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Engaging Community College Students in Artificial Intelligence Research through an NSF-Funded Summer Research Internship Program

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Engaging Community College Students in Artificial Intelligence Research through an NSF-Funded Summer Research Internship Program

Abstract

Supported by the National Science Foundation's Improving Undergraduate STEM Education: Hispanic-Serving Institutions (IUSE-HSI) Program, a collaborative summer research internship initiative united a public four-year institution with two local community colleges to offer community college students significant engineering research opportunities and hands-on experiences. In the summer of 2023, ten students from the community college in computer science and engineering participated in an eight-week research internship project in four research labs at a four-year university. One of the internship projects aimed to develop and implement real-time computer vision on an energy-efficient cortex-m microprocessor. This project explores a unique approach to engaging community college students in the realm of artificial intelligence (AI) research. By focusing on the development and implementation of real-time computer vision on energy-efficient Cortex-M microprocessors, we offer a practical and educational avenue for students to delve into the burgeoning field of AI. Through a combination of theoretical understanding and practical application, students are empowered to explore AI concepts, gain proficiency in low-power computing, and contribute to real-world AI projects. Furthermore, the project offered student interns a valuable opportunity to refine their research capabilities, particularly in the realms of scientific writing and presentation, while simultaneously boosting their self-assurance and enthusiasm for pursuing STEM careers in the field of AI.

Introduction

Community colleges play a crucial role in advancing STEM (Science, Technology, Engineering, and Mathematics) education by providing accessible pathways for students from diverse backgrounds to enter and excel in these fields [1]. These institutions offer affordable tuition, flexible scheduling, and a supportive learning environment, making STEM education more attainable for many individuals who may not have access to traditional four-year universities. Additionally, community colleges often collaborate with local industries to develop specialized programs tailored to the needs of the regional workforce, ensuring that students graduate with relevant skills and knowledge. By offering foundational STEM courses, associate degrees, and transfer opportunities to four-year institutions, community colleges serve as vital pipelines for cultivating the next generation of STEM professionals and fostering innovation and economic growth within communities.

Introducing Artificial Intelligence (AI) to community college students is essential to prepare them for the rapidly evolving landscape of the modern workforce. As AI becomes increasingly integrated into various industries, including healthcare, finance, manufacturing, and technology, possessing a foundational understanding of AI concepts and applications is becoming a crucial skill set for professionals in virtually every field [2]. By introducing AI to Community college students, institutions can empower them with the knowledge and skills needed to thrive in the digital age. This exposure not only broadens students' career opportunities but also cultivates critical thinking, problem-solving, and innovation abilities that are essential for success in the 21st-century economy. Moreover, familiarizing students with AI technologies early on fosters a deeper understanding of ethical considerations, biases, and societal impacts, enabling them to become responsible and informed users and contributors to the development of AI solutions. Ultimately, integrating AI education into Community college curricula equips students with the competencies necessary to adapt and excel in a world where AI is increasingly shaping our daily lives and professional landscapes.

To bridge this gap and build capacity for student success, San Francisco State University (SFSU) has partnered with two local Hispanic-Serving Institution (HSI) community colleges, Skyline College and Cañada College. This collaboration involves developing and implementing several strategies through the Strengthening Student Motivation and Resilience through Research and Advising (S-SMART) project, which is funded by the National Science Foundation's HSI Improving Undergraduate STEM Education (IUSE) program. One of the strategies developed is the S-SMART Summer Internship Program, which offers community college students who have limited previous research experience meaningful opportunities to engage in engineering research with close mentorship from faculty and peer mentors, as well as gain hands-on teamwork experience. Research has shown that close mentorship and teamwork can enhance academic performance, increase retention and persistence to graduation, improve confidence and self-efficacy, and enhance career preparation, particularly among URM students [3]–[6]. The eight-week summer internship program aims to have ten to twelve community college students from diverse backgrounds in group research projects across several engineering disciplines within research labs at SFSU School of Engineering.

In 2022, the S-SMART Summer Research Internship Program was piloted with a cohort of ten students participating in four research projects across three engineering disciplines - civil engineering, computer engineering, and mechanical engineering. Detailed information about recruitment and selection of program participants, program Activities, and participation research labs can be found in our first-year ASEE paper [7].

In 2023, faculty advisors from the S-SMART program selected 10 students to engage in research across four research labs: the Transportation Engineering Laboratory, Controls for Assistive and Rehabilitation Robotics Laboratory, Intelligent Computing and Embedded Systems Laboratory, and the Mobile and Intelligent Computing Laboratory (MIC Lab). <u>This paper presents a segment of the second-year development, specifically highlighting the integration of cutting-edge AI research opportunities tailored for community college students at MIC Lab.</u>

S-SMART Summer Research Internship Project: Development and Implementation of Real-Time Computer Vision on Energy-Efficient Cortex-M Microprocessor

Background and Objectives

In recent years, the proliferation of computer vision applications across various domains has been remarkable, revolutionizing industries such as autonomous vehicles [8], surveillance systems [9], medical imaging [10], and augmented reality [11]. However, the deployment of real-time computer vision systems on resource-constrained devices remains a significant challenge, particularly in terms of power consumption and computational efficiency.

This project aims to address this challenge by focusing on the development and implementation of real-time computer vision algorithms on energy-efficient Cortex-M microprocessors. Cortex-M processors, renowned for their low power consumption and small form factor, present a promising platform for deploying vision-based applications in battery-operated or embedded systems.

The primary objectives of this project include:

1. Algorithm Selection and Optimization: Identifying and optimizing computer vision algorithms suitable for real-time execution on Cortex-M microprocessors [12]. This involves exploring techniques such as algorithmic pruning, quantization, and algorithm-hardware co-design to achieve a balance between computational complexity and accuracy.

2. System Integration and Hardware Acceleration: Developing software frameworks and hardware accelerators tailored to the Cortex-M architecture to streamline the execution of computer vision tasks. This involves leveraging features such as SIMD (Single Instruction, Multiple Data) instructions, DSP (Digital Signal Processing) extensions, and custom hardware modules to offload computationally intensive operations from the CPU.

3. Power Efficiency Optimization: Investigating power-efficient design methodologies at both the algorithmic and hardware levels to minimize energy consumption without compromising performance. This includes dynamic voltage and frequency scaling, task scheduling, and power gating techniques to exploit energy-saving opportunities during idle periods or low computational load.

4. Real-Time Performance Evaluation: Conducting comprehensive performance evaluations to assess the real-time capabilities of the developed system under various operating

conditions. This involves benchmarking against standard datasets and real-world scenarios to validate the system's responsiveness, accuracy, and energy efficiency.

5. Application Demonstration and Deployment: Demonstrating the practical utility of the developed real-time computer vision system through application prototypes in diverse domains such as smart surveillance, industrial automation, and IoT (Internet of Things) devices. This includes deploying the system on Cortex-M-based hardware platform and evaluating its performance in real-world environments.

Overall Design and Challenges

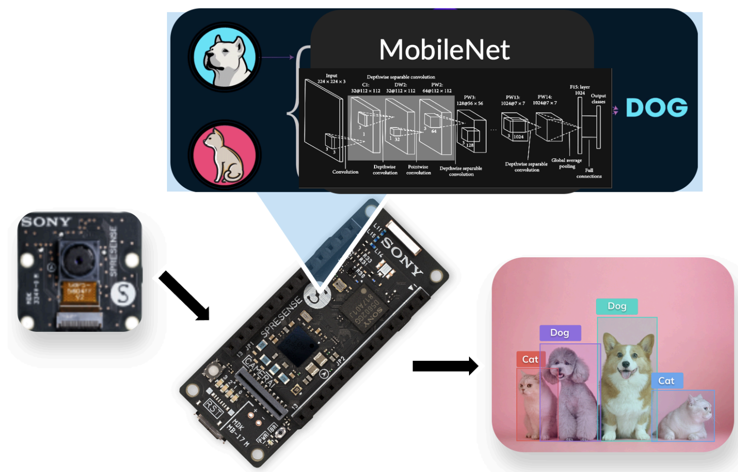


Figure 1. Real-Time Computer Vision on Energy-Efficient Cortex-M Microprocessor.

As shown in Fig. 1, in pursuit of our overarching goal to integrate AI models into microcontrollers, the primary objective for this summer is to focus on implementing image classification using deep learning on the Sony Spresense microcontroller. Specifically, real-time traffic light detection was developed on the microcontroller. We have selected the Sony Spresense [13] for our project due to our collaboration with SONY's Sensing Solutions University Collaboration Program [14] and the board's impressive features. Its multi-core architecture, advanced power management, and low power consumption are specifically designed for machine learning (ML) and other cutting-edge applications. The main board, depicted on the left, is supplemented with additional extensions in its kit. Embedded systems on the Sony Spresense include integrated GPS, audio output, microphone input, and camera interface, offering a wide array of possibilities for deploying various ML applications on the platform. This versatility makes Sony Spresense an excellent choice for prototyping and testing ML applications. Furthermore, utilizing Spresense enables edge computing, leading to reduced latency, real-time decision-making, and enhancing security and privacy by eliminating the necessity for cloud-based processing.

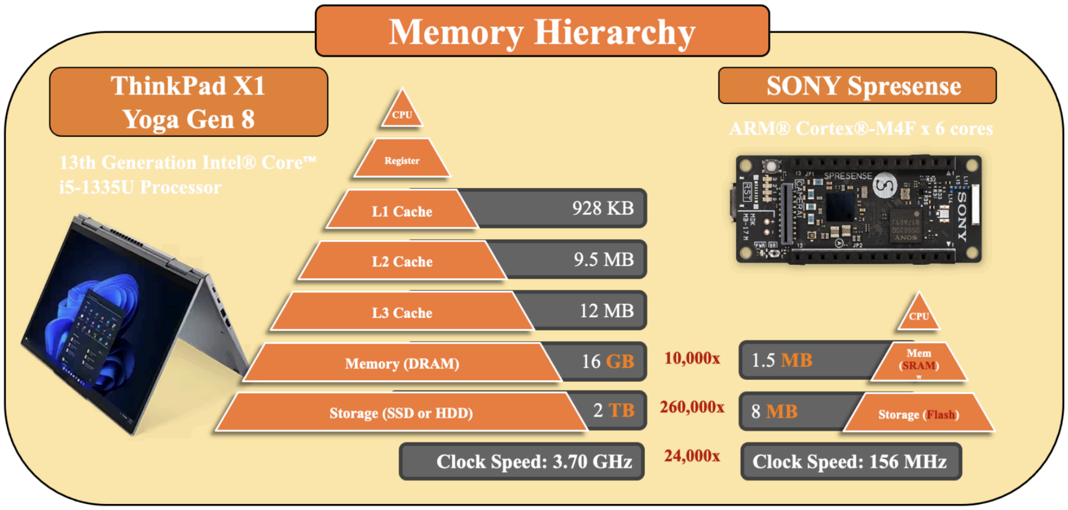


Figure 2. Design Challenges: Limited On-Device Hardware Resources.

As depicted in Figure 2, the memory hierarchy of the Sony Spresense microcontroller is relatively restricted, posing significant challenges in deploying AI models on microcontrollers. Sony Spresense primarily consisting of 1.5 MB SRAM and 8 MB FLASH. While the microcontroller is responsible for processing data and instructions in a computer system, it cannot directly access long-term storage where data is stored. Instead, it must first retrieve the data from storage and transfer it to the memory hierarchy for processing. This underscores the importance of the memory hierarchy in a computer system, ensuring that frequently accessed data resides in the fastest memory layers for quick and efficient access by the CPU. Compared to a typical laptop like a ThinkPad, the memory hierarchy of the Spresense is simpler, comprising mainly flash memory and SRAM. SRAM is volatile, meaning data is retained only when powered, while flash memory is non-volatile, preserving data even when power is off. Given that SRAM may be occupied with other operations, its effective size is typically smaller than the nominal 1.5 MB. The CPU cannot directly access flash memory, hence SRAM is utilized to hold memory for each operation. Although Spresense's memory capacity is significantly smaller than standard laptops, it remains powerful in its own right, optimized for low-power applications. To illustrate the scale of operation, a comparison between Spresense and a typical ThinkPad Yoga [15] reveals substantial differences: Spresense's memory is approximately 10,000 times smaller than a 16 GB storage capacity, 260,000 times smaller than a 2 TB storage, and its clock speed is around 24,000 times slower than a typical ThinkPad Yoga's 3.70 GHz clock speed. Despite these differences, Spresense's optimization for low-power applications ensures it delivers robust performance within its intended domain.

Method:

Data Collection: Data collection forms the foundational step in deep learning development, where extensive datasets comprising images of traffic lights in various conditions are amassed.

These datasets encompass diverse scenarios such as different lighting conditions, weather conditions, occlusions, and angles to ensure the robustness of the trained deep learning model. We utilize an open-source data source from Kaggle, comprising more than 2500 images of traffic lights categorized by color: red, green, yellow, and back. Class 'black' indicates looking at the traffic light from the back or from the side. Images were gathered from CARLA, which is an open-source autonomous driving simulator, nonetheless, images themselves can be used for real-world traffic lights [16].

Deep Learning Model Development: MobileNet [17], a lightweight convolutional neural network architecture, has been adopted for traffic light detection due to its efficiency in terms of computational resources and memory footprint. The development of MobileNet involves training the neural network on the open-source dataset prepared earlier. During training, the neural network learns to extract relevant features from the input images and classify them into different categories corresponding to the states of traffic lights. Fine-tuning techniques, such as transfer learning, are often employed to adapt pre-trained MobileNet models to the specific task of traffic light detection, enhancing the model's accuracy and generalization capabilities.

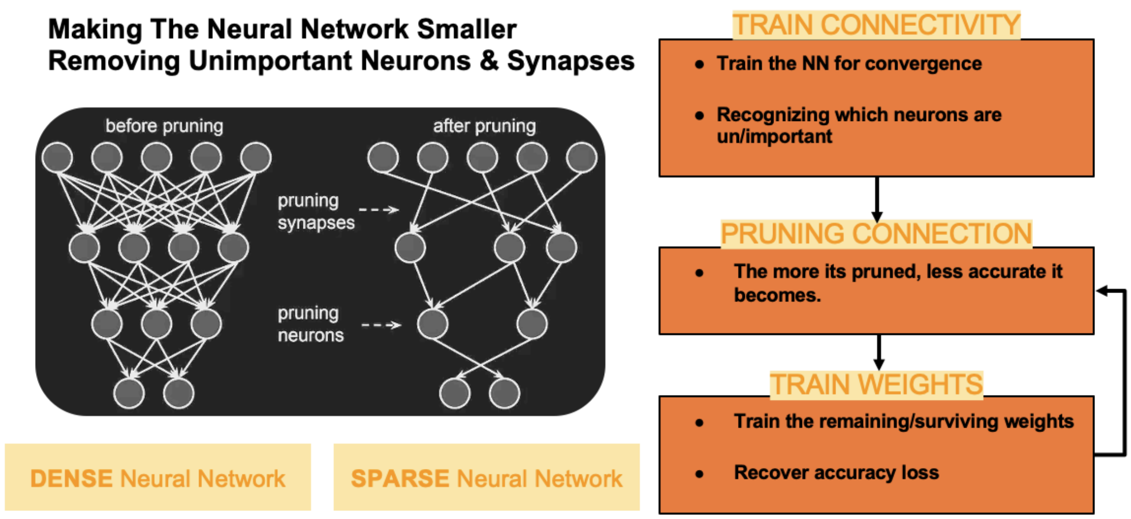
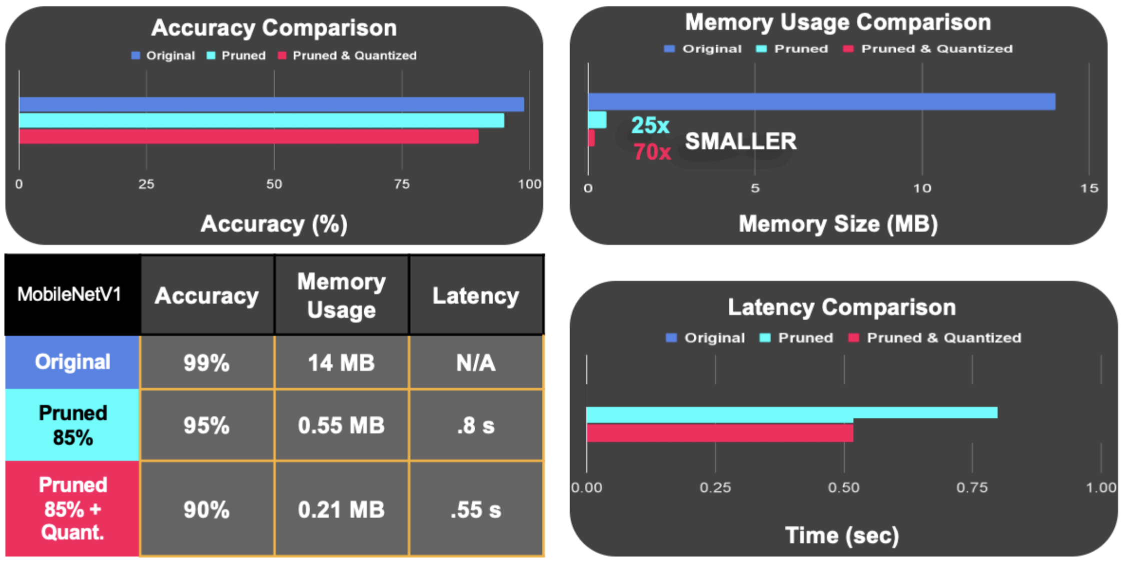


Figure 3. Neural Network Optimization by Deep Compression.

Neural Network Compression: As shown in Fig. 3, filter pruning [18] is a technique used in neural networks to reduce model size and computational complexity by removing unnecessary or redundant filters (also known as kernels or feature maps) from convolutional layers. In convolutional neural networks (CNNs) [19] [20], filters are responsible for detecting specific features or patterns within input data. Filter pruning involves identifying and removing filters that contribute minimally to the network's overall performance while retaining essential information. This process typically involves iteratively evaluating the importance or contribution of each filter based on certain criteria, such as its activation patterns, gradients, or impact on model accuracy. By pruning redundant filters, filter pruning can significantly reduce the number of parameters in a neural network, leading to a more compact model with reduced memory footprint and computational requirements. Additionally, filter pruning can help improve the network's inference speed and efficiency, making it more suitable for deployment on resource-constrained devices or real-time applications.

Experiment Results



MobileNetV1	Accuracy	Memory Usage	Latency
Original	99%	14 MB	N/A
Pruned 85%	95%	0.55 MB	.8 s
Pruned 85% + Quant.	90%	0.21 MB	.55 s

Figure 4. Experiment Results: Real-time Performance on Sony Spresense.

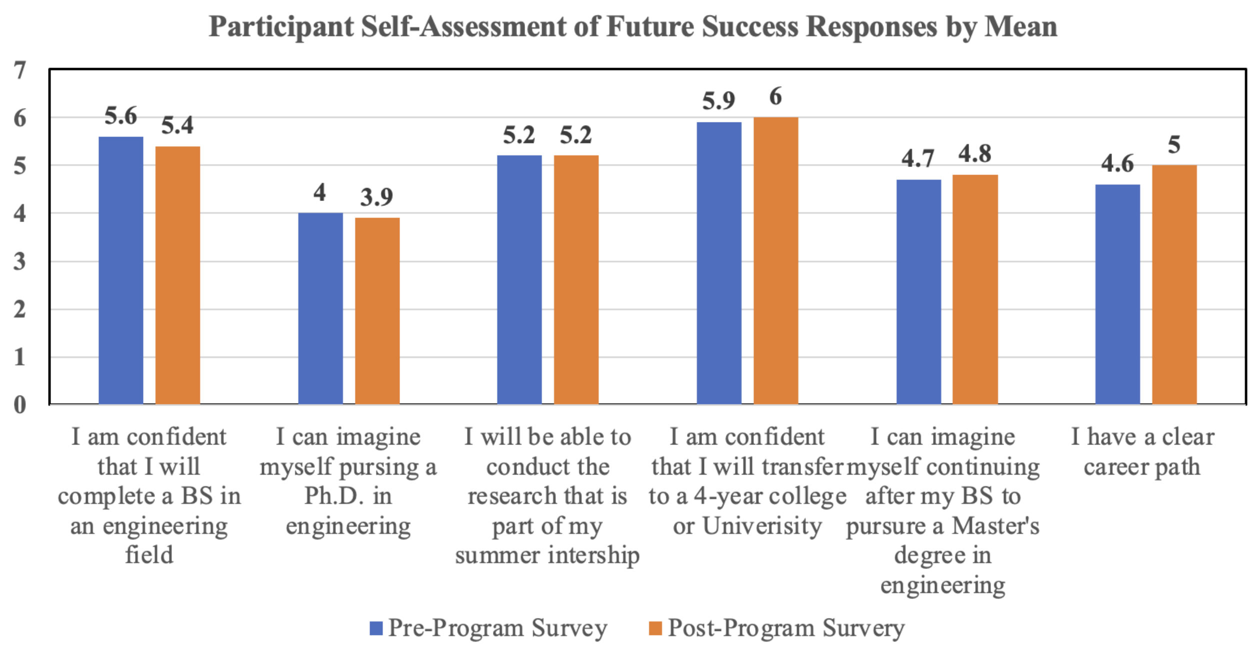
Experiment Setup: The dataset was split into training and testing sets to assess the model's performance on unseen data. Metrics such as accuracy and loss are commonly used to quantify the network's ability to correctly detect and classify traffic lights. Additionally, hardware evaluation metrics like memory usage and latency provide insights into the model's real-time performance on the microcontroller.

Experiment Results: After deploying the model on the Sony Spresense, we conducted experiments to evaluate the memory usage and inference latency across three different stages: the offline trained model, the model with pruning, and the model with pruning and quantization. Initially, the original model achieved an accuracy of 99%. However, due to its extensive memory requirements, it could not be deployed on a microcontroller with a limited memory capacity of 1.5 megabytes. The model consumed approximately ten times more memory than what was available. To address this limitation, we pruned 85% of the model, resulting in a model size reduction of 25 times. This trimmed-down model proved suitable for deployment on the microcontroller; however, it incurred an inference latency of approximately 0.8 seconds, equivalent to a frame rate of around 1 frame per second (fps). Subsequently, we applied quantization to further improve efficiency. With quantization, the inference latency improved to approximately 0.55 seconds, corresponding to around 2 fps. Additionally, quantization reduced the model size by a considerable factor of 75 compared to the original model. Although the accuracy of the model decreased to 90%, this trade-off between model size reduction and a slight decrease in accuracy allowed for successful deployment on the microcontroller, providing an effective balance between memory usage and inference speed.

Limitations and Future Work: Using an open-source traffic light detection dataset presents both limitations and avenues for future work. One limitation lies in the variability and representativeness of the dataset. Open-source datasets may lack diversity in terms of traffic light appearances, environmental conditions, and camera perspectives, which can limit the model's ability to generalize to real-world scenarios. Future work in this domain could focus on addressing these limitations by augmenting the dataset with more diverse and representative images. This could involve collecting data from multiple sources, including different geographical locations, weather conditions, and traffic scenarios. Furthermore, there is potential for exploring novel architectures or training strategies specifically tailored for traffic light detection, aiming to achieve higher accuracy and robustness in real-world applications.

External Evaluation Results of the 2023 S-SMART Summer Internship Program

The external evaluator of the S-SMART program administered surveys to community college interns both before and after the program. At the beginning of their internship experience, participants completed a survey designed to provide baseline data on their research backgrounds, knowledge, interests, and perceptions. The ten interns completed the survey on June 5, 2023. Additionally, post-program surveys were given to student peer mentors and faculty members, separately. These surveys aimed to gauge the motivations and perceptions of student interns regarding cutting-edge research, their academic objectives, and the skills essential for success in research and academia. The findings from the student survey, summarized in Figures 5, 6, 7, and 8, provide insights into the perspectives of interns before and after their internship experiences.



1 - Strongly Disagree	2 - Disagree	3 - Slightly Disagree	4 - Slightly Agree	5 - Agree	6 - Strongly Agree

Figure 5. Results from the survey on student self-assessment of future success (responses by mean). Question: Please indicate your level of agreement with the following statements.

Figure 5 presents a comparative analysis of participants' self-assessment regarding their future success in the field of engineering, measured before and after a certain program, as indicated by the terms "Pre-Program Survey" and "Post-Program Survey." The assessment is based on a Likert scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree). It is evident that the program had a positive impact on the participants' confidence and vision of their academic and professional futures. Notably, there was an increase in confidence regarding transferring to a 4-year institution, from 5.9 to a perfect 6, and a slight rise in envisioning the pursuit of a Master's degree, from 4.7 to 4.8. The assessment of having a clear career path also increased from 4.6 to 5. The graph indicates that the program may have particularly bolstered participants' confidence in immediate academic progress and clarity in their career trajectory.

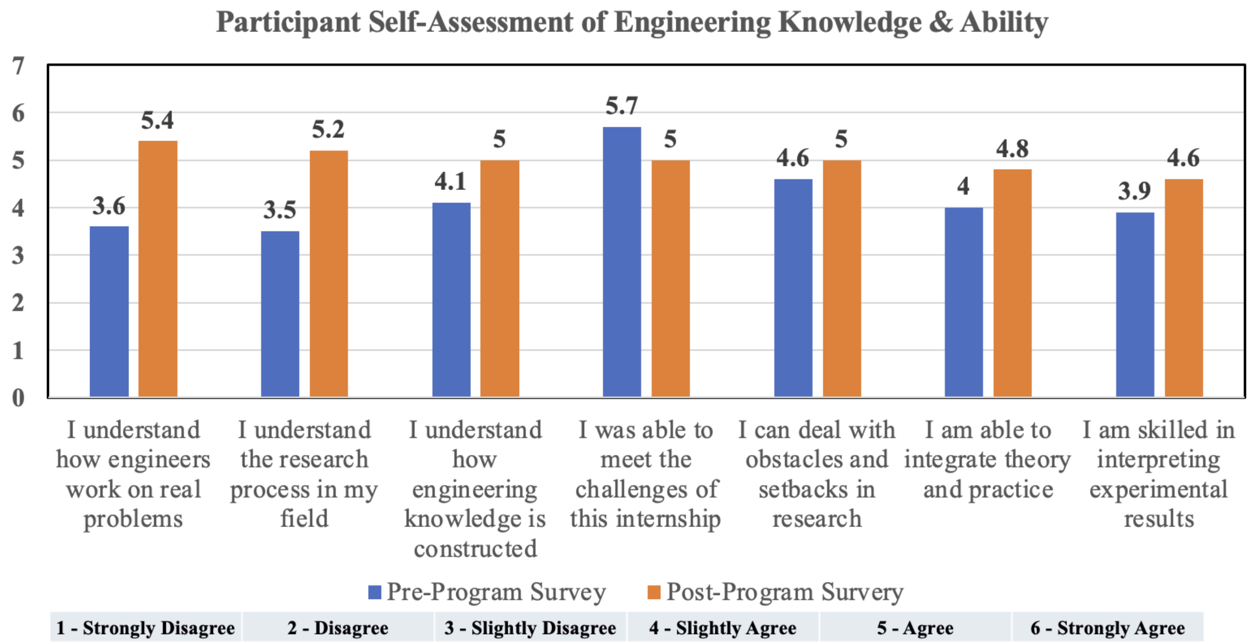


Figure 6. Results from the survey on student self-assessment of engineering knowledge & ability (responses by mean). Question: Please indicate your level of agreement with the following statements.

Figure 6 shows participant self-assessments of engineering knowledge and abilities before and after a program. Overall, there were significant gains in those assessments. For example, participants' understanding of how engineers work on real problems improved from a mean of 3.6 to 5.4 post-program. Knowledge of the research process in their field also increased from 3.5 to 5.2. However, the ability to meet the challenges of the internship decreased slightly from 5.7 to 5. These results suggest that the program was generally effective in enhancing participants' engineering knowledge and practical skills.

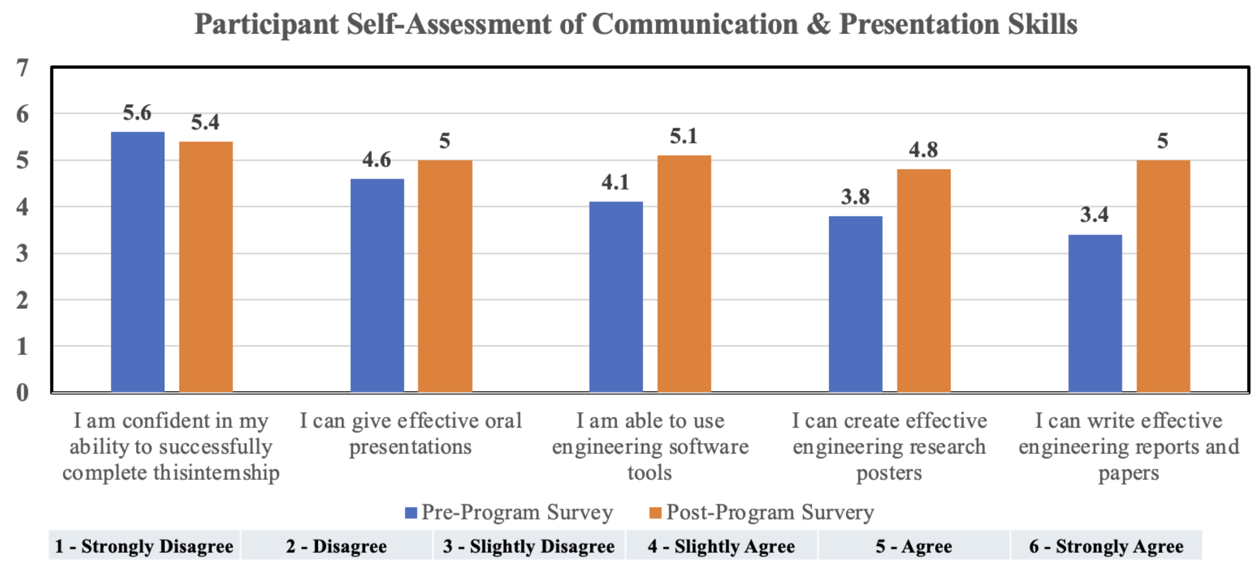


Figure 7. Results from the survey on student self-assessment of communication and presentation skills (responses by mean). Question: Please indicate your level of agreement with the following statements. (1-Strongly Disagree, 6-Strongly Agree).

Figure 7 presents participant self-assessment results on communication and presentation skills before and after a program. Post-program, participants reported a slight decrease in confidence in completing the internship, from 5.6 to 5.4. The ability to give effective oral presentations remained fairly stable, with an increase from 4.6 to 5. The use of engineering software tools showed an improvement from 4.1 to 5.1, indicating enhanced technical proficiency. The capability to create effective research posters saw a significant rise from 3.8 to 4.8, reflecting improved research communication skills. The skill in writing effective reports and papers saw a notable increase from 3.4 to 5, suggesting a substantial enhancement in writing competency. Overall, the data suggests the program strengthened participants' communication skills, particularly in writing and software tool usage.

Figure 8 compares pre- and post-program participant self-assessments on engineering career knowledge and skills. Participants reported a slight improvement in their ability to work independently, with scores rising from 5.2 to 5.5. The perceived effectiveness as a team member slightly decreased from 5.5 to 5.4. A marginal decrease was also observed in feeling part of a learning community, from 5.6 to 5.3. Participants' understanding of how engineers think saw a notable increase from 4 to 5.1. There was a slight improvement in having a clear understanding of career opportunities in engineering, with the mean score increasing from 4.8 to 4.9. Lastly, enjoyment and inclination towards making laboratory research a career showed a small rise from 4 to 4.3. Overall, the graph indicates that the program had a positive impact on participants' career knowledge and skills, with particularly notable gains in understanding engineering thought processes and career clarity.

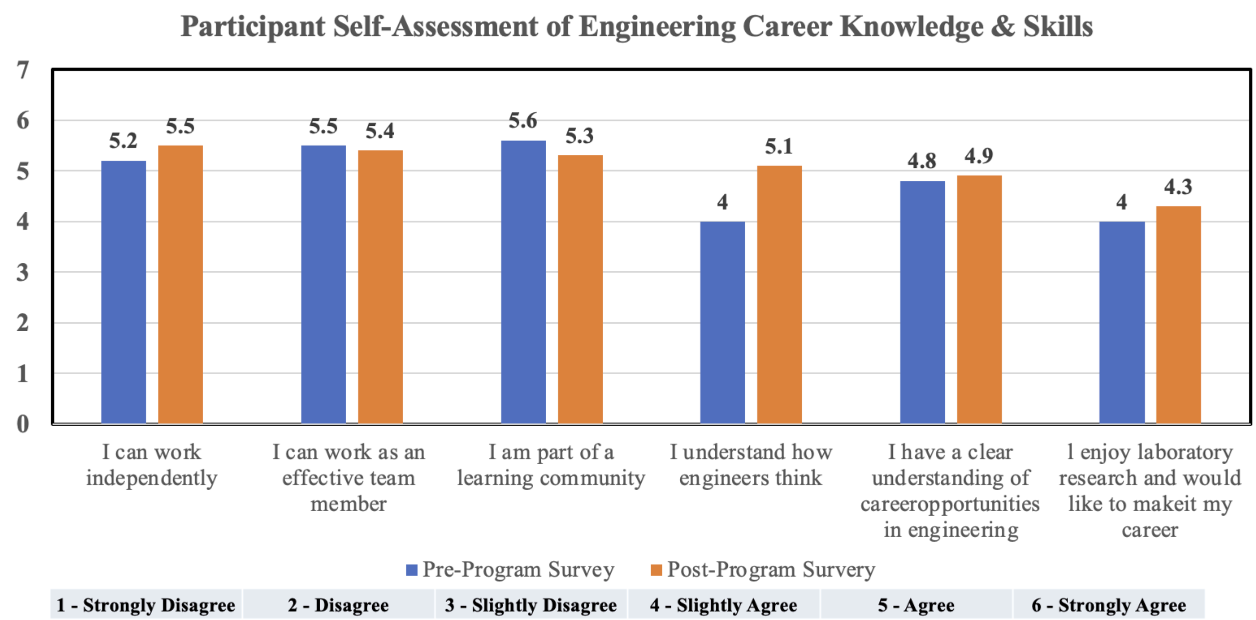


Figure 8. Results from the survey on student self-assessment of engineering career knowledge & skills (responses by mean). Question: Please indicate your level of agreement with the following statements.

Conclusion

In its second year, the S-SMART Summer Research Internship program not only continued its impactful provision of opportunities for first- and second-year community college students, particularly those from underrepresented minority (URM) groups but also integrated the burgeoning field of AI. By incorporating AI methodologies and technologies into the research projects, the program expanded its scope and relevance, aligning with contemporary trends in engineering and technology. Through mentorship from faculty advisors and student peer mentors, participants engaged in innovative research projects that leveraged AI tools, fostering a collaborative environment conducive to both skill acquisition and academic growth. Notably, the program maintained its commendable track record of attracting URM and female students, surpassing overall engineering enrollment rates.

Survey data collected before and after the program underscored its positive impact on students' confidence in their ability to transfer and earn a bachelor's degree in engineering, as well as their enhanced understanding of career pathways and opportunities, including those related to AI. Moreover, participants reported significant improvements in various skills, including mental acuity, communication proficiency, and laboratory techniques, with AI-specific skills being particularly highlighted. The research conducted by students yielded tangible outcomes, including the presentation of several conference papers and posters at prestigious events like the American Society for Engineering Education Pacific Southwest Section (ASEE PSW)

Conference, marking a noteworthy accomplishment in their academic journey, augmented by their immersion in AI-driven projects.

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