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Translating Industry-Sponsored Neuromorphic Vision Research into Modular Learning Units for Engineering Courses

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Upon graduation he became an Assistant Professor of Engineering Science and Mechanics at the Virginia Polytechnic Institute and State University. In 1987 he joined the Department Electrical and Computer Engineering at UMASS Lowell as its Analog Devices Career Development Professor. Dr. Thompson has served on the executive boards of the Cooperative Research Fellowship program of Bell Laboratories (1991-1999) and the AT&T Labs Fellowship Program (1996-2006).

At Bell Laboratories Dr. Thompson created with the Vice President of Research and Nobel laureate, Arno Penizas, the W. Lincoln Hawkins Mentoring Excellence Award (1994). This award is given to a member of the research staff for fostering the career growth of Bell Labs students and associates. This award is ResearchÄôs highest honor for mentoring contributions. In 1998, AT&T Labs instituted a similar award named for Dr. Thompson.

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His awards include the US Presidential Award for Excellence in Mentoring; Tau Beta Pi Eminent Engineer; James E. Blackwell Scholar; AT&T Bell Laboratories Cooperative Research Fellowship. He is cited in WhoÄôs Who among African Americans, Education, and Technology Today; American Men and Women of Science, West Babylon Alumni Hall of Fame; He is a Fellow of the Acoustical Society of America and cited for his fundamental contributions to theoretical and computational acoustics. He is senior member of IEEE, and a member of the American Physical Society and Sigma Xi. He has published reesearch in acoustics, control theory, fluid mechanics, heat transfer, linear and nonlinear systems, and telecommunications.

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Translating Industry-Sponsored Neuromorphic Vision Research into Modular Learning Units for Engineering Courses

Abstract

Industry-university collaborations can play an important role in exposing engineering students to emerging technologies and real-world problem contexts. However, translating research driven and industry sponsored projects into scalable, course ready instructional materials can be challenging. This paper presents a case study of the Neuromorphic Imaging and Processing for Tracking and Evaluation at the Edge (NIPTEE) project, illustrating how an industry-sponsored research effort can be transformed into modular learning units for integration into engineering curricula. These modules present a pathway from undergraduate capstone projects to graduate research, providing a range of educational topics from system-level design, to benchmarking, and trade-space analysis. Insights gained from student projects were organized into modular learning units covering industry problem formulation, event-based sensing, embedded acceleration, performance benchmarking, and engineering decision making. This paper describes a collaborative structure supporting module development, organization of learning units, supporting pilot implementations within engineering courses. By emphasizing transferable skills, the proposed approach enables instructors to incorporate emerging technologies into existing courses without requiring extensive curriculum redesign.

I. Introduction

Industry-university collaboration is recognized as an important need in the degree pathway for students to acquire the skills needed to be competitive in dynamic work environments. Previous studies have shown that industry-sponsored projects, capstone project mentoring, and collaborative research experiences can provide students with exposure to industry needs while building networks and mentor relationships. Industry projects are typically unstructured and open-ended, helping to build multidisciplinary problem solving skills and professional engineering practices [1]. These partnerships have been shown to improve student participation in research while engaging industry stakeholders to help shape learning outcomes that reflect real-world expectations [2], [3]. For example, some models have shown how industry-sponsored experiential learning can reinforce the connection between academic learning outcomes and real-world engineering practice [4].

In our College of Engineering, this practice includes industry professionals serving as adjunct instructors, sponsoring undergraduate capstone and graduate research projects, and participating in summer bridge programs for newly enrolled engineering students. In collaboration with industry partners, including a defense contractor and a technology provider, a 12-credit graduate certificate in Digital Engineering was developed in response to the Digital Engineering Strategy Initiative of the Department of Defense in 2018 [5]. The certificate consists of a four-course sequence offered to industry professionals and graduate students, emphasizing team-based, hands-on projects using industry-aligned platforms, tools, and languages. Delivered through synchronous online instruction, the program focuses on developing systems thinking skills and familiarity with industry workflows [6].

Despite the benefits, integrating emerging technologies into engineering curricula can be difficult. A rapidly evolving technological landscape, limited access to specialized hardware and/or software, and the overhead required to translate research-driven projects into course-ready material remain challenging [7]. Previous work in industry-academia partnerships has shown that, while capstone projects and sponsored research can expose students to advanced technologies, these experiences do not necessarily scale to widely reusable curriculum-level implementations [8].

These challenges are evident in domains such as sensing, embedded computing, artificial intelligence, and machine learning. Technologies such as neuromorphic vision sensors (NVS), FPGA acceleration, and real-time benchmarking are increasingly relevant in defense, aerospace, and edge computing applications, but they have a limited presence in the current undergraduate engineering curricula.

This paper presents a case study of an industry-university partnership on the Neuromorphic Imaging and Processing for Tracking and Evaluation at the Edge (NIPTEE) project. NIPTEE, which investigates the performance evaluation of NVS, has progressed from three successive years of undergraduate capstone projects to a graduate research project. This ongoing long-term industry-university collaboration requires strong mentorship and teamwork among all participants—faculty advisors, graduate students, and industry affiliates. It requires sustained communication with progress updates, in-person interaction among all team members, and administrative support with access to university resources to conduct experiments and computational studies.

The goal of this work is to demonstrate how emerging technologies, combined with industry insights and co-creation models, can be transformed into scalable educational modules that promote system-level thinking and trade-space analysis. Rather than training students on a specific platform, the approach emphasizes transferable skills that support informed design decisions across application domains. This approach also supports alignment with accreditation frameworks such as ABET by emphasizing measurable learning outcomes related to design, analysis, and communication in engineering contexts.

The paper is organized as follows. Section II motivates the industry problem space and discusses how emerging technology applications can bridge engineering research and educational outcomes with career readiness. Section III describes the modular design of NVS and benchmarking methods for integration in selected courses. Finally, section IV summarizes key observations and outlines future directions for expanding this work further into different curricula.

II. Bridging industry applications of emerging technology in engineering research and education

A. Industry problem space

In defense, aerospace and emerging edge-computing applications, engineers are tasked with designing systems that perform sensing, perception, and decision-making under strict operational constraints. Applications such as aerial surveillance, autonomous navigation, and situational awareness require reliable detection and tracking of objects in dynamic environments while operating within limitations of size, weight, power, and cost (SWaP-C). These constraints fundamentally shape system design choices and require engineers to reason between sensing modalities, computing architectures, and performance metrics.

Recent advances in sensing and embedded intelligence have expanded the range of technologies available to address these challenges. In particular, emerging sensing modalities and hardware acceleration platforms enable new approaches to real-time processing at the edge. However, the introduction of these technologies also increases system complexity, given that design decisions need to account for trade-offs between accuracy, latency, energy consumption, and cost of deployment. In practice, engineers must evaluate performance across multiple dimensions to determine which solution is ideal in different operational contexts.

System benchmarking plays an important role in this decision making process. In industry, engineers rely on benchmarking to compare system designs and evaluate performance under various constraints such as latency, power consumption, and resource utilization. Interpreting these results and using them to guide design choices is a key skill for engineering practice. As a result, benchmarking activities can be important in project-based learning to help students develop decision making skills, systems-level thinking, and design choice justifications [9], [10].

An overview of industry-university collaboration for the NIPTEE project is shown in Fig. 1. During the first year, the collaboration begins with an industry defined problem space in which operational needs, constraints, and success metrics are established and presented to the university team. These requirements help shape the academic objectives and the scope of research. This initial phase is followed by the participation of interested students who work with faculty and industry mentors to develop a research plan and timeline.

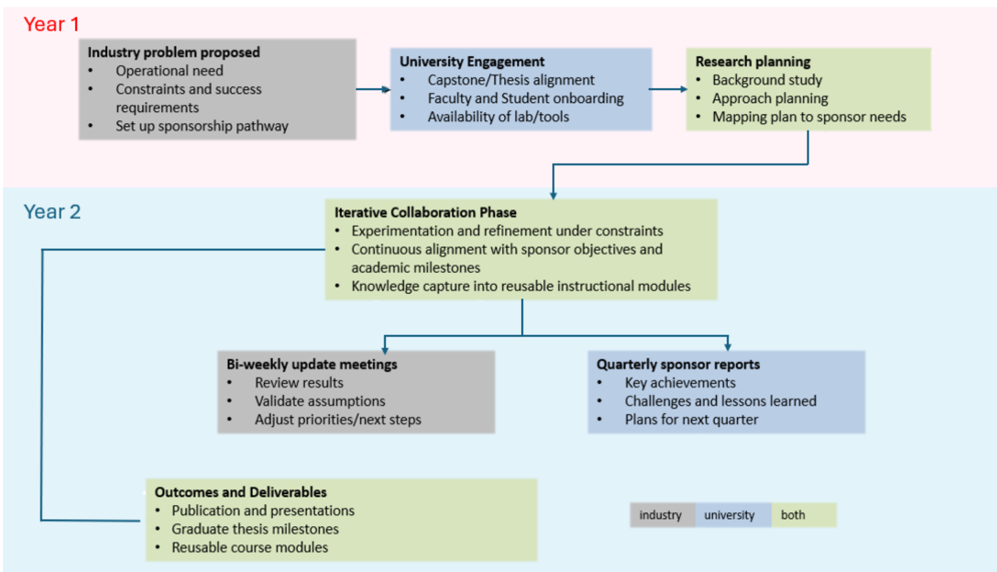

Figure 1. Overview of the NIPTEE life-cycle of an industry-PhD collaboration based on the industry problem space

In Years $2-4$, graduate students focus on experimentation and problem solving, iteratively refining their approach as results are derived. Throughout this period, students regularly report progress to industry and academic mentors, allowing requirements or project scope to be adjusted based on technical findings and feedback.

The dissemination of research and the transfer of knowledge occur throughout the collaboration with publications, presentations, and thesis deliverables based on the project scope. Although the timeline in Fig. 1 illustrates a four-year progression, the duration and emphasis of each phase may vary depending on the number of participants, the results, and the continued participation of the industry.

B. Graduate student training for co-creation of educational modules with industry

Effective student interaction with industry professionals requires training in the important skills of communication and interdisciplinary problem exploration. Through an NSF Innovations in Graduate

Education (IGE) project, the authors developed several training modules that included (i) co-creation strategies and societal concepts to promote respectful collaboration; (ii) techniques for formulating effective messages in writing and presentations tailored to various audiences; and (iii) the design of educational modules along guidelines for assessing learning outcomes. These were implemented in the form of interactive workshops, peer review exercises, and interactions with guest speakers [11, 12].

As a multi-institution collaboration effort involving three different universities, the authors proposed a co-creation-based educational model with the goal of equipping graduate engineering students with skills in interdisciplinary research and engagement with industry mentors. This model was structured based on a project-based learning framework. It began with identifying a research problem that was aligned with students' interests, progressed through collaborative work with faculty and industry experts, and ended with public products, such as conference papers and online educational modules. This project involved a diverse group of participants, including graduate engineering students from different disciplines, faculty mentors from engineering, psychology, and sociology, and industry partners.

Research topics were selected to address emerging topics that align with industry needs. These topics include cyber-physical systems (CPS) in the context of structural health monitoring, human balance systems with implications for healthcare of the aging population, and an augmented reality application as a tool for up-skilling and re-skilling future workforce [13, 14].

The graduate student co-authors of this paper were among the first cohort to receive training in the NSF IGE project. The skills acquired were beneficial in the design of educational modules adopted in the case study presented in this paper.

In these co-creation projects, industry partners brought their expertise to provide practical perspectives on research topics. Through a co-creation process, students can gain an understanding of the expectations of the workforce, while industry partners can support the development of desired workforce skills to bridge skill discrepancies that have been identified in several studies [3], [15].

The resulting educational modules were designed to improve accessibility for different learners, allowing for a wider dissemination of the projects across a diverse range of students and multiple institutions. The modules have been integrated into courses such as a summer bridge program for incoming undergraduate students and undergraduate engineering courses, including linear control systems. Student feedback on the CPS module, for example, highlights increased awareness of the inter-connectivity of CPS, its relatability to what they learn in classes, and how it is applied in real-world systems.

This prior implementation informed the design approach adopted in the NVS case study presented in this paper.

III. Modular design of industry-related problems for engineering course integration

A common challenge in industry-university collaborations is the absence of established coursework that directly addresses emerging technologies and problem contexts introduced by industry partners. As a result, graduate students engaged in sponsored research often acquire foundational knowledge independently, supported by faculty mentorship and iterative interaction with industry affiliates. Although this model can be effective for individual research training, much of the domain knowledge acquired remains implicit and confined to a small group of students.

The modular learning units developed in this work aim to address this gap by formalizing background knowledge, system context, and analytical approaches encountered during the research process. By capturing these elements as scalable educational modules, the approach enables faculty to integrate industry-relevant content into existing courses and exposes a broader population of students to emerging topics. In this way, modules serve as a mechanism for transferring knowledge between cohorts and promoting transferable learning aligned with industry practice.

A. NIPTEE case study context

The case study described in this work is supported by a collaboration that promotes research, education, and workforce-relevant skill development. This collaboration includes three main groups: industry mentors, faculty advisors, and students. Figure 2 shows the different roles and responsibilities of these stakeholders and how the iterative collaboration phase of Fig. 1 is carried out.

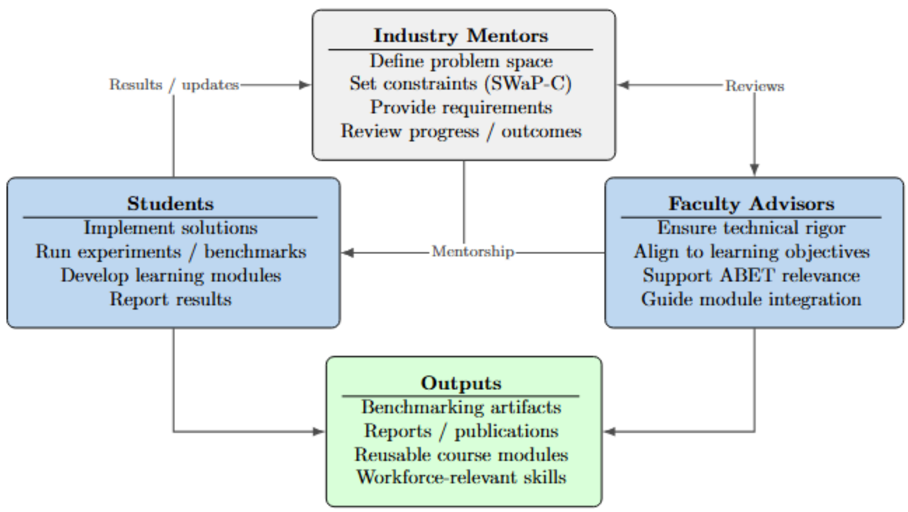

Figure 2. Roles and interactions in the NIPTEE project during the iterative research stage.

The NIPTEE project provides the case study presented in this paper. The collaboration began as a sequence of undergraduate capstone projects, each building upon the outcomes and limitations identified in the previous year's capstone project.

These projects were motivated by industry interest in novel sensing technologies capable of reducing data redundancy and supporting low latency and low power detection at the edge. Figure 3 shows the evolution of this industry-university collaboration. At each stage, identified challenges and system constraints informed the scope and direction of the ensuing projects.

Building on the capstone work, the project evolved into graduate level research supporting multiple doctoral projects. The NIPTEE project, which is a direct progression from the capstone project, focuses on system integration and performance benchmarking of neuromorphic vision–based detection and tracking pipelines deployed on embedded computing platforms. In addition to this work, this same industry-university collaboration has supported other graduate research efforts that build on the same interest in neuromorphic sensing technologies. These include: (i) the development of dynamical models for physical systems of interest, serving as a foundation for digital twins, leveraging NVS data

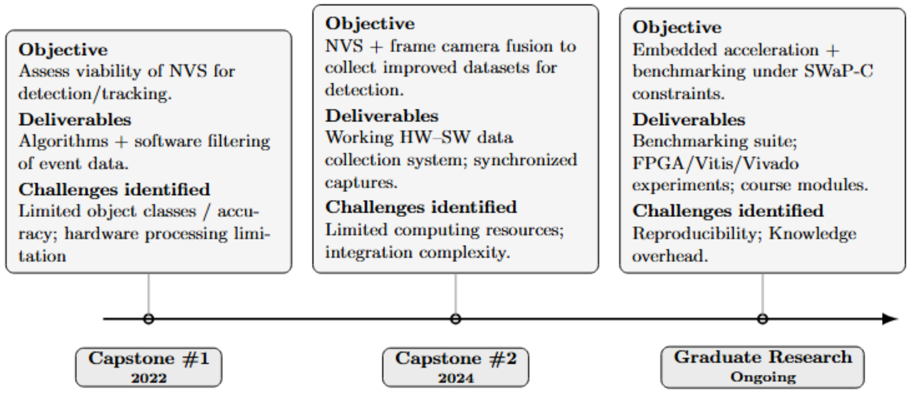

Figure 3. Visual timeline of project evolution from successive capstone efforts to the NIPTEE graduate research.

to inform system states and evaluate dynamic performance; (ii) the use of NVS for human motion analysis for healthcare oriented applications.

B. Student contributions enabling module development

During the undergraduate capstone phase, students developed two proof of concept subsystems to support event-based sensing experiments. First, a filtering system was created to analyze event data, remove noise from the camera output, and isolate events or objects of interest (Figure 4). Second, a synchronized event-frame system was developed to align an event camera with a frame-based camera for reference capture and metadata collection (Figure 5). These capstone prototypes highlighted limitations and gaps in event-based sensing. They informed the transition into the graduate phase of the collaboration.

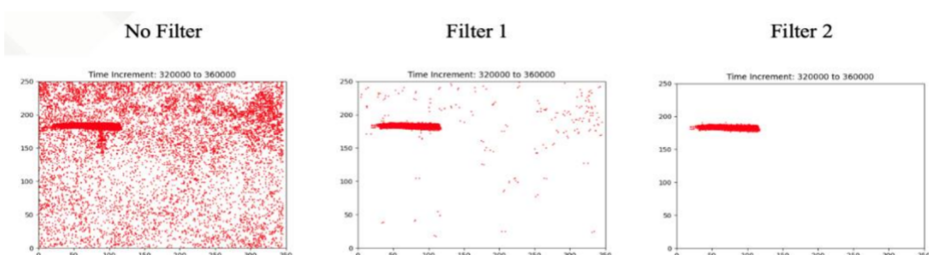

Figure 4. Capstone Project #1: Noise removal filter for neuromorphic vision sensor data to improve object classification.

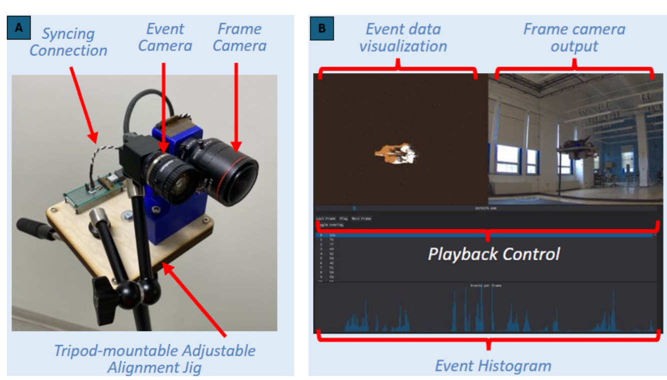

Figure 5. Capstone Project #2: The Jig and user interface for synchronizing event and frame cameras

1). Consolidation of capstone deliverables into graduate project

The graduate phase shifted from exploratory prototypes to structured workflow development. Two objectives guided this phase: (i) formalize data collection and curate a reusable dataset repository, and (ii) develop a repeatable inference and benchmarking workflow for analysis. Figures 6 and Fig. 7 show the resulting repository and metadata structure.

```
NIPTE - Data Repository Guide.xlsx
Dataset
|   ├ NVS
|   |   ├ recording_2024_10_30-16-11-57_nerfGun.raw
|   |   ├ ...
|   ├ Frame
|   |   ├ recording_2024_10_30-16-11-57_WIN_nerfGun.avi
|   |   ├ ...
```

Figure 6. NIPTEE dataset repository organization.


```
session_id: static_drone_01
location: UML Robotics Lab
timestamp: 2025-04-02 14:35:00
camera_status: Static w/ Ego-Motion Induced
object_types:
  - Drone
  - Nerf Dart
motion_characteristics: Linear, occluded, high speed
event_file: events.raw
frame_file: frame.avi
notes: Lighting: low, Occlusion present near corners
```


Figure 7. NIPTEE metadata structure.

Using this curated dataset, students implemented and evaluated a detection and tracking inference pipeline. Examples of outputs from running this algorithm and tracking the trajectory of an object are shown in Figs 8 and 9.

Figure 8. Drone downward trajectory tracking.

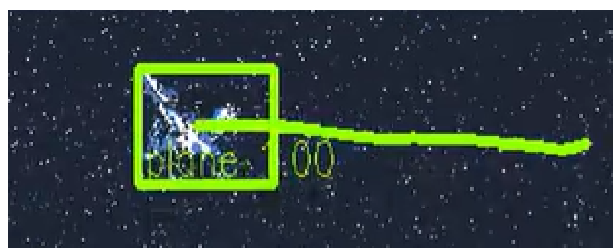

Figure 9. Plane lateral trajectory tracking.

Throughout this phase, students disseminated progress through sponsor briefings and research publications, which also inform the design of the modular learning units described next.

2). Translation from Industry-Sponsored Graduate Project to Educational Modules

Insights gained through the NIPTEE collaboration were translated into a sequence of five modular learning units, each aligned with a distinct stage of the project lifecycle, from problem formulation to performance driven decision making. This structure allows instructors to adopt the full sequence as a project-based experience or selectively integrate individual modules into existing courses. Students begin by understanding the operational context and system context of a detection and tracking application, then are introduced to sensing technologies; how these systems can be integrated into different application scenarios; the importance of performance benchmarking, tradeoff analysis, and decision making. Table I shows a brief overview of the different modules implemented, their main focus, and the corresponding learning outcomes.

Table I
OVERVIEW OF MODULAR LEARNING UNITS AND EDUCATIONAL OBJECTIVES

Module	**Focus**	**Learning Outcome**
Module 1	Industry problem context and system constraints	Students can identify operational constraints and articulate an industry-driven engineering problem.
Module 2	Neuromorphic vision sensors and event-based data	Students understand event-based sensing principles and their impact on system design.
Module 3	Embedded acceleration and system integration	Students can describe hardware/software co-design and embedded system architectures.
Module 4	Benchmarking and performance evaluation	Students can interpret benchmarking metrics and relate them to system objectives.
Module 5	Trade-space analysis and engineering decision-making	Students justify engineering decisions using performance trade-offs and constraints.

The learning outcomes defined in Table I align with established engineering education frameworks, including ABET student outcomes [16]. In particular, modules emphasizing system integration and benchmarking (Modules 3 and 4) support students' ability to apply engineering design principles under realistic constraints (ABET Outcome 2) and analyze and interpret data (ABET Outcome 6). The trade-space analysis module (Module 5) further reinforces decision-making in the presence of competing requirements, reflecting real-world engineering practice. Additionally, module activities and deliverables promote effective technical communication (ABET Outcome 3) through written reports and design justification exercises.

Each module is a combination of instructional pages with some background, a brief literature survey on the state of the art, assignments, and deliverables related to the specific module topic. An example is shown in Figs 10 and 11. The first shows an overview of the second module implemented for NIPTEE, and the second shows a section of the page from that module which introduces students to the concept of neuromorphic vision sensors, where they acquire a fundamental grasp of the type of data that is being used throughout the application pipeline.

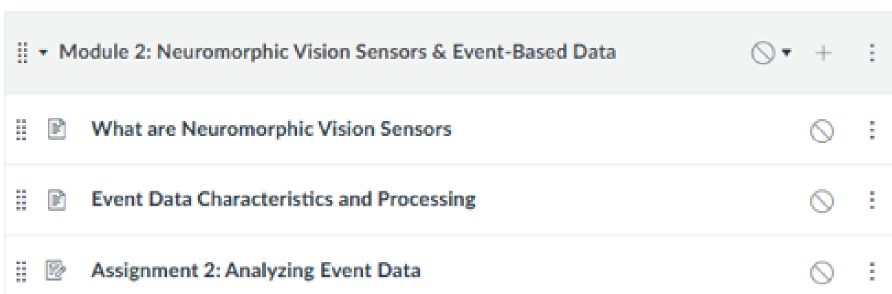

Figure 10. Student developed canvas course for NIPTEE: Benchmarking for Project-Based Learning: Module 2.

C. Evaluating Learning Outcomes from NIPTEE Modules

To complement the design and development of the modular learning units, a pilot implementation will explore their integration within an existing engineering course.

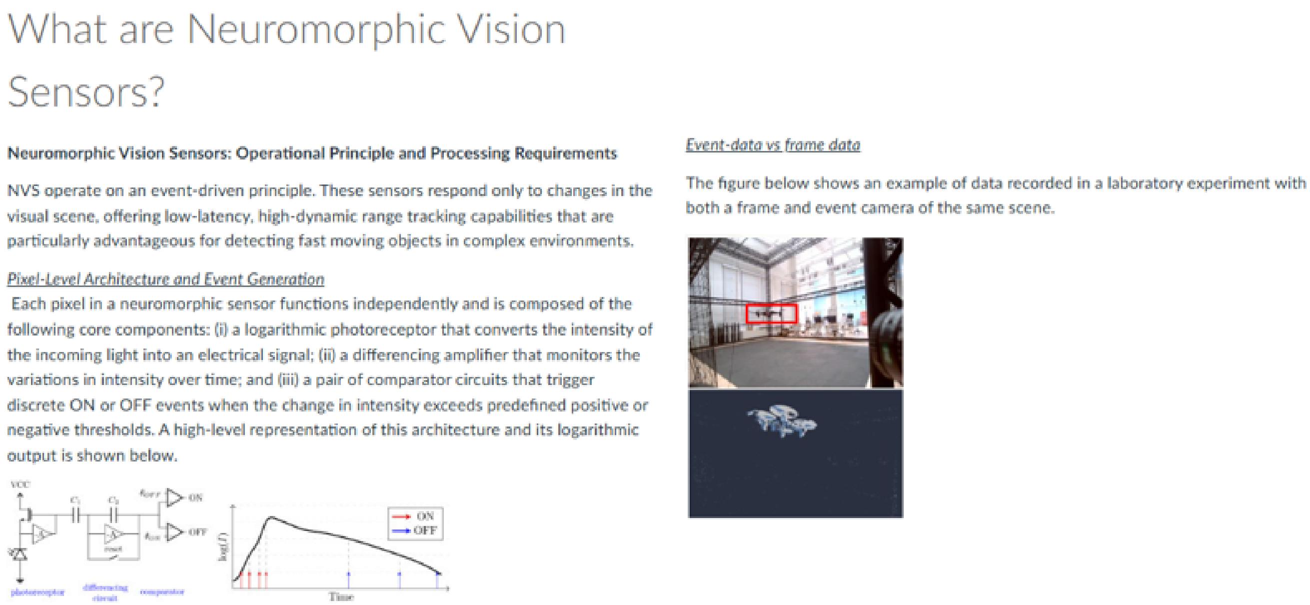

Figure 11. Benchmarking for Project-Based Learning: Module 2: 2.1 ”What are Neuromorphic Vision Sensors?”

1). Pilot setting and implementation

In the proposed pilot, selected modules from the NIPTEE sequence will be incorporated into a graduate-level engineering course, *Advanced Digital System Hardware Design (ADS)*, taught by a faculty mentor involved in the collaboration. Modules will be introduced as supplemental instructional material aligned with existing course objectives, including digital system design, hardware acceleration, and system-level performance evaluation. Students will engage with the modules through guided readings and associated assignments or discussion prompts.

Figure 12 shows how concepts derived from the NIPTEE project, particularly those related to embedded acceleration, benchmarking, and hardware trade space analysis, are mapped to topics and learning outcomes from the ADS syllabus.

NIPTEE Module Content	Course Topics				
	Architecture Docs	RTL/VHDL	SoC/AXI	Timing	Benchmarking
Module 3: Embedded Acceleration & System Integration					
HW/SW partitioning of detection pipelines	✓	✓	✓		
FPGA-based accelerator integration (IP cores)		✓	✓		
SoC-level integration (CPU + FPGA)	✓		✓		
Architectural trade-offs (latency)	✓			✓	
Module 4: Benchmarking & Performance Evaluation					
Latency and throughput measurement				✓	✓
Resource utilization analysis (LUTs, BRAM, power)					✓
Timing closure under design constraints				✓	
Module 5: Trade space analysis and engineering decision making					
Design trade-space analysis	✓			✓	✓

Figure 12. Mapping of NIPTEE module content to ADS learning concepts.

2). Evaluation measures

The pilot will be evaluated based on various measures.

Survey: At the end of the module sequence, students will complete a short survey to assess the relevance to course content and the perceived connection to real-world engineering practice. Open-ended prompts will be included to capture qualitative feedback on which module components were most or least useful and how the module design and content can be improved.

Student deliverable assessment: Student work associated with the modules will be evaluated using a rubric aligned with the learning outcomes in Table I. Example artifacts include: (i) a short benchmarking interpretation memo (Module 4) in which students compute and interpret performance metrics from the provided results; and (ii) a trade-space justification exercise (Module 5) in which students argue for a design choice under some established constraints. The results of this initial pilot will guide iterations on both module content and assessment methods.

IV. Conclusions and future work

This paper describes how a long-term, industry-sponsored neuromorphic vision research collaboration was translated into modular learning units that can be integrated into existing engineering courses. By formalizing research-driven learning into modular content, the approach supports continuity and knowledge transfer beyond individual student projects. Rather than focusing on the learning of specific tools or platforms, the modular design emphasizes transferable conceptual understanding. The proposed pilot shows an example pathway for embedding emerging technology concepts into established engineering courses through targeted instructional module inserts.

Future work will focus on evaluating the educational impact of the modules through the planned pilot study. The results from this evaluation will inform any refinements to existing modules and guide their integration into additional engineering courses.

From a research perspective, the ongoing NIPTEE project will continue to generate experimental data and technical results that can be incorporated into future modules, supporting both curriculum development and continued graduate research through a dynamic industry-academia collaboration.

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