DETERMINING THE EFFICIENCY OF A SMART SPRAYING ROBOT FOR CROP PROTECTION USING IMAGE PROCESSING TECHNOLOGY
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تحديد كفاءة روبوت الرش الذكي لحماية المحاصيل باستعمال تقنية معالجة الصور

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ABSTRACT
A system was used to detect injuries in plant leaves by combining machine learning and the principles of image processing. A small agricultural robot was implemented for fine spraying by identifying infected leaves using image processing technology with four different forward speeds (35, 46, 63 and 80 cm/s). The results revealed that increasing the speed of the agricultural robot led to a decrease in the mount of supplements spraying and a detection percentage of infected plants. They also revealed a decrease in the percentage of supplements spraying by 46.89, 52.94, 63.07 and 76% with different forward speeds compared to the traditional method.

الملخص
استخدم نظام لاكتشاف الإصابات في أوراق النبات من خلال الجمع بين التعلم الآلي ومبادئ معالجة الصور. تم تنفيذ روبوت زراعي صغير للرش الدقيق عن طريق تحديد الأوراق المصابة باستخدام تقنية معالجة الصور بأربع سرعات أمامية مختلفة (35 ، 46 ، 63 و 80 سم/ث). أظهرت النتائج أن زيادة سرعة الروبوت الزراعي أدى إلى انخفاض كمية رش المكملات ونسبة الكشف عن النباتات المصابة. كما انخفضت نسبة رش المكملات بنسبة 46.89 و 52.94 و 63.07 و 76٪ مع السرعات الأمامية المختلفة مقارنة بالطريقة التقليدية.

INTRODUCTION
One of the fundamental changes in human history is the "agricultural revolution", followed by the "industrial revolution", which contributed to the increase in the production of services and manufactured goods by greatly reducing the number of workers in the agricultural field (*Terzi et al., 2019*). Artificial intelligence technologies have also been developed. AI-based image processing applications are rapidly spreading in industrial agriculture. This technique has been used in various fields in the agricultural field, the most important of which is the fruit classification process using the image algorithm analysis technique. This technique proved successful with a high efficiency of 93.33% in the classification of pepper fruits using a Pixy2 camera *(Al-Sammarraie et al., 2021)*. Agricultural robots have also been used in modern technologies. Usually, these robots are electromechanical machines that are directed by a computer program or an electronic circuit. *(Dengyu et al. 2016)* developed a laboratory-type system controlled by image processing that could make various measurements on plants, extract types, growth rate, yield, and similar contents with great success. Artificial intelligence techniques have also been used in the diagnosis of plant diseases, as the application of pesticides in agriculture causes some negative aspects that affect human health and the environment. As a result of the intensive and unconscious use of agricultural pesticides, the pesticide itself or the by-products used may remain in the food, soil, water and air. Negative influences appear on other non-target organisms, humans and natural imbalances. Therefore, research is being conducted on ways to reduce pesticide spraying or control weeds or pests *(Malasli, 2010)*. The total production of pesticides in the world is approximately 3 million tons per year, and annual sales of pesticides range between 25-30 billion dollars *(Delen N, 2008)*. Herbicides and pesticides account for more than 70% of their use. The other pesticide groups had a 5% share. When evaluated in monetary terms, 31% of consumption consists of pesticides, 26% herbicides and 20% fungicides *(Tiryaki et al., 2010)*. The production of agricultural pesticides worldwide is increasing rapidly and new drugs are being developed daily. Therefore, the types of drugs used are increasing. Herbicides have the largest share of this increase, and it is estimated that the use of herbicides will become more widespread in the future. However, drugs used in chemical control have negative effects on human health, the environment, the natural balance and the increase in production costs; pesticides should be used sensitively and have minimal drug loss (*Çetin et al., 2018*). Therefore, the world today tends to use modern technologies that depend on image processing and automatic learning to spray pesticides accurately at different levels.

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The development of weed control techniques has become a priority for the research community to increase crop yields and reduce costs, as well as the negative repercussions of herbicides *(Slaughter et al., 2008)*. *(Ali et al., 2017);* used a method to detect and classify major citrus diseases. The proposed technique applies a color difference algorithm to separate the affected area. Moreover, the pathology was classified using color graphs and compositional features. The authors claimed to have an accuracy of approximately 99.9%. *(Iqbal et al., 2018)* surveyed various methods used to detect and classify diseases in the leaves of citrus plants. They reported that only 22% of herbicides are required to reduce unwanted vegetation when applied in a precise manner. The authors identified the strengths and weaknesses of various image processing, segmentation, feature extraction, and classification methods. *(Søgaard et al., 2007);* introduced an automated system that uses a weed detection system to control the accurate dosing of herbicides. Weeds were detected using computer vision technology from data obtained through an independent vehicle resulting in a 50% reduction in herbicide use. *(Hossain et al., 2018)* used Support Vector Machine (SVM) to detect three different types of tea leaf diseases and achieved an accuracy of 90% using 150 training images and 50 test images. A similar process was used to detect anthracnose and canker disease and achieved 95% accuracy using 200 training images and 100 test images *(Gavhale et al., 2014)*. *(Sladojevic et al., 2016)* used a Convolutional Neural Network (CNN) classifier to identify 13 types of diseased leaves on 30,000 images. The system automatically detected diseases with an accuracy of 96.3%. *(Ferentinos, 2018),* has also improved the implementation of the CNN classification. Their proposed method can identify 58 diseases from 25 plants with 99.53% accuracy from 87,848 images. In addition, they used fine-tuning to significantly affect the overall resolution. *(Mohanty et al., 2016)* applied this approach to detect 26 out of 14 crop species with 99.35% accuracy using 54,306 images as a dataset.

Many disease detection algorithms require expensive and high-performance machines. In addition, it is difficult to obtain a high resolution. Moreover, a large number of human resources are needed to detect these diseases by naked eye. Therefore, it requires the use of smart agricultural sprinklers that can detect plant injuries or any other symptoms that appear on the leaf of the plant in real-time and can adjust the required amount of agrochemicals. This will lead to lower cost and improved spray quality by ensuring optimum application of spray materials, reducing farmer's exposure to toxic agricultural chemicals and reducing environmental impact. Robots have become a major part of our daily lifestyle and they have a wide scope in agricultural engineering. They play a vital role in the development of new technology. In this study, a model of a small agricultural robot was designed and implemented to spray pesticides or liquid fertilizers accurately at four different forward speeds (35, 46, 63 and 80 cm/s) based on the methodology of modern technology. This disease may cause several symptoms in the leaves. Therefore, the methodology used is to develop a system that detects plant diseases or any problem that appears in the leaf of the plant due to high heat, humidity, or a problem with the salinity of the soil effectively through the application of image processing and machine learning. This methodology can also detect healthy leaves. If any disease is detected, it determines the exact percentage of the pesticide or liquid fertilizer in the area affected by the disease.

MATERİALS AND METHODS

The methodology proposed in this research consists of five steps: image collection, image processing using Matlab software, image segmentation, Feature Extraction (color), data collection acquisition and description and finally programming the small agricultural robot to spray pesticides or liquid fertilizer at different levels and accurately. Figure 1 shows the proposed system.

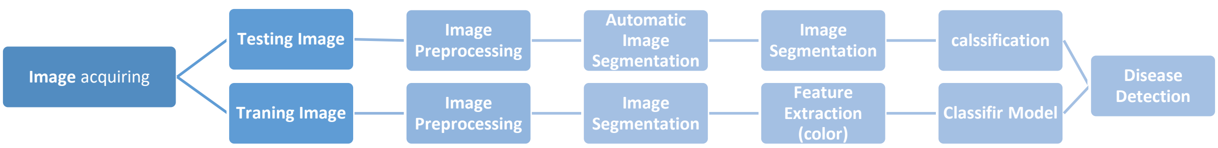


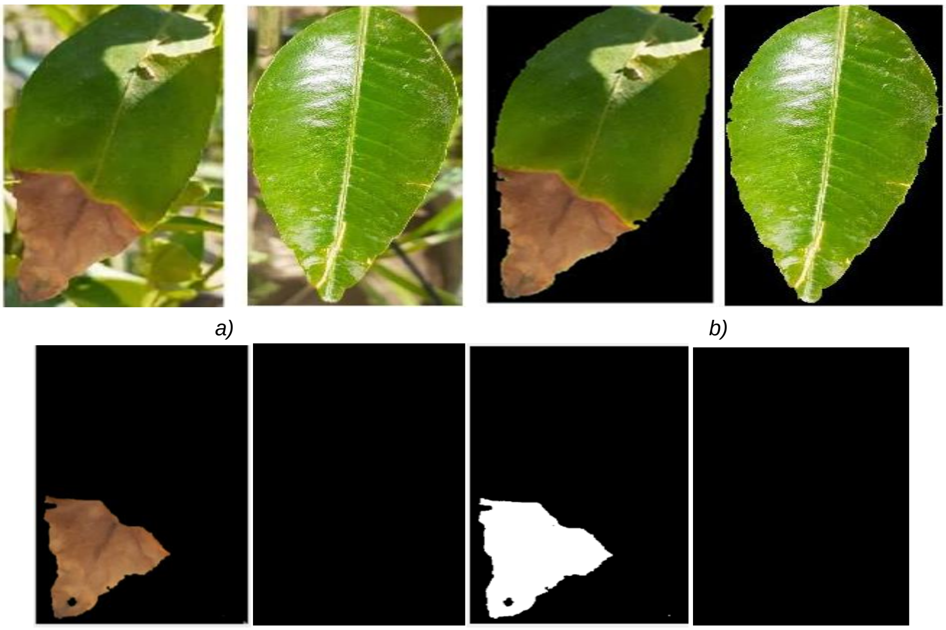
Fig. 1 - System methodology

As mentioned previously, the agricultural robot can detect leaves that show problems other than disease. Therefore, the term "infected plants or infected leaves" is adopted in the research. Images of the citrus Aurantium were taken from the College of Agricultural Engineering Sciences / University of Baghdad fields.

Reddish-yellow leaves are discovered due to heat and high humidity, or the cause may be due to the salinity of the soil. To treat soil salinity, improve its physical and chemical properties and activate beneficial microorganisms, a humic acid solution was added to an agricultural spraying robot. Some images were taken in the laboratory for laboratory calibration and the rest were taken from the field. The proposed model recognizes the following items:

1. Infected leaves.
2. Uninfected leaves.

Matlab software was used to process the plant images and the background of the image was removed leaving only the image of the Leaf. To detect the disease, it is necessary to remove the green parts of the image. After these operations, the only remaining part (Greenness elimination mask) showed symptoms significantly. Figure 2 shows the stages of the display of the affected part of the leaf.



a) *b)* *c)* *d)*

Fig. 2 - Image process

a) Original image; b) Primary image; c) Greenness elimination mask; d) Image thresholding

By observing the images of the affected and healthy areas, it can be seen that they have differences in color, edges and shapes. Therefore, all these features were used to classify the infected leaves. All these processes are shown in Figure 2. A green pixel was removed from the image because it represents the healthy area of the leaf. After removing it, only the affected part remains as we have already removed the background. Therefore, the perimeter of the diseased area can be easily detected now because of heat, humidity, or soil salinity.

As shown in Figure 3, the graph equation applied to the color tone of the affected leaf was applied. Using the Otsu thresholding algorithm, each image was converted into a binary image. This process separates each infected part away from the uninfected parts, the infected parts appear white and the rest black.

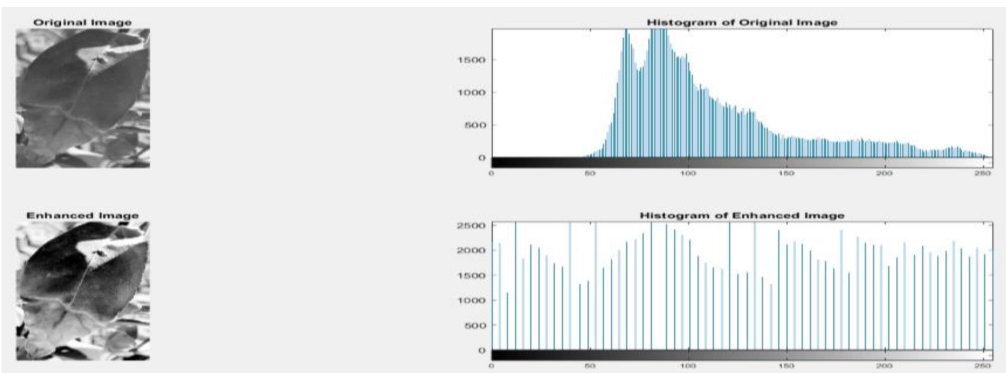


Fig. 3 - Histogram equalization on the hue of an image

RGB color space is designed to define colors in a cube unit using the added color mixing method. These three colors are mixed with a certain intensity to display any color on the digital screen. RGB color space can be considered as a three-dimensional space with format axes in red, green and blue (Figure 4). The colors to be created can be expressed in terms of the coordinates of these three primary colors *(Sabancı, 2014).*

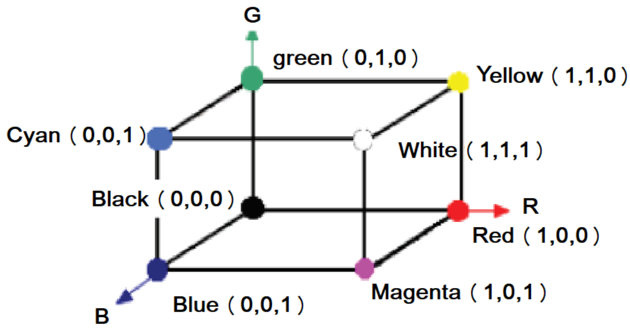


Fig. 4 - RGB color space coordinate axes

The image was classified into RGB channels to identify the plant leaf in the image, the image was taken by the digital camera on the micro-spray robot. Equation 1 was used to get the red value index, which will be targeted to select red-colored entities in image processing algorithms *(Ramaraju et al., 2014)*.

$$F = R - 0.5G - 0.5B \tag{1}$$

Where:

R is the red coefficient; G is the green coefficient; B is the blue coefficient of the image respectively. To distinguish red color information, the values of green (G) and blue (B) were multiplied by 0.5 and subtracted from the value of red (R). The purpose of this function is to determine how close color (F) is to red.

From the spatial point of view of infected and intact places, it was noted that both have different colors. Therefore, the features of the color chart can be used to classify infected plant leaf from uninfected. The image was converted to RGB scale (red, green, blue). When the image is converted to RGB the color chart is drawn. It can be observed in Figure 5 that the RGB scale is different for both images. The proportion of red in infected leaves is greater than in healthy leaves; in contrast, the proportion of green in healthy leaves is greater than in infected leaves.

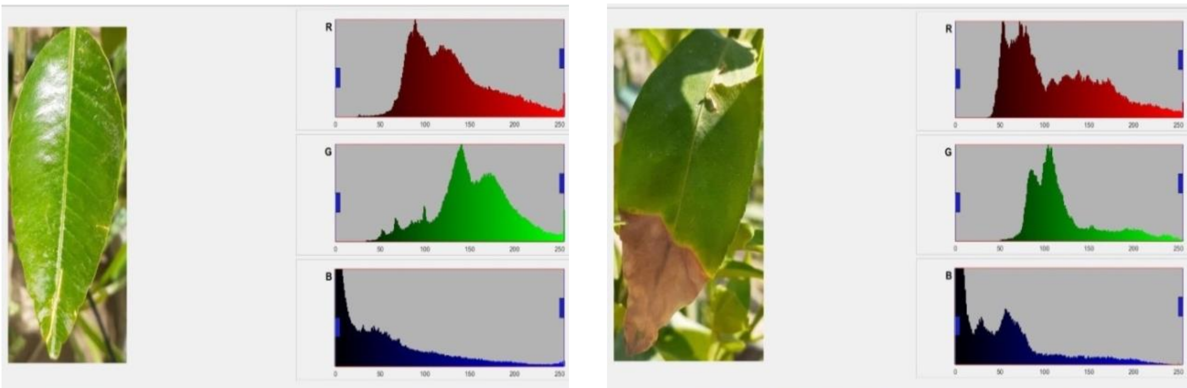


Fig. 5 - RGB scale for infected and healthy plant leaf

To demonstrate the previous conclusion, the proportion of the three colors in each region can be determined. Each pixel consists of three separate components, these ingredients weigh the primary colors red, green and blue that make up the color of the Pixel. Each component pixel of the image has red, green and blue values ranging from 0-255.

Figure 6 shows matrices for the three-color values of specific areas of healthy and infected leaves.

As discussed early, the healthy leaf image will show a higher percentage of green over red and blue, Figure 6.b. shows the lowest percentage of green color is 100, that the highest percentage of red color is 75, i.e. G< R and that indicates a healthy leaf, while Figure 6.a. shows that highest percentage of green color is 92 and the lowest percentage of red color is 138, i.e R<G which leads to conclude that this leaf was infected.

R: 73 G: 104 B: 10	R: 75 G: 106 B: 13	R: 74 G: 104 B: 14	R: 73 G: 103 B: 13	R: 72 G: 102 B: 12
R: 73 G: 104 B: 10	R: 75 G: 106 B: 13	R: 74 G: 104 B: 14	R: 73 G: 103 B: 13	R: 72 G: 102 B: 12
R: 70 G: 104 B: 9	R: 73 G: 104 B:11	R: 72 G: 103 B: 10	R: 71 G: 101 B: 11	R: 70 G: 100 B: 112
R: 70 G: 102 B: 5	R: 71 G: 103 B: 6	R: 71 G: 102 B: 8	R: 69 G: 100 B: 6	R: 68 G: 100 B: 6

R: 140 G: 90 B: 57	R: 140 G: 90 B: 57	R: 140 G: 90 B: 57	R: 140 G: 90 B: 57	R: 140 G: 90 B: 57
R: 140 G: 90 B: 57	R: 142 G: 92 B: 57	R: 142 G: 92 B: 59	R: 140 G: 90 B: 57	R: 138 G: 88 B: 55
R: 139 G: 89 B: 57	R: 141 G: 91 B: 58	R: 141 G: 91 B: 58	R: 140 G: 90 B: 57	R: 138 G: 88 B: 55
R: 139 G: 89 B: 56	R: 139 G: 89 B: 56	R: 139 G: 89 B: 56	R: 139 G: 89 B: 56	R: 138 G: 88 B: 55

a) *b)*

Fig. 6 - RGB value matrices

a) Infected; b) Healthy

Robot assembly

In traditional spraying methods, the nozzle is always open during spraying. Thus, spraying is carried out in places where there are no infected plants. In this study, a small high-performance robot with a mechanism for spraying liquid fertilizer based on image processing was designed. Precision spray robot was developed with a digital camera to acquire real-time leaf images, as the infected leaf image is captured by this camera, the spray will automatically start and nozzle spray will continue as long as the captured image is recognized as infected. For the robot to work successfully in the experimental environment, it is necessary to provide key kinetic abilities. First, infected leaves detection using an image that digital camera capture, second sprays the infected leaves that have been diagnosed by a designed spraying system (static discharge pump and nozzle). To successfully achieve these two processes, DC motors, wheel system and camera module are integrated for image analysis.

The microcontroller-based robot consists of a digital camera compatible with the Arduino Uno as well as a transceiver module. Industrial Pixy2 camera was used to capture real-time images of leaves. Due to its low cost and ease of use, it is commonly used in small projects related to robotics and artificial intelligence. The camera used has Omnivision OV9715 sensor, 1/4", 1280 × 800. It can receive 50 images per second (1 image per 20 milliseconds) and can be connected to a computer through USB. In addition, it is very lightweight at 27 g with a low power consumption of up to 140 mA *(Omosekeji, 2018)*. The camera with the Arduino Uno controller is connected using the serial communication protocol. L293d motor driver shield was also used to drive 4 DC motors and one DC pump with a discharge of 240 l/h that is driven by a DC motor by connecting to the required terminals. The Arduino Uno board represents an actual programming platform based on ATmega328 and is operated with an input voltage of 5.5 V and has a maximum operating frequency of 20 MHz *(Krishna et al., 2012)*. The power supply for Arduino Uno can be either via a USB connection, DC power supply or both. It is also a high-performance device with a low-power 8-bit AVR microcontroller with 32 KB in the system and advanced reduced instruction set computing *(Abdullah et al., 2012).* It also consists of an I/O port and software development environment. It has 13 digital I/O pins (6 of which can be used as PWM outputs), 6 analog inputs, a USB connection, a power socket, an ICSP head, and a reset button. It has everything needed to support the microcontroller. It can be simply plugged into a computer using a USB cable. The C programming language controller program is written in an editable format for processing sensor data. The work is also based on the Bluetooth Command Sending and receiving module. The remote control is a smart Android device with a Bluetooth app. Thus, the receiving area has an Arduino Uno board as a controller and an HC-05 Bluetooth module as a remote communication module for exchanging data over short distances (using short-wavelength UHF radio waves in the ISM range from 2.4 to 2.485 GHz). The range is about 5-30 meters, these units are based on the Cambridge BC417 wireless Bluetooth radio chip with a frequency of 2.4 GHz *(Jayantilal, 2014)*. When the Bluetooth application is launched and connects to the current system via Bluetooth, the robot will receive wireless commands using the functions programmed in the application. The robot moves in four directions: forward, backward, right and left. In forward movement, the four DC motors will move in the same direction and for the rear movement, the DC motors will reverse their direction. For left and right movements, the motors of one side will rotate depending on the direction of rotation. L293d motor driver shield was used as a two-way robot wheel controller.

This motor driver shield allows us to easily and independently control and drive the DC motors. It is ideal for robotic applications and perfectly suited to microcontrollers that only require control lines for each motor. Figure 7 shows the motor drive shield with Arduino and Bluetooth.

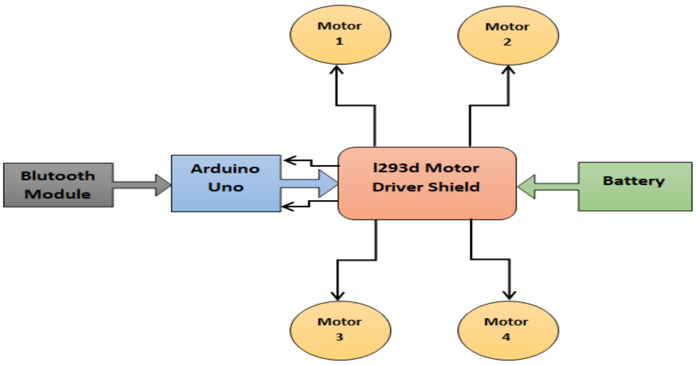


Fig. 7 - Arduino motor driver shield

The circuit consists of an Arduino UNO board, HC-05 Bluetooth Module, L293d motor driver shield, four 250 rpm geared DC motors (wheel rotation speed can be controlled by application) and an 11V rechargeable battery. The TX and RX pins of the Arduino are connected to the Rx and Tx pins of the Bluetooth module. The Bluetooth module is equipped with a voltage of 5V. The power supply was obtained by connecting the Lipo Battery as a power source for the first stage of the moving robot. This battery can save from mAh1800 of current and average voltage 11.1 V. These batteries are useful in terms of being rechargeable for many business robotic. Three solar cells were also used as battery charging sources with an average voltage of 15v and 660 mA, each cell gives 5V and 220 mA. Figure 8 shows the overall connection of the agricultural robot electrical circuit.

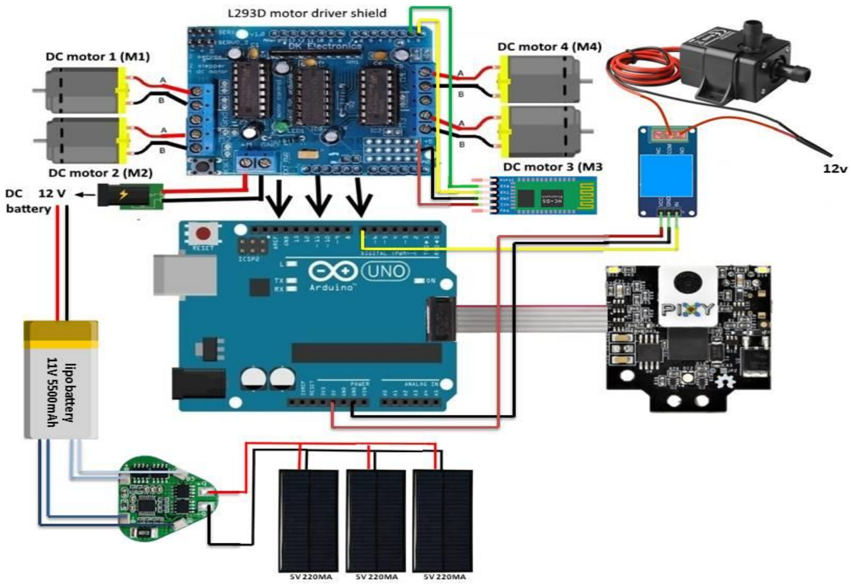


Fig. 8 - Agricultural robot diagram

Procedure

Images of infected citrus leaves were used in the experiment, these images were taken from the experiment field, image algorithms and analysis were performed to identify the infected leaves from healthy ones; as mentioned before, a threshold value of red color was chosen, the obtained images data were used as a reference to the microcontroller unit using Matlab and Arduino IDE software. The developed system works fast and stable. The proposed prototype robot was tested inside a greenhouse in the fields of the Agricultural Engineering Sciences College/ University of Baghdad. Four different speeds (35, 46, 63 and 80 cm/s) were used with a distance of 10 meters. Pixy2 camera was placed at a height of 50 cm from the ground to obtain real-time field images of plant leaves. As the proposed robot is a prototype and for the experimental test data was taken from the lower part of the plant, as the robot detects infected leaves (red color index exceeds a threshold value), control signal was given to the spray pump to spray liquid fertilizer using a spray arm, consisting of a nozzle with a screw valve, a specified amount of agricultural pesticides was applied depending on the operating time. The liquid fertilizer amount spraying was calculated for three levels of ground speed of the agricultural robot, comparing the amount of spraying with the manual method and studying the amount of discharge in the spraying of the starter. Figure 9 shows the experiment.

Fig. 9 - Robot prototype in the field

RESULTS

The experiment was conducted in a greenhouse for a distance of 10 meters. 20 planted pots were arranged along 10 meters, 12 of the plants being infected. By detecting 12 infected plants on the precise spray robot movement path, the amount of liquid spray fertilizer used in conventional spraying has been compared with the developed system. The robot applied approximately 1-7 ml of liquid spray in the micro-spray state of every single plant, the nozzle height was 50 cm and there were four different forward speeds (35, 46, 63 and 80 cm/s). The savings rates in the amount of liquid spray applied to infected plants were determined using a precision spray robot, according to ground speed. The results are shown in Figure 10.

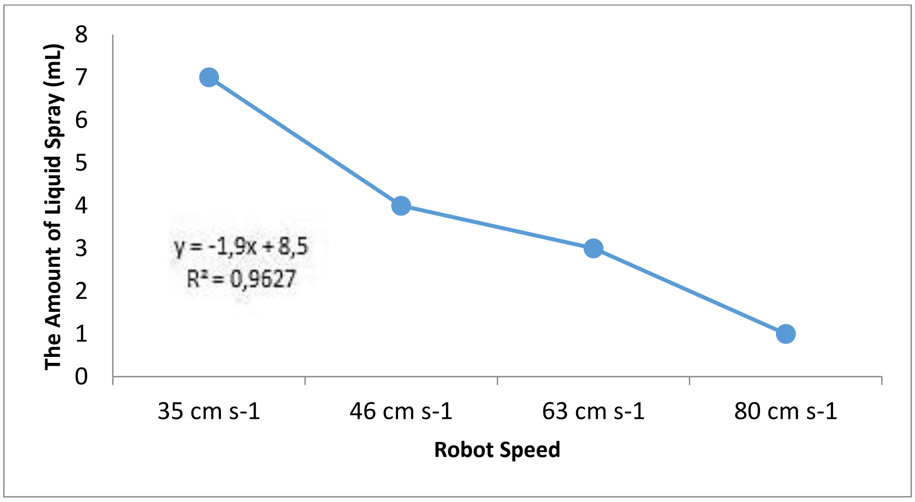


Fig. 10 - Robot speed vs liquid spray

As shown in Figure 10, the amount of fertilizer was reduced as the ground speed increased. The 80 cm/s speed shows the lowest spraying liquid fertilizer amount of about 1 ml while the 35 cm/s speed gives the highest spraying liquid fertilizer amount of 7 ml per infected plant. Increasing the speed of the spray robot leads to a decrease in the amount of liquid spray applied to the grass *(Sabancı, 2014)*. Regression equations and determination coefficients were calculated showing the relationship between ground velocity and the amount of liquid fertilizer spraying. It turns out that there is a polynomial relationship between ground velocity and the amount of liquid fertilizer spraying. The coefficient for determining regression equations is 96.27%. From this concept, it is clear that there is a clear inverse relationship between ground speed and the amount of liquid fertilizer spraying.

The amount of spray fluid changes according to the frequency of image capture as well as the percentage of detection of plant diseases. the spraying time increases with the decrease in ground speed because the value of the red color will take longer in the image frame as the agricultural robot moves forward. The rate of detection of infected leaves is also higher as the ground speed decreases. Therefore, the amount of pesticide applied was also higher.

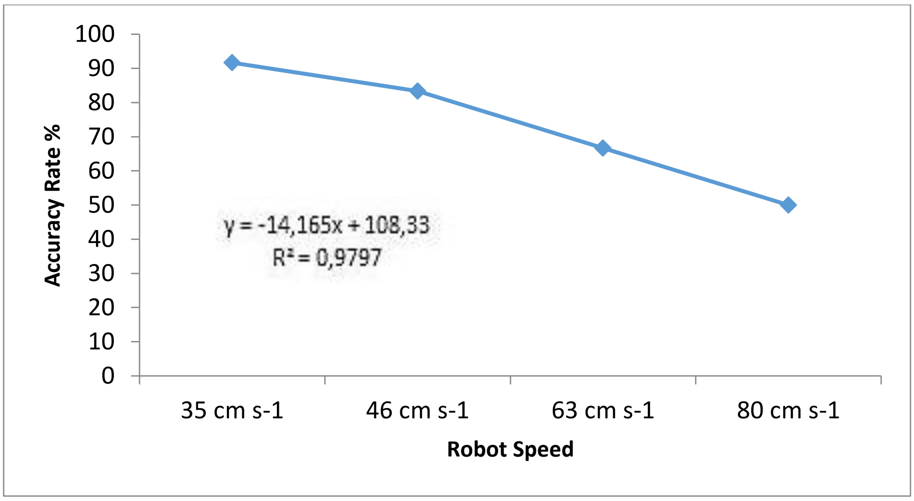


Fig. 11 - Robot speed vs. accuracy rate

As shown in Figure 11, the detection of plant diseases decreases as the ground speed increases. The 80 cm/s speed was recorded as the lowest rate of detection of plant diseases of 50%; the highest detection of plant diseases of 91.66% was measured for 35 cm/s speed. As the speed of the developed spray robot increases, the amount of spray liquid applied to the plant leaves decreases. As the speed of the micro-spray robot increases, the rate of images received by the webcam decreases *(Sabancı, 2014)*. Regression equations were calculated and coefficients showed that there was a distinguishing mark between the speed and the amount of liquid fertilizer spraying. The coefficient for determining the regression equations is 97.97%. This result shows that there is a clear inverse relationship between the ground speed of the precise spray robot and the amount of liquid fertilizer spraying.

In comparison with the traditional spraying method, for a distance of 1 meter approximately 6 - 77 ml liquid spray was applied using the robot system, while 25 - 145 ml of liquid spray was applied in the case of the traditional spraying. Figure 12 shows the relation between robot speed vs. spray amount for both techniques.

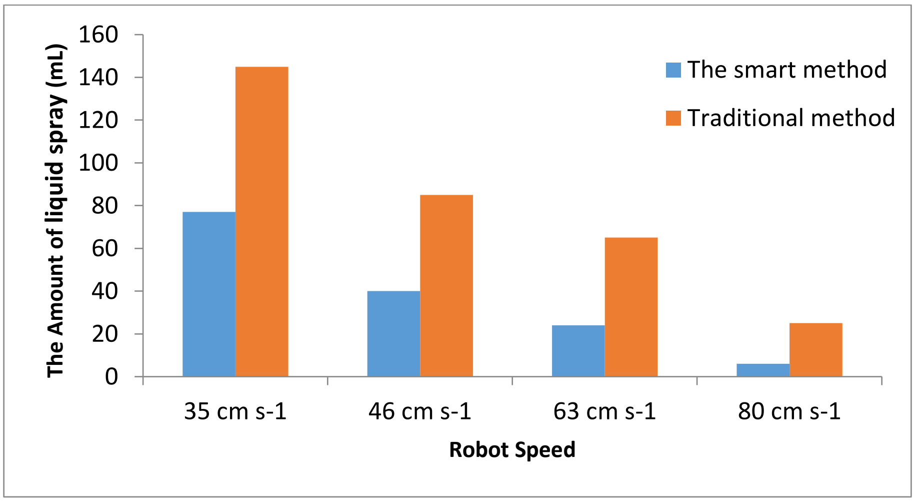


Fig. 12 - Robot speed vs. Spray amount for both techniques

Figure 12 shows that by increasing ground speed, the spraying rate decreases in both traditional and robotic ways. The spraying rates by using the traditional method are 145, 85, 65 and 25 ml while the rates of 77, 40, 24 and 6 ml are for robot spraying, respectively. When the speed of the precision spray robot increases from 35 cm/s to 46 cm/s, that is, the speed increase by 31.42% results in an 84.09% decrease in the amount of liquid spray applied by the smart method while the proportion of spraying by the traditional method decreased to 41.37%. The smart method gave a 46.89% (68 ml) reduction in the spraying rate compared to the traditional method at a first speed.

When the speed of the precision spray robot increases from 46 cm/s to 63 cm/s, the speed increases by 36.95%. This will reduce the amount of liquid spray by 40% using the smart method, while the traditional method gave a decrease of 23.52%. The smart spraying method gave a 52.94% (45 ml) reduction in the spray rate compared to the traditional method at the second speed. The third speed gave an average decrease of 63.07% (41 ml) compared to the smart and traditional method. Increasing the speed of the spray robot from 63 cm/s to 80 cm/s gave an increase in the ground speed of the agricultural robot by 26.98% resulting in a decrease in the spray rate by 75% in the smart method and 61.53% in the traditional method. The smart method gave a 76% reduction in the spray rate (19 ml) compared to the traditional method at the fourth speed.

Williams et al., (2000) states that the spray rate for weed control by developed sensors decreased by 11.5-98% compared to the amount of medicine applied compared to conventional methods. *Feyaerts et al., (1999)* found a 90% reduction in the amount of medication in image processing applications for herbicides. *Watchareeruetai et al., (2006)* showed that using image processing techniques, reported a 90-94% reduction in the use of chemical pesticides in spraying by detecting weeds in the grass.

CONCLUSIONS

The infected plants will be detected and the liquid will be sprayed only on the infected plants instead of the entire field using a precision agricultural robot. Human, environmental and animal health will be protected due to low pesticide or liquid fertilizer consumption. The precision spraying system developed in the experiment on 20 pots for a distance of 10 meters saved 46.89, 52.94, 63.07 and 76% of pesticide with different forward speeds respectively compared to the traditional method. The amount of liquid spray sprayed on infected plants has changed inversely with the speed of the precise spray robot. As the speed of the developed spray robot increased, the amount of liquid spray being sprayed on the infected plants decreased. When the speed of the precision spray robot increases from 35 cm/s to 46 cm/s, that is, the speed increase by 31.42% results in an 84.09% decrease in the amount of liquid spray applied by the smart method. The proportion of spraying by the traditional method decreased to 41.37%. When increasing the ground speed of the micro-spray robot from 46 cm/s to 63 cm/s, that is, increasing the speed by 36.95% reduced the amount of liquid spray by 40% using the smart method, while the traditional method gave a decrease of 23.52%. Increasing the speed of the spray robot from 63 cm/s to 80 cm/s gave an increase in the ground speed of the agricultural robot by 26.98% resulting in a decrease in the spray rate by 75% in the smart method and 61.53% in the traditional method. The excessive use of herbicides leads to significant contamination of both soil and Water Resources indirectly, or in the case of excessive spraying of liquid fertilizers, will lead to material losses. When the study was developed and applied in one of the greenhouses of the citrus Aurantium plant, liquid fertilizers applied only to the infected plants, in this case, there will be no drug fertilizers on the uninfected plants. The developed sensitive spraying system model can be developed and used in greenhouses to spray variable-level herbicides. The same system can be used to spray plants in vegetable fields and use liquid fertilizer, and input costs can be reduced.

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