CottonHusker: Deep learning enabled robot for real-time automated cotton picking

Kunjan Theodore Joseph, Ankita Kalra, Krishna Muvva, Amlan Balabantaray, Shaswati Behera, CheeTown Liew, Santosh Pitla

***Abstract*—In the global cotton industry, the United States stands as the third largest country producing approximately 20 million cotton balls annually worth $7 billion [1]. However, the labor-intensive and monotonous nature of cotton harvesting, along with the need for post-work sanitation, necessitates the automation of these 3D (Dirty, Dull, and Dangerous) tasks [2]. This paper presents the efforts of CottonHusker robot where we address the challenge of automating selective cotton harvesting. The outcomes demonstrate promising results, showcasing the viability of the proposed approach. The robot's ability to autonomously detect and harvest cotton in controlled laboratory conditions, while navigating around obstacles, marks a significant step towards addressing the challenges posed by 3D tasks in the cotton industry. As we continue to refine and enhance the system's robustness, this research offers a compelling contribution to the realm of agricultural automation.**

***Index Terms*—Robotics, Cotton Harvesting, Computer Vision, Deep Learning, Robot Navigation, Automation, Robot Operating System (ROS)**

I. Introduction & Background

The agricultural industry, particularly the cotton sector, faces challenges in automating labor-intensive tasks such as harvesting due to the inherent complexity of detecting and picking cotton balls. In response, we present the CottonHusker agricultural robot, developed to address these challenges by integrating cutting-edge technologies. Automated selective cotton-picking plays a crucial role in shaping the sustainable future of agriculture in several significant ways like improved labor efficiency and workforce attraction resolving concerns related to labor shortages, especially during peak harvesting seasons and making the work more appealing. It promotes reduction in chemical usage, as traditional cotton harvesting methods often involve the application of chemicals to aid in defoliation, making the cotton easier to pick, reducing the need for such chemicals, leading to a decrease in environmental pollution and potential harm to farm workers. It reduces labor costs augmenting economic stability which further encourage farmers to adopt more sustainable practices in other aspects of their operations. Manual cotton harvesting can be disruptive to the local environment, leading to soil compaction and habitat destruction [6]. Automation minimizes such disturbances, helping to preserve soil health and support biodiversity in and around farmlands. By utilizing advanced technologies like computer vision and robotics, automated cotton-picking can operate more efficiently than traditional methods. This energy efficiency translates to reduced fuel consumption and associated greenhouse gas emissions. Automation can provide more consistent and reliable harvesting, reducing the vulnerability of cotton crops to weather fluctuations and extreme conditions associated with climate change [5]. Automated cotton-picking contributes to the sustainability of agriculture by improving labor conditions, conserving resources, reducing chemical usage, preserving ecosystems, enhancing economic viability, and fostering technological innovation. These benefits collectively pave the way for a more resilient, efficient, and environmentally conscious future for cotton farming and agriculture as a whole. The following sections entail our approach, methodologies, and results in creating deep learning enabled robot for the autonomous harvesting of cotton.

Authors are with Machine Automation and Agricultural Robotics (MAARS) Laboratory, Department of Biological Systems Engineering, University of Nebraska-Lincoln, NE 68583, USA {theo.joseph, akalra2, krishna, abalabantaray2, sbehera3}@huskers.unl.edu, {cliew2, spitla2}@unl.edu

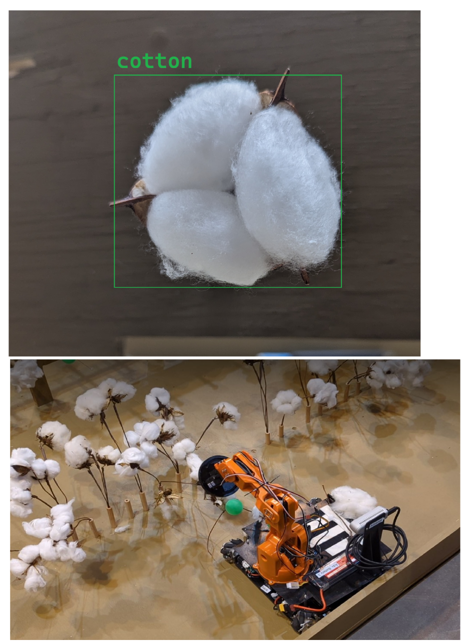

Fig. 1. Detection of cotton in test dataset; the robot in action at the cotton arena.

II. Method & System

The goal of this robot was to autonomously navigate through an arena and collect ripe cotton and deliver it to known location. The hardware components of our Cottonhusker robot are listed as follows-

1) **Intel Depth Camera (Sensor):** The Intel RealSense d435 Depth Camera employs advanced depth perception technology to accurately detect and locate cotton balls amidst surrounding vegetation, facilitating precise harvesting.
2) **ToF Distance Sensor (Sensor):** Utilizing laser technology, the time of flight (ToF) Distance Sensor assesses distances to potential obstacles, allowing the robot to navigate safely by adjusting its trajectory to avoid collisions.
3) **Omnidirectional mecanum Wheels (Actuator):** Omnidirectional Wheels grant the robot versatile maneuverability, enabling seamless movement in any direction across diverse terrains.
4) **Robotic Arm (Actuator):** The Robot Arm, with multiple degrees of freedom, extends and positions itself with precision to reach and collect cotton balls from plants.
5) **Gripper (Actuator):** The custom designed Gripper delicately yet securely collects cotton balls, minimizing damage and ensuring effective harvesting.
6) **Chassis (Chassis):** Providing structural support, the chassis safeguards the system's integrity by housing all integrated components and acting as a storage base for the cotton.
7) **Intel NCS 2(DL Accelerator):**The Intel Neural Compute Stick 2 accelerates deep learning processes, rapidly identifying cotton balls through real-time analysis of visual data. This allows for an inference rate of 10 fps.
8) **Minix Mini PC (Computer Board):** Serving as the central processing unit, the Minix Mini PC (8GB RAM, Intel Pentium processor) orchestrates data flow, communication, and decision-making among software modules.

The software architecture is pivotal in orchestrating the robot's autonomous actions. Cottonhusker robot has harnessed the power of the Robot Operating System (ROS) due to its modular and robust nature. The software system is divided into three primary interconnected modules:

1) **Vision Node:** At the core of the cotton detection process is the Vision Node. Equipped with a Convolutional Neural Network (CNN), this node runs detection inferences at a frequency of 10Hz. We implemented a Single-Shot MultiBox detector (SSD) model for detection of ripe (white) cotton balls and image to world coordinate conversion for guiding actuation [4]. The deep learning model was optimized using OpenVINO toolkit for running accelerated inference. SSD is renowned for its real-time object detection capabilities and is adept at handling various object sizes within an image. Its primary purpose is to identify and locate ripe cotton balls within the robot's field of view. Once a cotton ball is detected, the Vision Node transfers the precise coordinates to the Robot Arm Node and signals the Navigation Node to halt the robot temporarily.
2) **Navigation Node:** Responsible for the robot's movement and path planning, the Navigation Node ensures smooth and obstacle-free navigation. In cases where the robot detects cotton, it pauses its movement to allow the Robot Arm Node to collect the cotton ball and reacts to feedback from the depth perception as well. This feature ensures that the robot effectively reaches the detected cotton without any hindrance.
3) **Arm Node:** Upon receiving the cotton boll's coordinates from the Vision Node, the Arm Node takes action. If a cotton ball is detected in the environment, the robot's arm moves to the specified coordinates by using inverse kinematics to convert to joint angles. This allows the robot to pick up the cotton with precision and deliver it to the storage compartment. Subsequently, it communicates with the Navigation Node, informing it whether the cotton is within reachable distance or not, as well as confirming the completion of the cotton-picking action.

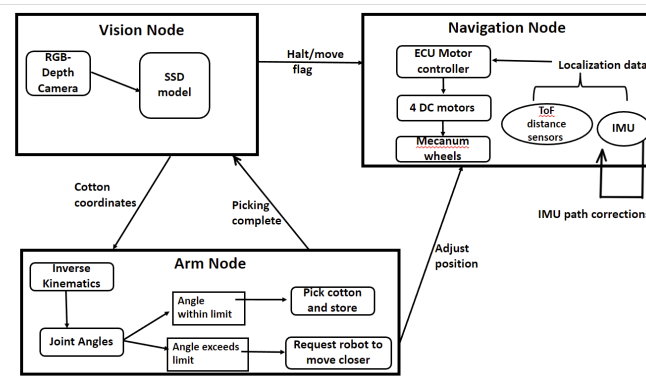

Fig. 2. A flowchart of component architecture and communication.

The overall software architecture ensures seamless cooperation between the modules, leading to an efficient and automated cotton-picking process.

III. Results

By utilizing the SSD model, the vision system can accurately and swiftly detect cotton balls under varying natural lighting conditions [3]. The SSD model performance on test data showed mean average precision (mAP) of 88.7%. SSD's inherent ability to capture objects at different scales, coupled with its low inference latency, enables the robot to promptly identify and locate cotton bolls. With the hardware acceleration, the model performed at an inference rate of 10 frames per second (fps). This contributes to the system's robustness and efficiency in navigating the agricultural field and picking cotton. The robot's performance was tested at the 2023 American Society of Agricultural and Biological Engineers (ASABE) Annual Meeting. The cotton field was set up during the ASABE Robotics Student Design Competition where robots competed in a timed trial. CottonHusker robot picked 23 grams of cotton, out of which 2.4 grams of foreign material was collected (approx. 90% efficiency) and won 3rd prize in the advanced division. It had won 1st prize in the same competition the previous year in 2022.

IV. Conclusion and Future Scope

In future, automated cotton-picking systems can be designed further to be more precise and targeted in their operations. This precision reduces waste by picking only mature cotton balls and leaving unripe ones behind. This conserves resources such as water, fertilizers, and pesticides that would have been used to nurture unripe bolls.

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