Design and Implementation of a Smart Agricultural Robot bullDOG (SARDOG)

Hovannes Kulhandjian, Yue Yang, Nicholas Amely

Department of Electrical and Computer Engineering, California State University, Fresno, Fresno, CA 93740, U.S.A.
E-mail: {hkulhandjian, yueyang625, namely}@mail.fresnostate.edu

***Abstract*—Over the past few decades, agricultural systems have encountered significant global challenges, including shortage of food supply, declining water availability, rising input costs, and diminishing agricultural labor. The advancement of Agricultural Technology (AgTech) in recent years has increased farm productivity and replaced manual monotonous tasks that are unsafe or inefficient for farm labor workers to do by hand. In this paper, we propose to develop and implement a smart agricultural robot named SARDOG that is based on the Farm-ng Amiga robot framework. SARDOG makes use of advanced artificial intelligence (AI), LiDAR, Internet-of-Things (IoT) sensors, and a robotic arm all of which work hand in hand to perform multiple intelligent farming tasks autonomously and effectively. SARDOG is capable of autonomous GPS-less navigation using LiDAR, picking fruits using the robotic arm, testing the soil properties using a robotic actuator sensor framework, it can follow the farmers in the field and carry the produce for them among many other applications. The purpose of SARDOG is to make multiple major farming processes more efficient, cost-effective, and humane, as well as to perform some new farming processes that are not widely explored.**

***Index Terms*—Precision Agriculture, Farm Robotics, LiDAR SLAM Navigation, Computer Vision, Deep Learning.**

I. Introduction

The world's population is expected to reach 9.7 billion by 2050, putting a strain on the global food supply. Efficient farming practices can help to increase crop yields and reduce food waste, which will be essential to meet the needs of a growing population. In recent years, there has been a rise in the use of robotics in the agricultural industry, particularly through the adoption of precision agriculture. Naik *et al.* [1] showcased a prototype of an agriculture robot that focuses solely on seed sowing.

Zhang *et al.* [2] used multi-sensor information with the RTAB-Map algorithm, by combining data from a red-green-blue depth sensor (RGB-D) camera and a single-line lidar, a gyroscope, odometers, and other sensors to achieve a task completion rate of 100%, surpassing the lidar-only scheme (45%) and the RGB-D camera-only approach (75%). Ramachandran and Sahin [3] explored the issue of navigation and mapping using RTAB-Map, utilizing the RGB and depth sensor for capturing accurate and real-time data. Wang *et al.* [4] presented a LiDAR location and navigation system based on multisensor fusion in urban road environments, utilizing a low-cost VLP-16 LiDAR as the primary sensor as well as with an inertial measurement unit (IMU) to eliminate motion distortion. Warku *et al.* [5] created a three-dimensional map of both indoor and outdoor environments using Velodyne VLP-16 to form a three-dimensional point cloud, and Xsens MTI-G-700 inertial measurement unit (IMU) to perform point cloud deskew, employing the Lidar Inertia Odometry via Smoothing and Mapping (LIO-SAM) algorithm. Mihai *et al.* [6] presented a machine learning-based approach for detecting pedestrians using Velodyne VLP-16, utilizing linear interpolation between layers, effectively creating 15 pseudo-layers to overcome the low resolution of the LiDAR. Velas *et al.* [7] estimated odometry by employing convolutional neural networks on Velodyne VLP-16 with IMU support, which can serve as a substitute for wheel encoders in odometry estimation or as a supplement when GPS data is unavailable, such as in indoor mapping scenarios.

MobileNet v2 is a popular and widely used lightweight Convolutional Neural Network (CNN) architecture that is often employed for people detection. Katiyar *et al.* [8] demonstrated that MobileNet-SSD surpasses traditional deep learning techniques in terms of detecting surface defects with greater frequency, accuracy, and precision, which is also resource-efficient as it requires minimal memory setup and utilizes the lower processing power of the CPU.

Zhang *et al.* [9] integrated MobileNet V2 with SSD to ensure both real-time performance and high recognition accuracy, which holds great importance in facilitating real-time detection and recognition capabilities on the Nao robot.

Song *et al.* [10] utilized multi-sensor technology to gather obstacle-related data, which is subsequently analyzed and identified, creating a robot obstacle avoidance method based on the analyzed obstacle information, enhancing the accuracy of obstacle avoidance and optimizing the robot's route.

Cen [11] introduced a method that utilizes laser technology for tracking and following individuals, while also ensuring avoidance of obstacles, incorporating a unique aspect of evaluating potential risks associated with a robot following a person in an unfamiliar setting.

You Look Only Once (YOLO) V5 algorithm is a powerful tool for weed detection and elimination due to its speed, accuracy, object localization capabilities, adaptability, and integration potential with automation systems. Zhang *et al.* [12] reviewed various techniques for detecting weeds and the use of weeder robots in precision weed management, divided into machine learning (ML) and deep learning (DL).

Unlike all the related works, our all-in-one solution SARDOG is a smart agricultural robot that can improve farming practices by automating repetitive tasks and enhancing crop productivity through individualized treatment of each plant

979-8-3503-7099-7/24/$31.00 ©2024 IEEE

with 7 features: Autonomous Navigation, People Following with Obstacle Avoidance, Weed Detection and Elimination, Smart Harvesting, Soil Data Acquisition, Crop Tailored Care, and Energy Harvesting. SLAM (Simultaneous Localization and Mapping) Navigation offers the advantage of comprehensive mapping and accurate self-localization within the map. While the Autonomous Navigation of a robot can raise concerns about collision hazards with humans in the field, we are using a combination of people detection and distance detection to avoid collisions. The combination of Computer Vision and Deep Learning methods has significantly contributed to SARDOG's precise weed detection and spraying system. For crop harvesting, a 6-axis robotic arm equipped with a Raspberry Pi and Computer Vision scripts for color and edge detection, and a servo-controlled adaptive gripper are utilized to pick the fruits. For IoT implementation, small solar-powered devices with microcontrollers and soil sensors can upload and store the data of soil for farm owners. The Automated Crop Care System with ArUco Marker Detection is designed to facilitate efficient and tailored care for different types of crops in an orchard. SARDOG can self-charge while in use which will save not only time but also money for the farmer. Furthermore, certain produce items, such as strawberries, would experience advantages during transportation on the SARDOG if conveyed within a shaded vehicle, shielded from direct sunlight – a provision offered by the Solar Canopy.

II. Proposed Design Methodology

A. SLAM Navigation using LiDAR

The Velodyne Puck LITE module, equipped with 16 channels, is employed for SARDOG. These channels spin to cover a full 360° around the module, producing individual point cloud maps. SARDOG utilizes the robot operating system (ROS) Noetic with an installed RTAB-Map wrapper, facilitating SLAM Navigation. This navigation technique allows SARDOG to create a detailed map of an entire crop field using a LiDAR sensor. To execute the steering commands from the RTAB-Map setup, SARDOG employs a ROS bridge to convert them into CANBUS protocols for motor control. The movement states are monitored and modified using Twist commands. Depthai-ROS package is used to retrieve the IMU parameters for Mapping.

B. People Following with Obstacle Avoidance

In order to enhance its autonomous navigation capabilities, SARDOG utilizes a deep learning model MobileNetV2 SSD as its people detection algorithm. MobileNetV2 is a lightweight Convolutional Neural Network architecture designed for efficient computation on mobile and embedded devices. Single Shot MultiBox Detector (SSD) is an object detection framework that combines object localization and classification into a single neural network. The people detection algorithm will identify people by passing each camera frame received from the same Oak camera port on SARDOG to the MobileNetV2 SSD model.

A Kivy application based on the NVIDIA Jetson Xavier NX assists as a visualization tool to detect people with bounding boxes, what message it will send to the CAN bus, and status indicators to show whether SARDOG is in autonomous mode or not.

Fig. 1: Mobile Joystick Application.

Employing detection outcomes, a collision avoidance algorithm initiates the transmission of relevant messages to the CAN bus, effectively regulating SARDOG's motion. The X-axis location of the bounding box center plays a pivotal role in establishing the position of detected individuals within the frame. Moreover, the ratio of a bounding box's height to that of the camera frame is harnessed to gauge the distance between SARDOG and individuals. When a farmer emerges out of a specific range in the camera's field of view, the NVIDIA Jetson Xavier NX, functioning as the controller, will transmit a message via its CAN bus to direct the SARDOG to advance toward the farmer's location.

In the event of a farmer making an abrupt change in direction, SARDOG will respond by promptly adapting its trajectory. This adjustment entails real-time modifications to its speed and angular rate, determined by the positioning of the detected bounding box within the camera frame. As SARDOG draws near to the farmer within a specified proximity, its controller initiates a message transmission via the CAN bus to halt its movement.

To augment the versatility and user-friendliness of our project, we incorporated the Virtual Network Connection (VNC) Viewer. This integration facilitates the operation of Kivy applications across diverse devices, including mobile phones. Figure 1 illustrates remotely directing SARDOG's movement using a phone. This implementation offers a smooth and user-intuitive experience, allowing farmers to issue advanced commands or intervene if any issues arise.

C. Precision Weed Elimination

Precision Weed Elimination was implemented on a Raspberry Pi with a 4K USB camera for wireless real-time weed detection and classification. A custom YOLOv5m object detection and classification AI model was created to be able to detect and classify two types of weeds (Poaceae and Brassicaceae). The dataset used to train the model was taken from the Weed-AI database: the roboweedmap dataset by Teimouri *et al.* [13]. Several sample images from the trained model are depicted in Fig. 2.

The model underwent training over the course of 40 epochs, and the most successful run outcomes were employed as custom weights for the weed detection program on the Raspberry Pi. Subsequent to training, the model was transferred to the Raspberry Pi, which was paired with the 4K USB Camera. Access was established wirelessly through SSH and VNC protocols. Subsequently, a Python script is executed to engage the camera, enabling real-time detection and classification of weeds. This process triggers the activation of the sprayer for the purpose of weed elimination.

Figure 3 shows a 5-gallon Capacity, 1 GPM, 12 Volt prayer in action after it detects e.g., a weed.

D. Smart Harvesting

A Hue Saturation Value (HSV) color mask script is employed to detect crop color and shape in real-time RGB video feeds, drawing bounding boxes around them. The center point of the bounding box tracks the crop's position in the output frame, enabling movement of the robotic arm's axes for precise gripping of the produce.

In Fig. 4, the operational robotic arm is depicted in the process of identifying an orange, determining its ripeness, and subsequently utilizing the attached camera to track its location. Employing both the gripper and a specialized 3D-printed attachment designed for orange harvesting, the robotic arm adeptly approaches the identified orange, picks it, and deposits it into a basket.

The Adaptive Gripper was not suitable for picking different types of fruits, accordingly, we have modeled and 3D printed an add-on attachment to the gripper to make it compatible with gripping e.g., oranges.

In Fig. 5, the captured image frame, displayed on the left, is transmitted to the algorithm for analysis. The algorithm's task involves detecting the presence of an orange and assessing its ripeness. A bounding box, as depicted on the right, encloses the center of the orange. The algorithm subsequently tracks the orange's location and guides the robotic arm toward it. Upon achieving sufficient proximity, the robotic arm adeptly retrieves the orange and deposits it into a designated basket.

The placement of the robotic arm on the SARDOG can be varied to fulfill various tasks, including weed detection and removal. While this study focuses on one application – harvesting fruits like oranges – the versatility of the system allows for the adaptation of the robotic arm to harvest different types of fruits. By designing supplementary attachments through 3D printing, the robotic arm can be customized for diverse harvesting needs.

E. Soil Data Acquisition

Compact and readily reproducible devices, comprising an ESP8266 microcontroller, a 5W mini solar panel, and various soil data sensors, are employed to consistently gather diverse soil condition data.

Numerous such IoT devices are strategically positioned across the field, harnessing solar power to ensure uninterrupted operation without the need for battery replacement. As SARDOG traverses the field, the ESP8266 modules establish

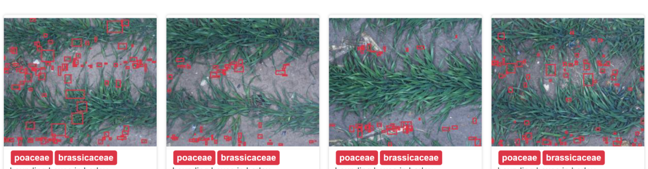

Fig. 2: Trained Models for Weed Detection.

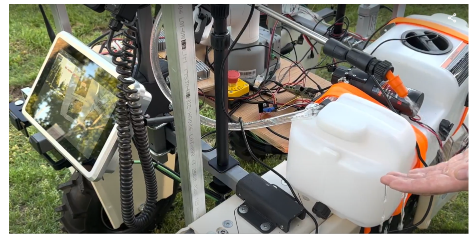

Fig. 3: Spot Sprayer (Ironton ATV).

connections with the onboard mobile hotspot WiFi, enabling them to transmit captured data to an HTML web page. This webpage can be accessed by NVIDIA Xavier, facilitating data storage in a designated directory, ultimately intended for analysis by farm proprietors. This process facilitates year-round data collection, enabling seasonal comparisons – for instance, assessing yield variations across different years.

The RS485 5Pin Soil PH NPK (nitrogen, phosphorus, and potassium), Temperature, and Humidity EC Sensor is a robust soil sensing instrument, adept at measuring seven parameters with precision and steadfastness. Illustrated in Fig. 6 is an IoT Device integrating an EC sensor, humidity sensor, and NPK sensor to facilitate the acquisition of soil data.

F. Crop Tailored Care

SARDOG optimizes spraying efficiency using ArUco markers for crop recognition and targeted spraying. A dedicated Kivy app detects these markers as SARDOG moves through the orchard. Its cameras capture plant images recognized by proprietary ArUco markers. The Computer Vision module identifies these markers, creating specifications for tailored actions, such as water volume, pesticide, herbicide dosage, and fungicide distribution.

SARDOG incorporates a linear actuator, as depicted in Fig. 8, that can be submerged into the soil as required to capture diverse soil parameters, encompassing soil salinity, pH, NPK levels, temperature, and humidity. This data acquisition process facilitates the analysis and correlation of potential irregularities between soil measurements and atypical plant growth. In instances where discrepancies arise, SARDOG promptly notifies the farmer, enabling swift corrective action

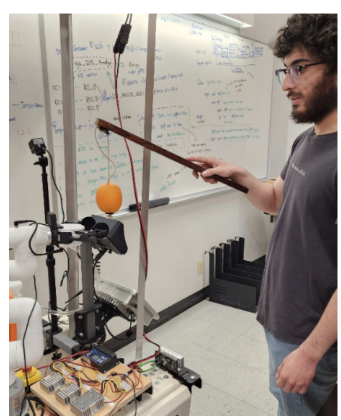

Fig. 4: Fruit Picking with the Robotic Arm.

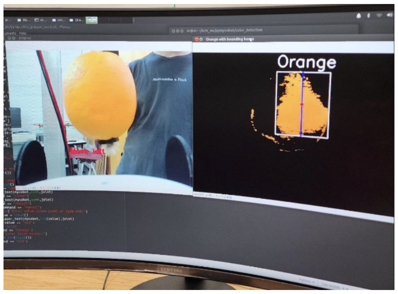

Fig. 5: Orange Detection and Following.

to address soil-related issues that might be affecting the orchard's nutrient balance.

G. Energy Harvesting

The SARDOG has a self-sustained power generation mechanism utilizing a 265W SunPower Solar Panel, as depicted in Fig. 11. For power distribution, we've established a power bus system, outlined in Figs. 9 and 10. This system employs a sequential configuration: solar power is initially directed through a 48V to 24V DC-DC buck converter (Converter 1), subsequently passing through a 24V to 48V DC-DC boost converter (Converter 2) to ensure voltage stability before charging the Amiga battery pack. The output of Converter 2 is further directed to a 24V to 12V DC-DC buck converter (Converter 3), generating a 12V output for powering the LiDAR, Sprayer Pump, and Linear Actuator. Moreover, the 12V output undergoes transformation through a 12V to 5V DC-DC buck converter to supply power to devices such as the Raspberry Pi and various other USB-dependent applications.

Considerable engineering effort was dedicated to the conception of the solar panel farm and the corresponding canopy, devised to accommodate a sizable solar panel measuring 31.4 inches by 61.4 inches and weighing 33.1 pounds. Our design needed to strike a balance between being lightweight and resilient enough to bear the panel's weight while enduring the abrupt movements of the SARDOG. To meet these criteria, we opted for aluminum L-shaped rails measuring 1.5 inches in breadth and 1/8-inch in thickness, providing robust support for the panel's load. Throughout the design process, careful consideration was given to ensure that the frames remained unobtrusive to the robotic arm, spray pump, and LiDAR.

With Vmax 40V, Imax 5.88A, Pmax 238W, SunPower 72 cell Solar Panel charges the SARDOG's battery pack in 2.5 hours during sunny days and 3 hours when in use.

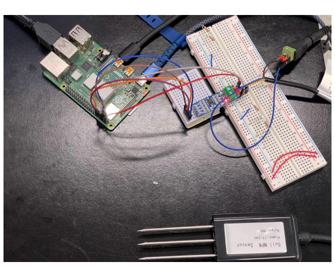

Fig. 6: Raspberry Pi to MAX485 to Soil Sensor.

Fig. 7: ArUco Markers Detection Application.

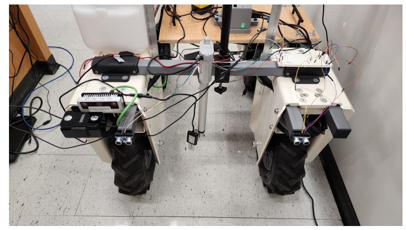

Fig. 8: Linear Actuator for Soil Data Aggregation.

III. Results and Discussion

The YOLO v5 model for Weed Elimination demonstrated commendable performance metrics, showcasing elevated precision, recall, and F1 score values. With an mAP@0.5 of 0.818 for all classes, the model adeptly maintains a harmonious equilibrium between precision and recall. Figure 12 corroborates the model's ability to accurately identify objects with a marked degree of certainty, detect a substantial quantity of objects, and achieve exceptional levels of both precision and recall.

A precision-confidence curve depicted in Fig. 12 (left) for all classes with a precision of 1 at 0.957 confidence means that the model is able to identify all of the positive instances when it is 95.7% confident in its prediction. This is a very good score, indicating that the model is able to identify true positives with a very high degree of confidence.

The F1 confidence-curve for all classes is 0.79 at 0.384 as shown in Fig. 12 (right), which means that the classifier is 79% accurate at identifying positive instances when it is 38.4% confident in its prediction. F1 is a measure of the harmonic mean of precision and recall. It is a more comprehensive metric than precision and recall because it considers both the number of true positives and the number of false positives.

IV. Conclusion

We've fully integrated cutting-edge tech into the Smart Agricultural Robot. Key achievements include autonomous GPS-less navigation using LiDAR and SLAM, People Following via Mobilenet SSD Deep Learning, and Collision Avoidance. All Computer Vision and machine learning operate seamlessly within ROS Noetic bridge architecture, presented through a user-friendly Kivy app. For precise herbicide spraying, real-time object detection is enabled by YOLO v5. Crop harvesting combines Computer Vision scripts, color,

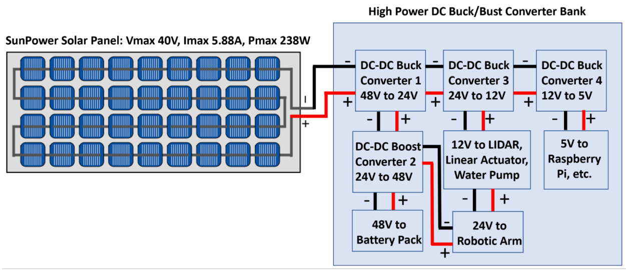

Fig. 9: Energy Harvesting System.

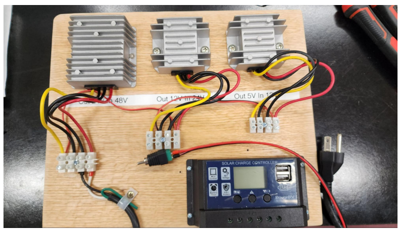

Fig. 10: Power Bank Bus Converters.

and edge detection with a robotic arm. The SARDOG framework includes diverse soil sensing and mounting mechanisms crafted via CAD and 3D printing, aided by IoT devices for soil insights, and optimizing crop nourishment. ArUco markers personalize crop care, while soil data correlation informs growth issues. Emphasis on energy conservation incorporates solar panels, ensuring SARDOG fully charges in just 2.5 hours. For a visual demonstration of our SARDOG in operation, a video showcase is available via this link [14].

V. Acknowledgment

The work was partially supported by the Economic Development Administration (EDA) Project Grant 077907908, Fresno-Merced Future of Food Innovation (F3) Coalition. Special thanks to the Lyles College of Engineering at California State University, Fresno for their support and to all the students who contributed to the SARDOG project. including Vidith Balasa, Jonathan Vazquez, Lawrence Rede, Luis Villanueva, Lauren Main, John Estrada and Tori Estrada.

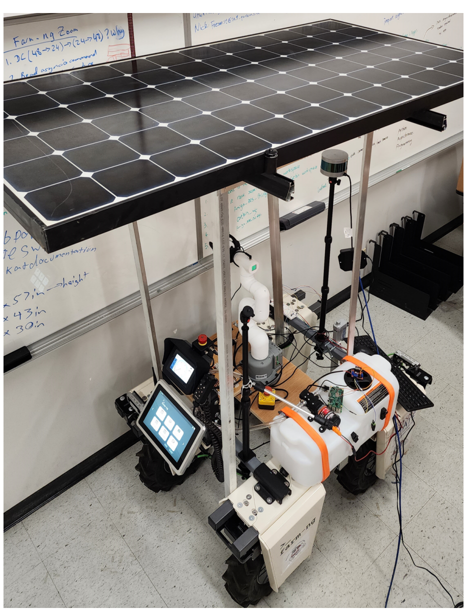

Fig. 11: SunPower Mounted on SARDOG.

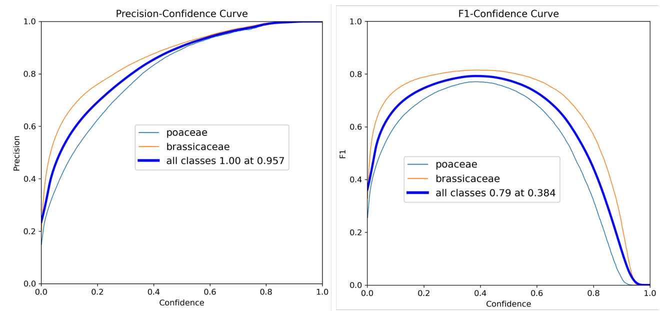

Fig. 12: Precision Confidence and F1 Confidence Curves.

References

[1] N. S. Naik, V. V. Shete, and S. R. Danve, "Precision agriculture robot for seeding function," in *2016 International Conference on Inventive Computation Technologies (ICICT)*, vol. 2, 2016, pp. 1–3.

[2] G. Zhang, Z. Zhisheng, X. Zhijie, D. Min, P. Meng, and J. Cen, "Implementation and research on indoor mobile robot mapping and navigation based on rtab-map," in *International Conference on Mechatronics and Machine Vision in Practice (M2VIP)*, 2022, pp. 1–6.

[3] S. Ramachandran and F. Sahin, "Smart Walker V: Implementation of RTAB-Map Algorithm," in *2019 14th Annual Conference System of Systems Engineering (SoSE)*, 2019, pp. 340–345.

[4] K. Wang, N. Jiasheng, and L. Yanqiang, "A Robust LiDAR State Estimation and Map Building Approach for Urban Road," in *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 2021, pp. 502–506.

[5] H. T. Warku, N. Y. Ko, H. G. Yeom, and W. Choi, "Three-Dimensional Mapping of Indoor and Outdoor Environment Using LIO-SAM," in *2021 21st International Conference on Control, Automation and Systems (ICCAS)*, 2021, pp. 1455–1458.

[6] S. Mihai, P. Shah, G. Mapp, H. Nguyen, and R. Trestian, "Towards autonomous driving: A machine learning-based pedestrian detection system using 16-layer lidar," in *2020 13th International Conference on Communications (COMM)*, 2020, pp. 271–276.

[7] M. Velas, M. Spanel, M. Hradis, and A. Herout, "CNN for IMU assisted odometry estimation using velodyne LiDAR," in *IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, 2018, pp. 71–77.

[8] A. Katiyar, S. Behal, and J. Singh, "Automated defect detection in physical components using machine learning," in *2021 8th International Conference on Computing for Sustainable Global Development (INDIACom)*, 2021, pp. 527–532.

[9] F. Zhang, Q. Li, Y. Ren, H. Xu, Y. Song, and S. Liu, "An Expression Recognition Method on Robots Based on Mobilenet V2-SSD," in *Inter. Conference on Systems and Informatics (ICSAI)*, 2019, pp. 118–122.

[10] X. Song, "Research and design of robot obstacle avoidance strategy based on multi-sensor and fuzzy control," in *2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA)*, 2022, pp. 930–933.

[11] M. Cen, Y. Huang, X. Zhong, X. Peng, and C. Zou, "Real-time obstacle avoidance and person following based on adaptive window approach," in *2019 IEEE International Conference on Mechatronics and Automation (ICMA)*, 2019, pp. 64–69.

[12] W. Zhang, Z. Miao, N. Li, C. He, and T. Sun, "Review of Current Robotic Approaches for Precision Weed Management," *Current Robotics Reports*, vol. 3, no. 3, pp. 139–151, Sep. 2022.

[13] N. Teimouri, R. N. Jørgensen, and O. Green, "Novel assessment of region-based cnns for detecting monocot/dicot weeds in dense field environments," *Agronomy*, vol. 12, no. 5, 2022. [Online]. Available: https://www.mdpi.com/2073-4395/12/5/1167

[14] H. Kulhandjian, "SARDOG Demo Fresno State," *YouTube*, May 2023. [Online]. Available: https://www.youtube.com/watch?v=xH7gShrxuqI