Research Statement — Kendall Koe

Feeding a growing population amid labor shortages, climate variability, and sustainability pressures demands technological innovation across every stage of food production. Robotics has the potential to revolutionize how we farm—automating labor-intensive processes and improving resource efficiency. My research focuses on developing intelligent robotic systems that integrate perception, control, and reasoning to operate reliably in unstructured agricultural environments. By uniting low-level precision control, adaptive manipulation, and high-level reasoning, I aim to create robots that work alongside humans to promote a more resilient and sustainable agricultural future.

My research journey bridges AI methods with practical field deployment, which gives me a distinct advantage in advancing agricultural robotics. Through collaboration with engineers, agronomists, and AI researchers, I have tested robots not only in simulations or laboratories but in actual greenhouses and fields—where lighting, occlusion, and unpredictability push systems beyond standard academic benchmarks. These experiences have shaped my ability to translate algorithmic insights into robust, real-world systems that can withstand the challenges of natural environments.

Perception and Control in Real-World Agriculture

My early work focused on the foundational problem of enabling precise robotic interaction in complex agricultural settings, where occlusion and uncertainty dominate. In my ICRA 2025 paper 1, I presented a co-designed visual servoing system that integrates a global detection camera with a local eye-in-hand camera, enabling a mobile manipulator to locate and harvest cherry tomatoes in dense, cluttered environments. Field trials demonstrated an 85% reach rate with an average cycle time of 10.98 seconds per fruit—evidence of true field viability. I have additionally collaborated with other researchers to develop algorithms to increase harvesting efficiency. I build on this foundation through my work on pest detection for precision spraying, where I compare lightweight and transformer-based models for on-board insect recognition. These studies reveal that smaller, task-specific networks outperform larger fine-tuned models in power-limited field robots, reinforcing the value of model efficiency and robustness over scale. This evaluates the limitation of current robotic hardware and exposed challenges with current large detection models. Together, these projects provide building blocks for reliable, low-level perception, and control in agricultural robotics.

Safe and Adaptive Manipulation:

To further improve reliability in cluttered, unstructured environments, my subsequent work explores adaptive hybrid manipulation systems that merge the compliance of soft actuators with the precision of rigid links. In my *Journal of Mechanisms and Robotics* paper[2], I developed a position and orientation controller for a hybrid rigid–soft arm using learned dynamics and trajectory optimization. The controller achieves 3.73 cm (<6% of arm length) and 17.78° error within 12.5 seconds—substantial gains over prior quasi-static approaches. Complementing this, my recent work introduces a real-time hybrid manipulator for obstacle-aware reaching, combining 3D scene reconstruction, shape-aware planning, and a learning-based behavior cloning controller that generalizes to unseen environments without retraining. These systems lay the groundwork for robots capable of safe, adaptive interaction with delicate plants, irregular terrain, and dynamic obstacles—a key requirement for real-world agricultural autonomy.

Reasoning and Human-Centered Task Planning:

Building on these capabilities, my ongoing research explores Vision-Language Models (VLMs) as high-level reasoning engines for agricultural robots. In this work, a VLM selectively queries visual and spatial inputs—such as local camera views and global maps—to plan and execute crop-monitoring tasks from natural language instructions (e.g., "Inspect the tomato plants and capture images of ripe fruits"). This approach democratizes robotics by enabling non-technical users to guide autonomous systems intuitively. I see this as the next frontier: connecting low-level control and high-level reasoning to create interactive, human-centered agricultural robots that adapt fluidly to complex missions.

Future Vision:

Looking ahead, my goal is to develop adaptable robotic systems that generalize across labor-intensive domains, extending lessons learned from agriculture to fields such as construction, logistics, and environmental monitoring. These domains share key challenges—unstructured environments, task variability, and human–robot coexistence—that demand robust, transferable solutions in perception, control, and reasoning.

One direction is pursuing the next generation of agricultural autonomy. Building on my prior control and manipulation work, I plan to develop adaptive crop-interaction frameworks that combine tactile sensing, 3D perception, and predictive control to improve harvesting, pruning, and precision spraying. These systems will adapt to plant variability and environmental dynamics in real time, enabling year-round operation in greenhouses and orchards through precise real time modeling of local regions where interactions occur. This work aims to establish agriculture as a model testbed for generalizable, real-world robotic learning—grounded in environmental uncertainty, deformable object handling, and high safety requirements.

Another direction I intend to pursue is the development of Domain-Transferable Learning Frameworks. Just as humans can transfer skills from one environment to another, my goal is to design cross-domain adaptation pipelines that allow perception and control policies trained in complex, low-data environments—such as agriculture—to generalize to other high-variability, safety-critical domains like medicine or planetary and underwater exploration. For example, a vision-based controller fine-tuned for fruit localization could be reparametrized for delicate surgical tasks or for identifying and manipulating fragile specimens in underwater or extraterrestrial environments—tasks that share the same need for compliance, precision, and adaptability.

My focus will be on low-data regimes where collecting and labeling data is inherently difficult, whether due to safety, ethics, or environmental constraints. Agriculture, medicine, and exploration settings all exemplify domains where robots must perform reliably despite incomplete world models. To address this, I plan to develop modular architectures and self-supervised adaptation strategies that reuse knowledge across domains, reducing the need for extensive retraining. By integrating model-based reasoning with continual learning from sparse, real-world feedback, these systems will achieve scalable autonomy in data-limited, uncertain environments—paving the way for robots that can adapt and assist wherever humans cannot safely go.

These research directions—developing adaptable, data-efficient robotic systems for agriculture, medicine, and exploration—not only push the boundaries of autonomy but also highlight the importance of hands-on, interdisciplinary learning. As a teacher-scholar, I aim to translate these challenges into the classroom, designing courses that integrate robotics theory, coding, and real-world experimentation. By engaging students in projects that mirror the complexity and impact of my research, I want to empower them to see how computing can solve societal challenges. Through mentorship and collaborative design, I hope to inspire students to become innovators and problem solvers, capable of applying engineering principles to diverse, high-stakes domains.

[1] Koe, Kendall, et al. "Precision harvesting in cluttered environments: Integrating end effector design with dual camera perception." *2025 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2025.

[2] Koe, Kendall, et al. "Learning-based position and orientation control of a hybrid rigid-soft arm manipulator." *Journal of Mechanisms and Robotics* 17.7 (2025): 071010.