INTELLIGENT AGRICULTURE ROBOT FOR TEA PLANTATION PRESERVATION : TEABOT

2023-044

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DECLARATION

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ABSTRACT

Maintaining large-scale tea states with proper watering and liquid fertilizing has been a challenge. Due to labor shortage, high initial implementation, and maintenance costs associated with alternate methodologies such as drip irrigation, and center pivot irrigation. “TeaBot” is an intelligent robot developed to water and liquid fertilize tea plantations using a low-cost method. TeaBot consists of major four components. Robot controller, automatic navigation component, tea stem detection for accurate water spraying, and the water jet to water and liquid fertilize the tea plantations efficiently autonomous navigation mechanism is essential. Tea plantations are cultivated according to a specific structure. Among the tea plantations and the navigation row, a clear pattern can be identified. The autonomous navigation mechanism is developed using a classic computer vision approach. The algorithm can detect the center of the navigating path and will pass the coordinates to navigate the robot. This feature it makes possible to water tea plantations which align on the left and right side of the navigation path simultaneously making the process more efficient. During varying environmental conditions such as high sunlight, shadow conditions, and small, medium, and larger-sized tea plantation navigation paths the algorithm performs accurately.

Keywords: Drip Irrigation, Center Pivot Irrigation, Autonomous Navigation, Computer Vision, **Path Identification**

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LIST OF ABBREVIATIONS

Abbreviation	Description
ML	Machine Learning
CNN	Convolutional Neural Network
AI	Artificial Intelligence
GPS	Global Positioning System
ROS	Robotics Operating System

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1. INTRODUCTION

1.1. Background Literature

The agricultural industry is a critical sector that directly impacts the global economy, human health, and society. The increasing trend of urbanization has resulted in reduced available land for cultivation, while the growing population has significantly driven up the demand for large-scale agricultural fields[1]. Health is a major factor in this scenario, as the quality of the agricultural industry depends on the health of the community. In this context, the tea industry plays a vital role in Sri Lanka's agricultural sector and serves as a major source of revenue in terms of foreign exchange earnings[2]. Its continued success is essential not only for Sri Lanka's economic stability but also for sustaining a livelihood for thousands of people involved in tea cultivation and production[2].

1.1.1. Tea Plantation Preservation

In economic, social, and health aspects, ensuring the quality of the tea industry is essential. Maintaining tea plantations in large-scale agricultural fields has been a significant challenge. Recent statistics indicate a declining contribution of the tea industry to the economy[2]. It has been identified that inefficient watering and liquid fertilization methods have contributed to a reduction in the quality of Ceylon tea[2].

Several major problems have emerged in maintaining large-scale tea plantation fields. These challenges include labor shortages and the associated high salaries, resource wastage during manual maintenance processes, inefficiencies in resource utilization, and failures in punctual watering and liquid fertilization procedures[2][3]. Addressing these issues is crucial not only for the sustainability of the tea industry but also for the economic and social well-being of the communities. Additionally, finding innovative and sustainable solutions to these challenges is imperative for the long-term success of the tea sector.

1.1.2. Currently existing Tea Plantation Preservation Methodologies.

Various methods have been explored to automate the process of liquid fertilization in tea plantations, including Center pivot irrigation[4], drip irrigation[5], and the use of intelligent robots. Center pivot irrigation involves the use of large wheels in the field, along with sprinklers and nozzles, to water the plants[4]. However, this method comes with a substantial initial cost and challenges in achieving precise watering, as some plantations near the wheels may receive excess water while others don't receive enough[4].

Drip irrigation systems, on the other hand, also require significant initial capital for implementing the necessary pipes, and maintenance costs can be high[5]. To ensure the preservation of tea plantations, there's a growing need for innovative, sensor-driven approaches enhanced through information technology[6], leading to the adoption of intelligent robots for plantation maintenance[7].

These robots have been developed for tasks such as liquid fertilizing and general fertilization in large-scale agricultural fields[8]. However, precise navigation of these robots within extensive fields remains a challenge[8]. To address this, some robots have been designed to utilize Lora (Long Range) technology, allowing stakeholders to provide instructions remotely[8]. Nonetheless, the implementation of robots using Lora technology can be costly, and providing manual instructions in large-scale agricultural fields can be complex[9].

Designing a robot for the precise liquid fertilization of tea plantations is a complex endeavor due to the challenges posed by accurate navigation in varying environmental and weather conditions[10].

1.1.3. Deep Learning-based approach for autonomous path navigation

Utilizing computer vision for robot navigation presents a promising solution to address the challenges previously discussed[7],[10],[11],[12],[13],[14]. The significant advancements in artificial intelligence have already demonstrated their potential to reduce resource wastage in large-scale agricultural fields[15]. Autonomous navigation using computer vision enables precise robot movement by identifying crop rows in diverse environmental and weather conditions[16].

Intelligent robots equipped with computer vision capabilities have proven successful in various agricultural tasks, including crop harvesting[17], crop growth monitoring[18], disease prevention[19], and plant irrigation and management[20]. This technology can be leveraged to efficiently water and fertilize tea plantations. Furthermore, the automated navigation eliminates the need for manual labor to control the robot[12], and the implementation of crop row detection using machine learning techniques can be achieved with relatively low capital investment[8], ensuring high processing accuracy[14].

There is a clear pattern of tea plantations in the estate which gives a good opportunity to develop a computer vision application to address the autonomous navigation of TeaBot. Deep learning semantic segmentation approaches are used to separate the tea plantations and navigation path[15]. U-Net[16], Mask-RCNN[16], Fully Convolutional Networks[17] these architectures can be used to develop the semantic segmentation model. The resultant mask can be used to predict the center of the navigation path. Deep learning based computer vision algorithms are heavy weighted[18]. Teabot requires navigate accurately, to make this process successful machine learning based segmentation model should be capable to process the results within one second. Due to the high resource consumption, lengthy output processing time deep learning-based computer vision algorithm is not the best approach to address the autonomous navigation. Therefore classic computer vision based algorithm[19] is suggested to address the problem.

1.1.4. Classic computer vision approach to autonomous path navigation

The utilization of classic computer vision algorithms in this approach is advantageous as it employs lightweight mechanisms to effectively distinguish between the navigation path and tea plantations[20]. This method notably mitigates the drawbacks associated with deep learning-based models. By leveraging the OpenCV Python library for addressing color separation, the resulting processing time is significantly reduced, rendering the algorithm highly efficient and lightweight. This approach showcases the practicality of leveraging established computer vision techniques to achieve accurate results with minimal computational resources, making it a valuable solution for various applications.

1.2. Research Gap

According to the above literature there are many methodologies suggested for autonomous navigation in large scale agricultural fields[21],[22]. Most of them depend on GPS(Global Positioning System) , lidar methodologies which requires a high initial cost to implement[9], and for some instances it provides a low accuracy[8],[21]. Automatic navigation is implemented using GPS , it has suggested that, when the robot is moving under the tree canopy it can block the GPS receivers' signals[23] which led to a very low accuracy[23].

Detecting the plantation rows automatically using computer vision provides more accuracy it requires low initial cost to implement[24]. A comparison has been made in between these methodologies[21] and it has suggested the advantages of using computer vision for automatic path detection[21]. As discussed earlier deep learning based approaches can be used to develop the algorithm[15],[25]. Deep learning models have high resource consumption, and lengthy output processing time[18], [26]. To address these issues powerful devices should be used to deploy the model. This research focuses on developing accurate solutions which are adaptable for every scenario using low-cost methodologies. A classic computer vision-based approach which is a lightweight, accurate algorithm is used to develop the autonomous navigation component. Classic computer vison-based algorithms have been used segment robot navigation paths but currently there are no solutions developed robots in tea industry.

Computer vision-based path identification can be applied for paths that have very clear pattern of plantations[21]. Among the tea plantation field there are some areas having a very clear pattern and some areas do not have a very clear pattern such as the weed density is high among the plantations, there can be various size of plantations among the paths. These factors should be considered when developing the computer vision algorithm. Moreover, there is no complete solution to address this scenario. This TeaBot research addresses the scenario. The path end identification has not been addressed in previous research[21],[27]. TeaBot can detect the path end using computer vision approach. This research proposes an automatic navigation mechanism which is adaptable for both very clear and noisy paths which gives promising results for every environmental condition.

Table 1.1: Comparison of available solutions vs. TeaBot

Research methodologies used for detecting the plantation rows automatically	Performing in equal accuracy for noisy paths	Capability of row center determination	Capability of detecting the plantation rows in various environmental conditions	Resource consumption, and cost associated
GPS based	✗	✗	✗	low
Laser and GPS	✗	✗	✗	low
Lidar based	✗	✓	✗	high
UltraSonic based methods	✗	✗	✗	high
Deep learning approaches	✓	✓	✗	high
TeaBot	✓	✓	✓	low

The proposed research solution will encompass all the features that were not previously introduced in past studies. As mentioned earlier, navigating through the middle of the crop rows presents an opportunity to simultaneously irrigate two plantations[28],[29]. Since TeaBot employs classic computer vision-based algorithms for implementation, it can more accurately detect the middle of the path compared to previous studies.

The table above demonstrates that TeaBot excels in detecting plantation rows even in noisy environments, such as areas with varying crop growth conditions (e.g., small plants, matured plants, newly planted areas, or areas with a high density of weeds)[15], as well as under varying weather conditions (e.g., changing sunlight, weather conditions, or areas with weeds)[25]. This superior performance is attributed to the development and optimization of algorithms that cover all possible scenarios. The proposed solution aims to provide stakeholders with a range of valuable features.

2. RESEARCH PROBLEM

When creating an autonomous navigation solution for agricultural robots, it should incorporate the advanced technological capabilities discussed previously. The proposed solution demonstrates the ability to:

- Center of the navigation path detection
- Producing good accurate results in varying environmental, weather conditions
- Giving good results in noisy paths

The TeaBot navigation algorithm will undergo further optimization based on the outcomes derived from testing phases. To effectively address the research problem, a comprehensive analysis of existing research gaps is essential. To bridge these gaps, innovative and creative ideas must be identified, thoroughly analyzed, and further research must be conducted to meet the requirements of stakeholders in large-scale tea fields, including farmers and agricultural field owners.

This study primarily focuses on the development of the autonomous navigation algorithm for TeaBot. Extensive research has been conducted to establish a robust computer vision-based algorithm. In the initial stage, an image segmentation model was explored to tackle the problem. The U-Net semantic segmentation model was selected due to its superior accuracy compared to other segmentation models[16]. Subsequently, a dataset was curated, and the model underwent optimization after thorough research.

Recognizing the limitations of the U-Net semantic segmentation model, such as high resource consumption, lengthy processing times, and reduced accuracy in noisy path conditions, dedicated research was undertaken to address these challenges. This led to the development of a classic computer vision algorithm that does not exhibit the aforementioned drawbacks[19],[20]. Following the creation of the classic computer vision algorithm, an additional algorithm was developed to accurately detect the center of the navigation path. Necessary optimizations were implemented based on rigorous testing phases.

3. RESEARCH OBJECTIVES

3.1. Main Objective

In the context of large-scale tea plantations, the application of liquid fertilization plays a vital role in preserving and optimizing crop yields. The demand for such preservation and crop enhancement necessitates the implementation of automated mechanisms due to a shortage of human resources, as previously mentioned. However, it's essential to acknowledge that existing automated methods, such as drip irrigation, center pivot irrigation systems, as well as GPS and lidar technologies, are susceptible to disruptions caused by changing environmental conditions, and their overall accuracy tends to be suboptimal.

To address these challenges effectively within the tea industry, the TeaBot robot is being meticulously designed. TeaBot will be engineered to autonomously perform liquid fertilization tasks with efficiency and precision. It will achieve this through its capability to navigate autonomously, primarily relying on computer vision-based path identification. The core objective is to ensure the targeted application of water and liquid fertilizer to the base of the tea plant stems, penetrating the soil to a depth of approximately five inches. TeaBot will employ pressurized water nozzles for this purpose, aiming to water and fertilize the plants effectively. The robot's controller will strive to maintain a constant speed to enhance the accuracy of the spraying process.

For autonomous navigation, a classic computer vision-based mechanism has been developed to identify the center of the path accurately. The positional error derived from this process is fed to the robot controller, which, in turn, adjusts the robot's wheels based on sensor readings related to speed and driving angles. The specific objective of this document centers on the development and implementation of the classic computer vision-based algorithm to facilitate TeaBot's automatic navigation within the tea plantation rows, adapting seamlessly to varying environmental conditions.

3.2. Specific Objectives

The following two specific objectives will be achieved to achieve the above-mentioned main objective.

3.2.1. Development of the classic computer vision algorithm

The input image undergoes a transformation process to create a color-segmented image where tea plantations are depicted in white, while the navigation path and background appear in black. This segmentation is achieved through the utilization of a classic computer vision algorithm, implemented using the OpenCV Python library. The algorithm leverages the HSV (Hue, Saturation, Value) color space to robustly distinguish between tea plantations and the surrounding terrain.

3.2.2. Development of the center path identification algorithm

This algorithm is developed based on the output results obtained from the classic computer vision algorithm. The output mask serves as the input image for this algorithm. The primary objective here is the development of a center path identification algorithm.

Within the resulting mask, the navigation path is distinctly depicted in black. This specific characteristic serves as the foundation for the development of the center path identification algorithm. The algorithm functions by calculating the vertical pixel value summation for each column in the mask. The range where the lowest values are observed corresponds to the navigation path.

Optimizing this algorithm is crucial for accurately pinpointing the center of the navigation path and transmitting the positional error to ensure precise robot navigation. This optimization process contributes significantly to TeaBot's ability to navigate with precision, thereby enhancing its effectiveness in maintaining the integrity of the tea plantations while improving overall operational efficiency.

4. METHODOLOGY

To attain precise autonomous navigation and execute efficient watering and liquid fertilization processes, the development of the TeaBot agricultural robot is delineated as follows.

Prior to commencing the development of TeaBot, an extensive requirement analysis was conducted, evaluating the feasibility of various methods to accomplish our objectives. The initial approach involved the creation of a deep learning-based computer vision algorithm for path center detection (Refer to Appendix 1). However, this approach proved impractical due to its resource-intensive nature, extended output processing times, and limited accuracy when dealing with noisy paths.

To address these challenges, a diverse dataset was meticulously assembled, and model optimization efforts were undertaken through hyperparameter adjustments. While this improved accuracy, the issues of high resource consumption and lengthy processing times persisted, necessitating the use of powerful hardware devices. However, this option was deemed financially prohibitive due to the associated hardware costs.

Consequently, an analysis was made to transition to a more cost-effective alternative, leading to the development of a classic computer vision algorithm. The classic computer vision approach proved to be highly compatible, capable of producing results within seconds, and demonstrated promising outcomes while mitigating the challenges.

4.1. Overall System Architecture

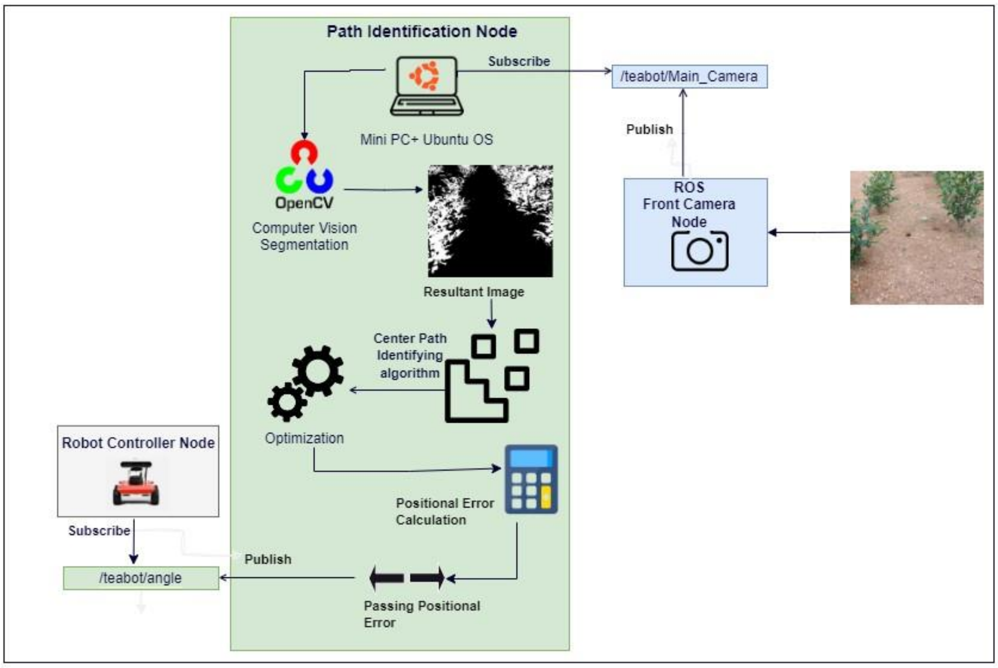


Figure 4.1: System overview diagram

TeaBot consists of five ROS nodes to communicate with each other. They are robot controller node, autonomous navigation node, tea stem detection node, water jet node and remote controller node. The autonomous navigation node is placed in the mini pc. A Logitech C310 web-camera is used to develop this functionality. The front web camera of TeaBot captures the video frame when the robot is navigating. The video frame is used for predicting the center of the navigation path. The web camera node is also located on the mini pc. Hosting the autonomous navigation node and the web camera in the mini pc allowed us to successfully implement non-functional requirements. In the initial stage of the implementation, we deployed the autonomous navigation node and the web-camera to the raspberry pi. With the overall functionalities of TeaBot the stem detection node and the corresponding side web-camera node were also deployed in the raspberry pi. When testing the robot in the actual environment the functionality of three web-cameras did not come to the expected level. Processing three web-camera simultaneously requires high computational power. The raspberry pi was not able to deliver the required processing power. Due to this reason, we used a mini pc to deploy all the web-cameras and the autonomous navigation and stem detection node. High resources available in the mini pc enabled many possibilities. All the cameras are working smoothly without any latency and the autonomous navigation functionality works accurately without any delay. Through the front camera video frame is captured every second and it will pass to the autonomous navigation functionality ROS topic. The next major functionality is to develop the computer vision algorithm to segment the input frame. Then the resultant mask will be used to implement the center path identification algorithm. When developing the computer vison application to segment the input image into a binary mask two approaches have been developed and tested. They are implementing a deep learning- based algorithm using U-Net semantic segmentation architecture and developing the algorithm using classic computer vision using python OpenCV library. Due to the low resource consumption and high accuracy the classic computer vision approach was decided to be used to develop autonomous navigation functionality. The other part of the above diagram explains the algorithm developed to identify the center of the navigation path. The resultant mask derived from the computer vison application is used as the input for this algorithm. The result from this algorithm is a positional error and it is passed to the robot controller to navigate the TeaBot in the center of the navigation path. These algorithms are further discussed in the upcoming section.

4.1.1. Development of the U-Net semantic segmentation model

According to the previous discussion, a video frame is captured from the front web-camera. This video frame is used as the input to develop the U-Net semantic segmentation model. When developing the deep learning-based computer vision model, a feasibility study was done. Amongst various segmentation models, including Mask-R-CNN[30], Fully Convolutional Network[30], DeepLab[31], and U-Net[16],[31],[32], the U-Net semantic segmentation model was selected based on its superior accuracy and notably efficient processing capabilities when compared to alternative models.

The development of the U-Net segmentation model involved a systematic approach, addressing a series of sub-objectives to enhance the accuracy and precision of the results. These sub-objectives encompassed the following steps:

1. Dataset creation and performing necessary data preprocessing technics.
2. Developing and training the U-Net model.
3. Testing and optimizing the model.
4. Analyzing the performance of the model.

Dataset was created. Video frames were captured using the robot's front camera. The robot navigated the various paths in many tea estates and the videos were captured. The dataset comprises every possibility of environmental conditions, plant conditions, and geographical and weather conditions. Considering environmental conditions, videos were captured during heavy sunlight, shadow, and misty weather and environmental conditions. All plantation conditions navigation paths having small tea plantations, medium and large sized tea plantations were covered. Video were taken in the paths having high weed density. Geographical conditions such as slopes high mountain areas were also considered when creating the dataset. The final dataset has equal contribution from each of these scenarios. From the collected videos frames were captured. The final data-set has 2000 frames.

Necessary data preprocessing technics were applied to the frames. Mainly data normalizing, transforming technics were applied. Frames were converted into the size of 512 x 512. For each frame the label was created. To achieve the objective, to navigate the TeaBot in the center of the navigation path, the autonomous navigation algorithm must be capable to separately identify the tea plantations and the navigation path. Accordingly, the semantic segmentation algorithm has been developed. During the data transforming phrase the tea plantations and the navigation path were color separated. Tea plantations were converted into white color and the navigation path was converted to black color. This process was done according to the Excess green index(ExG)[30],[31]. Excess green index explains color separate green vegetations from the background colors and achieved through this equation.

ExG = 2(Green) – (Red) – (Blue)

For each pixel in the image this transformation is applied. In the RGB original frame the red, green, and blue channel were captured and the channel pixel value for green is doubled and the red channel, and blue channel value is separated from that value. The label is created using this methodology. Then the green areas or the tea plantations are colored in white and the background, navigation path is color in black. The labels were also converted to 512 x 512 size.

The U-Net semantic segmentation model was constructed utilizing a carefully partitioned dataset, with 80% allocated for training purposes and the remaining 20% designated for testing and evaluation. In the initial stages of model implementation, Google Colab was employed due to its high GPU processing capabilities, which proved instrumental in training the model efficiently.

The primary Python libraries employed in the implementation of the U-Net model were TensorFlow and Keras, renowned for their suitability in deep learning applications. The architecture of the U-Net model predominantly consists of convolutional layers, max-pooling layers, and up-sampling layers. Notably, the convolutional layers were optimized using the ReLU activation function, introducing non-linearity to facilitate the model's capacity to learn intricate data patterns.

Given that the model serves the purpose of semantic segmentation, the final convolutional layer was augmented with a sigmoid activation function. This choice aligns with the model's objective to assign pixel-wise classifications to the input data, effectively distinguishing between different semantic elements within the images.

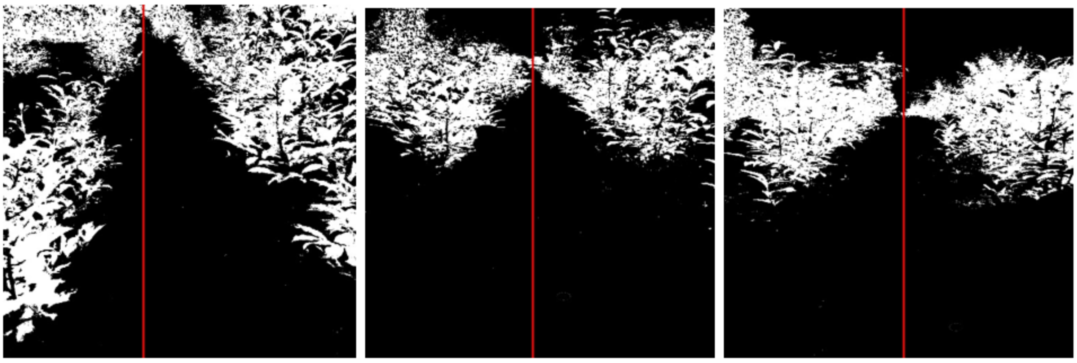
During training, the model underwent 20 epochs, with a learning rate set to 0.001. These hyperparameters were meticulously fine-tuned to achieve optimal performance. As a result of this rigorous training regimen, the U-Net semantic segmentation model exhibited a commendable testing accuracy of 88%. For a visual representation of the created U-Net semantic segmentation model, please refer to the image provided below.

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 32, 32, 3)]  0           []

 conv2d (Conv2D)                (None, 32, 32, 64)   1792        ['input_1[0][0]']

 conv2d_1 (Conv2D)              (None, 32, 32, 64)   36928       ['conv2d[0][0]']

 max_pooling2d (MaxPooling2D)   (None, 16, 16, 64)   0           ['conv2d_1[0][0]']

 conv2d_2 (Conv2D)              (None, 16, 16, 128)  73856       ['max_pooling2d[0][0]']

 conv2d_3 (Conv2D)              (None, 16, 16, 128)  147584      ['conv2d_2[0][0]']

 max_pooling2d_1 (MaxPooling2D)  (None, 8, 8, 128)   0           ['conv2d_3[0][0]']

 conv2d_4 (Conv2D)              (None, 8, 8, 256)    295168      ['max_pooling2d_1[0][0]']

 conv2d_5 (Conv2D)              (None, 8, 8, 256)    590080      ['conv2d_4[0][0]']

 max_pooling2d_2 (MaxPooling2D)  (None, 4, 4, 256)   0           ['conv2d_5[0][0]']

 conv2d_6 (Conv2D)              (None, 4, 4, 32)     73760       ['max_pooling2d_2[0][0]']

 conv2d_7 (Conv2D)              (None, 4, 4, 32)     9248        ['conv2d_6[0][0]']

 dropout (Dropout)              (None, 4, 4, 32)     0           ['conv2d_7[0][0]']

 max_pooling2d_3 (MaxPooling2D)  (None, 2, 2, 32)    0           ['dropout[0][0]']

 conv2d_8 (Conv2D)              (None, 2, 2, 1024)   295936      ['max_pooling2d_3[0][0]']

 conv2d_9 (Conv2D)              (None, 2, 2, 1024)   9438208     ['conv2d_8[0][0]']

 dropout_1 (Dropout)            (None, 2, 2, 1024)   0           ['conv2d_9[0][0]']

 up_sampling2d (UpSampling2D)   (None, 4, 4, 1024)   0           ['dropout_1[0][0]']

 conv2d_10 (Conv2D)             (None, 4, 4, 32)     131104      ['up_sampling2d[0][0]']

 concatenate (Concatenate)      (None, 4, 4, 64)     0           ['dropout[0][0]',
```

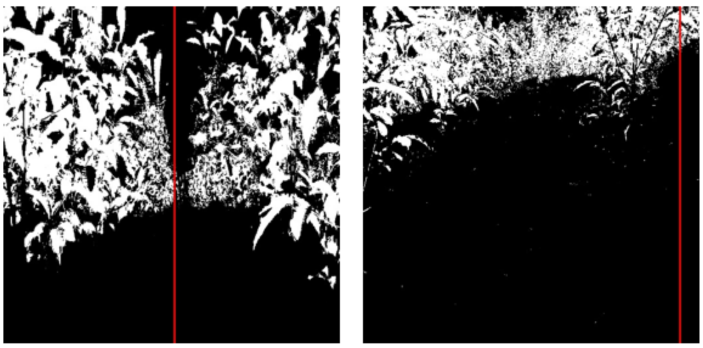
```
 conv2d_12 (Conv2D)             (None, 4, 4, 32)     9248        ['conv2d_11[0][0]']

 up_sampling2d_1 (UpSampling2D)  (None, 8, 8, 32)    0           ['conv2d_12[0][0]']

 conv2d_13 (Conv2D)             (None, 8, 8, 256)    33024       ['up_sampling2d_1[0][0]']

 concatenate_1 (Concatenate)    (None, 8, 8, 512)    0           ['conv2d_5[0][0]',
                                                                  'conv2d_13[0][0]']

 conv2d_14 (Conv2D)             (None, 8, 8, 256)    1179904     ['concatenate_1[0][0]']

 conv2d_15 (Conv2D)             (None, 8, 8, 256)    590080      ['conv2d_14[0][0]']

 up_sampling2d_2 (UpSampling2D)  (None, 16, 16, 256)  0          ['conv2d_15[0][0]']

 conv2d_16 (Conv2D)             (None, 16, 16, 128)  131200      ['up_sampling2d_2[0][0]']

 concatenate_2 (Concatenate)    (None, 16, 16, 256)  0           ['conv2d_3[0][0]',
                                                                  'conv2d_16[0][0]']

 conv2d_17 (Conv2D)             (None, 16, 16, 128)  295040      ['concatenate_2[0][0]']

 conv2d_18 (Conv2D)             (None, 16, 16, 128)  147584      ['conv2d_17[0][0]']

 up_sampling2d_3 (UpSampling2D)  (None, 32, 32, 128)  0          ['conv2d_18[0][0]']

 conv2d_19 (Conv2D)             (None, 32, 32, 64)   32832       ['up_sampling2d_3[0][0]']

 concatenate_3 (Concatenate)    (None, 32, 32, 128)  0           ['conv2d_1[0][0]',
                                                                  'conv2d_19[0][0]']

 conv2d_20 (Conv2D)             (None, 32, 32, 64)   73792       ['concatenate_3[0][0]']

 conv2d_21 (Conv2D)             (None, 32, 32, 64)   36928       ['conv2d_20[0][0]']

 conv2d_22 (Conv2D)             (None, 32, 32, 2)    1154        ['conv2d_21[0][0]']

 conv2d_23 (Conv2D)             (None, 32, 32, 1)    3           ['conv2d_22[0][0]']

==================================================================================================
Total params: 13,642,917
Trainable params: 13,642,917
Non-trainable params: 0
__________________________________________________________________________________________________
loading data
```

Figure 4.2: U-Net model layers

After performing necessary testing, the center path identification algorithm is created. Frame will be input, and the U-net semantic segmentation model creates the resultant mask. This algorithm takes the mask as the input. For each vertical column of the mask the pixel value summation is taken, and the minimum range of the summation value is considered as the navigation path. The center of the range of columns is considered as the center of the navigation path. The algorithm is further discussed in section 3 of this part of the paper. Results derived from the U-Net semantic segmentation model are represented in the below image.



The red color line represents the predicted center of the path for some masks (The images are in the original color).The developed U-Net semantic segmentation model has high resource consumption, and it was identified that the model gives inaccurate resultant masks for very noisy paths. To optimize the model in these scenarios a more resilient dataset was created including noisy frames of paths. In the next testing phrase, it gave much better resulting masks, but for some scenarios the model resulting masks were not accurate. Inaccurate results are shown in the below image (images are in the original color).



The TeaBot has a speed of $0.3ms^{-1}$ and the algorithm should be capable of producing the results within a second. The algorithm resulting time is much lengthier, it takes around 4-5 seconds to produce output. Due to these reasons, it was considered to create a classic computer vison approach to solve these problems.

4.1.2. Development of the Classic Computer Vision algorithm

Due to the disadvantages of the U-Net semantic segmentation model a new approach creating a lightweight algorithm prioritizing computational efficiency and streamlined functionality was considered to address the autonomous navigation of TeaBot. There a classic computer vision approach was suggested[19],[20]. The algorithm is mainly based on python OpenCV library and HSV color space. Tea plantations are cultivated in a particular pattern, but for some areas a clear pattern cannot be identified. There are areas having noisy paths. Each video frame much be color optimized to derive more accurate results. A video frame is captured every second and using the OpenCV python library the image was split into red, green, blue channels. Each channel is optimized, and the frame was created again.

To identify the navigation path the algorithm must be capable of detecting the tea plantation and the navigation path. To detect the navigation path separately the input frame is color separated. There the tea plantation is converted into white color and the navigation path is converted into black color. The color separation is obtained by HSV color space. The HSV color space is used to identify all the ranges of green color of the tea plantations. There a low, upper range for the HSV color space is defined. Necessary values were assigned to hue, saturation, and value variables to capture all the green color ranges in the tea plantations. Trial and error method was used to derive more accurate ranges. The captured range is converted into white color then the tea plantations are converted into white color. The remaining areas of the frame were converted into black color. This resultant image is used to detect the center of the navigation path.

The resultant image is an input to the second algorithm which is discussed in the next section of this literature. There the center of the navigation path is identified using pixel value summation for each vertical column of the resultant image. The lowest summation range is considered as the navigation path. In the below images it illustrates the resultant mask from the classic computer vison algorithm and the predicted navigation path.

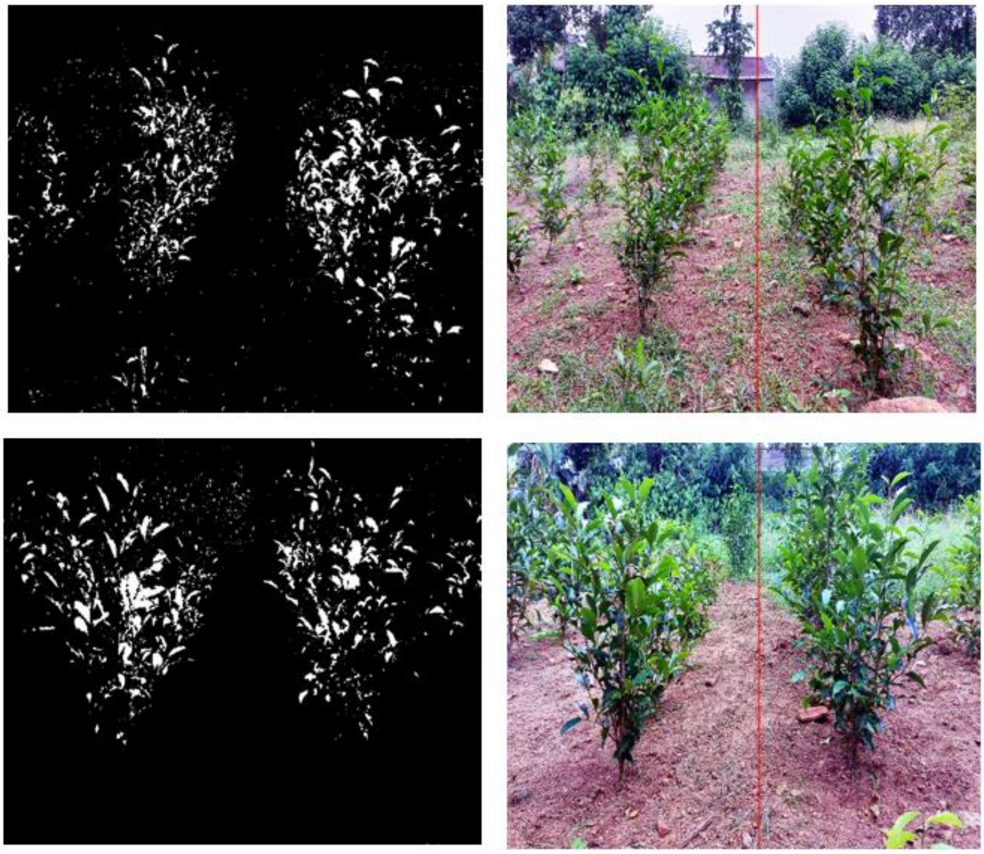


Figure 4.3: Resultant image from the classic computer vision algorithm and the center path identification

To implement the autonomous navigation of TeaBot classic computer vision-based algorithm is used. According to these factors the advantages of the classic computer vision algorithm are discussed over the deep learning U-Net semantic segmentation model.

- Overall accuracy
- Output resulting time.
- Allocated resources

For the noisy paths the classic computer vision algorithm is more accurate generating the resultant mask. In the tea field there are more areas that have noisy paths. The classic computer vision-based algorithm is tested in the actual environment and the algorithm can result in the output within a second. The algorithm is light weighted.

4.1.3. Development of the center path identification algorithm

The resulting mask of the deep learning-based U-Net semantic segmentation model, and the classic computer vision algorithm-based on OpenCV are applied to this algorithm to detect the center of the navigation path.

The resulting mask has tea plantations in white color and navigation path in black color. Accordingly, in the resultant mask for each vertical column pixel value summation is calculated. The columns having the lowest summation can be considered as the navigation path. The column index of the navigation path is captured, and the middle of that column index is the center of the navigation path. For paths having very clear pattern of tea plantations the methodology suggested can be applied. The algorithm is optimized to capture the navigation path more accurately. Trial and error method is mainly used in the development phrase. The lower range of summation is captured, and there can be a few ranges that have the lower range of summation. If the weed density is high among the navigation path the pixel values summation can be affected. If there are few regions having the lower range of pixel value summation, calculate the distance among each range and if they are close to each other merge those regions and take the middle of the final region. This algorithm performed well during the testing in the actual environment.

The actual path is detected, and the robot position is considered as the exact middle of the input frame. The positional error is calculated.

Positional error = actual path column index – robot position column index

The position error can be a positive or a negative value. If it is a positive value the center of the navigation path is located towards the right side of the robot, and if the derived values are negative the center of the navigation path is located towards the left side of the robot. The positional error is passed to the robot controller. According to the positional error given the robot controller will adjust the wheels and the motor drivers and drive the robot in the center of the navigation path. Some of the results derived are represented below. By continually monitoring the position error and adjusting its path accordingly, the robot can navigate through the center of the path.

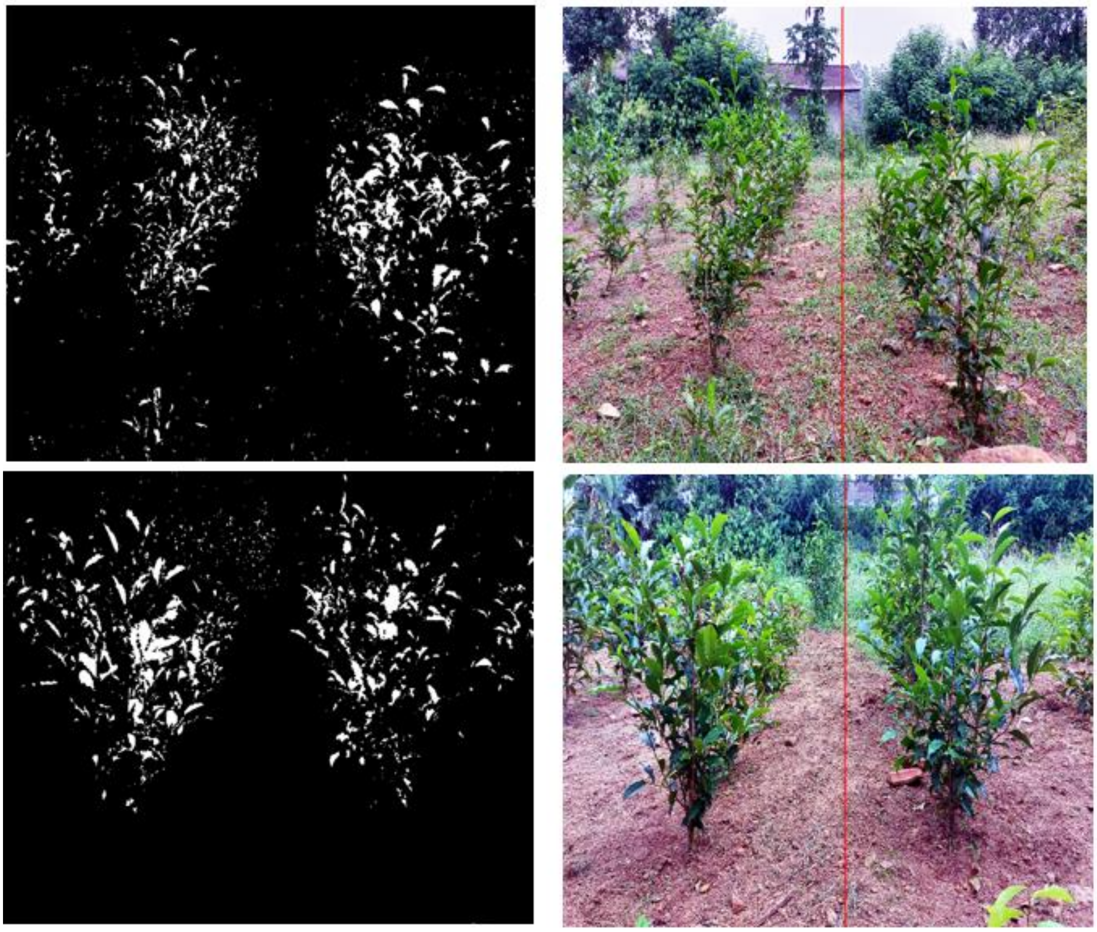


Figure 4.4: Classic computer vision predictions

Further approaches are made to discuss the derived results from the algorithm. A graph was created to represent the distribution of tea plantations and the navigation path. For each resultant mask from the classic computer vision algorithm this graph is created for further discuss the results.

The x-axis contains the column index, and the y-axis contains the column pixel value summation for each vertical column considered. The below images represent the frame captured and the corresponding graph created.

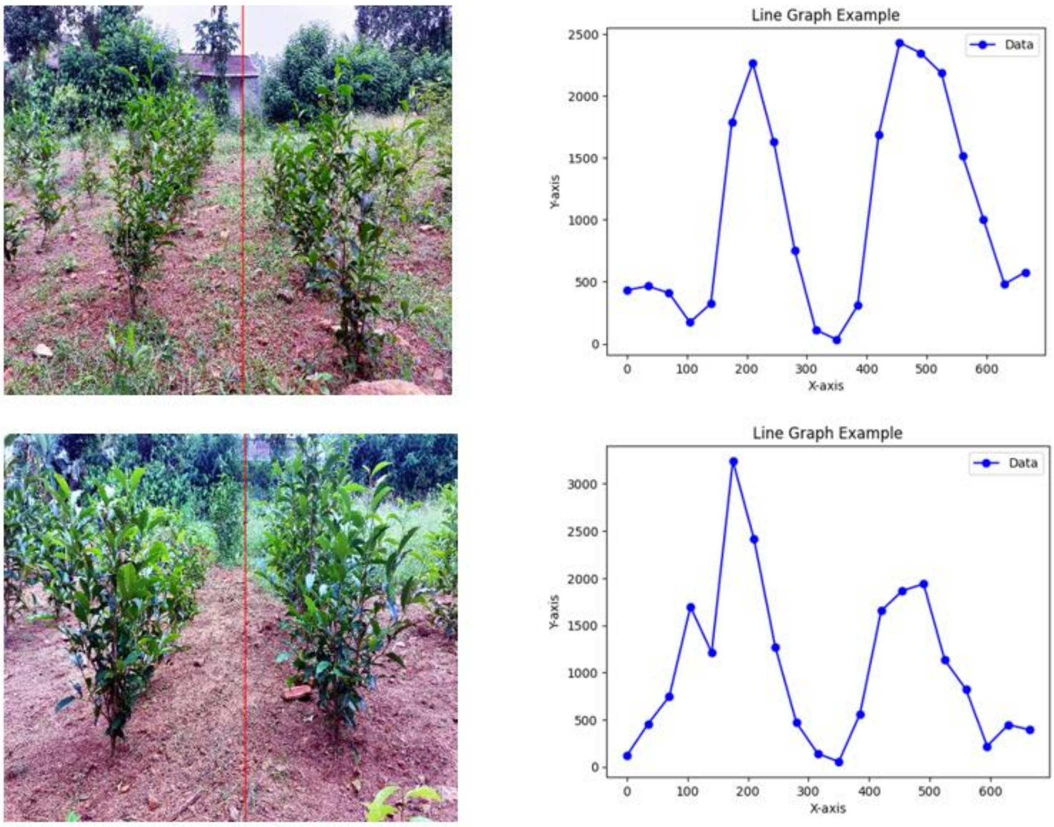


Figure 4.5: Frames identified the center of the navigation path and the corresponding graphs

4.2. Commercialization of the Product

The pricing approach should primarily revolve around the concept of value. This entails aligning the pricing structure with the perceived value that TeaBot provides to its customers in the form of time and cost savings, enhanced accuracy, and improved productivity. The Pro variant should command a premium price point, substantiating its additional functionalities and comprehensive customer support, while positioning the Standard edition as a more economical choice. Both mechanisms have long-term very productive advantages.

The two commercializing mechanisms can be further elaborated as follows.

- Standard Version
  This version will allow us to cater to a wider range of potential customers, with a pricing spectrum spanning from $250 to $400. The commercial price will depend on the area of the agricultural field and the amount of maintenance required. The essential TeaBot hardware and basic deep learning capabilities are incorporated into the Standard version. The hardware will include all the necessary parts and the classic computer vision-based automatic navigation, manual navigation for the users if they prefer to use it. Computer vision base automatic stem detection and precise liquid fertilizing.

- Pro Version
  The Pro version of TeaBot justifies a higher price point due to its inclusion of advanced features. Very high-quality hardware components, very well-trained machine learning and deep learning algorithms, accurate hazard detections. The pro version will be more suitable in varying environmental conditions. It has very good quality technical support and training packages for the employees to handle the robot. The pricing for this package may vary, falling within the range of a few hundred dollars, typically between $550 and $850. It depends on the area of the agricultural field and the amount of work.

If the clients are willing to buy more robots to sustain their agricultural farmers more discounts and offers can be arranged.

Exploring bundled pricing options that encompass TeaBot, along with maintenance and software updates, can streamline the purchasing process for customers. This approach not only simplifies their decision-making but also guarantees continuous support and access to the latest features. Moreover, it fosters long-term customer relationships and enhances the overall value proposition.

As a sustainable product TeaBot will have a good marketing and financial strategy. Volume discounts, upgrades and add-ons, competitive advantage, cost structure analysis is some of the mechanisms we are hoping to apply.

- Volume discounts
  Incorporating volume-based pricing discounts for customers interested in deploying multiple TeaBots can act as a powerful incentive, particularly for large tea estates or cooperatives seeking to invest in multiple units. By offering tiered pricing structures based on the number of units purchased, we not only encourage economies of scale but also establish a mutually beneficial relationship with our valued clients. This approach not only supports their expansion plans but also enhances the overall affordability and attractiveness of TeaBot solutions for these enterprise customers.

- Upgrades and add-ons
  Offering flexible options for customers to acquire add-on features or seamlessly upgrade from the Standard version to the Pro version at any time adds a layer of adaptability to our pricing strategy. This approach empowers customers to begin with the more cost-effective Standard version and then conveniently scale up their capabilities as their requirements evolve. Furthermore, it not only caters to changing customer needs but also nurtures an ongoing relationship with our clients, ensuring that they can access advanced

features as they become relevant for their operations. By providing this versatility in our pricing structure, we enhance customer satisfaction and create a sustainable growth model for TeaBot.

- Competitive advantage
  Maintain vigilant and ongoing surveillance of the pricing strategies adopted by competitors in the market. This practice ensures that TeaBot's pricing structure not only stays competitive but also accurately mirrors the compelling value it brings to our customers. Regular market assessments and price adjustments will enable us to respond effectively to changes in the competitive landscape, keeping our offerings in sync with market dynamics. By embracing this dynamic pricing strategy, we can remain adaptable and agile, aligning our prices with customer expectations and ever-evolving industry standards while preserving our unique value proposition.

- Cost structure analysis
  Frequently evaluate the cost structure across manufacturing, distribution, and support functions. This proactive approach is instrumental in not only preserving our profit margins but also ensuring our competitiveness in the market. By continually assessing our cost components, we can identify opportunities for optimization, cost savings, and operational efficiency improvements. This not only safeguards our profitability but also empowers us to allocate resources strategically, invest in innovation, and maintain a sustainable market presence.

Strategic pricing tactics play a pivotal role in enhancing TeaBot's appeal to potential customers and securing its long-term viability and profitability within the market. It's imperative to maintain a dynamic approach to pricing by regularly reviewing and, if necessary, adapting our pricing strategies to stay competitive. This adaptability not only expands our product's reach but also maximizes its impact, allowing us to meet evolving customer needs while sustaining a healthy bottom line. The synergy between effective pricing and product innovation will further solidify our position as an industry leader.

5. TESTING, RESULTS & DISCUSSION

5.1. Testing

TeaBot's autonomous navigation component was tested in multiple phrases. Initially the autonomous navigation component was tested individually. This testing phrase can be considered as alpha testing. And the components of the robot were integrated. The overall performance of the TeaBot was tested in the second phrase which is known as Beta testing. This was performed in the tea estate.

5.1.1. Alpha testing

During this phase, we conducted tests to evaluate the functionality of each functional unit and the overall system. The alpha testing was performed by our in-house development team, and as a result, we conducted unit testing concurrently at the end of the development process for each functional unit. Developed classic computer vision algorithm were tested. The autonomous navigation component was tested according to these factors. Developing an accurate agriculture robot using a low-cost method is the focus in this research. Accordingly, the autonomous navigation component is developed considering those factors.

- Reliability

  The reliability of the component was tested. Initially to address the autonomous navigation a semantic segmentation bases U-Net architecture was developed. The developed model was high resource consuming and had a lengthy output processing time. Due to the draw backs classic computer vision-based algorithm was developed.

  This classic computer vision-based algorithm performs well in noisy paths, also can process an output within a second. The resource consumption of this algorithm is very low. The algorithm can detect the center of the navigation path in every possible scenario. The algorithm is adaptable to environmental conditions as high sunlight, shadow, slope and high geographical areas, paths having high density of weed. Testing was performed in each of the scenarios. The algorithm performed well in most of the cases. The below images show some of the scenarios discussed, and the algorithm could detect the center of the navigation path.

Figure 5.2: Areas with big tea plants, high sunlight condition

Figure 5.1: Areas with high weed density

In this testing phrase the performance of the autonomous algorithm was prioritized. Accordingly, the algorithm could detect the center of the navigation path in most of the scenarios. The developed algorithm is reliable.

- Accuracy

The classic computer vision-based navigation algorithm is more accurate. There were some inaccurate scenarios as well. The areas having lower density of green color can be considered as a challenge. This areas are optimized further according to HSV color optimizations.

- Response time

The response time is comparatively high. The algorithm can process and give output within a second.

5.1.2. Beta testing

In this phrase overall functionality of the autonomous navigation system was tested. Since the autonomous navigation system is developed using various steps the testing was done in all those phrases. The testing in U-Net semantic segmentation model can be further elaborated as follows. The main six steps were carried out using trial and error method and since each step is highly dependent on the previous stages necessary optimizations are made during the development process.

1. Data set collection.

   Data set was collected emphasizing all the environmental and weather conditions. Tea plantation navigation images were captured in high sunlight, shadow environment, and in various geographical regions. The dataset was split into 80% training dataset and 20% testing dataset. Splitting was done randomly, and the testing dataset does not contain duplicates of the training data.

2. Data Preprocessing.

   In this stage the mask image was created for the training dataset. The mask contains a black and white image , the white area represents the tea plantations, and the black area contains the background of the tea plantation field. The preprocessed images were created using python language and HSV color separation. The U-Net semantic segmentation model was used to predict the binary mask of the testing dataset. The accuracy of these masks is verified using manual testing.

3. Model development.

   The U-Net semantic segmentation model was developed.

4. Model training and testing.

   The model was trained using the training dataset and the testing dataset was used to capture the metrics such as accuracy, precision, recall, and f1 score.

The accuracy was around 88%, and the f1 score is around 86%.

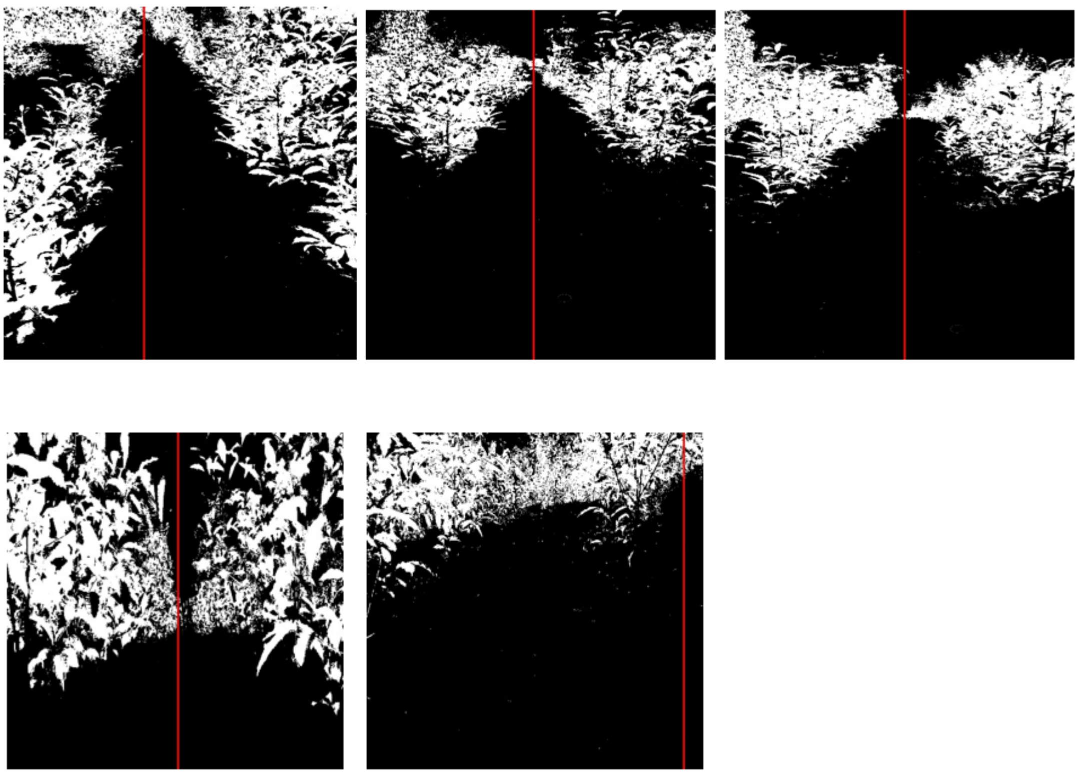
5. Test in the field.

   The model was deployed to the mini pc and tested in the real environment. During this phrase it was identified that the model is high resource consuming and has a lengthy output processing time.

6. Analyze the results.

   The derived results were analyzed.

Some binary masks and the identified center of the navigation path using U-Net model are represented below.



Due to the drawbacks of the segmentation model a novel classic computer vision-based method was developed. The novel method was tested in steps.

1. Generation of the mask.

The mask is generated using the real time view of the tea estate. Python OpenCV library is used to color separate in this step. Manual testing is done to verify the accuracy of this step.

2. Testing in the tea estate.

   The classic computer vision-based navigation methodology was tested in the real tea estate. It gives accurate results and has a faster output processing time.

It can be stated that due to the lower output processing time, lower resource consumption, and accurate results the classic computer vision-based mechanism is more accurate.

5.1. Results

As mentioned above, U-Net semantic segmentation model has an 88% accuracy and an 87% F1 score. The model has a lengthy output processing time like 4-5s, and it was high resource consuming. Also, the model was not capable of identifying the center of the navigation path in complex environments. Such as areas having high weed density, areas which do not have a clear pattern of tea plantations are some of them.

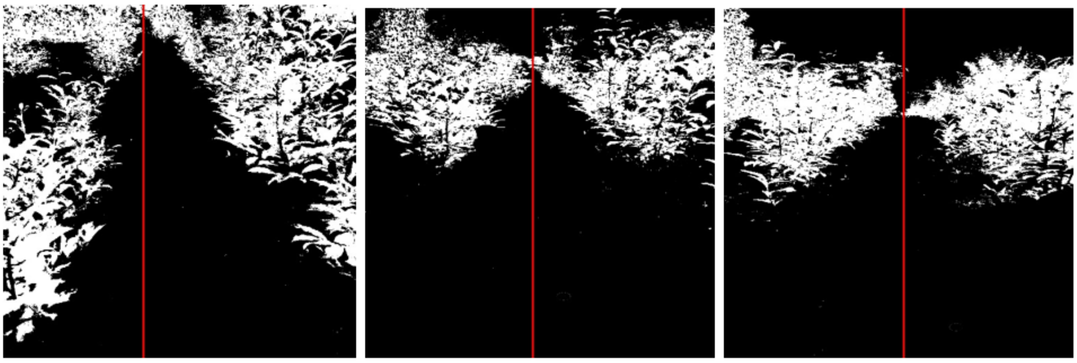


Figure 4.65: Accurate results for UNet model

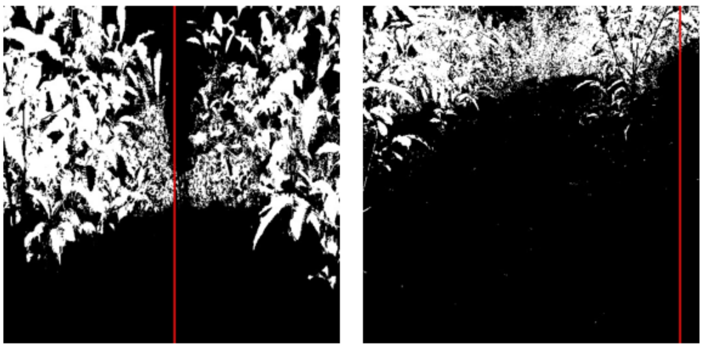


Figure 4.7: Inaccurate results for UNet model

The results of the classic computer vision-based methodology have promising results. The algorithm can detect the center of the navigation path within a second. And the results are accurate. To further discuss the results a graph was generated. The x-axis has the column value of pixels, and the y-axis has the pixel column value summation. The graph as a double gaussian curve shape. The results are further optimized using the results derived from the graphs. Below are some results of the classic computer vision based autonomous navigation mechanism.

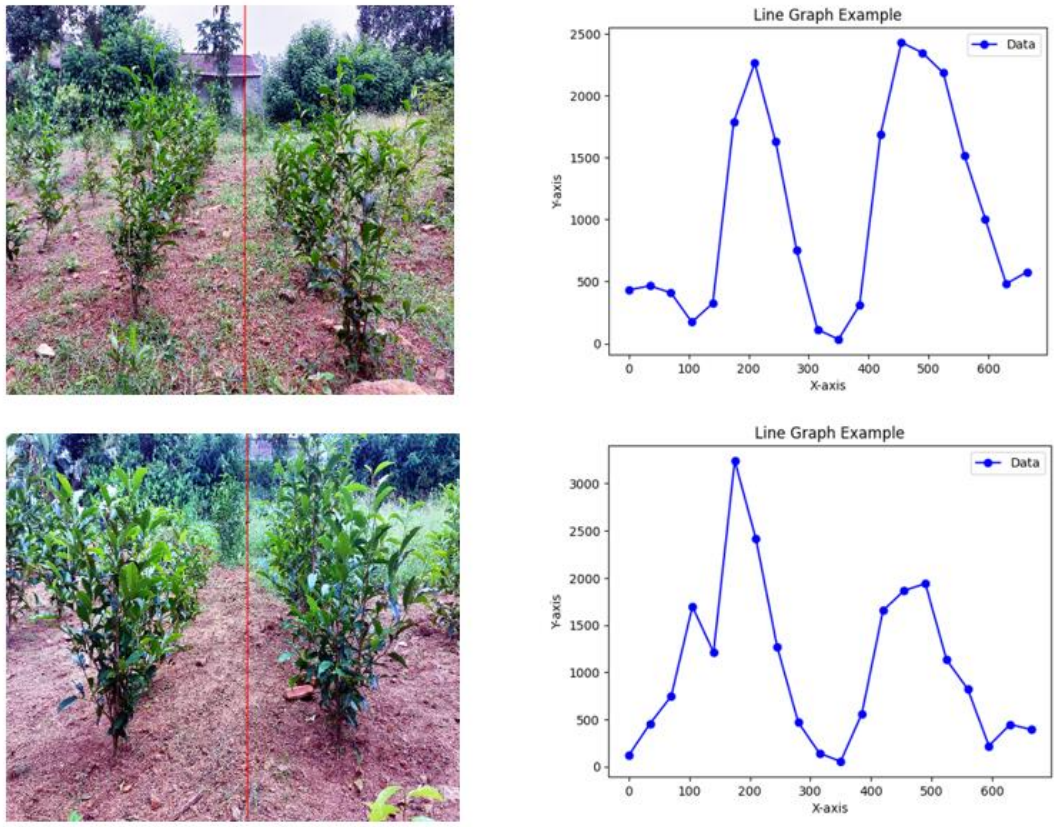


Figure 4.8: Frames identified the center of the navigation path and the corresponding graphs

5.2. Research Findings

In this segment, we present a comprehensive summary of the research outcomes stemming from the TeaBot project, encompassing a broad spectrum of insights gained from both the review of existing literature and the empirical testing outcomes that have been extensively documented in prior sections of this report. Furthermore, we will delve into the specific research discoveries made within the domain of Communications, shedding light on the noteworthy findings that have emerged from this particular facet of the study. The amalgamation of information extracted from these sources forms the basis of our comprehensive research findings, offering a rich perspective on the project's outcomes and their implications.

- Resource optimized development.

  TeaBot is developed considering the availability of resources and using the most optimum methodology to derive the results. Since it was identified that the deep learning based semantic segmentation U-Net model is high resource consuming and as a better mechanism classic computer vision-based methodology was developed. The classic computer vision-based mechanism is lighter weighted and capable of deriving more accurate results.

- Real time navigation.

  The algorithm grounded in computer vision exhibited the ability to deliver immediate real-time outputs, guaranteeing the robot's capacity to swiftly make decisions while navigating. This real-time processing capability not only enhanced the robot's responsiveness but also played a pivotal role in optimizing its overall efficiency throughout the navigation process.

- Effective communication among components.

  The communication framework integrated into TeaBot proved instrumental in enabling the seamless exchange of data between various components of the robot via ROS nodes. This harmonious interplay of components, fostered by the communication framework, played a crucial role in maintaining synchronization throughout the entire course of navigation and the liquid fertilization process. Furthermore, this enhanced coordination not only bolstered the efficiency of the robot but also contributed to its successful operation in achieving its designated tasks with precision and reliability.

- Reliability.

  The communication module showcased an exceptional level of reliability in upholding the consistent flow of data and synchronization among the diverse subsystems of the robot. This robust reliability ensured that the robot's different components could function in unison, guaranteeing the seamless coordination necessary for its successful operation. This dependable communication infrastructure not only supported the robot's performance but also significantly contributed to the overall efficiency and effectiveness of the system, ultimately leading to its successful navigation and execution of tasks. Moreover, this noteworthy reliability in data management added an extra layer of assurance to the entire TeaBot project.

6. CONCLUSION

The emergence of the TeaBot marks a significant breakthrough in the tea industry, offering a game-changing solution to address crucial needs in tea cultivation. This innovative autonomous robotic system is purposefully designed to streamline essential tasks such as watering and fertilization across extensive tea estates. With its sophisticated engineering tailored for off-road conditions, TeaBot promises to revolutionize the sector.

In this in-depth exploration, we will thoroughly examine the capabilities of the TeaBot, shedding light on the valuable insights gleaned from our evaluation of its navigation methods. A particular focus will be given to the role of image processing and its resource consumption efficiency, providing a comprehensive understanding of its operational prowess.

Furthermore, our investigation will spotlight the exceptional precision of the TeaBot's robotic arm, emphasizing its potential to reshape the tea industry. By offering a cost-effective alternative and significantly reducing the reliance on manual labor, the TeaBot not only enhances productivity but also upholds the integrity of tea estates, ensuring a sustainable and profitable future for the industry.
The TeaBot plays a central and indispensable role in the management of vast tea estates. Its automation of labor-intensive tasks such as watering and fertilization not only enhances operational efficiency but also results in substantial cost savings, all the while guaranteeing a consistent and pinpoint level of care for tea plants. What truly distinguishes the TeaBot is its purpose-built design, meticulously engineered to excel in the challenging off-road terrains often found in tea plantations. This unique design is complemented by its remarkable autonomous navigation capabilities, which liberate it from the need for constant human oversight and intervention.

The TeaBot's capacity to adapt and thrive in these rugged, plantation-specific conditions ensures that it can consistently deliver the precision and efficiency needed to maintain the health and productivity of tea crops. This combination of specialized design and autonomy is poised to be a transformative force in the tea industry, ushering in a new era of sustainable, cost-effective, and technologically advanced tea estate management.

The autonomous navigation component of the TeaBot makes the process of liquid fertilization more efficient and effective. The classic computer vision-based navigation methodology can travel the robot in the center of the navigation path. It helps to fertilize the tea plantations more effectively. The end of the tea plantation row can be identified using a novel mechanism, and there a red color stick is used to detect the end of the navigation path. The tea estate tea plantations are cultivated in a clear pattern. There is a pattern among the tea plantations and the navigation path. A classic computer vision-based navigation method is more suitable to address the automatic navigation.

The TeaBot's exceptional precision is evident through its robotic arm, which possesses the capability to accurately disperse water over considerable distances when precisely aligned. This precision assures that tea plants receive the requisite care without any wastage, thereby fostering the development of healthier and more sustainable tea estates. The economic benefits of the TeaBot are significant, as it provides a cost-efficient solution by automating vital tasks and diminishing the dependency on manual labor.

Moreover, the incorporation of the TeaBot into tea estate management makes a significant contribution to the preservation of the estates' inherent integrity. Through its precision, autonomous operation, and off-road proficiency, the TeaBot guarantees the delivery of optimal care to the tea plants. This results in the cultivation of healthier crops and the enduring maintenance of the estates' aesthetic allure. In essence, the TeaBot is not merely a cost-effective technological solution but also a dedicated guardian of the time-honored traditions and scenic beauty associated with tea estates.

The introduction of the TeaBot marks a substantial industry paradigm shift by dramatically diminishing the dependence on manual labor. It obviates the need for strenuous and repetitive tasks, yielding not only substantial cost savings but also enhancing the well-being of the workforce.

In summary, the TeaBot's transformative impact on the tea industry is unequivocal. It adeptly addresses the critical requirements for efficient estate management, cost reduction, and labor reduction. Its versatile adaptability across various platforms and resource-efficient approach make it accessible to a broader spectrum of tea estate proprietors, ensuring the promise of a more sustainable and profitable future for the industry.

As this pioneering technology continues to evolve and advance, its influence on the tea cultivation sector is poised to expand, offering an even more efficient and sustainable future, characterized by increased productivity and reduced environmental impact.

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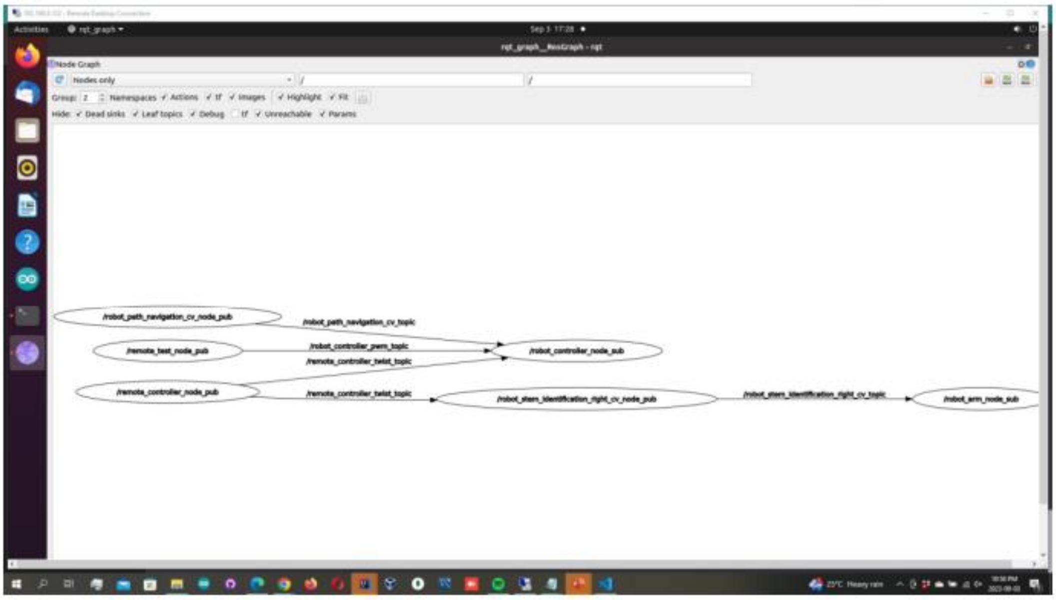
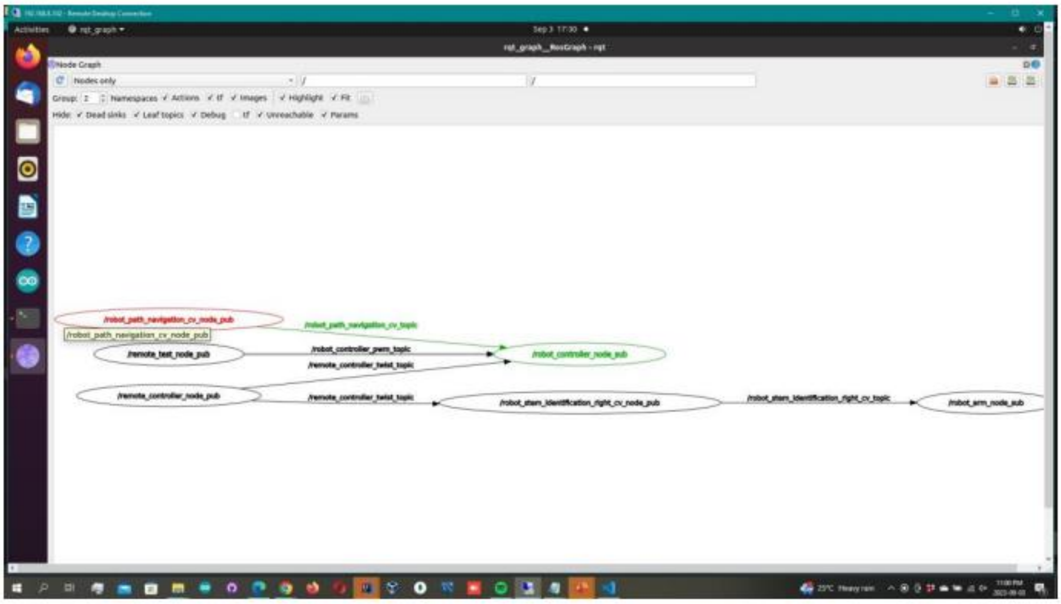
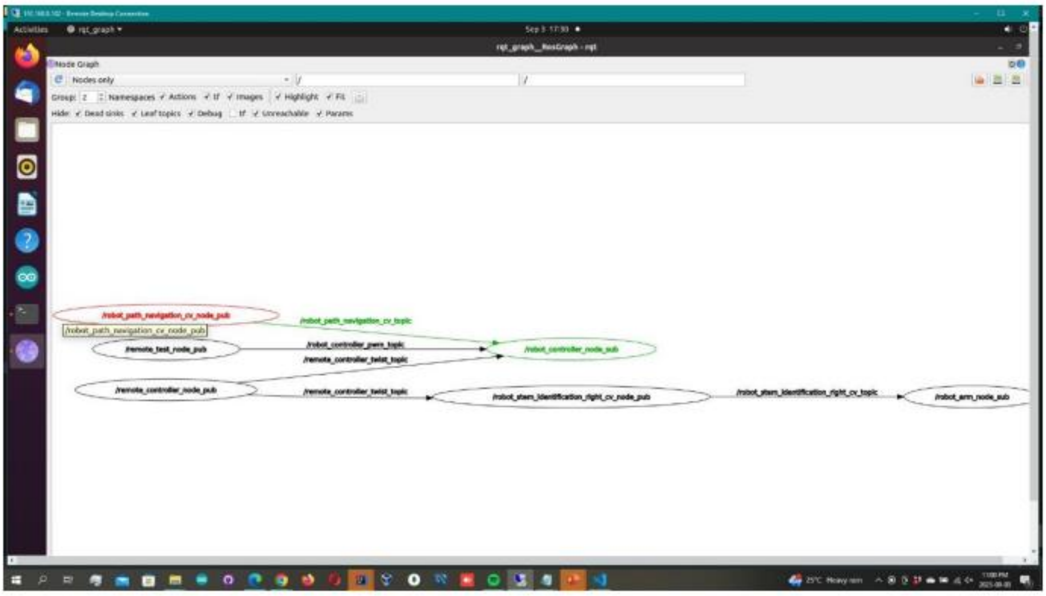
APPENDICES

Appendix 1: ROS Node Graphs



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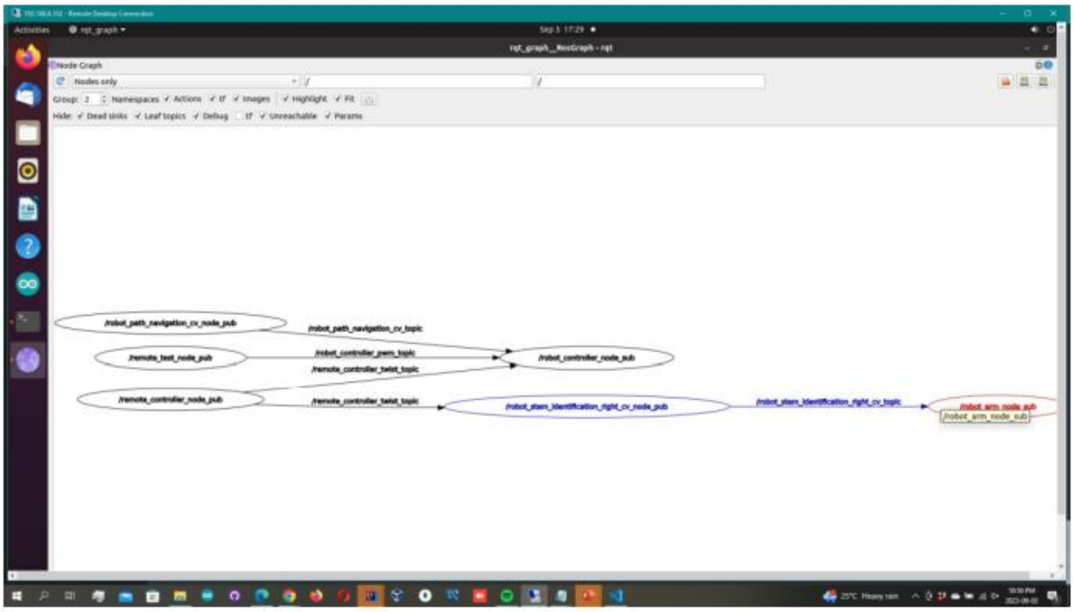
/robot_path_navigation_cv_topic
/remote_test_node_pub
/robot_controller_pwm_topic
/remote_controller_twist_topic
/robot_controller_node_sub
/remote_controller_node_pub
/robot_stem_identification_right_cv_node_pub
/robot_stem_identification_right_cv_topic
/robot_arm_node_sub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/robot_path_navigation_cv_topic
/remote_test_node_pub
/robot_controller_pwm_topic
/remote_controller_twist_topic
/robot_controller_node_sub
/remote_controller_node_pub
/robot_stem_identification_right_cv_node_pub
/robot_stem_identification_right_cv_topic
/robot_arm_node_sub

Appendix 2: Budget Justification

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	1	90,000
12V 65Ah battery	1	45,000
12V 8Ah battery	1	5,000
Camera	3	15,000
Liquid nozzles	2	3,000
Servo motors	8	9,600
Total		**220,000**

Appendix 3: System Overview Diagram