Hardware Implementation of Deep Learning based Plant Recognition for Robotic Harvesting

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Abstract. Harvesting delicate and valuable fruits, vegetables and herbs requires a large amount of manual labor, which is less and less popular nowadays due to relatively low salaries and many health problems faced by the workforce. Traditional robotic harvesting methods, on the other hand, often struggle with the complexities of different plant structures, which results in a huge difference in the quality of harvested products, as well as in the price of hand-harvested products compared to machine-harvested ones. To address these challenges, an advanced robotic system implies a solution that integrates deep learning-based plant recognition, an adequate embedded system, and a specially designed end-effector. Deep learning, particularly Convolutional Neural Networks (CNNs), has proven effective in image processing tasks, making it suitable for accurate plant identification. The design of the end-effector is very important part and incorporates soft robotics and adaptive grippers to handle delicate produce gently, reducing damage and mimicking human touch. Finally, selecting the right hardware platform is crucial for balancing low power consumption, high accuracy, and reliability. The NVIDIA Jetson series, offers powerful GPU capabilities to accelerate deep learning inference, with each model providing different levels of performance and energy efficiency. By integrating advanced technologies, this research aims to contribute to the evolution of agrorobotics, offering a more adaptive and efficient harvesting approach, ultimately improving agricultural processes and sustainability.

Keywords: Robotic Harvesting, Plant Recognition, Embedded Systems, End-Effector, Neural Networks, Agrorobotics.

1 Introduction

Efficient harvesting faces significant challenges due to the decrease in popularity of manual labor. Low wages and health problems among the workforce have reduced the availability of skilled human labor for harvesting tasks, creating an urgent need for innovative solutions. Machine learning, and neural network algorithms in particular, have garnered considerable attention for their remarkable accuracy in various domains such as image processing, natural language processing, and data analytics. These successes have inspired their application to more complex tasks, including efficient plant harvesting, making them a novel and promising avenue for research.

The integration of deep learning-based plant recognition with an appropriate embedded system forms the basis of this approach. By leveraging the high accuracy of neural networks for plant identification and the efficiency of modern embedded systems, robotic systems capable of handling delicate and valuable crops with precision can be developed. This not only addresses the labor shortage but also enhances the quality and sustainability of agricultural practices.

This paper will explore the selection of suitable hardware platforms, specifically focusing on the efficient implementation of deep learning algorithms on NVIDIA Jetson series. By advancing these technologies, the goal is to improve agricultural processes and promote sustainability.

2 State of the Art

Robotic harvesting has emerged as a critical area of research aimed at addressing the growing labor shortages and enhancing efficiency in agriculture. Traditional robotic systems, which often rely on rule-based approaches for plant recognition and harvesting, face significant challenges due to the inherent variability in plant structures and environmental conditions. These limitations necessitate the development of more sophisticated methods that can adapt to diverse agricultural settings [1].

Deep learning, a subset of machine learning, has revolutionized various fields by providing high accuracy in complex tasks such as image and speech recognition. In agriculture, deep learning, particularly Convolutional Neural Networks (CNNs), has been applied successfully to tasks like disease detection, crop classification, and plant counting [2]. CNNs are known for their ability to automatically learn hierarchical features from raw pixel data, making them particularly effective for image recognition tasks. CNNs can achieve high accuracy in recognizing and classifying different plant species and their growth stages.

One of the key advancements in the application of deep learning for plant recognition is transfer learning. This technique involves using pre-trained models on large datasets and fine-tuning them for specific agricultural tasks. Transfer learning reduces the need for extensive labeled datasets, which can be challenging to obtain in agriculture, and has been shown to significantly improve the performance of plant recognition models [3-5].

Object detection models like YOLO (You Only Look Once) have been adapted for real-time plant detection [6]. These models not only recognize plants but also determine their locations, which is crucial for robotic harvesting. Their ability to process images quickly and accurately makes them suitable for real-time applications in dynamic agricultural environments [7]. In addition to object detection, segmentation networks such as U-Net have been employed to precisely delineate plant boundaries. This capability is essential for identifying the exact parts of the plant to be harvested, thus improving the precision and efficiency of robotic harvesting systems. U-Net and similar architectures have proven effective in various agricultural applications, providing detailed and accurate segmentation of plant images [8].

The design of the end-effector, which interacts directly with the plants, is another crucial aspect of robotic harvesting systems. Recent advancements have focused on soft robotics, incorporating soft materials to handle delicate fruits and vegetables without causing damage. These designs often use pneumatic actuators and flexible materials to mimic the gentle touch of human hands, significantly reducing the risk of bruising or damaging the produce [9]. Additionally, adaptive grippers that can adjust their shape and force based on the plant's properties have been developed, enhancing the versatility and efficiency of the harvesting process [10, 11].

Integrating deep learning models with robotic systems involves several challenges, including real-time processing, robustness to environmental variations, and energy efficiency. Algorithm optimization techniques are essential for reducing the computational load and power consumption of deep learning models and improving farm productivity [12]. Sensor fusion, which combines data from multiple sensors such as cameras, LIDAR, and tactile sensors, further enhances the accuracy and reliability of plant recognition and harvesting decisions [13]. Extensive field testing in real-world agricultural environments is necessary to fine-tune these systems and ensure their robustness and reliability.

Choosing the appropriate hardware platform for deploying deep learning models is crucial, especially in resource-constrained environments such as agricultural fields. Embedded systems must have a balanced performance, energy consumption and cost to ensure optimal efficiency and effectiveness in real-world applications. The NVIDIA Jetson series has emerged as a prominent choice for edge AI applications, owing to its robust GPU capabilities that accelerate deep learning inference tasks [14]. These embedded systems offer a compelling solution for deploying sophisticated neural network models directly at the edge, without relying on cloud-based processing. This is particularly advantageous in agricultural settings, where reliable internet connectivity may be limited, and real-time decision-making is essential.

The main question behind this research is how to improve the efficiency of harvesting delicate plants. Conventional methods lack the precision and adaptability necessary to handle different plant structures, leading to variations in product quality and prices [15]. Various researchers are introducing robotics and machine learning for harvesting, but there are still significant gaps. In particular, current solutions often lack scalability, real-time processing capabilities, comprehensive technology integration, economic viability analysis, end-effector design considerations, etc. In addition to this, in addressing the inefficiencies of current methods, the biggest problem is the inability of embedded system support to meet the demands of complex algorithms for harvesting methods. Various optimization methods are also proposed, including refining predictions through post-processing steps, increasing memory efficiency in embedded systems, and offloading resource-intensive layers to the CPU for improved processing and reduced latency [16]. Together with these and many other strategies, the ultimate goal is to contribute to a more adaptable and efficient solution for agricultural harvesting.

3 Methodology

This study represents an advancement in the fields of robotics and machine learning, building upon previous research endeavors. It specifically targets the development of smart solutions based on neural networks, with a primary focus on prioritizing energy efficiency, compact form-factor, and affordability. This emphasis arises from the recognition of the crucial balance required between accuracy, speed, and power consumption in such systems.

The research delves into the intricate architectural parameters of NVIDIA Jetson and related embedded systems. These parameters are essential as they significantly influence the intelligence and efficiency of agricultural harvesting operations. By examining these features, the study aims to optimize the design and implementation of neural network-based solutions for agricultural tasks [17]. It is based on the use of deep learning algorithms in combination with appropriate embedded systems. This strategic combination is key in improving plant recognition capabilities, thereby increasing the overall efficiency and adaptability of the harvesting process. Through iterative refinement and optimization of these algorithms within the constraints of selected embedded systems, the research seeks to achieve significant improvements in the performance and reliability of agricultural robotic systems.

Table 1. Comparison of relevant parameters of featured embedded systems.

Name	System on Chip	Processor	Clock Speed (GHz)	GPU	RAM (GB)	Storage	Power (watts)
NVIDIA Jetson Nano4GB	NVIDIA Tegra X1	ARM Cortex-A57	1.43	NVIDIA Maxwell	4	16GB eMMC	5-10W
NVIDIA Jetson Xavier NX 16GB Module	NVIDIA Xavier NX	6-core NVIDIA Carmel ARM®v8.2 64-bit	1.9	384-core NVIDIA Volta with 48 Tensor Cores	16	16GB eMMC 5.1	10W, 15W, 20W
ASUS Tinker Board 2S (4GB)	Rockchip RK3399	ARM Cortex-A72, ARM Cortex-A53	2	ARM Mali-T860 MP4	4	16GB eMMC	3-5W
Google Coral Dev Board	NXP i.MX 8M	ARM Cortex-A53, ARM Cortex-M4F	1.5	Vivante GC7000 Lite	1	8GB eMMC	5-10W

Raspberry Pi 4B	Broadcom BCM2711	ARM Cortex-A72	1.5	Broadcom VideoCore VI	8	microSD	2.5W and 7.6W
UDOO BOLT V8	AMD Ryzen Embedded V1605B	AMD Ryzen Embedded	2	AMD Radeon Vega 8 Graphics	32	/	10-25W
ROCK Pi 4 Model B	Rockchip RK3399	ARM Cortex-A72, ARM Cortex-A53	1.8	ARM Mali-T860 MP4	4	eMMC, microSD, M.2 SSD	5-10W
Mochabin-5G 4GB	Marvell ARMADA 7040	ARM Cortex-A72	1.4	/	4	16GB eMMC	5-10W
Banana Pi M64	Allwinner A64	ARM Cortex-A53	1.2	ARM Mali-400 MP2	2	8GB eMMC	5-10W
Orange Pi R1 Plus	Rockchip RK3328	ARM Cortex-A53	1.5	ARM Mali-450 MP2	1	microSD	2-5W
Khadas VIM3 Pro	Amlogic A311D	ARM Cortex-A73 (A53)	2.2	ARM Mali-G52 MP4	4	32GB eMMC	5-10W

Finally, principles from mechatronics and robotics guide the design of a specialized end-effectors with compliant mechanisms, sensors, and actuators, optimizing the delicate crop manipulation.

The NVIDIA Jetson family emerges as a standout choice, recognized for its high-performance capabilities as an embedded system (Table 1.). Leveraging the computational power and efficiency of Jetson devices ensures optimal real-time processing capabilities during harvesting operations. This strategic positioning of the Jetson embedded systems within the research framework underscores its pivotal role in facilitating the implementation of advanced neural network-based solutions for agricultural applications.

4 Discussion

To achieve accurate and adaptive plant harvesting, it is necessary to create an advanced algorithm that integrates deep learning-based plant recognition with the computational capabilities of the chosen embedded system. The algorithm is designed to precisely identify the location of the plant and determine the optimal approach for harvesting, ensuring minimal product damage and maximum efficiency. This involves the use of

CNN architectures, which are particularly suited to image recognition tasks due to their ability to learn spatial hierarchies of features from input images. CNN training involves collecting a diverse dataset of plant images, including different growth stages and environmental conditions, followed by pre-processing steps such as normalization and upscaling to improve model robustness. Transfer learning is then used, where a pre-trained model on a large dataset is fine-tuned on an agricultural dataset, using existing learned features and adapting them to the specific task of plant recognition. To ensure that the model runs efficiently on embedded systems, optimization techniques such as model truncation and quantization are applied to reduce model size and improve inference speed without significantly compromising accuracy. Depth-separable convolutions and other layer optimizations further improve computational efficiency, making CNNs more suitable for real-time applications.

Embedded systems, such as those from the NVIDIA Jetson series, offer a combination of high-performance computing, energy efficiency, and dedicated GPU resources, which are necessary to accelerate deep learning tasks. The NVIDIA Jetson series, including models such as Jetson Xavier NX and Jetson Nano, stands out as an excellent platform due to its superior features compared to other embedded systems. The GPU architecture of Jetson devices enables parallel processing of neural network computations, significantly speeding up inference times compared to traditional CPU-based systems. This acceleration is critical for achieving real-time responsiveness in tasks such as plant recognition and autonomous navigation for robotic harvesting equipment. In addition to their computing power, Jetson devices are designed with energy efficiency in mind, making them suitable for battery-powered or solar-powered agricultural robots (Fig. 1.). The ability to perform complex deep learning tasks with minimal energy consumption is essential to extend operational autonomy and reduce overall energy costs in agricultural operations.

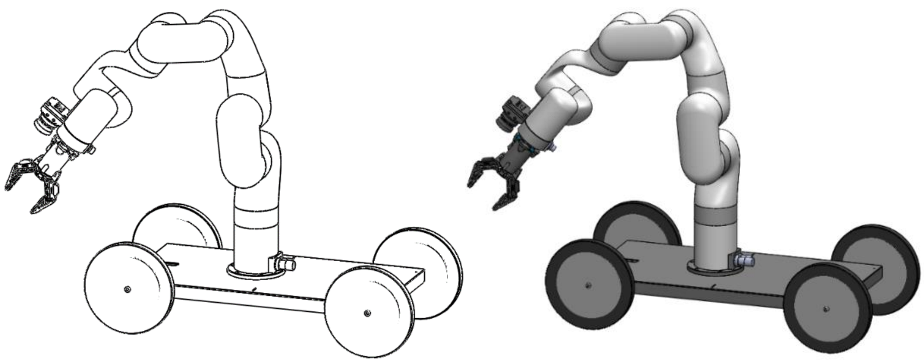

Fig. 1. Schematic illustration of the mobile robotic harvester.

The Jetson Xavier NX series stands out as one of the most powerful in the Jetson family. With a 384-core Volta GPU microarchitecture with 48 Tensor Cores, this architecture is built to perform neural network operations efficiently, making it ideal for real-time deep learning applications. Furthermore, Xavier offers flexible power modes of 10W, 15W, and 20W, allowing users to tailor the system’s performance to the specific requirements of the harvesting operation.

On the other hand, if the focus is shifted to minimizing board size, energy consumption and costs, Jetson Nano is an excellent alternative for the proposed solution, offering a compact form with low consumption and very good performance. Although it has an NVIDIA Maxwell GPU for hardware acceleration, the Jetson Nano works efficiently in two power modes of 5W or 10W. Even though this model doesn’t include specialized deep learning accelerators, it remains a cost-effective solution suitable for not too demanding applications.

Depending on market demands and combining the computing power of NVIDIA's embedded systems with a specialized algorithm, improved agricultural robotics can be achieved, providing an efficient and sustainable solution for delicate plant harvesting.

5 CONCLUSION

The integration of advanced technologies, such as deep learning and embedded systems, is crutial in development of efficient and adaptive robotic harvester. The NVIDIA Jetson series, particularly Jetson Xavier NX and Jetson Nano, provide a range of options tailored to different performance and cost requirements. The Jetson Xavier NX, with its high computing speed and flexible power modes, is ideal for complex real-time deep learning tasks, while the Jetson Nano offers a smaller, more compact and energy-efficient solution for less demanding applications.

Using these platforms, agricultural robotics can achieve significant improvements in the quality and efficiency of harvesting operations. These improvements not only advance harvest accuracy and reliability reducing the incidence of damaged produce, but also address labor shortages and lower operating costs.

Moreover, the increased efficiency and adaptability of robotic systems contribute to more sustainable agricultural practices by optimizing resource use and minimizing waste. As these technologies continue to evolve, their application in agrorobotics promises to drive further innovation and improvements in agricultural practices, ultimately promoting greater productivity and environmental protection.

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