends on GPS(Global Positioning System) , lidar methodologies which requires a high initial cost to implement[9], and it provides a low accuracy[8],[25]. Detecting the plantation rows automatically using computer vision provides more accuracy it requires low initial cost to implement[44]. A comparison has been made in between these methodologies[25] and it has suggested the advantages of using image segmented models for automatic path detection[25]. Automatic navigation is implemented using GPS (), it have suggested that, when the robot is moving under the tree canopy it can block the GPS receivers signals [23] which lead to a very low accuracy[23]. Moreover there is no complete solution for identifying the end of the tea plantation rows and successfully turning and entering to a new plantation [25],[41]. TeaBot research suggest to detect the end of the path using the existing environmental conditions of the tea agricultural fields using image segmentation algorithms.

Table 1.2: Comparison of former research

Research methodologies used for detecting the plantation rows automatically	Performing in equal accuracy for varying conditions of crop growth	Capability of row center determination	Capability of detecting the plantation rows in varying field conditions (Adaptive Navigation)	Identifying the end of the plantation rows and entering to a new path
GPS based	✗	✗	✗	✗
Laser and GPS	✗	✗	✗	Using reflective tapes
Lidar based	✗	✓	✗	✓
Machine learning techniques	✓	✓	✗	✗
UltraSonic based methods	✗	✗	✗	✗
TeaBot	✓	✓	✓	✓

The proposed research solution will contain all the features that was not proposed in the previous studies. As mentioned above by navigating through the middle of the crop rows provide the opportunity to water two plantations simultaneously[21],[28]. Since TeaBot is using image segmentation algorithms to implement is capable of detecting the middle of the path more accurately than in the previous studies. The above table reveals that TeaBot is capable of detecting the plantation rows in varying crop growth (ex: areas having small plants, matured plants, areas which have started for planting)[12] conditions and varying field conditions (ex: changing sunlight, weather conditions, areas having weeds)[22] than the other approaches, because algorithms will be trained using a large unbiased dataset[45] collected covering all the possibilities, and the capability for feature extraction[46] in sematic segmentation models[47]. The proposed solution will provide the stakeholders various features.

1.3 Research Problem

To fill the research gap innovative, creative ideas should be identified and those should be analyzed accurately, and more research work need be done to analyze the requirements of large-scale tea fields stakeholders (ex: farmers, agriculture field owners). Majority of developed research have focus on, developing automatic navigation using various sensors, which requires high cost in the initial implementation, and maintenance. Also, above discussed methodologies are not suitable for varying environmental conditions. When the research question is addressed, a specific methodology will be followed to fill the research gap. The main research problem is, **How to create an image segmentation methodology to detect the tea plantation rows more accurately to help the robot navigate automatically**, and several research questions will be arise when addressing the main problem.

1. Does the robot navigate significantly better using image segmentation when task performing time is considered?
2. Does the robot perform significantly better even in varying environmental conditions?
3. Does the robot identify the end of the path, and enter to a new path significantly better than using lidar technologies?

2 OBJECTIVES

2.1 Main Objective

In large scale agriculture fields, liquid fertilizing the tea plantations is essential to preserve the tea plantations, which will led to harvest the optimum crop from the plantations. As mentioned above, due to lack of human resources automated mechanism is needed to preserve the tea plantations. As discussed earlier automated mechanisms such as using drip irrigation, center pivot irrigation mechanisms, using GPS or lidar technologies will not be resilient to varying environmental conditions, and their accuracy is comparatively low. The TeaBot robot will be specifically designed to overcome above mentioned problems and make the liquid fertilizing, fertilizing tasks effective and efficient in tea industry. TeaBot will be capable of moving automatically using the computer vision-based path identification. To maintain the plantations water and liquid fertilizer should be added to the end of the stem of the tea plants, and it should drip around five inches deep into the soil. To make that process effective TeaBot will be capable of detecting the end of the stem using computer vision-based image processing mechanism. Using pressurized water nozzles TeaBot will be capable of watering and fertilize the plants. The robot controller will try to make the robot's speed constant to make the spraying process more accurate.

To navigate automatically, computer vision-based mechanism will identify the path and provide the coordinates to the robot controller then to maintain constant speed robot controller will adjust the wheels, considering the sensor reading of the speed and the driving angles. In emergency situations, such as when navigating robot faces any obstacles(ex: tree branches have fallen to the path) it will be identified through an object detection algorithm and notified to the administrator. A hose will be dragged and plugged at the end of the robot, if the hose gets stuck it will immediately stop navigating and inform the administrator. If the stakeholders need to manually control the robot a manual remote controller will be developed too. This proposal document mainly focuses on navigating the robot automatically using computer vison-based methodology. The specific objective of this document is: **the development of the image segmentation model to navigate automatically in the tea plantation rows in varying environmental conditions.**

2.2 Specific Objectives

These three objectives must be met to fulfil the above-mentioned main goal.

2.2.1 Development of Dataset

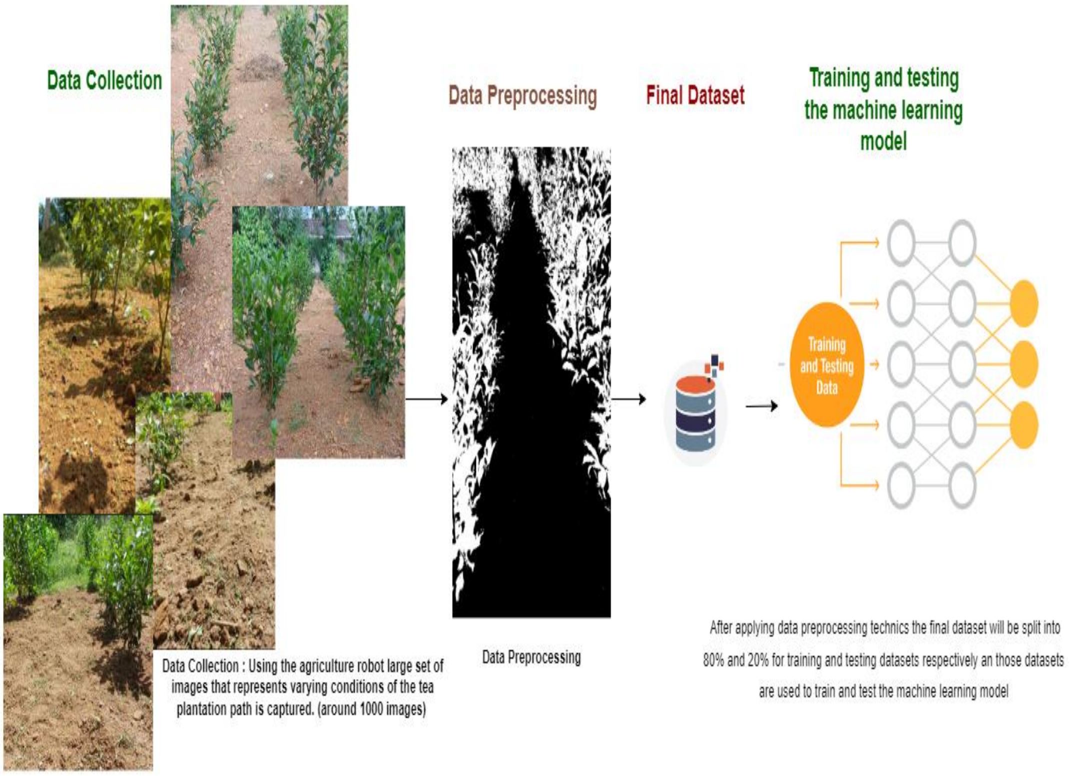

Figure 2.1:Dataset creation

According to the proposed solution, image segmented computer vision-based methodology will detect the navigation path. To implement the machine learning model initially creating a good dataset is vital. Images will be collected using the robot. To collect the dataset the robot will be navigated in the tea plantation rows and photos will be captured during that process. Average number of images to train a machine learning model is around 1000-5000[50]. So around 3000 images of the tea plantation path will be collected. To make the model unbiased images will be collected covering every area of the tea plantation rows (ex: areas having very small plants, middle sized plants, matured plants, areas which have not cultivated yet, and areas having weed). Also, to navigate with a good accuracy in varying environmental conditions dataset should be collected considering those factors as well. So images will be captured during the time having high sunlight, low sunlight, when the shadow of the plantation are varying, in the areas having various geometrical effects(ex: slop, curves).

And the tea plantation images dataset will be transformed and label appropriating to the machine learning model.

2.2.2 Machine learning model development and testing the model.

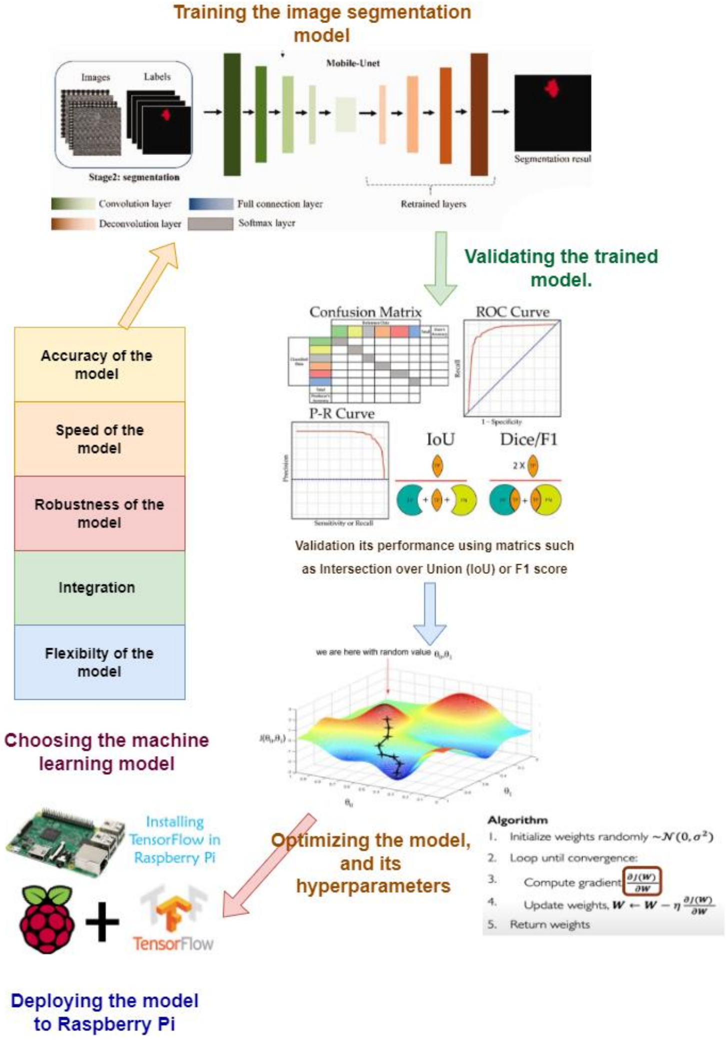

Figure 2.2:Machine learning model

Development of the image segmentation model to detect the tea plantation row is the main part of the proposed research problem. Initially a suitable image segmentation[51] model should be selected according to the requirements. There are several image segmentation models. Such as U-Net, Mask R-CNN, Fully Convolutional Network (FCN), DeepLab, SegNet[51]. U-Net model will be selected to develop the image segmentation model. Dataset will be divided into train and testing datasets(80% and 20% respectively) and model will be train and evaluated.

2.2.3 Communicating with the robot controller

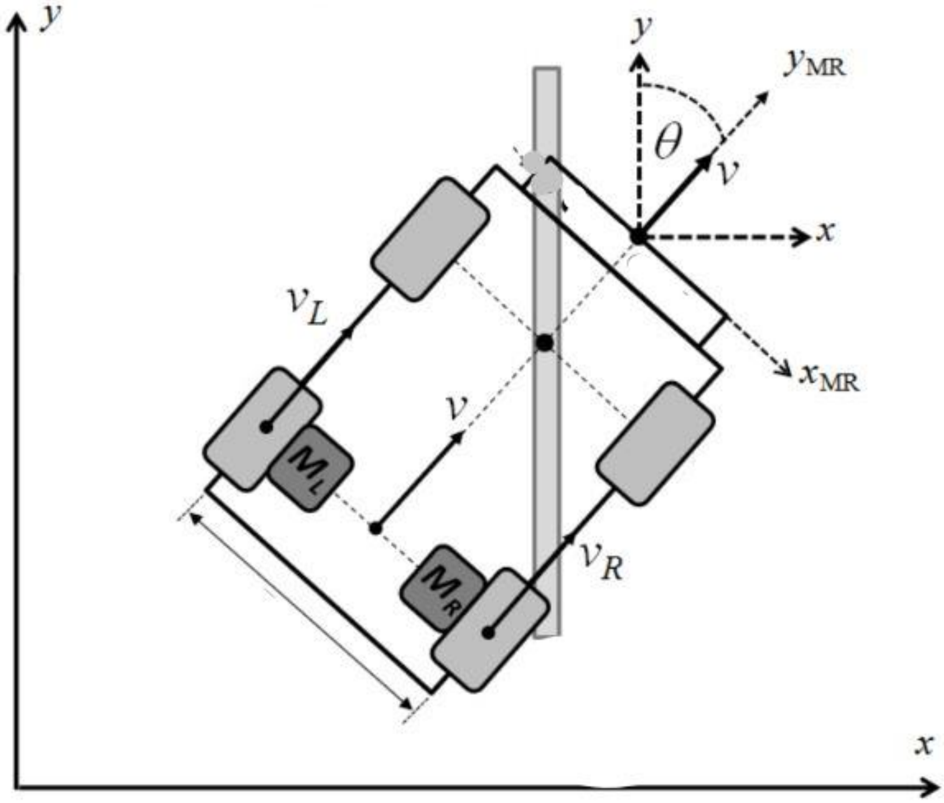

Figure 2.3:Communication with robot controller

Final output of the image segmentation model is the coordinates the robot should navigate. The coordinates will be provided to the robot controller. Then the controller will adjust the wheels according to the detected speed and then the robot will navigate automatically. This task requires proper communication should be made with the robot controller.

3 METHODOLOGY

TeaBot, the proposed research, would be developed in the following ways to deliver efficient, effective maintenance to the tea plantations.

3.1 Requirement Analysis

By doing several fields visits and interviews with stakeholders of large-scale tea agriculture fields (ex: farmers, tea estate owners). Maintaining the tea plantation via constant liquid fertilizing is the burning problem in large-scale tea fields. Due to lack of human resources, high resource wastage, and high initial cost to make the processes automatic are some of the major reasons for above mentioned problems.

Did a thorough survey on plants, soil conditions, road conditions, and varying environmental conditions. Did a requirement gathering of liquid fertilizing the plants in both dry and wet seasons. After analyzing the requirements, the automatic navigation process using image segmentation methodology is developed.

3.2 Feasibility Study

Most of the large-scale tea fields are spreading for few acres, having various environmental conditions. Such as slope, high curvy geographical effects, having high humidity. Some of the areas have poor network connectivity. So, all these factors are considered to develop the automatic navigation process of the robot.

3.3 Implementation

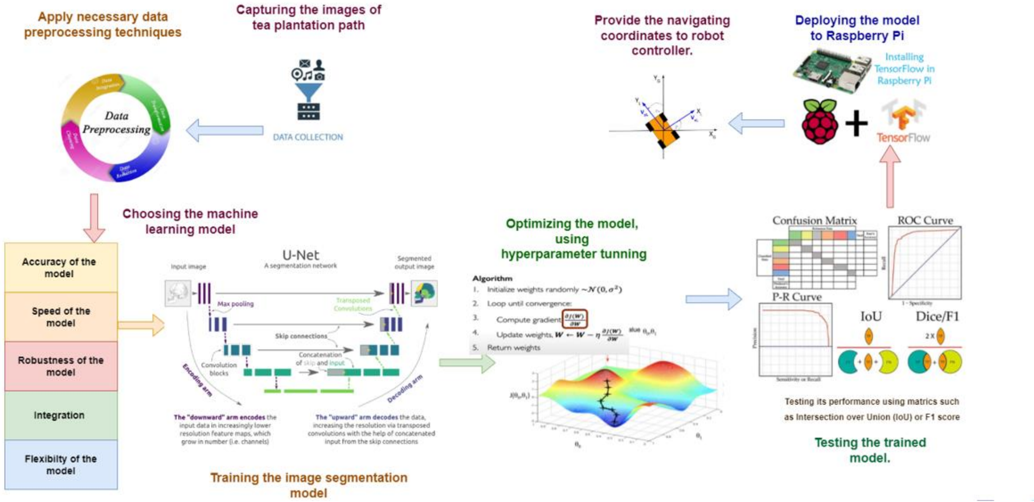

Figure 3.1: System overview diagram

TeaBot is developed using cutting edge software, hardware, and cloud technologies. The robot chassis is developed with 2 x 2 feet dimensions with a strong mechanical structure. The robot have four 8 inches wheels to maintain the body. All the four wheels are powered by 12V motors, and the front and rear wheels are parallelly connected left and right separated. The motors are driving with motor drivers. Motor drivers are connected to the Raspberry Pi. The motors and the Raspberry Pi are driving with 45 ampere battery and 12V battery respectively. The Robotic Operation System is using for the software operations. All the programs are doing with python. To send and receive data among other nodes ROS uses separate nodes with the publisher subscriber on the top of topics. The motor cameras, pressure pumps, and water nozzles are centralized with the Raspberry Pi. Raspberry Pi can execute python libraries for the image segmentation models. The robot executes as one package.

This proposed paper mainly focuses on developing the automatic path detection algorithm using image segmentation. For the implementation, initially dataset should be created. To make the model unbiased videos of the navigating path will be captured using the robot. Robot will be moved and using a camera videos are captured. The videos will be captured considering all the conditions. Such as videos will be captured in varying crop growth conditions, weed density, weather conditions (ex: sunlight, shadow, atmosphere conditions), geographical conditions. Frames are created from the captured videos and around 3000 of dataset will be created. As the next step data preprocessing will be done according to the requirements. Techniques such as data normalizing, image thresholding will be applied. Images will be resized to 512x512, and to separately identify the path, and the background of the captured images image thresholding will be applied. In original images every pixel has a value using image thresholding we will convert these pixel values into a predefined value (ex: from 0-1). After applying image thresholding in the images, pixels having zero values (color in black) will define the navigating path, other background (tea plants) areas will be displayed in white color having the pixel value equal to one. This is done using the excess green index techniques. There every pixel in the original image will be converted into a new value using this equation,

Excess green index = 2 *(green)-red-blue

So finally, preprocessed images will be created. The images will be segmented into separate regions.(Tea plants areas, navigating path) Other data processing steps are carried out accordingly. Then a suitable machine learning model will be selected. There accuracy of the model, training time, flexibility when deploying the model will be considered. Then the chosen model will be developed and trained. After training the model necessary testing is done for the accuracy, precision, recall , intersection over union methods are used. Finally, the model will be deployed to the robot controller, and then the robot is tested in an actual tea plantation field.

3.4 Development of the image segmentation model to navigate automatically.

A new aspect of image segmentation model will be developed to detect the tea plantation rows automatically. As above discussed, when constructing the model three main aspects are considered.

1. How to detect the middle of the navigating path.
2. Detect the end of the path and identify the new path to enter.
3. Provide a good path detecting accuracy for varying environmental conditions (ex: rainy, sunlight is high and low)

The proposed image segmentation model should be capable to fulfill the above tasks. Initially the dataset will be saved in a cloud platform (Azure). To implement the model google colab, jupyter notebook and anaconda is used. The model will be trained and tested using the above IDE, and the model will be deployed in the Raspberry Pi.

3.5 Work Breakdown Structure

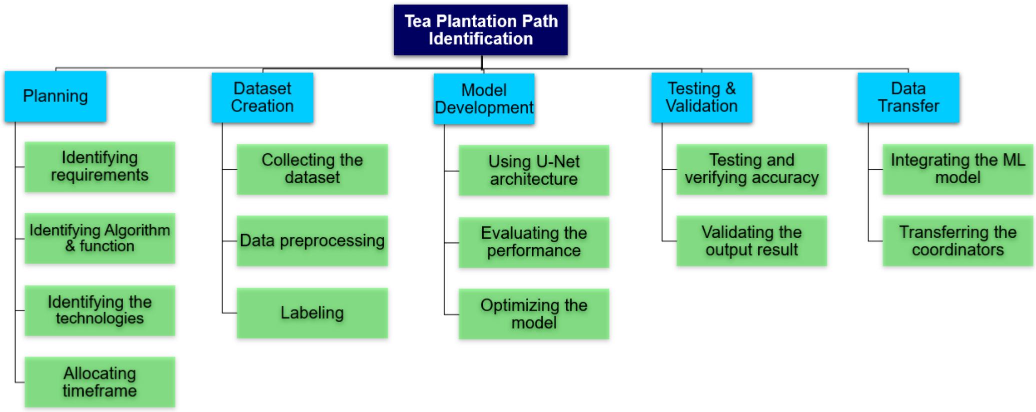

Figure 3.2:Work Breakdown Structure

3.6 Testing

Testing will be done at multiple stages using multiple methodologies. To test the image segmentation model developed to detect the tea plantation rows and navigate automatically below mention methods are used. After creating the dataset will be separated to 80%, and 20% for training and testing datasets. Then the model will be implemented and it will be trained using the training dataset. Testing dataset will be used to validate the developed image segmentation model. These matrices are used to evaluate the model.

1. Precision and recall values : precision detects the true positive values to among all positive detections, recalls measures true positive values among all actual positives. To be an unbiased model all precision, recall, and accuracy values should have a higher value. (Normally above 95%)

2. F1 score : this combines both precision and recall values and provide one matrix.

3. Intersection over union method : It represents the overlap between the image segmented mask and the ground truth mask. Higher value indicates the better results.

4. Finally after integrating the other components the robot will be tested in an tea estate and the automatic navigation process is also evaluated there.

3.7 Gannt Chart

This proposed research is planned to carry out as follows to meet the required deadlines without any conflicts. Project implementation will be started in April and expected to complete by September while testing will be carried out from September to November. The proposing research project will be completed by December 2023.

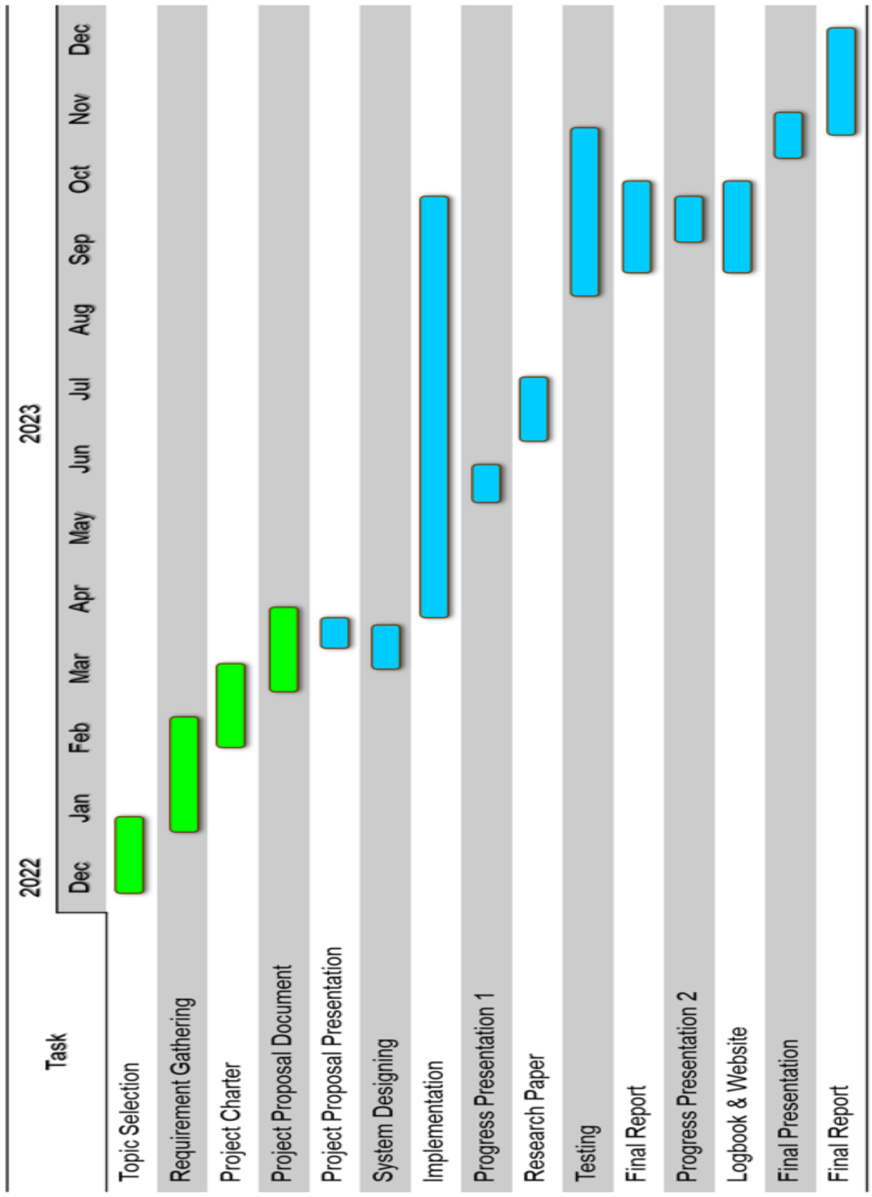

Figure 3.3:Gannt chart

4 DESCRIPTION OF PERSONNEL & FACILITIES

Ms Shashika Lokuliyana is in charge of this study. She is a Senior Lecturer in Department of Computer Science and Network Engineering, Faculty of Computing, Sri Lanka Institute of Information Technology (SLIIT), Malabe, Sri Lanka.

As Lecturer in the Department of Computer Science and Network Engineering, Faculty of Computing, Sri Lanka Institute of Information Technology (SLIIT), Malabe, Sri Lanka, Ms Narmada Gamage is co-supervising this project.

Mr. Rajitha de Silva is the external supervisor in this project. He is a PhD scholar of University of Lincoln, England, UK.

This research will be conducted by the following 4 members as shown below.

1. Gunawardana I.I.E – He is responsible for developing the robot controller,
    a. Creating the robot chassis and the mechanical parts.
    b. Creating the PID(Proportional Integral Derivative) controller to navigate the robot.
    c. Identify the background hazards using object detection algorithms.
    d. Creating the manual controller for the robot.

2. Bamunusinghe G.P – He is responsible for developing the intelligent nozzels,
    a. Creating the hardware mechanism for water spraying.
    b. Tuning the water spray motors according to the robot’s motion.
    c. Spraying water to the plants according to the relative velocity of the robot by using the 4 nozzles (nozzles will be controlled with stepper motors) to the groups of plants.

3. Premathilake H.T.M – She is responsible develop an algorithm to precisely identify the end of the stem,

a. Initially identify the data requirements. Gather the dataset.
b. Develop the machine learning algorithm to precisely detect the end of the stem of the tea plant.
c. Train the machine-learning model.
d. Testing and optimize the model.

4. Perera P.V.Y – She is responsible for the parallel research component of developing the image segmentation model to detect the tea plantation path automatically with varying environmental conditions,
   a. Develop of the dataset.
   b. Selecting the most suitable machine learning algorithm and train the model.
   c. Test and optimize the model .
   d. Communicate with the robot controller and provide the navigating coordinates.

5 BUDGET & BUDGET JUSTIFICATION

Table 5.1: Estimated Budget

Item	Quantity	Amount (LKR)
Rubber wheels	4	4,000
Sprocket, chain and wheel (gear system)	4	10,800
Iron frame	1	15,500
Motors	4	14,000
43A Motor drivers	4	5,400
Raspberry Pi zero w	1	5,600
12V 45A battery	1	30,000
Camera	3	15,000
Liquid nozzles	2	3,000
Servo motors	8	9,600
Total		**112,900**

6 REFERENCES

[1] M. Calabi-Floody *et al.*, "Smart Fertilizers as a Strategy for Sustainable Agriculture," *Adv. Agron.*, vol. 147, no. 45, pp. 119–157, 2018, doi: 10.1016/bs.agron.2017.10.003.

[2] Thushara S.C., "Sri Lankan Tea Industry: Prospects and Challenges," *Proc. Second Middle East Conf. Glob. Business, Econ. Financ. Bank.*, no. August, pp. 22–24, 2015, [Online]. Available: http://globalbizresearch.org/Dubai_Conference2015_May/conference/psd/D533.pdf

[3] S. A. O'Shaughnessy *et al.*, "Identifying advantages and disadvantages of variable rate irrigation: An updated review," *Appl. Eng. Agric.*, vol. 35, no. 6, pp. 837–852, 2019, doi: 10.13031/aea.13128837.

[4] A. Shilpa, V. Muneeswaran, and D. Devi Kala Rathinam, "A Precise and Autonomous Irrigation System for Agriculture: IoT Based Self Propelled Center Pivot Irrigation System," *2019 5th Int. Conf. Adv. Comput. Commun. Syst. ICACCS 2019*, pp. 533–538, 2019, doi: 10.1109/ICACCS.2019.8728550.

[5] B. Jayant, K. Dahiya, A. Rukhiyar, R. Raj, and R. K. Meena, "a Review of the Drip Irrigation System," *J. Eng. Res. Appl.*, vol. 01, no. 01, 2022, doi: 10.55953/jera.2022.1103.

[6] D. D. Bochtis, C. G. C. Sørensen, and P. Busato, "Advances in agricultural machinery management: A review," *Biosyst. Eng.*, vol. 126, pp. 69–81, Oct. 2014, doi: 10.1016/J.BIOSYSTEMSENG.2014.07.012.

[7] H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, "Computer vision technology in agricultural automation —A review," *Inf. Process. Agric.*, vol. 7, no. 1, pp. 1–19, 2020, doi: 10.1016/j.inpa.2019.09.006.

[8] A. S. SPOORTHI, T. D. SUNIL, and M. Z. KURIAN, "Multipurpose Agriculture Robot Using Lora," *Int. J. Adv. Sci. Innov.*, vol. 2, no. 1, 2021.

[9] J. M. Marais, R. Malekian, and A. M. Abu-Mahfouz, "LoRa and LoRaWAN testbeds: A review," *2017 IEEE AFRICON Sci. Technol. Innov. Africa, AFRICON 2017*, pp. 1496–1501, 2017, doi: 10.1109/AFRCON.2017.8095703.

[10] Seema, A. Kumar, and G. S. Gill, "Automatic Fruit Grading and Classification System Using Computer Vision: A Review," *Proc. - 2015 2nd IEEE Int. Conf. Adv. Comput. Commun. Eng. ICACCE 2015*, no. 5, pp. 598–603, 2015, doi: 10.1109/ICACCE.2015.15.

[11] T. U. Sane and T. U. Sane, "Artificial Intelligence and Deep Learning Applications in Crop Harvesting Robots-A Survey," *3rd Int. Conf. Electr. Commun. Comput. Eng. ICECCE 2021*, no. June, pp. 12–13, 2021, doi:

10.1109/ICECCE52056.2021.9514232.

[12] D. Aghi, S. Cerrato, V. Mazzia, and M. Chiaberge, “Deep Semantic Segmentation at the Edge for Autonomous Navigation in Vineyard Rows,” *IEEE Int. Conf. Intell. Robot. Syst.*, pp. 3421–3428, 2021, doi: 10.1109/IROS51168.2021.9635969.

[13] I. Beloev, D. Kinaneva, G. Georgiev, G. Hristov, and P. Zahariev, “Artificial intelligence-driven autonomous robot for precision agriculture,” *Acta Technol. Agric.*, vol. 24, no. 1, pp. 48–54, 2021, doi: 10.2478/ata-2021-0008.

[14] M. Bakken, R. J. D. Moore, and P. From, “End-To-end Learning for Autonomous Crop Row-following,” *IFAC-PapersOnLine*, vol. 52, no. 30, pp. 102–107, 2019, doi: 10.1016/j.ifacol.2019.12.505.

[15] K. Mochida *et al.*, “Computer vision-based phenotyping for improvement of plant productivity: A machine learning perspective,” *Gigascience*, vol. 8, no. 1, pp. 1–12, 2018, doi: 10.1093/gigascience/giy153.

[16] S. Fountas, N. Mylonas, I. Malounas, E. Rodias, C. H. Santos, and E. Pekkeriet, “Agricultural Robotics for Field Operations,” *Sensors 2020, Vol. 20, Page 2672*, vol. 20, no. 9, p. 2672, May 2020, doi: 10.3390/S20092672.

[17] C. McCool, I. Sa, F. Dayoub, C. Lehnert, T. Perez, and B. Upcroft, “Visual detection of occluded crop: For automated harvesting,” *Proc. - IEEE Int. Conf. Robot. Autom.*, vol. 2016-June, pp. 2506–2512, 2016, doi: 10.1109/ICRA.2016.7487405.

[18] R. H. L. Ip, L. M. Ang, K. P. Seng, J. C. Broster, and J. E. Pratley, “Big data and machine learning for crop protection,” *Comput. Electron. Agric.*, vol. 151, pp. 376–383, Aug. 2018, doi: 10.1016/J.COMPAG.2018.06.008.

[19] T. Akram, S. R. Naqvi, S. A. Haider, and M. Kamran, “Towards real-time crops surveillance for disease classification: exploiting parallelism in computer vision,” *Comput. Electr. Eng.*, vol. 59, pp. 15–26, Apr. 2017, doi: 10.1016/J.COMPELECENG.2017.02.020.

[20] Q. Su, N. Kondo, M. Li, H. Sun, D. F. Al Riza, and H. Habaragamuwa, “Potato quality grading based on machine vision and 3D shape analysis,” *Comput. Electron. Agric.*, vol. 152, pp. 261–268, Sep. 2018, doi: 10.1016/J.COMPAG.2018.07.012.

[21] S. Bonadies and S. A. Gadsden, “An overview of autonomous crop row navigation strategies for unmanned ground vehicles,” *Eng. Agric. Environ. Food*, vol. 12, no. 1, pp. 24–31, 2019, doi: 10.1016/j.eaef.2018.09.001.

[22] R. de Silva, G. Cielniak, and J. Gao, “Towards agricultural autonomy: crop row detection under varying field conditions using deep learning,” 2021, [Online]. Available: http://arxiv.org/abs/2109.08247

[23] N. Shalal, “A REVIEW OF AUTONOMOUS NAVIGATION SYSTEMS IN AGRICULTURAL ENVIRONMENTS N.,” vol. 2, pp. 1–16, 2010.

[24] T. D. Le, V. R. Ponnambalam, J. G. O. Gjevestad, and P. J. From, “A low-cost and efficient autonomous row-following robot for food production in polytunnels,” *J. F. Robot.*, vol. 37, no. 2, pp. 309–321, 2020, doi: 10.1002/rob.21878.

[25] S. G. Vougioukas, “Agricultural Robotics,” *Annu. Rev. Control. Robot. Auton. Syst.*, vol. 2, pp. 365–392, 2019, doi: 10.1146/annurev-control-053018-023617.

[26] F. Rovira-Más, “Sensor architecture and task classification for agricultural vehicles and environments,” *Sensors*, vol. 10, no. 12, pp. 11226–11247, 2010, doi: 10.3390/s101211226.

[27] J. Billingsley and M. Schoenfisch, “The successful development of a vision guidance system for agriculture,” *Comput. Electron. Agric.*, vol. 16, no. 2, pp. 147–163, Jan. 1997, doi: 10.1016/S0168-1699(96)00034-8.

[28] G. Fevgas, T. Lagkas, V. Argyriou, and P. Sarigiannidis, “Coverage Path Planning Methods Focusing on Energy Efficient and Cooperative Strategies for Unmanned Aerial Vehicles,” *Sensors*, vol. 22, no. 3, 2022, doi: 10.3390/s22031235.

[29] H. Seyyedhasani and J. S. Dvorak, “Dynamic rerouting of a fleet of vehicles in agricultural operations through a Dynamic Multiple Depot Vehicle Routing Problem representation,” *Biosyst. Eng.*, vol. 171, pp. 63–77, 2018, doi: 10.1016/j.biosystemseng.2018.04.003.

[30] C. Cariou and Z. Gobor, “Trajectory planning for robotic maintenance of pasture based on approximation algorithms,” *Biosyst. Eng.*, vol. 174, pp. 219–230, 2018, doi: 10.1016/j.biosystemseng.2018.07.009.

[31] R. F. Norris, “M Achine V Ision I Dentification of,” no. 1989, pp. 1–14, 2000.

[32] M. Montalvo *et al.*, “Automatic detection of crop rows in maize fields with high weeds pressure,” *Expert Syst. Appl.*, vol. 39, no. 15, pp. 11889–11897, 2012, doi: 10.1016/j.eswa.2012.02.117.

[33] J. Gai, L. Tang, and B. L. Steward, “Automated crop plant detection based on the fusion of color and depth images for robotic weed control,” *J. F. Robot.*, vol. 37, no. 1, pp. 35–52, 2020, doi: 10.1002/rob.21897.

[34] M. Henke, K. Neumann, T. Altmann, and E. Gladilin, “Semi-automated ground truth segmentation and phenotyping of plant structures using k-means clustering of eigen-colors (Kmseg),” *Agric.*, vol. 11, no. 11, 2021, doi: 10.3390/agriculture11111098.

[35] W. Weng and X. Zhu, “INet: Convolutional Networks for Biomedical Image Segmentation,” *IEEE Access*, vol. 9, pp. 16591–16603, 2021, doi: 10.1109/ACCESS.2021.3053408.

[36] L. Yang *et al.*, “Identifying Working Trajectories of the Wheat Harvester In-Field Based on K-Means Algorithm,” *Agric.*, vol. 12, no. 11, 2022, doi:

10.3390/agriculture12111837.

[37] F. Gul, W. Rahiman, and S. S. Nazli Alhady, “A comprehensive study for robot navigation techniques,” *Cogent Eng.*, vol. 6, no. 1, pp. 1–25, 2019, doi: 10.1080/23311916.2019.1632046.

[38] J. Li, J. Yin, and L. Deng, “A robot vision navigation method using deep learning in edge computing environment,” *EURASIP J. Adv. Signal Process.*, vol. 2021, no. 1, 2021, doi: 10.1186/s13634-021-00734-6.

[39] V. Nekrasov, J. Ju, and J. Choi, “Global deconvolutional networks for semantic segmentation,” *Br. Mach. Vis. Conf. 2016, BMVC 2016*, vol. 2016-Septe, pp. 124.1-124.14, 2016, doi: 10.5244/C.30.124.

[40] K. Fue, W. Porter, E. Barnes, C. Li, and G. Rains, “Evaluation of a stereo vision system for cotton row detection and boll location estimation in direct sunlight,” *Agronomy*, vol. 10, no. 8, 2020, doi: 10.3390/agronomy10081137.

[41] R. Carelli, “Agricultural Robotics,” no. September, pp. 48–58, 2013.

[42] A. Wang, W. Zhang, and X. Wei, “A review on weed detection using ground-based machine vision and image processing techniques,” *Comput. Electron. Agric.*, vol. 158, no. January, pp. 226–240, 2019, doi: 10.1016/j.compag.2019.02.005.

[43] Y. Ye *et al.*, “Orchard manoeuvring strategy for a robotic bin-handling machine,” *Biosyst. Eng.*, vol. 169, pp. 85–103, 2018, doi: 10.1016/j.biosystemseng.2017.12.005.

[44] A. S. Aguiar, F. N. Dos Santos, J. B. Cunha, H. Sobreira, and A. J. Sousa, “Localization and mapping for robots in agriculture and forestry: A survey,” *Robotics*, vol. 9, no. 4, pp. 1–23, 2020, doi: 10.3390/robotics9040097.

[45] D. Bini, D. Pamela, and S. Prince, “Machine Vision and Machine Learning for Intelligent Agrobots: A review,” *ICDCS 2020 - 2020 5th Int. Conf. Devices, Circuits Syst.*, pp. 12–16, 2020, doi: 10.1109/ICDCS48716.2020.243538.

[46] D. Aghi, S. Cerrato, V. Mazzia, and M. Chiaberge, “Deep Semantic Segmentation at the Edge for Autonomous Navigation in Vineyard Rows,” *IEEE Int. Conf. Intell. Robot. Syst.*, pp. 3421–3428, 2021, doi: 10.1109/IROS51168.2021.9635969.

[47] R. Miyamoto, M. Adachi, Y. Nakamura, T. Nakajima, H. Ishida, and S. Kobayashi, “Accuracy improvement of semantic segmentation using appropriate datasets for robot navigation,” *2019 6th Int. Conf. Control. Decis. Inf. Technol. CoDIT 2019*, pp. 1610–1615, 2019, doi: 10.1109/CoDIT.2019.8820616.

[48] L. Panigrahi and K. Verma, “Segmented Region based Feature Extraction for Image Classification,” *2021 IEEE Int. Conf. Emerg. Trends Ind. 4.0, ETI 4.0 2021*, pp. 1–7, 2021, doi: 10.1109/ETI4.051663.2021.9619307.

[49] W. Jia, Y. Tian, R. Luo, Z. Zhang, J. Lian, and Y. Zheng, “Detection and

segmentation of overlapped fruits based on optimized mask R-CNN application in apple harvesting robot," *Comput. Electron. Agric.*, vol. 172, no. March, p. 105380, 2020, doi: 10.1016/j.compag.2020.105380.

[50] Y. J. Zhang, "A survey on evaluation methods for image segmentation," *Pattern Recognit.*, vol. 29, no. 8, pp. 1335–1346, 1996, doi: 10.1016/0031-3203(95)00169-7.

[51] X. Liu, L. Song, S. Liu, and Y. Zhang, "A review of deep-learning-based medical image segmentation methods," *Sustain.*, vol. 13, no. 3, pp. 1–29, 2021, doi: 10.3390/su13031224.

7 APPENDICES

7.1 Plagiarism Report

proposal report

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