Pre-Training for Perception and Control of a Robotic Arm Mounted on a Legged/Wheeled Robot for Injecting Plants in the Plantation Farm

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***Abstract*—This paper presents the pre-training for perception and control of a Robotic arm that is mounted on a top of Legged/Wheeled Robot (according to the users preference or environmental conditions) for injecting the medicine into the diseased plants in the plantation farms. It is a challenging and robust task for a human to roam in the plantation field and spot out the diseased plant and inject in its stem, instead according to the condition user/farmer can either select a legged robot (for confined space) or wheeled robot and mount the 4 DOF arm with a vision based sensor. The work in this paper into two important parts. Primarily pre-training the system to identify the diseased plant and then control of the manipulator to inject into the stem of the plant. The sensors used in this project are LiDAR for navigating itself between the plants and a vision based sensor (camera) for identifying the diseased plant.**

Keywords—Perception, Control, Robotic Vision, Robotics

I. Introduction

In this paper we are interested in solving the issue faced by plantation farmers regarding the spread of serious diseases among their plants (having tender stem), such as moko and panama disease. To combat these diseases, injecting medicine into the stem of the infected plants is one of the most effective methods. These diseases are really dangerous as they spread very fast and end up spoiling the whole plantation yield. To solve this kind of problem in a plantation field a Robot has to be developed that can work faster in a tough environment like plantation farms. For that we are designing a Robot that can navigate into the plantation farms and detect the diseased plants and inject the medicine with the 4 DOF Robotic arm that is mounted on it. However, the traditional approach of manually locating the diseased plants and injecting them is labor-intensive. This paper proposes a solution to this problem using a robot, which involves three main steps: first, identifying the position of the plant; second, determining if the plant is healthy or diseased; and third, if the plant is diseased, administering the injection using the 3 DOF arm mounted on top of the robot.

The primary step is to navigate the robot in the plantation field. It is a traditional method followed since ages where farmers plant the sapling in rows and columns as their stems grow bigger as they grow. This type of orientation is an advantage in navigating the robot in such an environment. The LiDAR sensor is used for navigating in the field, as it's one of the efficient ways to plan and navigate. The LiDAR is fixed on the Robot (Legged or Wheeled), the robot is programmed in a way where its first step is to stop in front of the plant maintaining enough distance between the plant and the robot, so that the arm can inject the stem of the plant if it's detected as diseased. The main concentration of this paper is after this first step which is important i.e. the vision based camera senses the plant and detects it as diseased or healthy as it was pre-trained. Then the action of injecting into the plant takes place if it is characterized as diseased.

II. Literature Review

There has been lots of research that has been going on to detect the plantation disease using different methods like Drones etc. Many Machine learning, deep learning algorithms have been used to detect the diseases of plants. In the Literature [1] we can find the comparison between different algorithms and its efficiency in detecting the different feature aspects of diseases of a plant. KNN has been used in the literature [1] too and the detection has given a great result but the output is highly dependent on the quality of data, there is also a chance that the detection may be based on the irrelevant features. It also requires a large storage place.

Whilst in Literature [3] region-oriented segmentation algorithm was used to determine the most common defects on the peel of citrus fruit. They have divided the fruit peel into segments before computing. This allowed them to gain the accuracy of 95% as it allows them to focus highly on the feature recognition. There are always problems with miscellaneous features that can affect the output as they can act like outlier for the detection.

Fuzzy Classier is also used in literature [1] to determine the disease, which gives a great output but the output is highly dependent on the data provided and also the rules built by the researcher. Even though it gives great outputs it is highly purpose dependent. The output gained from the classifier supports the designers thoughts instead of classifying it unbiased. Fuzzy is a really good way of approach but as it is rule based system it doesn't cope up with every system.

In the literature [1] SVM is also used in detection and comparison with other methods, it finds the common feature out of the same classes and allocates that into groups. SVM also gave a great output as the user can design to categorize based on the similar features identified. But it also depends more on the outlier. As they can affect a lot in providing a low error output.

III. Detection

The process of detecting the diseased plant is the most important part of this paper. In this paper, diagnosing some of the most common types of disease like moko, panama etc. took place. These types of diseases can be cured by injecting a certain type of medicine into the stem of the plant when the plant is in its tender age.

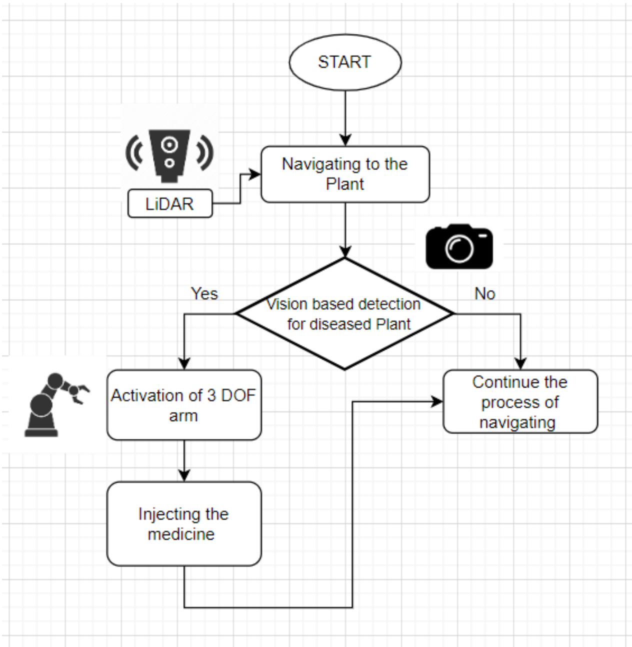

Fig. 1. Flowchart of the process

A. *Detection of diseased plant*

All the plants can't be just categorized into diseased or not diseased. There are many levels of the plant being diseased. As this paper concentrates on the category of plants having tender stems. The most important criteria of determining the disease plant for this category of plants is its color. The diseased plants have bright yellow color, Brownish and Black spots on the stem and leaves. Determining the portion/area that is covered with such spots determines the level/stage of disease that the plant is infected with. High Humidity, High soil pH leads to these kinds of disease. For this process we have collected 4872 pictures of the diseased plants and 4512 pictures of the healthy plants both from open source and agricultural farms and used it to pre-train the system.

Some of the existing methods/algorithms used for determining the diseased plants are: SVM, Fuzzy Classifier, KNN etc. In this paper the algorithm generated was tested using multiple images, after the masking was done to the collected picture using an edge detection algorithm, RGB values for every pixel were found out in the form of a matrix. The stage of disease was determined using the percentage of colors. Out of 9384 samples, results of 10 samples are shown in the table 1. These parameters will help in classifying them into the categories of 5, to categorize we will be using BPN. The training will be done by assigning initial weights to the following parameters based on the experts advice about the effect of each parameter on final

Fig 2. sample pictures used for feature extraction

	Percentage Contribution				
Sample	Light Yellow	Bright Yellow	Brown Spots	Black Shade	Total
S-1	0.14%	12.93%	9.63%	0.00%	22.70%
S-2	1.63%	4.82%	12.83%	6.29%	25.57%
S-3	3.83%	1.98%	0.63%	0.91%	7.35%
S-4	0.00%	0.00%.	0.00%	0.01%	0.01%
S-5	1.12%	7.23%	12.11%	1.27%	21.73%
S-6	2.91%	0.12%	6.48%	3.45%	12.96%
S-7	0.63%	0.00%	11.15%	1.45%	13.23%
S-8	0.43%	4.91%	12.83%	9.11%	27.28%
S-9	0.02%	0.00%	0.00%	0.01%	0.03%
S-10	0.02%	10.50%	0.12%	6.87%	17.51%

Table 1: Percentage contribution

output of categorizing them plays an important role in the final action of the robot i.e. is injection of the medicine into the stem of the plant.

IV. Categorizing the Diseased Plants

After taking the inputs regarding the identification, classification and categorization of the disease in multiple categories. The following steps were followed in the algorithm to train the system. The first step was to perform the task of masking using an edge detection algorithm so that the background images were eliminated as they could contribute to increasing the error of the result. After masking the percentage contribution of light yellow, bright yellow, light brown, dark brown and black spots are found out. Now the training is done using BPN.

A. *The Forward Pass:*

Here there are 4 inputs to the network that are the features that contribute to the output and there are 5 outputs which are the categories that the plants are divided into.

$$\text{Net } h_j = \sum W_x i_y \qquad \text{-- Eq. 1}$$

$$\text{Out } h_j = (1 + e^{-Net\, h_j})^{-1} \qquad \text{--Eq. 2}$$

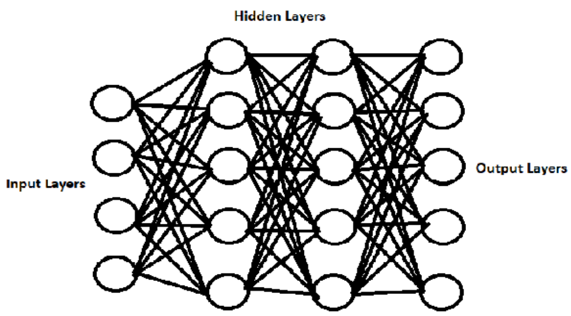

Fig 3. Neural Network

Eq 1 and 2 are used to compute the process of forward pass. After the forwards pass, we can find out that the target has not been reached, So the weights between every node need to be uploaded after finding out the error.

B. *Calculating the Error*

Finding out individual error values and summing it up to find the total error contributed.

$$\text{Error} = \frac{1}{2}(Target\ O_j - Out\ O_j)^2 \qquad \text{--Eq. 3}$$

$$E_{total} = \sum E_x \qquad \text{---Eq. 4}$$

After repeating the processes and finding out the total error of the neural network. The process of updating the weights have to be done as the weights assigned in the forward pass of the first step were the tentative weights. After forward pass the error has been calculated as we have assigned the target. To reach closer to the assigned target the weights have to be updated and iterations have to be performed till it satisfies the given condition.

C. *Backward Propagation*

To minimize the error the weights have to be updated. The backward propagation is performed. For understanding purpose, if the backward propagation is performed from the first node of output with respect W1

$$\frac{\partial E_{total}}{\partial W_1} = \frac{\partial E_{total}}{\partial out\ o_1} \text{x} \frac{\partial out\ o_1}{\partial net\ o_1} \text{x} \frac{\partial net\ o_1}{\partial W_3} \text{x} \frac{\partial W_3}{\partial out\ h_2} \text{x} \frac{\partial out\ h_2}{\partial net\ h_2} \text{x} \frac{\partial net\ h_2}{\partial W_2} \text{x} \frac{\partial W_2}{\partial out\ h_1} \text{x} \frac{\partial out\ h_1}{\partial net\ h_1} \text{x} \frac{\partial net\ h_1}{\partial W_1} \qquad \text{–Eq. 5}$$

After back propagation and finding out the value of $\frac{\partial E_{total}}{\partial W_1}$ the new weight W_1^* is found out.

$$W_1^* = W_1 - \eta \frac{\partial E_{total}}{\partial W_1} \qquad \text{– Eq. 6}$$

After performing the same action for all the nodes and updating the weights, the same process of forward pass is performed and verified with the target. If the target is not matched the weights are updated again till the target value is reached. The new set of data will be trained using the previous attained weight values and all the data which is collected is given as input and the system is trained to categorize and detect the defective plant.

V. Results of Training

After the training is done and the output collected is as follows. Refer Fig 4. for the output. Out of a total 9384 samples, 50% of the data was used for training and the testing data was 50%. All the images were resized into 400x300 and trained. The remaining 50% data was given as test input which has been categorized into the above shown

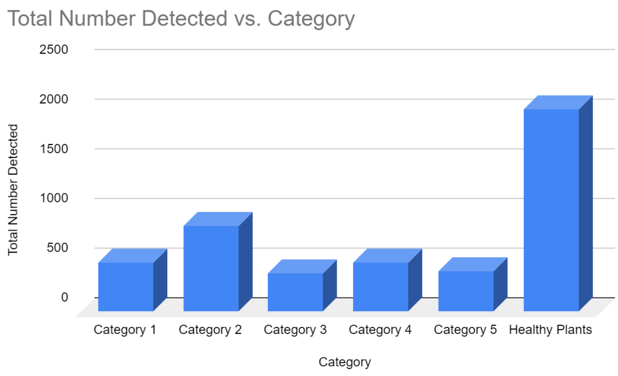

Fig 4. Bar Graph for the samples tested

Categories. After the testing the accuracy of determining unhealthy plants is 93.47%. The average probability of determining the correct category is 0.8892.

VI. Controlling Manipulator

After the pre-training the difference between the diseased and the healthy plant will be determined. If the plant is determined as unhealthy the manipulator has to inject the medicine into the plant based on its category division. The scope of this paper is also the controlling of the manipulator based on the identification of the diseased plant. Here the role of the 4 DOF Robot arm that is mounted on the top of the robot is to perform the task of injecting in the stem of the plant. The reason for selecting the 4 DOF arm is because of its easy controllability and reachability in the environment. The end effector is just to hold the modified syringe, the wrist joint is to control the angle of piercing into the plant, The other joints are for the reachability to the plants stem

A. *Introduction*

After the process of pre-training is finished, the 4 DOF manipulator shown in Fig 5. that has been placed on the top of the robot injects the liquid into the stem of the plant. To inject the arm has to pierce the needle of the syringe held by the end effector of the robotic arm. The syringe is an automated needle which quantifies the amount of medicine to be injected based on the category division done by the vision based camera with the intelligence obtained by pre training with huge data.

B. *Inverse Kinematics*

The task of this arm is to pierce the syringe inside the stem of the plant, for that the arm should move to the stem of the plant. The location of the distance from the base of the robot will be sensed by the LiDAR attached to the base of the parent bot. From there the X, Y coordinate of the base of the plant will be sensed by the Robot. To determine the Z coordinate, human help is needed. When the robot is sent in the plantation field the plants would have grown at a certain

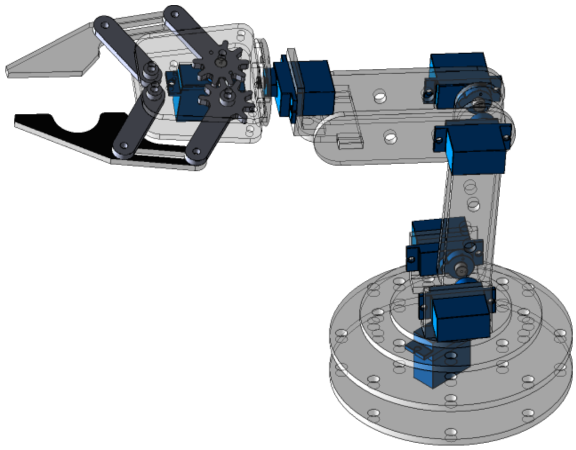

Fig 5. 4 DOF Robotic Arm CAD Model

height, as all the plants in the plantation plant will be planted at the same height, the average height of the plantation field would be almost same. After the user feeds the height of the plant, the stem's height could be measured using that. So, we have the X,Y,Z coordinates with respect to the base. Using that we can find the coordinates with respect to the base of the arm.

Inverse kinematics has been found out using the MATLAB using the Robotic System Toolbox as we know (X,Y,Z) position with respect to the base of the robot and also link lengths.

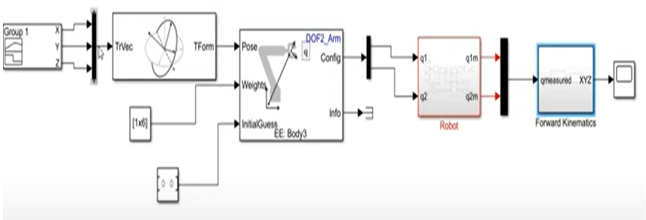

Fig 6. Simulink model to find Inverse Kinematics

The inverse kinematics output gives angles for each motor to reach the destination. When the Arm moves in that direction the syringe needle gets inserted into the plant and later the actuator does the work of injecting it and later the robot reaches the home position after the task is finished.

C. Control System

Out of 4 motors only 3 are controlled as the end effector can be manually controlled separately as it has only one task of holding the syringe. So the remaining three motors contribute to the working of the arm. Simulink is used to build up the control structure. PID controllers are used to control the Arm. Similar control structure was made for all the three motors and integrated into a common one. The gain block has been attached at the last to scale down the

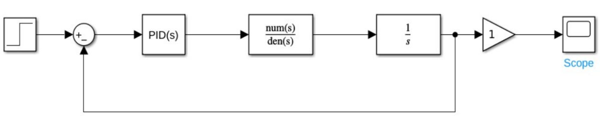

Fig 7. Simulink Model of the control Structure

output. The control structure was tested with step input to check the stability of the system and to find parameters like settling time etc.The output of each motor is highly stable and average settling time is approximately 3 seconds.o for the arm to reach its final destination it will take approximately 3 seconds after that the action of injecting can take place by the help of an automated actuator. The outputs for the control structure when step input is given as test input has been recorded.

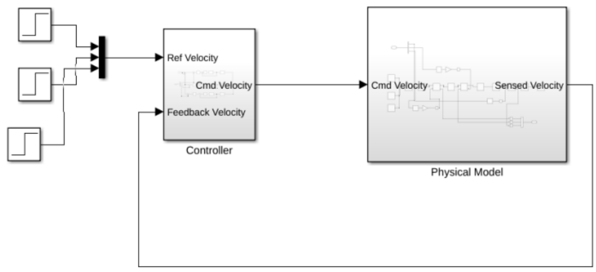

Fig 8. Fully Integrated Simulink Model

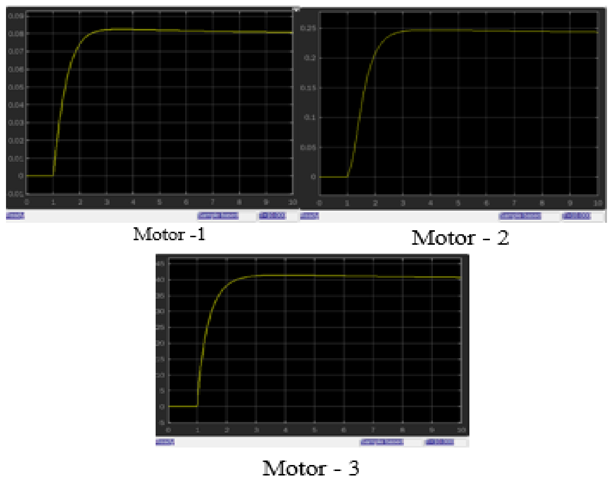

Fig 9. Output graphs for control structure

The following model can be altered by slightly changing the transfer function with respect to the requirement in the field.

In this paper the focus was towards the pre-training to determine/detect the diseased plants and categorize them among healthy plants. After categorizing the process of treatment i.e. injecting the plants. So the controlling of 4 DOF Manipulators was performed.

VII. Future Works

In this paper only the process of training and working of the arm that is mounted has been determined. The work has to be carried on to control the parent robot (Wheeled/ Legged) in the farming field as it is highly difficult to manage it in the environment of a highly uneven floor. Integrating the present system which is explained and the parental robot should be carried out in a real time environment as it was tested only in simulation.

VIII. References

1. Neelakantan, P., 2021. Analyzing the best machine learning algorithm for plant disease classification. *Materials Today Proceedings*, pp.2214-7853..
2. Medhi, E. and Deb, N., 2022. PSFD-Musa: A dataset of banana plant, stem, fruit, leaf, and disease. *Data in Brief*, *43*, p.108427.
3. Blasco, J., Aleixos, N. and Molto, E., 2007. Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. *Journal of Food engineering*, *81*(3), pp.535-543.
4. Meyer, G.E., Hindman, T.W. and Laksmi, K., 1999, January. Machine vision detection parameters for plant species identification. In *Precision agriculture and biological quality* (Vol. 3543, pp. 327-335). SPIE.
5. Goh, A.T., 1995. Back-propagation neural networks for modeling complex systems. *Artificial intelligence in engineering*, *9*(3), pp.143-151.
6. Heermann, P.D. and Khazenie, N., 1992. Classification of multispectral remote sensing data using a back-propagation neural network. *IEEE Transactions on geoscience and remote sensing*, *30*(1), pp.81-88.
7. Zuo, Y., Qiu, W., Xie, L., Zhong, F., Wang, Y. and Yuille, A.L., 2019. Craves: Controlling robotic arm with a vision-based economic system. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 4214-4223).
8. Aggarwal, L., Gaur, V. and Verma, P., 2013. Design and implementation of a wireless gesture controlled robotic arm with vision. *International Journal of Computer Applications*, *79*(13).
9. Owomugisha, G., Quinn, J.A., Mwebaze, E. and Lwasa, J., 2014, December. Automated vision-based diagnosis of banana bacterial wilt disease and black sigatoka disease. In *International conference on the use of mobile ICT in Africa* (pp. 1-5).
10. Carlos Millan, *4 DOF Robotic Arm*. (November 28th, 2016). Available: https://grabcad.com/library/4-dof-robotic-arm-1

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