# Development of Agricultural Robot Platform with Virtual Laboratory Capabilities

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***Abstract*—Agricultural robots are called to help in many tasks in emerging clean and sustainable agriculture. These complex electro-mechanical systems can actually integrate artificial intelligence (AI), the Internet of Things (IoT), sensors, actuators, and advanced control methods to accomplish functions in autonomous or in collaborative ways. Before the deployment of such techniques in the field, it is convenient to carry out laboratory validations. These last could be at the sub-system, e.g., sensors or servos operation, or the whole system level. This paper proposes the development of the hardware and software parts of a platform of agricultural robot. The proposed system, highly motivated by the restrictions imposed by COVID-19 context, enables laboratory tests virtualization while keeping real-time functionalities**

***Index Terms*—Robotics, Virtual laboratory, Real-time systems, Modeling**

## I. Introduction

The main challenge of the agricultural industry is to meet the food demand of a growing population without increasing or while reducing the environmental footprint of its activities. Agriculture needs a transformation to deliver sufficient food and nutrition to humanity. On the one hand, improving production efficiency is necessary to meet this demand increase, which is evaluated to be doubled by 2050. On the other hand, the transformation of this vital industry also needs the modernization of distribution and access; the reduction of greenhouse gas emissions from land use and farming; the mitigation of losses in biodiversity and habitats; the minimization of unsustainable water withdrawals; and the elimination of water pollution from agricultural chemicals. [1].

Different points of view can be employed to analyze the sustainability of farming depending on the stakeholder behind the study; however, in most cases, about 74% of studies, the social, economic and environmental priorities appear as the main points to be considered [2]. To cover these three aspects, the robotics technology comes to fill some gaps, e.g., it can be envisaged to increase safety and improve work conditions, to enhance productivity, and to reduce the use of chemical products. The agricultural robots can support farmers to accomplish different tasks which can be grouped in four main groups: guidance, detection, action and mapping [3]. These important task groups are at the origin of many research works looking for enhanced precision, low complexity, and high energy efficiency [4]. Thus, the new era of agricultural robots covers applications like water and nutrition monitoring and control, diseases and bug monitoring and remedies, soil monitoring and preparation, crop health monitoring and intervention, machinery for nursery production, pesticide and herbicide application, harvesting, and environment monitoring and control for photosynthesis optimization [4], [5].

In the last years, We evidenced a considerable increase in the use of the Internet of Things (IoT) and artificial intelligence (AI) technologies covering smart factories, smart grids and smart farming [5], [6]. This technological revolution comes with more powerful digital processors: microcontrollers, multi-core computers, Field Programmable Gate Arrays (FPGAs) and Graphics Processing Unit (GPU) which enable the deployment of artificial intelligence (AI) methods, edge computing and IoT. AI methods in robotics applications can be employed in many tasks, e.g., to improve the quality of detection, classification or recognition of diseases [7], or to optimize the growing and biomass production process of plants [4]. This promising scenario of smart farming supported by artificial intelligence and robotics not only in controlled environments of greenhouses but also in open-field motivates the research to push beyond the limits of precision and high efficiency agriculture [8], [9].

Hardware in the loop real-time emulation, co-simulation and test beds platforms are necessary to validate hardware parts, e.g., converters and actuators, and control algorithms before their deployment in real field scenarios [10], [11]. These platforms with virtual and physic elements enable the tests of the system under controlled scenarios covering normal and extreme situations permitting the tuning and refining of control algorithms. We propose in this paper the development of hardware and software components of a platform of agricultural robot. The proposed system, highly motivated by the constraints of the COVID-19 context and developed during the pandemic, enables the laboratory tests virtualization while keeping real-time functionalities. The remainder of this paper is organized as follows, section II presents a general description of the proposed system; section III and IV describe respectively the communication & control framework and the modeling of the agricultural robot; sections V and VI provide respectively preliminary results and concluding remarks.

## II. General Description of the Agricultural Robot Platform

### A. Context and Motivation

As mentioned in the introduction, the modernization of the agricultural sector includes intelligent machines and systems looking for smart farming processes. This paper aims to propose an agricultural robot platform to validate in laboratory the base functions of navigation, detection, action, and mapping. The platform must be useful for open-field farming applications and validate AI methods and IoT features in the precision and high-efficiency farming scenario.

### B. Proposed platform

The proposed platform is intended to support the functions described hereafter which can be seen as sub-systems of the whole agricultural robot platform.

***Vision and Image Recognition:*** To be able to perform a precise action on a type of plant, the robot must be able to identify it. In addition, plant identification must be made quickly since the robot moves through the plantations and be reliable since the action depends on the type of plant. We propose, by this sub-system, an artificial intelligence-based image recognition mainly supported by machine learning. More specifically, we employ the open-source DIGITS tool designed by NVIDIA. DIGITS is based on the DetectNet neural network, which is itself based on GoogleNet. This tool permits to perform object detection giving presence confirmation and location in the treated image. The open-source software LabelImg made it possible to identify the images' objects while exporting them in KITTI format. A NVIDIA Jetson AGX Xavier [12], which is equipped with 512-core Volta GPU with Tensor Cores and 8-core ARM v8.2 64-bit CPU, is employed as the main processor unit of the robot platform. It is charged of image recognition process and acts as server for the integration of other components.

***Soil Parameters Measurement:*** This sub-system permits to obtain the information of most important characteristics of soil by using two different types of sensors. The first sensor, JXBS with RS485 interface, provides the information of PH (acidity), NPK (Nitrogen, Phosphorus and Potassium), electric conductivity, temperature, and humidity; the second, SHT10 using I2C interface, provides in a complementary way the information of temperature, and humidity. Table I lists the measured parameters and the characteristics for standard agricultural soils.

***Four-wheel-drive (4WD) Locomotion:*** This sub-system enables the navigation of the agricultural robot with independently controlled direction and velocity of each wheel. Each angle position is controlled by means of ANNIMOS 60kgf-cm servomotors and each velocity by means of 60RPM HD premium planetary gear DC motors with magnetic encoders. For each wheel, Roboclaw 2x30A is employed as power electronics drive for the DC motors (and servos) by means of the PWM generated from a Nucleo-144 (STM32L496ZG-P) which is connected via serial link to the main processor (NVIDIA Jetson AGX Xavier).

***Structure Reconfiguration:*** Complementary to the previous sub-system, this one enables the in-field and automated reconfiguration of the width and height of the robot to adapt to different crops. A set of linear actuators is arranged so that when the ranks in the field dictate, the robot decreases or increases its width. In addition, depending on the height of the plants according to their type and maturity stage, the robot can change its ground clearance.

***Power monitoring:*** Considering the huge importance of energy efficient operation of farming robots with limited energy storage capacity, and the study of the impact of operation modes over the lifetime and health of batteries; this sub-system permits the monitoring in real-time of power and energy use. The sub-system permits the reading and storage of the voltage, current, and temperature profiles of the battery used as embedded source during the process of charging or discharging.

TABLE I
Measured Soil Parameters

| Parameter | Standard Agricultural Soils * |
|---|---|
| PH (Acidity) | $6.0 - 7.4$ |
| Electric Conductivity | $100 - 1400\mu S/cm$ |
| Nitrogen | $13.4 - 40$ ppm |
| Phosphorus | $15 - 100$ ppm |
| Potassium | $41 - 160$ ppm |
| Humidity | $> 70\%$ |
| Temperature | $18.5 - 24°C$ |

*Specific characteristics are defined for each type of crop, e.g., typical NPK for corn fields are 23, 16 and 107ppm. from: http://www.gocorn.net/, http://www.omafra.gov.on.ca

Fig. 1 shows a simplified block diagram of the proposed agricultural robot platform. We can distinguish three (3) main groups of elements or parts, the first which correspond to the mobile and configurable platform itself, the second which is associated to the in-field installed measurement systems, in our case the measurement of humidity and temperature at specific locations in the field, and the third which correspond to the remote programming, testing and virtual laboratory. It is important to highlight that the first part can work as an autonomous system as it is intended to go outside the laboratory. The second part can be used independently as an IoT measurement system, e.g., the data can be sent to a cloud platform like ThingSpeak of Mathworks (https://www.mathworks.com/products/thingspeak.htm). The third part can also be used independently to perform completely virtual tests of controllers targeting the model of the robot or including some parts of the hardware (field measurements or mobile platform).

## III. Communication And Control Framework

### A. Robot Operating System (ROS)

When building a robot system, a complex part is the control and communication of each subsystem. ROS is an open-source and flexible framework that offers a collection of tools to

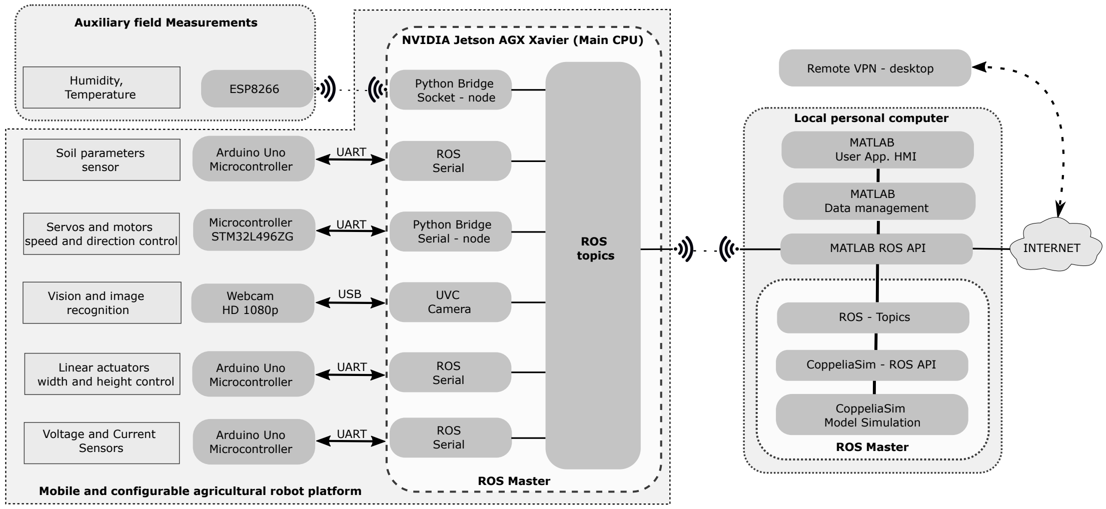


Fig. 1. Simplified diagram of the proposed platform of agricultural robot.

solve this problem; it makes possible the generation of code shared with researchers and developers, allowing the world of robotics to advance rapidly and encourage collaborative development [13]. In addition, being open-source, ROS has a large community that continuously maintains and improves the system. Numerous articles show that this framework is very suitable for mobile robots equipped with cameras and multiple sensors [14], [15]. One of the greatest qualities of ROS is its modularity. As illustrated in Fig. 2, each node in the system represents a subsystem of the robot which communicates in peer to peer. Nodes do not know of the existence of other subsystems, a "Master" program is used to register each node in the network and its address, like a DNS server. This node network configuration allows each subsystem to maintain its independence, so if one part stops functioning, there is no effect on other subsystems. The nodes use "topics" on which they can publish information to be transmitted to all the other nodes which have subscribed to the topic. The information is published on the network and is available to any node that wishes it. This allows scalability and openness of the system. In our case this makes it possible, for example, to give information to both the physical robot and its virtual model which is presented in section IV.

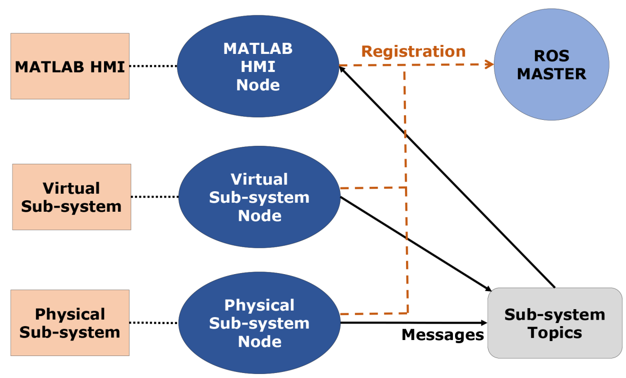


Fig. 2. ROS conceptual diagram.

### *B. Framework Implementation*

ROS is based on a TCP / IP; all nodes must be on the same network and communicate with each other. We opted for a wireless LAN Wi-Fi network because our robot is mobile and some sensors not being on the platform. Thus, we used a Wi-Fi card on a Raspberry as a hot-spot. This way, all the subsystems can connect to a common network, independent of the environment. The IP address of the ROS Master was fixed. Nodes do not need a fixed IP address since they are registered to the ROS network by communicating with the ROS master. Therefore, once the Master is set up, subsystems can be added to the network easily. The framework provides a library that allows serial communication between embedded devices, e.g., microcontrollers, and ROS. Therefore, the library was used to link sub-systems in the platform that can not be connected to the Wi-FI network. For the STM32 which controls the servo motors we do not have libraries, but ROS offers a python API, so we just had to create a very simple python program to make the UART-Node connection. Likewise, we created a socket server using Python for wireless devices to allow them to transmit their information within the ROS network. A script is used to establish the socket connection, to create the node, and to publish the data on the ROS network. As illustrated in Fig. 3, this configuration makes possible to create as many topics as available sensor data, for example for the SHT10 sensor we have the "/ SHT10 / temperature" and "/ SHT10 / humidity" topics. This allows a very clear organization of the information available for the monitoring and control of the robot platform. ROS provides a MATLAB API that we can use to create an HMI interface for the robot monitoring and control. Thus, we have implemented an application on MATLAB that creates a node on the network, retrieves the sensor data by subscribing to ROS Topics, and sends commands to control the robot by publishing

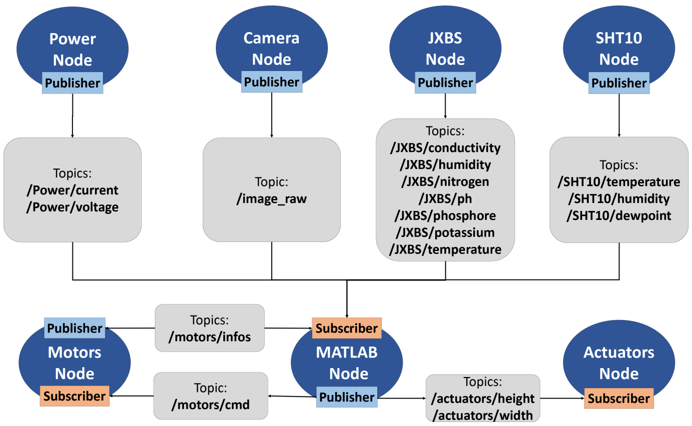


Fig. 3. ROS topics definition for the monitoring and control of the robot platform.

in ROS topic. A view of the HMI is presented in Fig. 4. Furthermore, a node that sends information from a camera located in the laboratory was used to implement visual feedback in the MATLAB HMI. This real-time feedback is particularly useful for the remote operation of the platform in the context of COVID-19 with limited access to laboratory facilities. This interface provides full control of the robot so we can verify that everything is going correctly. However, since ROS is independent, it also means that the robot platform can work even if the interface is not started.

## IV. Agricultural Robot Modeling

This section explains the modeling of the agricultural robot platform, including the reasons of the choice of the software used for this purpose.

### A. Fast Review of Modeling Approaches

In order to model the designed robot, different software solutions have been considered to choose the one that would best fit the needs of the project. Many robotic simulators are indeed available: the following are the six deemed to be the most fitted for this robot. They can all be obtained for free and can easily be integrated to ROS.

*1) MORSE:* the Modular OpenRobots Simulation Engine (MORSE) is a generic simulator for academic robotics. It is modular (new actuators or sensors can be easily added) and provides realistic 3D simulation scenes. However, it does not have a graphical user interface and is only controlled from the command-line, which makes it harder to learn for beginners compared to most robotic simulators.

*2) OpenRAVE:* the Open Robotics Automation Virtual Environment (OpenRAVE) is an environment mainly focused on simulating motion planning algorithms for robotics. It has one of the best calculating capacities of robotic simulators However, the agricultural robot developed in this work is quite out of its specialty. Moreover, these resources are not especially needed to simulate a single robot without the need for extreme precision (such as grasping movements).

*3) Webots:* Webots is one of the most used simulators for agricultural applications. It provides a wide range of sensors, has a user-friendly graphical interface and has open-source APIs, which makes it easier to use a precise programming language with specific libraries.

*4) Gazebo:* Gazebo is probably the simulator with the best integration with ROS. It also has a great flexibility, is able to perform accurate simulation and is able to perform well even with complex scenes, and it has a large community of active contributors.

*5) CoppeliaSim:* the last simulator is CoppeliaSim, previously named Virtual Robot Experimentation Platform (V-REP). It has a user-friendly interface and an excellent integration with ROS. Also, it supports several APIs for different programming languages such as C/C++, Python, Java, MATLAB/Octave. It obtained good reviews from users [16] and offers functionalities like the possibility to edit CAD models inside the software. That is a strong point against Gazebo which does not have this feature [17]. Therefore, this software is suitable for the robotic system implemented in this paper regarding all the advantages mentioned before.

### B. Model Development using CoppeliaSim

The simple interfacing of CoppeliaSim with ROS makes switching between the command of the real robot and the tests on the model easy. As shown in Fig. 5, one can choose between both just by modifying the ROS master called in the MATLAB script that launch the graphical user interface. By choosing the IP address of the NVIDIA Jetson the actual robot will be controlled, and choosing the IP address of the ROS master linked to CoppeliaSim will allow the model the be the one to receive the commands and to send back the simulated results like the values of the soil parameters. As it is not possible, to our knowledge, to directly get soil parameters in CoppeliaSim, these values have been calculated using simple functions based on the position of the robot to allow the testing of control algorithms in the future. These calculations are done inside child scripts linked to the model in CoppeliaSim. These child scripts are used to control the robot: they take care of the ROS messages published on the command topic and control the motors and other actuators consequently, and they publish as well on the other topics the information defined to be sent back to the user via the HMI (Fig. 4). The final model is shown in Fig. 6. It has all the functionalities of the actual robot except the sub-system of power monitoring, and it has been placed into an environment close to reality (on an uneven bumpy floor and with plants to see) so that the tests are as informative as possible.

## V. Preliminary Results

We have performed some laboratory tests and obtained preliminary results from the proposed platform.

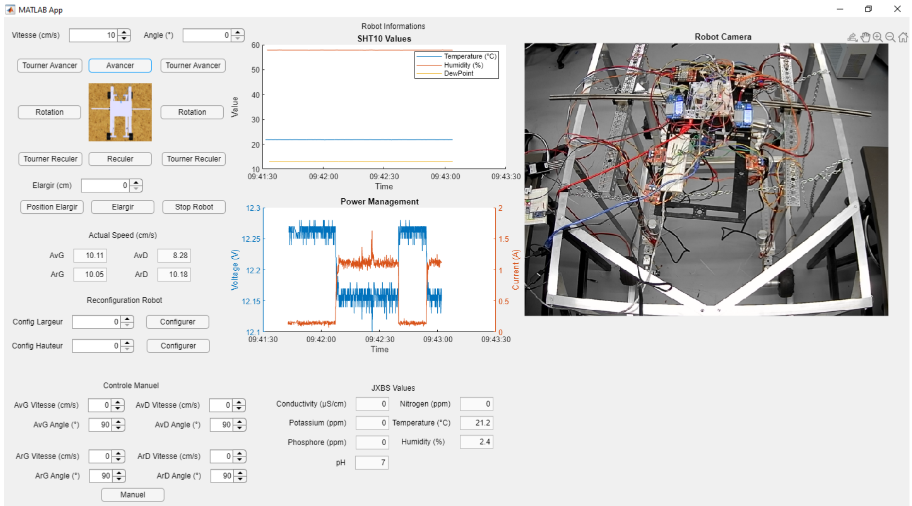


Fig. 4. HMI for the monitoring and control of the robot platform including real-time video feedback.

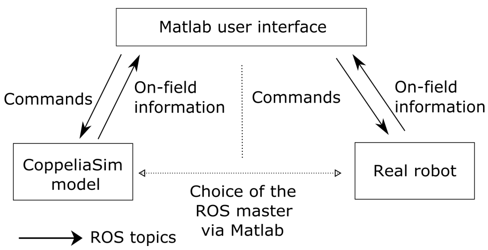


Fig. 5. Position of the model inside the project.

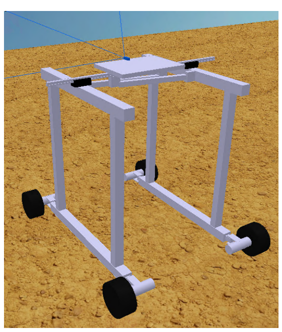

Fig. 6. Model of the agricultural robot platform under CoppeliaSim.

***Vision and Image Recognition:*** We trained the system to detect *Ambrosia artemisiifolia L.*, *Ragweed* or *"Herbe à Poux"* , in French, which is widespread and considered responsibly of agricultural losses particularly in soybean fields in southern Quebec; and that is also known as strong allergen affecting population health in urban areas [18]. Preliminary results using a training database containing 200 positive samples covering different stages of maturity permitted us to identify and locate it with a mean accuracy of 45% while the best accuracy was 75%. Sometimes, the system confused the target plant (*Ragweed*) with small ferns (e.g., *Botrychium virginianum*) also present in Quebec. However, the latter is more abundant in wetlands and in forests and less often in agricultural fields. An illustrative example of the detection of *Ragweed* at mature stage is presented in Fig. 7.

Fig. 7. Example of inference for detection of *Ambrosia artemisiifolia L.* also known as *Herbe à Poux* in Quebec.

***Measurement of soil parameters:*** Fig. 8 presents a sample of results for the measurement of PH and the concentration of Nitrogen (N) Phosphorus (P), and Potassium (K) for standard soil without specific fertilizing treatment. We can notice that, except for the PH, the measurements are zero before the sensor is plugged in the soil, and the readings are stabilized after approximately three minutes.

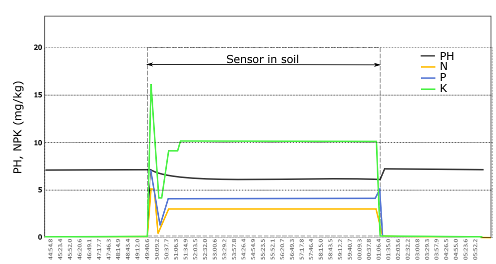


Fig. 8. Example of measurement of soil parameters using JXBS sensor.

***Robot Operation Power Measurement:*** We performed some laboratory tests to corroborate the operation of each component of the platform. Also, the power consumption of the platform is measured as shown in Fig. 9.

***Four-wheel-drive (4WD) Speed Measurement:*** Fig. 10. shows the speed measurements of the 4 wheels of the mobile platform. These measurements can be used to implement a strategy that can optimize the power consumption of the robot by controlling the speed of each wheel.

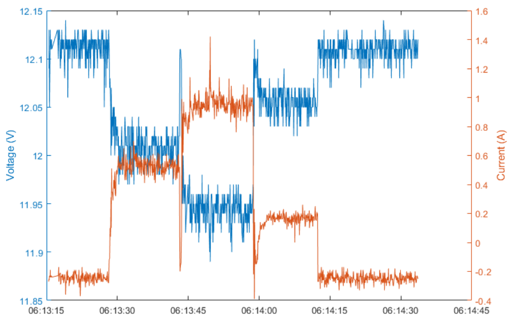


Fig. 9. Example of power consumption measurement of the platform

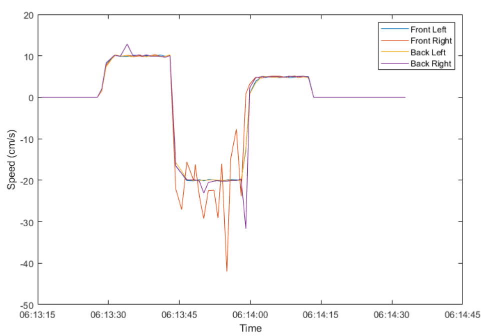


Fig. 10. Speed of the platform wheels

These results confirmed us the correct operation of each sub-system and the advantages of using the modular implementation supported on ROS.

## VI. Conclusion and Future Work

This paper proposes the development of an agricultural robot platform; the proposed system is intended for research and educational purposes and enables real-time monitoring and the tests of control algorithms and artificial intelligence methods. The system includes the hardware prototype and its twin model developed using CoppeliaSim, which enables the virtualization of some laboratory tests before the field tests in agricultural farms. We employ ROS as the communication and control framework, MATLAB and Python for high-level programming, which brings us an open, scalable and modular test bench for robotics and control.

Current and future works include implementing positioning and navigation sub-systems and using the developed platform to evaluate energy-efficient operation strategies for the robot in agricultural fields. We also work on the improvement of the *Ragweed* detection accuracy by retraining the system using a larger dataset and expanding it to recognize other species.

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