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Design of Smart Weed Control System with Consideration of Herbicide Persistence Using Supervised Learning

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One of the factors that affect the quality and quantity of crops is due to stress factors caused by weeds. The presence of weeds in a field of crop is always stressful for the crop plant due to the competition for nutrients, light and moisture. Conventional sprayers have been reported to reduce these negative impacts by simply reducing the herbicide use through selective spraying -targeting only weeds and avoiding the crops. But these systems are inconsiderate to the effects of herbicides' soil persistence. Soil pH influences the persistence of herbicides especially for triazine. In alkaline soils (higher pH), lesser amount of these herbicides is bound to soil particles, making more available for plant uptake, to which the herbicide persists much longer. As a response to this dilemma, a model that utilizes machine learning and machine vision implemented on an actual sprayer robot was developed to distinguish weeds from crops and considers the soil pH for weed management. The study achieved an accuracy of 77.90 % for weed detection and 64 % for soil pH determination through image processing. The overall precision of the sprayer robot was 89.19 %. The data indicates a promising result as an attempt in considering herbicide persistence through soil pH in weed management. This study further the support and adherence to the principles of conservation agriculture.

1. Introduction

Weeds are unwanted plants that interfere with the activities and welfare of mankind. The presence of weeds in a field of crop is always stressful for the crop plant due to the competition for nutrients, light and moisture. Losses in agriculture due to weeds have already been reported. In Philippines, weeds reduce rice yield from 44 % to 96 % as they compete with rice for nutrients, sunlight, and water (Maramara, 2022). Filipino farmers are leaning towards the use of herbicides because it is cost effective and requires less labour than other methods. Although the use of herbicide is cost efficient, it is still a big part in the expenses of the agricultural industry. One of the ways to measure the potential effect of herbicides to the soil is through its persistence. Soil pH is one of the factors that determine the length of time that the herbicide persist (Curran, 2016). The use of herbicide should be controlled in such a way that it has the optimal persistence in soil. One way to solve this is through the reduction of soil pH for agricultural activities (Khamis et al., 2017) through phototrophic bacterium, but this might not be applicable or accessible to some farmers. Non-chemical approach for weed management such as physical weed control (Fontanelli et al., 2015) is another option which is not currently accessible here in the Philippines. Although several factors can directly and indirectly affect the nutritional quality of crops such as, soil factors, weather and climatic factors, the crop and cultivar, postharvest and storage, and fertilizer applications (Hornick, 1992), only the automation of weed management through fertilizer applications with consideration of soil pH will be considered in this study since it is also considered as one of the factors that contribute to crop's quality and quantity. Other factors will not be investigated in this study.
Herbicides had contributed to killing off the weeds in the crop field, however the application of herbicides had also presented negative impacts especially in the soil (Shukla and Devine, 2008). Artificial Intelligence and robotics have been a significant help in the studies of weed management as part of precision agriculture (Punithavathi et al., 2023). In the same manner that image processing has proven to be viable as seen in the study of Montañez (2021) through level identification of soil pH and macronutrients and the study of Puno et al.

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(2017) through determination of soil nutrients and pH level using image processing. In the best of our knowledge, there has never been an attempt in weed management that considers herbicide persistence before spraying. This study will attempt to explore the possibility of weed control system that considers herbicide persistence to lessen the negative effects of herbicide especially for crop rotation and soil degradation. The scallion's variant of the onion crop was used as it is a good example of crop cultivated in rows and because onion yield is affected by the presence of weeds as well.

2. Materials and Methods

The operation of the system is shown in Figure 1. The acquired image will be the input of two preprocessing systems, one that uses the Single Shot Detector (SSD) MobileNet V2 model for weed detection and counting, as well as for the classification of pH levels of the soil. The SSD MobileNet V2 was an ideal option especially for mobile and small devices. The output of the two models was the input of the decision-making system, and constituted the action of the robot, whether it will spray or not spray herbicides to the target weeds.

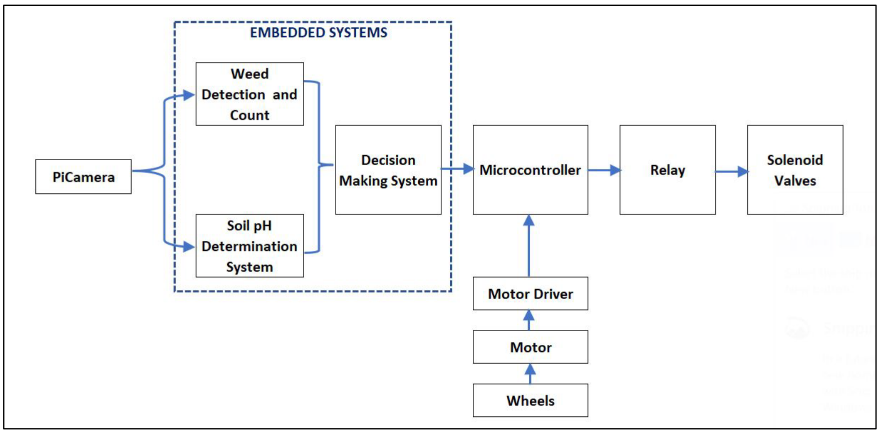

Figure 1: Conceptual framework of the proposed system

2.1 Input: Image Acquisition

The input images used for image processing were acquired using a Raspberry Pi 8-megapixel Camera Module 2. The camera deployed was the PiCamera with a viewing angle of 62.2 by 48.8 degreesz and was mounted facing downwards attached to the front of the robot at a height of about 45 cm from the ground. The 45 cm was chosen to be able to at least capture three seed growth in a frame. The image acquisition was done in the presence of natural light.

2.2 Weed Detection and Counting

The weed detection model used Single Shot Detector (SSD) framework as its underlying target detection framework and MobileNet V2 as its feature extraction framework. The Mobilenet V2 base network of the SDD model extracts the feature map, it uses Depth Wise Separable Convolutions on the input data with the use of filters to produce a feature map. Depth Wise Separable Convolution performs a two-step convolution namely, Depthwise Convolution and Pointwise Convolution. Depthwise performs separate convolution for every channel, while Pointwise Convolution combines the feature map that the depth wise convolution made to generate a new feature map. Then, Linear Bottlenecks structures were used to reduce the amount of data that flows through the network and the Inverted Residual Structure for the improvement of the flow of gradient through the network. The output of the extraction is a feature layer of size m x n (number of locations) with p channels. Then, 3 x 3 convolution filters for every cell of the image were applied within the feature layer. For each location, k bounding boxes were generated to compute the c class scores and the 4 offsets relative to the default bounding shape. Each feature map later defines a scale value. The scale value was combined with the target aspect ratios to compute for the width and the height of the default boxes. If the corresponding default boundary box has an Intersection over Union (IoU) greater than 0.5 with the ground truth, the match is positive. Positive matches computes for the mismatch between the ground truth box and the predicted boundary box for the predictions from the positive matches to get closer to the ground truth. Lastly, the non-maximum suppression was used to remove duplicate predictions pointing to the identical object.

The output from the SSD model is an image with the detected weeds inside default boundary boxes as seen in Figure 2a and 2b. The number of weeds was obtained by counting the objects detected with an IoU score greater than 0.5. The location of each weed detected was acquired by calculating the center coordinates of the boxes, given by the height and width of each boundary box.

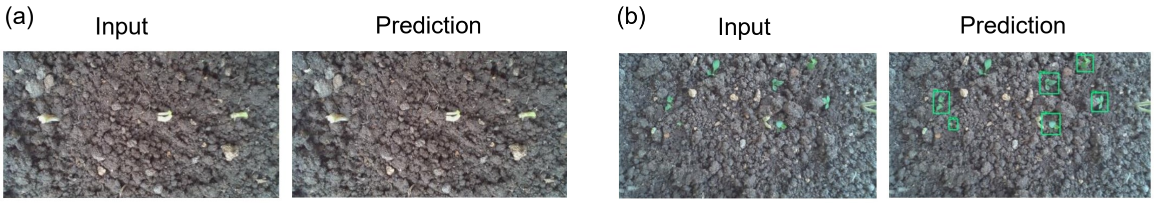

Figure 2: (a) weed detection (no weeds but with crops, (b) weed detection (with both weeds and crops)

2.3 Soil pH Determination

The soil pH determination process starts by segmenting out the weeds and crops from the captured image so that the soil pH prediction model will only make its prediction on the soil only. This process starts out by first converting the imported raw image taken by the field-facing camera to the HSV color space -see Figure 3. This is done because separating the colors is much easier to do when using Hue, Saturation, and Value as the parameters. A mask is then created by declaring a range of values which will select the green areas in the image. This mask is then inverted using the bitwise “not” operation so that it has zero values on the green parts of the image. This inverted mask and the HSV image is then compared using the bitwise “and” operation. This will effectively zero out the green parts of the original raw image. The HSV image is then returned to its original RGB color space as seen in Figure 3.
The average values on each channel of the RGB color space for the image is then determined. Using these parameters, a prediction is generated by the soil pH determination model. The output predictions are 0,1, and 2 which represents Good soil, Slightly Alkaline soil, and Alkaline soil.

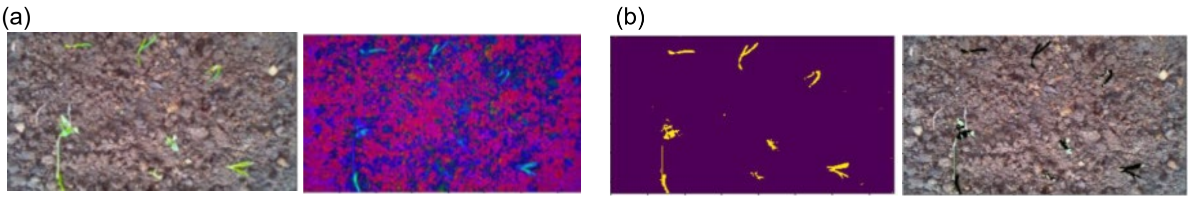

Figure 3: (a) raw image and the image in HSV color space (left-right), (b) image mask, and the segmented image (left-right)

The soil pH determination model was developed by training supervised learning algorithms using a dataset from the University of the Philippines Los Baños - College of Agriculture. The dataset has three input parameters, which are the mean values of the Red, Green, and Blue channels of the input image, and 1 output parameter which is either 0, 1, or 2. Seven types of machine learning algorithms were trained on the created dataset of RGB values and corresponding soil ph. These seven algorithms are Logistic Regression, Linear Discriminant Analysis, K-Nearest Neighbors, Decision Tree, Naive Bayes, Support Vector Machines, and Multilayer Perception. The K-Nearest Neighbors (KNN) algorithm performed the best and was selected as the algorithm for the soil pH determination model. The model is implemented in a Raspberry Pi 3 Model B+ as it has sufficient computing power for a real-time application and is mobile enough to be deployed in a field.

2.4 Decision: to spray or not to spray

The decision-making model was based on a decision tree algorithm as it provides 98 % accuracy compared to other supervised learning algorithms that we run. The dataset was based on two features which are the soil pH and weed count with its respective class. For soil pH values represented by 0 means that the soil was slightly alkaline, the output was labeled as not spray regardless of weed count value. For soil pH values represented by 1 means that the soil was good, the output was labeled as spray, regardless of weed count value.
Weed count only matter in soil pH values represented by 2 classified as alkaline soil. The degradation rate of triazine in a higher soil pH range is slower and lesser particles are bound to the soil, making it more available for plant uptake (Curran, 2016). As soil pH increases, the degradation rate of the triazine also decreases but lesser particles are bound to the soil. This causes the herbicide to be more available for plant uptake. Weed count form 0-6 means no need to spray, but if the weed count is from 7-15 (to which we consider as significant) then spray will turn on.

The dataset was divided into attributes and labels and then into training and testing sets. The class for the new data was predicted using “predict()” function in Scikit-Learn library. The output of the system was a binary value of 0 if not spray and 1 if spray. The model was developed using Python programming language. It is implemented on the same Raspberry Pi 3 Model B+ as the Soil pH Determination model as it has enough compute power to handle both models at real-time rate. We categorized the soil pH of 6.0 to 6.6 as good for spraying, 6.7 as slightly alkaline, and pH of greater than 6.7 as alkaline. The basis of this is from (Curran, 2016) especially for Triazine herbicide and onion’s soil pH preference of growth here in the Philippines (Brosas, 2023).

2.5 The Smart Weed Control System

The system was mounted on a four-wheeled vehicle as seen in Figure 5. A rectangular platform design for the vehicle was selected to achieve flexibility in the layout of the embedded systems. The spray system (herbicide tank, pump, solenoid valves) were mounted at the back of the vehicle to avoid dripping to the embedded devices during activity. The space in between wheels was 55 cm apart, enough for it to pass through one seedbed. The vehicle in total was 50 cm high and 50 cm long. The wheels have an outer diameter of 13.6 cm equipped with a 12 V DC Motor with Encoder to monitor and control the speed of the vehicle. A motor driver was used to control the input power to the motors. The mount for the sprayer system is a two-wheel drive system. See Figure 5 for the actual implementation of the design.

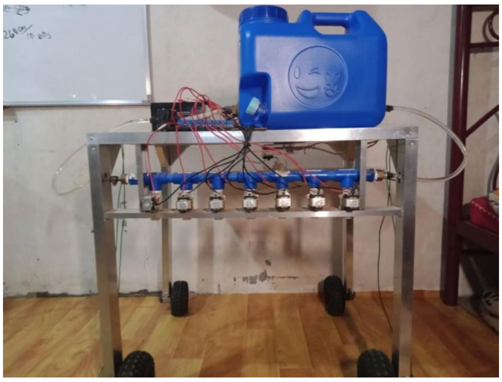

Figure 5: The smart weed control system

Upon detection, the detected bounding box relative coordinates were used to calculate which nozzle would be triggered, distance of the target to the nozzle, and the spray time. Eq(1) shows the calculation of which nozzle would be triggered (NP) and Eq(2) shows the calculation used to determine the distance of the target to the nozzle (TD). After every frame of detection, a string of data having the calculated values will be sent to the Arduino spray controller for processing and triggering of the nozzles. The data from the computational unit was used to calculate the spray time of the nozzle along with the speed of the vehicle in m/s. Eq(3) shows the calculation of the spray time (ST). After calculating ST for each nozzle to be triggered, the spray controller will send a signal to the relays that would trigger the selected solenoid valve.

$$NP = \left(6 \times X_{target}\right) + 1 \tag{1}$$

$$TD = (Y_{target} \times 0.3) \tag{2}$$

$$ST = TD/speed \tag{3}$$

3. Result and Discussion

For the data gathering, a plot of soil was prepared where weeds are placed randomly along with crop plants. The test bed was limited to 1 seedbed with only 1 type of soil pH, which is Good soil pH. Because soil pH takes a lot of time to change even with the use of catalysts, altering the soil pH was not an option for the researchers. The only changing factors for the tests are the weed count and location. For the prototype demonstration, since there is only one available testbed with only one type of soil pH, variations in the soil pH input of the decision-making system were employed. This is done to simulate different scenarios to represent the behavior of the prototype.

3.1 Weed Detection Test

It includes assessing the performance of the model in detecting weeds from an image captured by the robot. The image from the camera-pi will be used in testing the model. The trials will be a variety of images from different scenarios: crop only, and crop with weeds. Shown below is a visual presentation of the performance of the weed detection system. In this test, precision and recall is not a necessary evaluation metric as the action of the whole system does not only rely on the detection of weeds, but also on the soil pH. The accuracy is only the relevant metric to measure the performance of the weed detection system. For a total of 25 trials, we got an average accuracy of weed detection of about 77.90 %.

3.2 The soil pH Test

The Soil pH test was evaluated to determine the accuracy of the model to predict the pH of the soil from the received image. Below are the parameters to be considered:

- P_{CC} refers to the number of predictions where the model correctly classified the acidic soil as acidic
- P_{CG} refers to the number of predictions where the model incorrectly classified the acidic soil as good
- P_{CK} refers to the number of predictions where the model incorrectly classified the acidic soil as alkaline
- P_{GC} represents the number of predictions where the model incorrectly classified the good soil as acidic
- P_{GG} represents the number of predictions where the model correctly classified the good soil as good
- P_{GK} represents the number of predictions where the model incorrectly classified the good soil as alkaline
- P_{KC} represents the number of predictions where the model incorrectly classified the alkaline soil as acidic
- P_{KG} represents the number of predictions where the model incorrectly classified the alkaline soil as good
- P_{KK} refers to the number of predictions where the model correctly classified the alkaline soil as alkaline

The accuracy was calculated as the ratio of the number of correct classifications to the total number of classifications. Table 1 is the formula used to compute for the accuracy of the soil pH model.

Table 1: Accuracy of the soil pH test

	Evaluation Metrics	Description
A_{PH}	Accuracy of the soil pH model	$(P_{CC}+P_{CG}+P_{KK})/(P_{CG}+P_{CG}+P_{CK}+P_{GC}+P_{GG}+P_{GK}+P_{KC}+P_{KG}+P_{KK})$

The soil pH determination system performed an average of 64 % accuracy as seen in Table 2. In this study, accuracy of this system is crucial as soil pH is a big factor in herbicide persistence. The mediocre performance of the system can be accounted on the lack of sufficient training data, and the inconsistent lighting conditions on the days when testing was done. Since there is only one test bed with one soil pH, only two out of the 9 possible outcomes from the confusion matrix were recorded.

Table 2: Summary of soil pH test

PCC	PCG	PCK	PGC	PGG	PGK	PKC	PKG	PKK	Accuracy
0	0	0	9	16	0	0	0	0	64 %

3.3 Decision-making test

The Decision-making model dictates the action of the robot. The Decision-making test will show that if the conclusion predicted by the model was accurate. Table 3 shows the performance of the model. The test of the Decision-making system delivered great results. A 100 % accuracy means that it correctly identifies if the detected weeds, with the corresponding soil pH, is a target or non-target. Targets correspond to a spray action, while non-targets correspond to a not spray action. Although the test was limited to only two input instances, the data showed promising performance.

Table 3: Summary of decision-making test

True Positive	False Positive	False Negative	True Negative	Accuracy
16	0	0	9	100 %

3.4 Sprayer test

The sprayer test dictates the overall performance of the system. The sprayer measures the accuracy, precision, and recall of the system. In this test, the targets will be defined by the weeds if the decision model concludes a spray action. The weeds will be defined as non-targets if the decision concludes a not spray action. The crop will be identified as non-targets regardless of the decision of the sprayer. The data in Table 4 shows a trade-off between the systems recall and precision. A high precision resulted in the system to have a low recall. This means that the system prioritizes selectivity or the ability to correctly identify targets than identifying all the targets. In this study, a higher precision is crucial as the aim of this research is to lessen the use of herbicide to avoid persistence and increase efficiency.

Table 4: Accuracy, precision, and recall

True Positive	AS	PS	RS
Average	74.17 %	89.19 %	58.01 %

4. Conclusions

The hardware implementation of the system was effectively tested and implemented successfully. The implementation of the three developed models namely: Weed Detection system, Soil pH Determination system, and Decision-making system on a robot showed a positive result. The tests achieved an accuracy of 77.90 % for weed detection and 64 % for soil pH determination through image processing. The overall precision of the sprayer robot was 89.19 %. This means that the robot carefully targets weeds and makes sure not to target the crops. The results indicate that a precision sprayer that considers herbicide persistence due to soil pH to reduce the negative effects in the environmental and to health hazards is achievable. Latest advances in the technologies employed by conservation agriculture for a safer and more efficient farming utilizes precision spray technologies. This study further these technologies in terms of reduced the costs, the crop damage, and the environmental and health risks as it considers the persistence or the rate of degradation of the herbicide on the soil.

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