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doi:10.15199/48.2023.08.16

Robotic vision based automatic pesticide sprayer for infected citrus leaves using machine learning

***Abstract** Smart farming has become a cutting-edge technology to address contemporary issues related to agricultural sustainability. Machine learning (ML) is the engine that powers this evolving technology. The study aims to develop a smart prototype robot to diagnose citrus trees (healthy or infected) using a convolutional neural network (CNN) algorithm. The results of the classification accuracy were 96%. And then, after spraying the affected areas with the pesticide, all farmers in the country can use it to protect themselves from the dangers of pesticides. The results were good and promising.*

Streszczenie.** Inteligentne rolnictwo stało się najnowocześniejszą technologią rozwiązującą współczesne problemy związane ze zrównoważonym rolnictwem. Uczenie maszynowe (ML) to silnik napędzający tę rozwijającą się technologię. Badanie ma na celu opracowanie inteligentnego prototypu robota do diagnozowania drzew cytrusowych (zdrowych lub zainfekowanych) za pomocą algorytmu konwolucyjnej sieci neuronowej (CNN). Wyniki trafności klasyfikacji wyniosły 96%. Następnie, po spryskaniu dotkniętych obszarów pestycydami, wszyscy rolnicy w kraju mogą go użyć do ochrony przed niebezpieczeństwami związanymi z pestycydami. Wyniki były dobre i obiecujące.* (Zrobotyzowany automatyczny opryskiwacz pestycydów oparty na technologii wizyjnej do zainfekowanych liści cytrusowych z wykorzystaniem uczenia maszynowego***)

Keywords: CNN, agri-Robot, citrus dieases, Jetson nano
Słowa kluczowe: robot ogrodowy, opryskiwanie, przetwarzaniue obrazu

Introduction

One of the oldest and most fundamental industries is agriculture [1]. Societies and economic development are dependent on the agricultural sector. Infectious organisms (bacteria, viruses, etc.). 25% of crops fail due to disease, insects, weeds, etc. As a result, we needed to continuously monitor plants to find plant diseases as soon as possible. Finding plant diseases visually or manually is a difficult task [2]. Numerous experts have put out a novel approach to increase yield plant productivity while working on various machine learning methodologies. Each approach has benefits and drawbacks. There are numerous machine-learning techniques used to recognize and classify plant diseases. mostly uses the CNN model for classification [3].

In the field, pesticides can be sprayed using one of two techniques.

- The first way, a person sprays the pesticide at a specific spot while carrying it in the back.
- The second method, a vehicle carries the pesticide. In both situations,

Dangerous compounds present in the pesticide may have negative effects on humans. [4].

Deep learning has received a lot of attention recently and is now one of the primary subjects in the fields of machine learning and artificial intelligence[5]. The system learns from the training dataset and automatically extracts features using deep learning methods. Deep learning can be used to solve a variety of computer vision-related problems, including picture categorization.[6].From household automation to military applications, the subject of robotics has experienced exponential growth. Due to the automated manufacture of agricultural vehicles, which has increased investment and research and is one application of robotics and equipment design in the agricultural sector, continuous monitoring of the sector is now possible[7]. Visible inspection is the traditional method for identifying plant diseases. After recent crop loss, this is possible, but the treatment won't be limited or worthwhile. The farmer must detect the infection before it spreads in order to prevent the tree from suffering catastrophic damage. It was achieved by improvements in vision, computer software, and biotechnology[8].

1.1 Mission objectives

The following succinct statement captures the goals of this thesis:

1. Development of a model for automated agriculture
2. Constructing a convolutional neural network (CNN) for citrus tree diagnosis (healthy and diseased).
3. The pesticide is then sprayed by the robot on the infected tree.

The planned effort uses the gadget to identify plant illnesses and treat them by misting the relevant pesticides, with the goal of making the automated system easily accessible to farmers [9]. These robots are now necessary for precise modern agriculture [10]. Plant protection and other agricultural uses have led to the development of robotic spraying systems.

1.2 Literature Survey

In [11], S. Rao, et al. delivered a study that emphasized the use of remote control and mild automation to facilitate farming activities. The goal of this paper's qualitative approach is to create a system that reduces operational expenses. By using solar energy and a power source to power the robot, it decreases the amount of time needed for tasks like weeding, digging, cutting, and plowing. In [12], Nurul et al. presented a paper focusing on flower and leaf recognition for identifying plants to CNN. Two datasets have been used for the training and testing. According to experimental findings, using only leaf images yields the highest accuracy for identifying plants, at 98%, compared to using only flower images or a combination of both, at 85% and 74%, respectively. In [13], Rincn et al. Exhibited a self-propelled, remote-controlled electric sprayer. Four alternative setups were tested on a tomato crop in a greenhouse to evaluate its efficacy. Specifically, the research demonstrated that a robotic spray application provides better penetration than a traditional manual sprayer for greenhouse, and subsequent research will focus on improving the robot's air assist system and other features to enhance the efficiency and amount of plant protection product reaching the intended target. In [14], Vinay et al. employed the CNN algorithm to find fruit flaws. Citrus images are gathered and separated into two categories: excellent and faulty, in order to identify and categorize the image dataset. The CNN model scored a 67 % accuracy rate on 150 pictures when it was applied without any pre-processing or data augmentation. The recommended model then used 1258 pictures, data pre-processing, and augmentation to boost CNN performance.

The accuracy of the suggested model is 89.1% . In [15], W. Jia, et al presented a research concentrating on a suggested Mask Region Convolutional Neural Network (Mask R-CNN)-based model for harvesting a robot vision detector. To make the model better suited for identifying and separating overlapping apples, it was enhanced. 120 random photos are used to evaluate the technique, and the Precision Rate was 97.31%..In [16], Sanida, Maria V., Theodora S., Argyrios S., and Minas D., et al. The paper proposed an augmented-CNN hybrid model for identifying tomato diseases, combining VGG blocks with an initiation module A high rate of classification accuracy is achieved by the model. Through precise and advanced simulations, the model's efficacy was examined, and the findings were contrasted with those of the most recent models. Nine different categories of tomato illnesses and one health category from PlantVillage make up the dataset utilized in this study. With an accuracy of 99.17%, the test set's findings are encouraging. The suggested approach offered a high-performance remedy for tomato crop diagnostics in the real agricultural setting.. In [17], Asad et al. suggested that the CNN model try to distinguish between fruit and leaf types with healthy fruit and those with prevalent citrus ailments (black spot, canker, scab, greening, and melanose). The PlantVillage datasets were used to compare the CNN model against other deep learning methods. Numerous metrics show that the CNN Model works better than the competition, and the test results show that the test accuracy was 94.55%.. In [18], Y. Yuu, et al. a CNN-LSTM-based vision system that is easily adaptable to different citrus processing plants and can work in conjunction with robotic grippers for real-time sorting. The faulty oranges in the field of vision were identified using a CNN-based detector, and they were momentarily categorized into the appropriate kinds. Based on sequential picture data, an LSTM-based predictor was employed to forecast the location of the oranges in a subsequent frame. The system was able to track damaged ones during rotation and determine their precise kinds thanks to the combination of CNN and LSTM networks. To govern visually guided robotic grasping using predictive control, their future course has to be forecasted as well. Based on the results of the experiments, a high detection accuracy of 94.1% was attained, and the route prediction error was within 4.33 pixels 40 frames later, which met real-time performance. The outcomes demonstrated the suggested system's potential for accurate and effective automated citrus sorting. In [19], R. Moreira, et al. The research In order to enable a mobile smart farm application, the research suggested a system called AgroLens, which showcases a novel architecture and is created with inexpensive, environmentally friendly technology. It functions even in places without internet access. AgroLens' real-time, AI-based disease classification system that uses leaf photos and achieves good classification performance using a smartphone was noted in the functional evaluation. According to their research, AgroLens can link hundreds of sensors in a smart farm without the processing burden of edge computing. The AgroLens architecture provides research with chances and pathways to implement and assess large-scale smart farm systems utilizing affordable technology..

2. Methodology

The system is basically divided into two important sections: The first section shows an overview of the CNN algorithm. The second section explains the types of hardware components used in the proposed robotics system. The field robot has a built-in digital camera. The field robot traverses the field while taking pictures of the leaves. The plants are then categorized as being both healthy and diseased. [20].

2.1 Dataset

(1750) photos of citrus trees are split into our unique dataset as shown in figure 1. Two classes of leaves (healthy and infected) are classified.

Healthy

infected

Fig. 1: Data Set Samples

2.2CNN algorithm

CNN has numerous levels embedded in it:: This layer is the Convolution layers, pooling layers, activation function layers, and fully connected layers are the four different types of layers that make up CNN.[21]

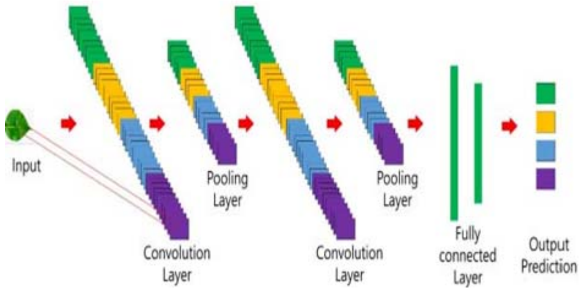

Fig 2: Main Structure of CNN [22]

Table 1. Structure of the Implemented CNN Architecture

Layer	Size
Convolution	32, 3, 3
Pooling	2, 2
Convolution	64, 3, 3,
pooling	2, 2
Convolution	96, 3, 3
pooling	2, 2
Convolution	128, 3, 3
pooling	2, 2
Convolution	256, 3, 3
pooling	2, 2
dense	512
dense	128
dense	1

2.3 proposed system

The CNN algorithm is used in the proposed system to process uploaded or acquired pictures. The CNN method is used to process images, and the processed results are then sent to the Jetson Nano 4G microcontroller in binary form (Jetson Nano specifications).The Agri-Robo is controlled by the microcontroller unit thanks to programming. The spraying mechanism is managed by the microcontroller unit. A tank for holding the pesticides, a sprayer, and a D.C. motor are all included in the spraying system. The robot may be moved in any direction to spray the pesticides in the appropriate spray area. DC motors are managed by the microcontroller using an L293D driver. This is designed to be a physical vehicle or robot that can visually inspect crops or farmland before spraying pesticides uniformly at a specific location. Figure 3 below displays a block schematic of the system's planned components.

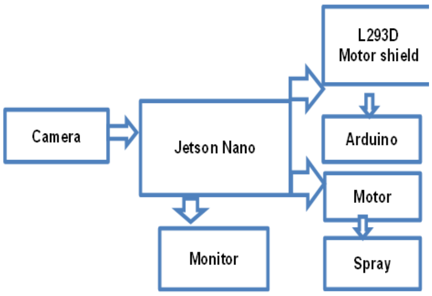

Fig 3 Block Diagram of the Proposed System's

Components

Jetson Nano,The NVIDIA development kit, which includes multiple neural networks for image classification, object identification, ,segmentation, and audio processing, can be run simultaneously on this small but powerful computer [23] (see figure 4 [24]).

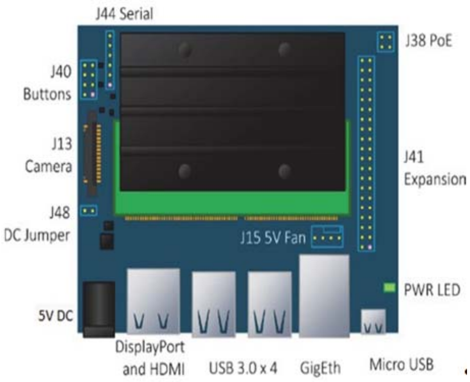

Fig. 4. Jetson Nano Kit

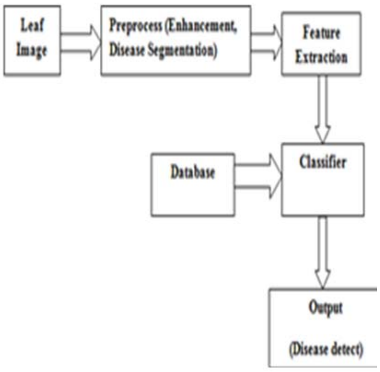

Fig.5 Block Diagram of the Proposed System

A camera is utilized to detect the obstruction, and the system is given the photos it has collected in order to determine the plant illness. as illustrated in Figure 5.
The proposed techniques involve the following steps:

1. *Input Image*

The robot first took the video to feed into the system.

2. *Data Pre-processing*

The noisy data in the image is removed during pre-processing. Data pre-processing includes the following steps: selection, cleaning, normalization, transformation, and feature extraction. The training set is the result.

3.*Feature Extraction*

The process of extracting features is finished. It is a method of dimensionality reduction that works well and turns the interesting components of an image into feature vectors. When a large or incompatible image or picture is needed to quickly finish activities like feature extraction and matching, a reduced feature representation is necessary. The characteristics of an image's segments can also be retrieved using this feature extraction.

3. *Feature selection by optimization*

uses deep learning to run an optimization process to choose the best features. Feature selection methods are widely employed in fields where there are lots of features but few samples or data points.

4. *Analysis of accuracy, recall, and precision*

Precision: A measure of precision is the proportion of accurately anticipated positive observations to all predicted positive observations.
Recall: The percentage of all sample elements that were actually retrieved is known as recall.
Accuracy: Accuracy serves as the evaluation criterion for classification models. It keeps track of how many of our model's predictions were accurate [25].

5. Detection of affected leaf.

7 . Spraying pesticide on affected plants.

Fig. 6 system modules

Table 2 *Jetson Nano* specifications

Specification	*Jetson Nano*
CPU	Quad core ARM A57 1.43 GHz
GPU	128-Core- Nvidia Maxwell
RAM	4GB - DDR4
Connectivity	Ethernet 10/100/1000
Ports	3x USB 2.0, 1x USB 3.0, HDMI, Camera Connector, M.2
Pins	40-Pin GPIO

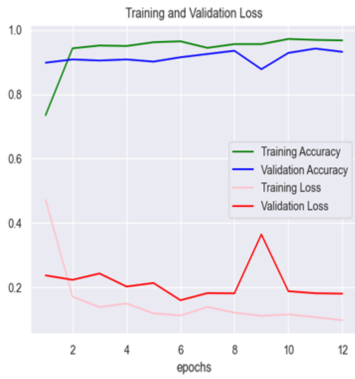

Fig 7. Training and validation Accuracies& Losses

3. Result and discussion

When comparing the human eye to an agricultural robot, t latter obtains complete information about the crop, it can more accurately diagnose plant illnesses. By using this robot to recognize and safeguard plants, it helps to reduce the amount of physical labor required. This research appears to explore a suggested CNN-based method to identify plant disease from leaf images. To verify the launch of the late-made model, various tests were conducted. More than 1750 remarkable images from Mosul's orange orchards were used to create another plant disease image library. According to our suggested system, the robot performs precisely. Accuracy of the training and validation findings was 96% and 93%, respectively. as shown in figure 6. While training and validation losses were 0.0980 and 0.1806, respectively, as shown in figure 7.

4. Conclusion

The accurate and successful categorization and detection of plant diseases is a crucial task for profitable crop farming and a means of preventing agricultural loss. The use of modern agricultural technology for healthy living, plant protection, and sustainable agriculture. It is feasible to apply image processing techniques to detect plant leaf diseases. The numerous techniques for effectively and successfully isolating a plant's sick section and applying a pesticide to a diseased plant were discussed in this study. The offered method is sufficient for identifying leaf diseases..

5.The futurework

For effective pesticide application in large areas, many robots can be connected together. By increasing the tank's capacity, the robot's capacity to carry pesticide may be expanded. Through IOT on any mobile device, a person may manually operate a robot.

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