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Student-Driven Machine Learning for UAS Thermal Imaging: An Experiential Learning Framework in Aerospace Engineering

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Abstract

This paper describes a series of student-driven research projects at Kennesaw State University's AERO Laboratory in which teams of undergraduate, graduate, and high-school students designed, trained, and deployed Machine Learning (ML) algorithms for Unmanned Aerial System (UAS) thermal imaging applications. Projects spanned head temperature estimation for search and rescue, human condition detection, photovoltaic array inspection, runway foreign object debris detection, and building facade heat-loss analysis. Rather than focusing solely on technical outcomes, this paper examines the educational framework that enabled students with no prior ML experience to contribute to publishable research within a single academic year. We describe the tiered mentorship model used to distribute responsibilities across experience levels, the specific challenges students faced when learning to collect radiometric data and train YOLO-based detection models, and the measurable impact of participation on student retention, course performance, and career readiness. Results indicate that hands-on UAS-based ML projects increased student engagement with core engineering coursework, improved confidence in computational tools, and produced five research outputs suitable for peer-reviewed venues. The paper concludes with recommendations for faculty seeking to replicate this model in other aerospace or interdisciplinary engineering programs.

Keywords: Engineering Education, Experiential Learning, Unmanned Aerial Systems (UAS), Machine Learning (ML), Thermal Imaging, Student Research

Introduction

Engineering education increasingly calls for curricula that move beyond traditional lecture formats and engage students in authentic research problems. Aerospace programs face a particular version of this challenge: the systems students will work with after graduation (autonomous vehicles, sensor-fused platforms, AI-driven decision pipelines) are evolving faster than most course catalogs can track. One response is to embed students directly in faculty research, so that learning happens through doing rather than through classroom simulation alone.

At Kennesaw State University, the AERO Laboratory has operated under this principle for several years. A sequence of student-led projects has explored the integration of Artificial Intelligence (AI) and Machine Learning (ML) with UAS platforms equipped with thermal imaging sensors. The technical applications, including head temperature estimation for search and rescue, human condition classification, photovoltaic defect detection, foreign object debris identification, and building facade heat-loss analysis, are described briefly in this paper, but they are not the primary contribution. The primary contribution is an account of how these projects were structured as educational experiences: who participated, what they learned, what went wrong, and what effect the work had on their academic trajectories.

The research teams intentionally mixed experience levels. A typical project included a graduate student leading model development, two or three undergraduates handling data collection and annotation, and in one case a high-school intern contributing to dataset management. The faculty advisor provided the research direction and UAS flight authorization, but day-to-day decisions about experimental design, labeling protocols, and model hyperparameter selection were made by the students themselves. This paper describes that process, its friction points, and the outcomes that resulted.

The remainder of the paper is organized as follows. We first review relevant literature at the intersection of UAS thermal imaging and engineering pedagogy. We then describe the project portfolio and the educational methodology used across all five efforts. A dedicated section on challenges and lessons learned addresses the difficulties students encountered. The expanded educational impact section presents retention data, self-reported learning gains, and career outcomes. We close with conclusions and recommendations for replication.

Literature review

UAS thermal imaging

Recent advances in UAS-based thermal imaging have expanded both application domains and methodological depth. Zhang et al.[1] survey UAS infrared thermography applications for building envelope thermal performance evaluation, highlighting persistent challenges in radiometric calibration and environmental interference. Ndlovu et al.[2] systematically review UAS thermal remote sensing for agricultural crop water status monitoring, emphasizing the role of high-resolution thermal sensors in precision irrigation management.

In search and rescue, Yeom[3] presents a YOLO-plus-Kalman-filter tracking pipeline for monitoring hikers from aerial thermal imagery. The HIT-UAS dataset[4] provides a high-altitude thermal benchmark for person and vehicle detection. On the processing side, Maes et al.[5] address radiometric alignment for structure-from-motion workflows, and Roth et al.[6] integrate ground reference points into flight planning for improved calibration in irregular terrain. Ramos et al.[7] evaluate how flight speed and camera angle affect thermographic quality for facade audits, and Daffara et al.[8] demonstrate a cost-effective 3D thermography system for building heat-loss detection.

To address data scarcity, Barišić et al.[9] introduce a synthetic augmentation pipeline for UAS thermal datasets, Li et al.[10] propose AnyTSR for adaptive thermal super-resolution, and Butt et al.[11] explore UAS-based landmine detection through infrared cues.

Experiential learning in engineering

The pedagogical foundation of this work draws from Kolb's experiential learning cycle[12], in which students move through concrete experience, reflective observation, abstract conceptualization, and active experimentation. In aerospace education specifically, capstone design courses have long served as the primary vehicle for hands-on learning, but several programs have begun integrating research-based project work earlier in the curriculum. Freeman et al.[13] demonstrated that active learning in STEM courses reduces failure rates by approximately 33% compared to traditional lecture, and the effect is particularly strong when projects involve real data and open-ended problem formulation. UAS-focused project courses have been reported at several institutions as effective tools for teaching systems engineering, sensor integration, and autonomous operations simultaneously, though most published accounts focus on fixed-wing or multirotor design rather than on the ML/AI pipeline that increasingly defines UAS capability.

Our work extends this literature by documenting how thermal-imaging ML projects specifically can serve as a vehicle for vertically integrated research teams spanning high school through graduate levels.

Project portfolio and technical overview

This section briefly describes the five projects that formed the basis of the student learning experience. Technical details are kept to the level needed to understand the educational challenges; fuller treatments of individual projects appear in companion technical papers.

Project 1: Thermal human head temperature estimation

Students implemented a dual-pipeline approach combining YOLOv11 segmentation with pose-assisted head localization to estimate human head temperature from radiometric thermal images captured by a Skydio X10 UAS (Fig. 1). One pipeline used upper-body mask slicing to approximate the head region; the other used detected keypoints for refined localization. Radiometric metadata embedded in each frame provided per-pixel temperature values.

Student roles: The graduate student (Ph.D., Interdisciplinary Engineering) designed both the segmentation and pose pipelines, wrote the radiometric extraction code, and trained the YOLOv11 models. One undergraduate student (Mechanical Engineering) assisted with data collection during flight sessions at altitudes of 20–60 feet across three separate outdoor sessions in Marietta, GA, and handled dataset annotation using Roboflow, labeling over 800 thermal frames. The graduate student walked the undergraduate through the annotation protocol and the logic behind each pipeline stage so they understood the technical rationale, not just the mechanics. The faculty advisor operated the Skydio X10 for all flights under FAA Part 107 authorization and co-collected data alongside the undergraduate, while also providing weekly project meetings for progress review and troubleshooting.

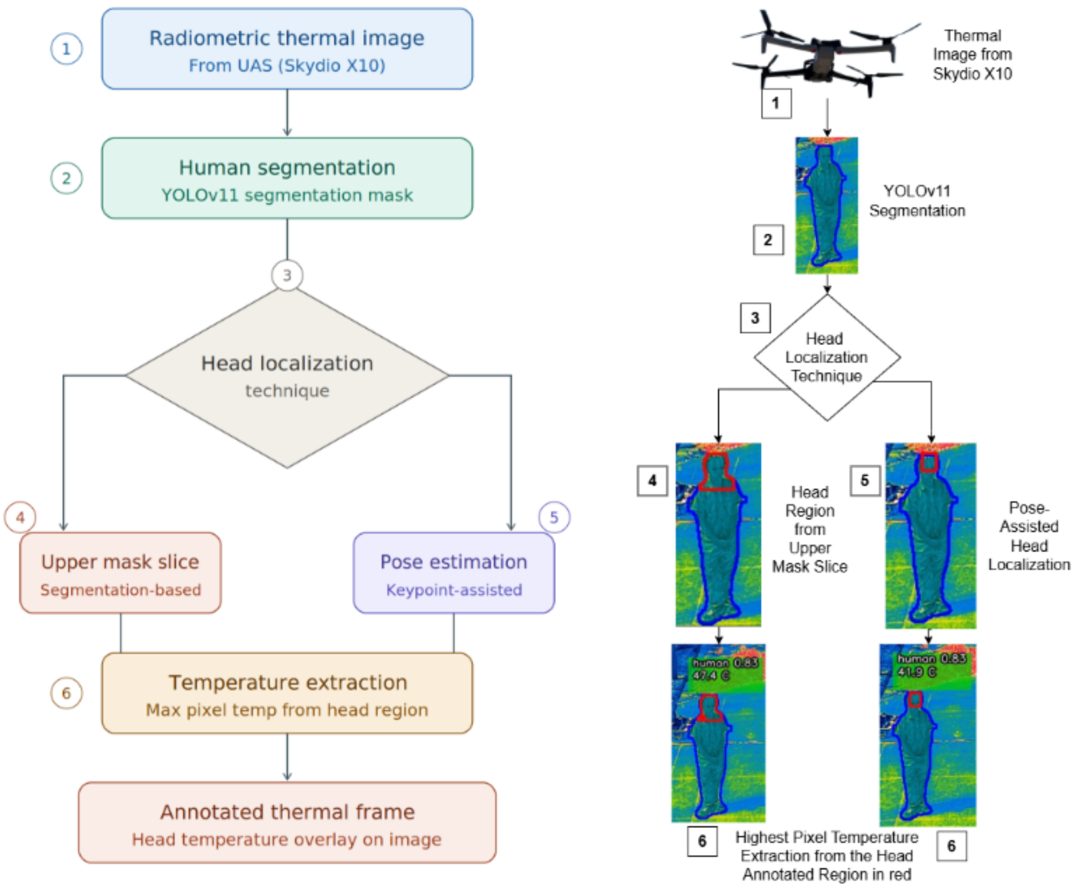


Figure 1: Dual-pipeline approach for head temperature estimation: YOLOv11 segmentation and pose-assisted head localization from Skydio X10 radiometric thermal imagery.

Project 2: Autonomous thermal-vision human condition detection

Students trained a custom YOLOv12 model on over 2,000 annotated thermal images to classify human postures as "Mobile" or "Immobile" in real time (Fig. 2). The model achieved inference speeds of 25–30 FPS on a ground-station laptop.

Student roles: The graduate student led all model training, hyperparameter tuning, and code development. One undergraduate (Mechanical Engineering) staged the mobile/immobile scenarios with volunteer subjects, performed annotation, and handled documentation. The faculty advisor operated the Skydio X10 for all thermal video data collection across multiple spectral modes. The graduate student conducted regular walkthroughs of the YOLO training process with the undergraduate so that labeling decisions were informed by their impact on model performance.

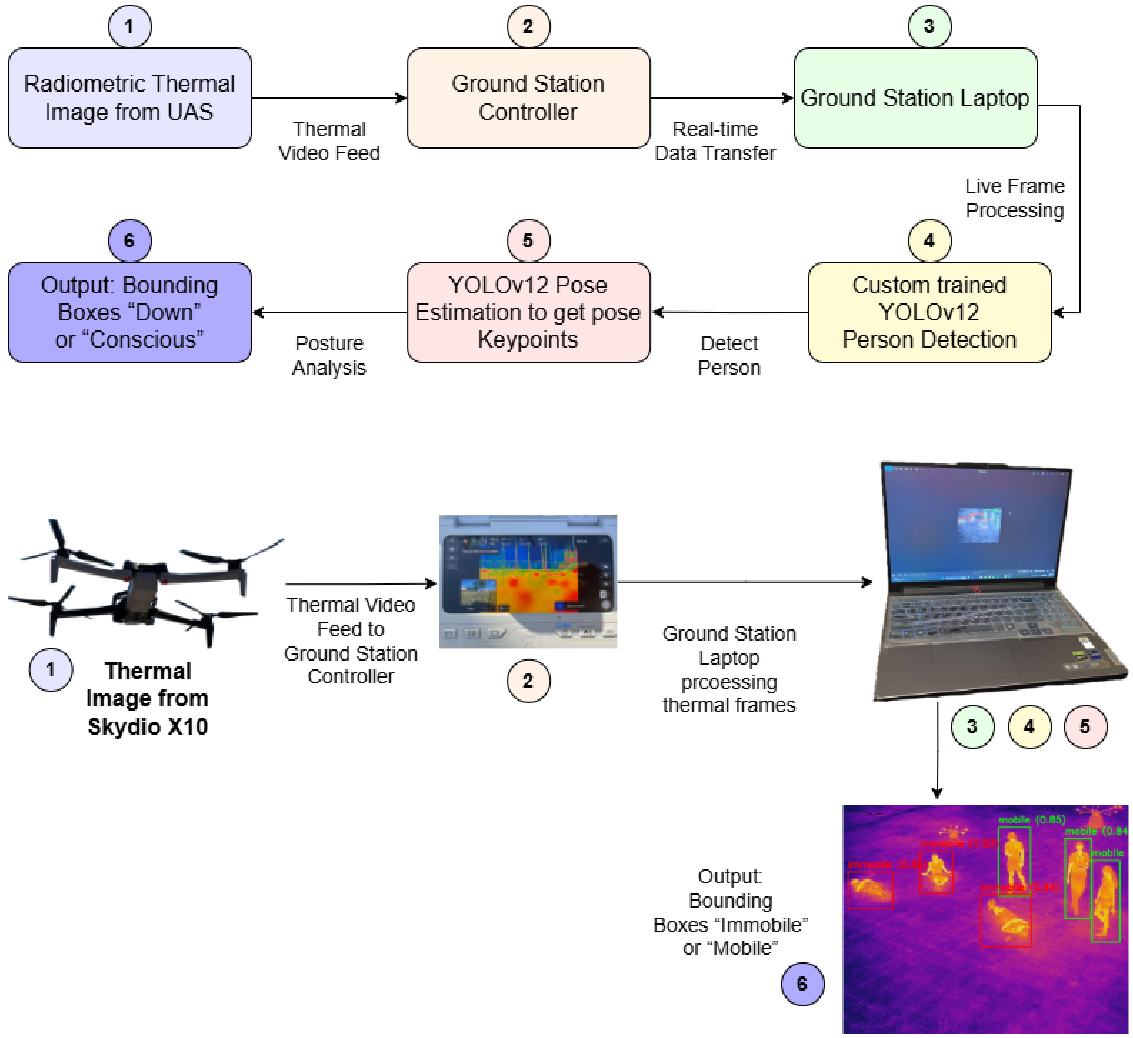


Figure 2: Autonomous thermal-vision human condition detection workflow using the Skydio X10 UAS and a custom-trained YOLOv12 model.

Project 3: Autonomous UAS-based photovoltaic array inspection

This project developed an automated pipeline for detecting and analyzing photovoltaic (PV) arrays using RGB and thermal imagery from a Skydio X10 with a FLIR Boson sensor (Fig. 3). A YOLOv12 model detected individual PV modules from RGB imagery; bounding boxes were then mapped to corresponding thermal frames for hotspot detection.

Student roles: The graduate student designed the full detection-to-thermal mapping pipeline and wrote the bounding-box projection code. One undergraduate (Mechanical Engineering) assisted with the data collection campaign at a campus rooftop solar installation and a commercial solar farm. The faculty advisor operated the Skydio X10 for all flights. The graduate student walked the undergraduate through the alignment logic and common failure modes (e.g., parallax offsets between the two camera sensors) so the student could identify misalignment during field data review.

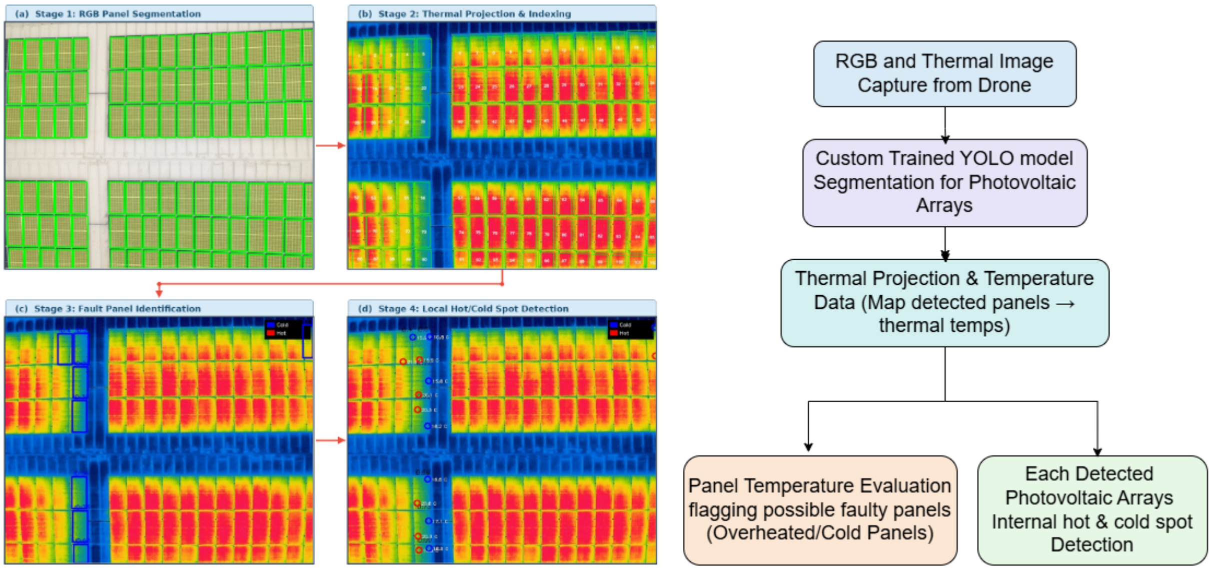


Figure 3: UAS-based photovoltaic inspection pipeline: RGB-based YOLOv12 panel detection followed by thermal hotspot analysis on corresponding radiometric imagery.

Project 4: Foreign object debris detection

Students developed an AI-assisted model for identifying Foreign Object Debris (FOD) on runway and pavement surfaces, comparing thermal and RGB imagery across multiple environments (Fig. 4). Several YOLO model versions were trained and tested on annotated datasets of diverse debris types.

Student roles: One undergraduate (Mechanical Engineering) designed and executed the debris placement protocol, scattering objects of known material and size on a parking lot test surface, and performed annotation. One high-school student contributed to the literature review on FOD detection standards, assisted with data collection and the data collection campaign, and helped organize the debris type catalog. The faculty advisor operated the Skydio X10 for all flights and coordinated access to controlled airside test areas. The graduate student developed all model training scripts, ran the comparative analysis across YOLO variants, and wrote the results discussion.

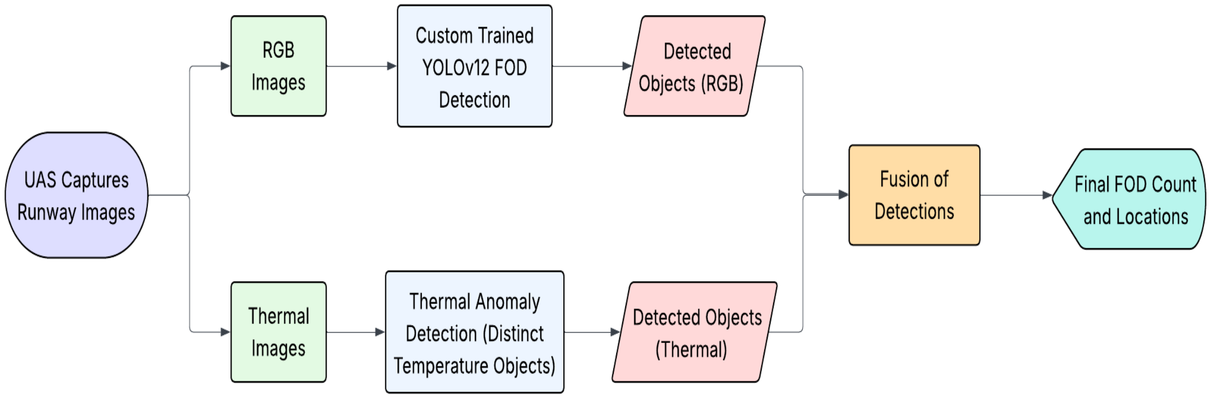


Figure 4: Foreign Object Debris detection pipeline using dual-modality (thermal and RGB) UAS imagery for runway safety applications.

Project 5: Building facade heat-loss detection

This project developed an end-to-end pipeline for automated detection of thermal anomalies on building facades using co-registered RGB and radiometric thermal imagery (Fig. 5). Unlike the YOLO-based approaches used in the other projects, this pipeline combined a vision-language model (Grounding DINO) with the Segment Anything Model 2 (SAM 2) for open-vocabulary building segmentation, meaning the system could segment any building type without task-specific training data. RGB and thermal images were aligned using a resolution-invariant homography calibrated from eight manually selected correspondences (mean reprojection error: 2.71 thermal pixels). K-means clustering then partitioned the segmented building mask into isothermal zones, from which the top-10 hottest and coldest spots were extracted and annotated with translucent ring markers on the aligned RGB output.

Student roles: The graduate student designed the full pipeline architecture (homography calibration, Grounding DINO + SAM 2 integration, K-means clustering, and spot extraction logic) and wrote the entire Python codebase. One undergraduate (Mechanical Engineering) assisted with data collection around multiple campus buildings with different facade materials (brick, glass curtain wall, concrete, stucco) and manually selected the eight RGB-thermal correspondence points needed for homography calibration. One high-school student contributed to the literature review, assisted with the data collection campaign, and handled documentation. The faculty advisor operated the Skydio X10 for all flights and identified target buildings based on expected thermal bridge locations from construction type.

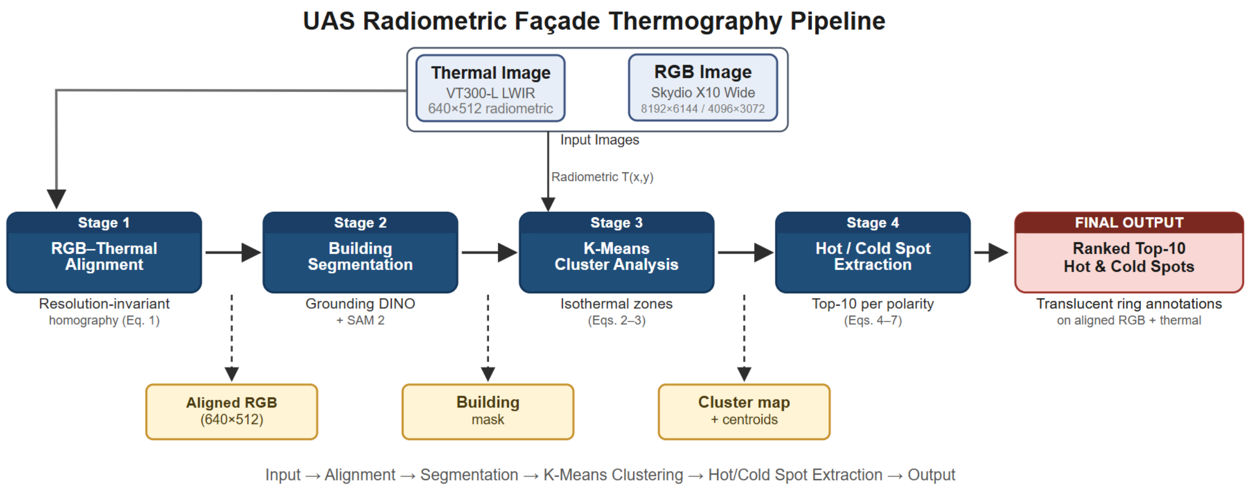


Figure 5: UAS-based radiometric facade thermography pipeline: RGB-thermal alignment via resolution-invariant homography, building segmentation using Grounding DINO + SAM 2, K-means isothermal clustering, and ranked hot/cold spot extraction.

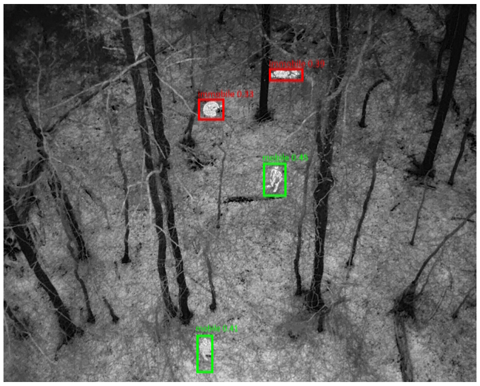
Results summary

Technical results are summarized briefly here; the educational outcomes that emerged from the process of obtaining these results are discussed in the following sections.

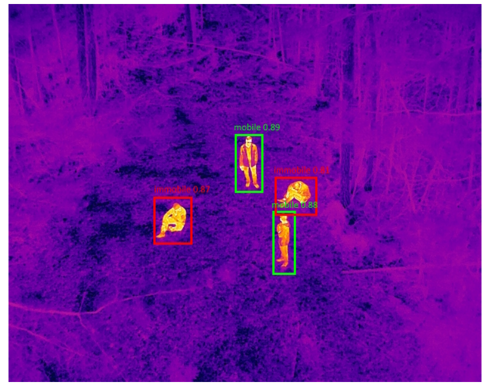
(a) Segmentation-based head temperature estimation.

(b) Pose-assisted head localization.

Figure 6: Project 1 results: Head temperature estimation from Skydio X10 thermal imagery using YOLOv11 segmentation (a) and pose-assisted localization (b). Both methods produced consistent readings within a few degrees Celsius of ground-truth measurements.



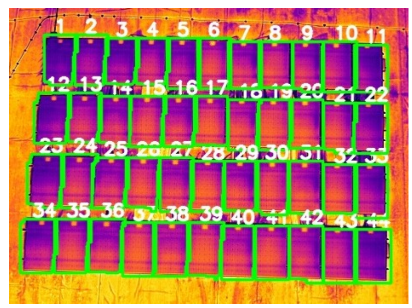
(a) Mobile and immobile detection.



(b) Varied posture and thermal conditions.

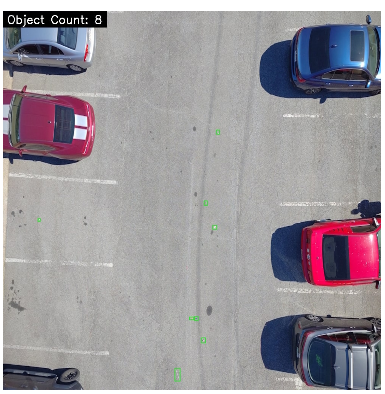
Figure 7: Project 2 results: Real-time classification of mobile versus immobile individuals using YOLOv12 on thermal video at 25–30 FPS.

(a) PV panel detection from RGB imagery.

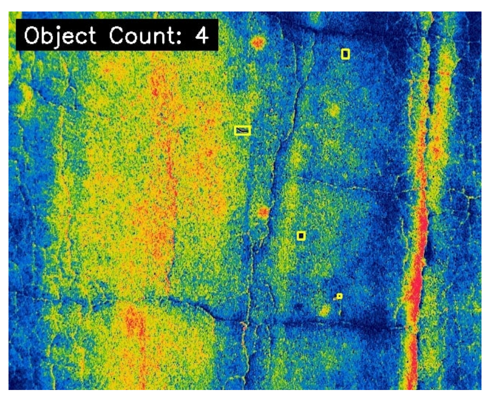


(b) Thermal anomaly identification.

Figure 8: Project 3 results: YOLOv12-based photovoltaic panel detection (a) and thermal hotspot analysis (b) on a rooftop installation.



(a) RGB debris detection (8 objects).



(b) Thermal debris detection (4 objects).

Figure 9: Project 4 results: Comparative FOD detection performance. RGB imagery identified 8 objects; thermal imagery detected 4 objects with distinct temperature signatures, confirming the complementary strengths of each modality.

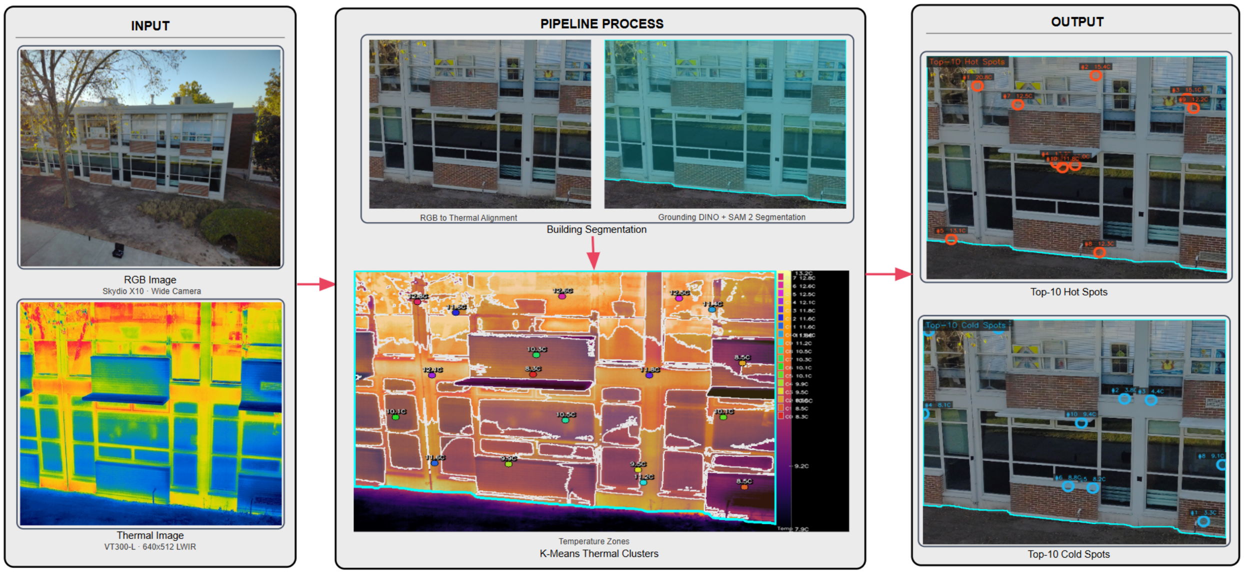


Figure 10: Project 5 results: Building facade heat-loss detection pipeline output. Left: input RGB and thermal imagery. Center: K-means isothermal cluster map with temperature zone boundaries overlaid on the segmented building mask. Right: ranked top-10 hot spots (red rings) and top-10 cold spots (blue rings) annotated on the aligned RGB output.

Across all five projects, the AI models achieved stable detection and analysis performance in thermal environments. The head temperature estimation pipeline produced readings within a few degrees Celsius of handheld thermometer ground truth. The human condition detector maintained balanced precision and recall at real-time frame rates. The PV inspection model distinguished faulty cells by surface temperature differentials. The FOD comparison confirmed that thermal imagery provides superior contrast for low-reflectivity debris under direct sunlight, while RGB performs better under uniform lighting. The facade thermography pipeline successfully identified thermal bridge locations consistent with known construction deficiencies (e.g., poorly insulated lintels above window rows), and the open-vocabulary segmentation approach generalized across building types without retraining. Collectively, the results demonstrate that both supervised (YOLO) and unsupervised/zero-shot (Grounding DINO + SAM 2, K-means) approaches have roles in UAS thermal analysis, and that exposing students to both paradigms broadened their understanding of the ML landscape.

Challenges and lessons learned

The projects described above did not proceed without difficulty. Documenting these challenges is important both for transparency and because the process of working through them constituted some of the most valuable learning.

Machine learning knowledge gap

Most undergraduate participants entered the lab with no prior exposure to deep learning, computer vision, or Python-based ML frameworks. The graduate student and faculty advisor addressed this through a structured onboarding process: students first completed a set of tutorials on YOLO architecture and the Ultralytics training pipeline, then practiced on a small toy dataset (detecting common objects on a desk) before working with thermal imagery. Even so, early training runs frequently failed due to incorrect annotation formats, mismatched image resolutions, or improperly configured hyperparameters. One team spent approximately two weeks debugging a model that would not converge before discovering that their label files used pixel coordinates instead of the normalized format YOLO expects. These debugging episodes, while frustrating, taught students to read error logs, inspect intermediate outputs, and test assumptions systematically. These skills transfer well beyond ML.

UAS operations and data collection

The Skydio X10 UAS was provided by the university and operated exclusively by the faculty advisor under FAA Part 107 authorization. Students participated in data collection by preparing test scenes (staging subjects for thermal imaging, placing debris for FOD detection, identifying target buildings), assisting with ground-level tasks during flights, and managing data transfer from the UAS to the ground-station laptop. Data collection sessions were weather-dependent, and multiple planned flights were canceled or rescheduled due to wind gusts exceeding the Skydio X10's operational limits. Students learned to build schedule buffers into their project timelines as a result. Observing the pre-flight planning process (airspace checks, weather assessment, battery management) gave students practical exposure to operational risk assessment even though they did not pilot the aircraft themselves.

Thermal data collection introduced its own difficulties. Early flights produced images with inconsistent radiometric readings because the camera's non-uniformity correction (NUC) cycle had not been allowed to stabilize before data capture began. Students learned through trial and error that the FLIR sensor required a warm-up period of several minutes, and that rapid changes in ambient temperature (such as transitioning from an air-conditioned vehicle to outdoor summer heat in Georgia) caused temporary calibration drift. These lessons are not typically covered in textbooks but are essential for anyone working with radiometric thermal sensors in the field.

Annotation quality and consistency

When multiple students annotated the same dataset, inter-annotator agreement was initially poor. Bounding box tightness, class labeling conventions (e.g., whether a person crouching should be labeled "Mobile" or "Immobile"), and handling of partially occluded subjects varied between annotators. The team addressed this by developing a written annotation guideline document and conducting a calibration session in which all annotators labeled the same 50-image subset, compared results, and discussed disagreements. After this calibration, labeling consistency improved substantially. This exercise gave students practical exposure to a problem that is well-documented in the ML literature but rarely experienced firsthand in coursework.

Computational constraints

The lab's GPU resources consisted of a single workstation with an NVIDIA RTX 3080 Ti, supplemented by the graduate student's personal laptop equipped with an RTX 4070. When multiple projects needed to train models simultaneously, students had to coordinate GPU scheduling across these two machines, which introduced them to job queuing and resource management. Some students experimented with Google Colab as an alternative, encountering its session time limits and storage constraints. These practical computing challenges taught resource-awareness that classroom assignments, which typically assume unlimited compute, do not.

Educational impact and student outcomes

This section constitutes the central contribution of the paper. The educational model used in the AERO Lab is described, followed by observed outcomes across several dimensions.

Team structure and mentorship model

The lab operated a tiered mentorship structure across all five projects. The faculty advisor defined research directions, secured equipment and flight authorizations, operated the Skydio X10 UAS for all data collection flights under FAA Part 107 authorization, reviewed all manuscripts, and held weekly meetings for each project to discuss progress and troubleshoot problems. A Ph.D. student in Interdisciplinary Engineering served as the day-to-day technical lead: designing all model architectures, writing all code, training all models, and mentoring the rest of the team on technical concepts and experimental design. Three undergraduate students (Mechanical Engineering) assisted with data collection, data annotation, data collection campaigns, and documentation. Three high-school students participated through outreach programs, contributing to literature review, dataset organization, and quality assurance.

This vertical integration was intentional. The graduate student developed leadership and communication skills by breaking down complex ML concepts for teammates with less technical background, ensuring that undergraduates understood not just what to annotate but why each labeling decision mattered for model convergence. Undergraduates gained research experience that is difficult to replicate in coursework alone. The high-school participants reported that the experience clarified their interest in engineering and directly influenced their college application decisions.

Skill acquisition

Participants entered the lab with varying levels of preparation. None of the undergraduate or high-school students had prior experience with YOLO, PyTorch, or radiometric thermal data processing. The graduate student addressed this gap through structured tutorials and hands-on walkthroughs before assigning independent tasks. By the end of their involvement, undergraduate and high-school participants had acquired working proficiency in several areas: Python scripting for data preprocessing and model evaluation; the conceptual basis of YOLO model training, validation, and inference; UAS data collection logistics including flight planning awareness and pre-flight procedures; thermal image interpretation including radiometric calibration considerations; dataset annotation using Roboflow along with development of labeling guidelines; technical writing and conference-paper preparation (all participants contributed to at least one manuscript); and version control with Git for collaborative code management.

Several of these skills are not formally taught in the mechanical or aerospace engineering curricula at the institution. Students consistently reported in exit interviews that the lab experience was the first time they had worked with a real neural network training pipeline, participated in UAS-based field research, or contributed to a peer-reviewed paper.

Impact on retention and academic performance

Of the seven students (three undergraduate, one graduate, three high school) who participated across the five projects during the 2024–2025 academic year, all three undergraduates remained enrolled in their engineering programs through the following semester. Two of these students had previously expressed uncertainty about continuing in engineering; both cited the lab experience as a factor in their decision to stay. While the sample size is small and no controlled comparison group exists, the 100% retention rate among undergraduate participants is notable given the institution's overall engineering retention rate.

Students also reported that the lab work improved their performance in concurrent courses. Two participants noted that debugging YOLO training failures gave them a much stronger grasp of matrix operations and loss functions when those topics appeared in their linear algebra and machine learning electives. Another student described how writing the methodology section of a conference paper helped them approach lab reports in other courses with greater structure and clarity.

Research outputs and professional development

The five projects collectively produced the following tangible outputs during a single academic year: five draft conference papers submitted to peer-reviewed venues (including this paper); one published journal article on dual-modality FOD detection (MDPI Drones); and multiple poster presentations at internal university research symposia.

Beyond these outputs, the experience shifted how students understood the research process. Several participants initially expected research to follow a clean, linear path from hypothesis to result. Encountering failed training runs, canceled flights, and ambiguous data forced them to adopt an iterative, problem-solving mindset that more accurately reflects professional engineering practice.

Comparison with traditional coursework

The lab experience differed from traditional coursework in several respects that students identified as valuable. First, the problems were open-ended: there was no answer key, and the "correct" model architecture or training strategy had to be discovered through experimentation. Second, failure was a routine part of the process rather than a grading penalty. Third, the work had external accountability: the data would be used in real publications, and sloppy annotation or careless flight planning had consequences beyond a grade. Fourth, the interdisciplinary nature of the projects (combining computer science, aerospace engineering, and thermal physics) required students to learn material outside their home discipline, mirroring the cross-functional collaboration common in industry.

These characteristics align with established findings in engineering education research that authentic, team-based project work improves both motivation and depth of learning relative to isolated problem sets.

Conclusions and future work

This paper has described a set of student-driven AI and ML projects at the AERO Lab that used UAS-based thermal imaging as both a research platform and an educational vehicle. The technical results, including functional detection and estimation pipelines for head temperature monitoring, human condition classification, PV array inspection, FOD identification, and building facade heat-loss detection, confirm that both supervised and zero-shot ML approaches can perform reliably in thermal environments when supported by carefully collected datasets. But the more important finding for the ASEE audience is that these projects, structured around a tiered mentorship model with explicit attention to student roles and iterative skill building, produced measurable educational outcomes: 100% undergraduate retention among participants, acquisition of skills not available in the standard curriculum, multiple peer-reviewed publications with student co-authors, and self-reported improvements in academic confidence and coursework performance.

The challenges documented here, including the ML knowledge gap, the difficulties of thermal data collection, annotation inconsistencies, and GPU resource constraints, are not incidental. They are the mechanism through which learning occurred. Students who debugged a failed YOLO training run learned more about neural network mechanics than a lecture on backpropagation could deliver. Students who watched a flight get canceled due to wind learned more about project planning than a Gantt chart exercise.

Future work will focus on three areas. First, we plan to formalize the assessment of educational outcomes through pre- and post-participation surveys with validated instruments (e.g., the CURE survey for undergraduate research experiences) to move beyond self-report data. Second, we intend to develop a structured onboarding curriculum, including tutorial notebooks and annotated example datasets, that other faculty can adopt to replicate this model without requiring extensive ML expertise themselves. Third, technically, we will pursue sensor fusion models combining thermal, RGB, and LiDAR modalities, deployment on embedded hardware (NVIDIA Jetson) for onboard inference, and adaptive flight planning for optimized data capture.

The combined efforts of undergraduate and graduate researchers at Kennesaw State University illustrate that AI-driven UAS thermal imaging can serve simultaneously as a productive research program and an effective platform for experiential engineering education. The key is treating educational outcomes not as a side effect of research, but as a co-equal design objective.

Acknowledgment

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In addition, AI-based writing assistance tools were used to improve grammar, clarity, and formatting during the preparation of this manuscript. All technical content, results, and interpretations remain the sole responsibility of the authors.

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