Canadians for 21st Century Learning & Innovation

DELL Technologies

INTEGRATING AI IN EDUCATION: TRANSFORMING LEARNING — AN AI USE CASE INITIATIVE FOR CANADIAN EDUCATION

AI-Enabled Visual Inspection and Measurement in Safety-Critical Industrial Environments

PROBLEM OF PRACTICE

In safety-critical industrial environments, the most important inspection data is often located in the most difficult, hazardous and high radioactive dose intensive places to access.

Inspection teams may be required to work within tight spatial constraints, under strict safety limits, and within short operational windows with constant exposure to radioactive dose. In these conditions, every minute spent on-site matters. Measurements must be taken quickly, often with limited opportunity to pause, re-check, or validate results before leaving the inspection area.

This creates a persistent tension: ***how can inspection teams maintain precision, consistency, and professional judgment while reducing the need for human exposure in hazardous environments?***

GEORGE BROWN POLYTECHNIC

AI Innovation

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Problem of Practice

For years, industrial inspection has relied on a combination of manual tools, visual estimation, and highly trained expertise. These methods remain essential, but they can also introduce variability. Two inspectors may interpret the same condition differently. Measurements may shift depending on camera angle, line of sight, access limitations, lighting, or time constraints.

At the same time, structural degradation such as wear, contact damage, displacement, and misalignment often develops gradually. Detecting these early changes requires consistency, accuracy, and repeatability. These conditions are difficult to guarantee when inspection workflows depend on rapid manual observation in constrained environments.

The guiding question for this initiative is: ***How can we assist human inspectors and reduce the hazard without losing the expertise that makes inspection reliable?***

This use case explores how AI-enabled computer vision can support safer and more consistent industrial inspection by turning images and video into measurable, reviewable, and structured data. Rather than replacing inspectors, the project investigates how AI can extend their reach, support their judgment, and help create a more repeatable process for visual inspection and measurement.

Intent

This initiative began with a practical question: can a camera feed become a reliable measurement tool?

The project explored how AI-enabled computer vision could transform inspection from a physically constrained task into a remotely supported, data-informed workflow. In safety-critical environments, the ability to collect visual information without prolonged human presence has significant implications for worker safety, operational efficiency, and inspection quality.

> “We’re not trying to replace the inspector. We’re trying to enable them more and extend their reach. The goal is to let them see more, measure more, and verify more while reducing risks, this is a human assist tool.”
>
> Project Team Reflection

Rather than beginning with a narrow focus on model performance alone, the team focused on the relationship between visual data and physical measurement. Could spatial information such as gaps, alignment, relative positioning, and contact points be extracted consistently from images and video? Could AI help make inspection outputs more repeatable, reviewable, and useful for human decision-making?

The project team worked through multiple iterations using controlled setups and recorded inspection scenarios. In the early stages, the focus was on object detection and segmentation, identifying relevant features and components within visual data. Initial results were promising, but they quickly revealed a deeper challenge.

In one test scenario, the same physical setup was recorded under different conditions. When measurements were extracted from the videos, the results varied, even though nothing in the physical environment had changed. This became a key learning moment for the team.

> “At first, we thought if the model could detect it, we were done. But we kept getting slightly different results. That’s when we realized detection is easy. Measurement is the real problem.”
>
> Team Reflection

Further testing showed that small changes in camera angle, frame selection, video resolution, and object positioning could influence measurement outputs. In one case, selecting a frame where the object was slightly off-center resulted in slightly different spacing measurements.

This shifted the project from model experimentation to pipeline thinking. The team began focusing not only on whether AI could identify features, but on how a full inspection process could produce measurements that were stable, explainable, and validated.

Intent

The project increasingly focused on:

- object detection and segmentation
- stable frame selection
- multi-frame comparison
- feature tracking across video sequences
- early image stitching exploration
- 3D spatial mapping from multiple camera feeds
- calibration against known references
- validation against physical benchmarks
- repeatable measurement logic
- optimization and real time capabilities

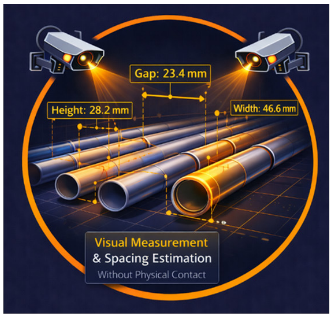
To support rapid experimentation and large-scale video processing, the project leveraged the **Dell Pro Max with GB10**, a deskside AI development system built on the NVIDIA GB10 Grace Blackwell Superchip. This Dell Pro Max with GB10 platform provided the GPU-accelerated training and experimentation environment needed to handle high-resolution video data, run real-time inference experiments, test multiple computer vision approaches in parallel, and move quickly between design, testing, and refinement.

Over time, the system evolved into a pipeline that integrates visual feature detection, segmentation, tracking, spatial estimation, post-processing, and measurement validation. Rather than relying on a single model output, the team focused on building a repeatable process that could be explained, tested, and improved.

How AI will help

Object Detection and Segmentation

3D Spatial Mapping from Multiple Camera feeds



Gap Measurement Without Dosage Risk

Early detection of degradation

Impact

The impact of this work extends beyond technical feasibility. It changes how inspection can be understood and approached in safety-critical environments.

Safety as a Standard

By enabling measurement through images and video, the system has the potential to reduce the need for prolonged physical presence in dose intensive or constrained environments. Instead of entering a space primarily to measure, inspectors may be able to review visual data remotely, validate conditions in advance, and reduce the time spent in high-risk areas.

This does not remove the need for human expertise. Instead, it changes where and how that expertise is applied. Inspectors remain central to the process, but AI-supported tools can help them review, compare, and verify information before, during, or after physical inspection.

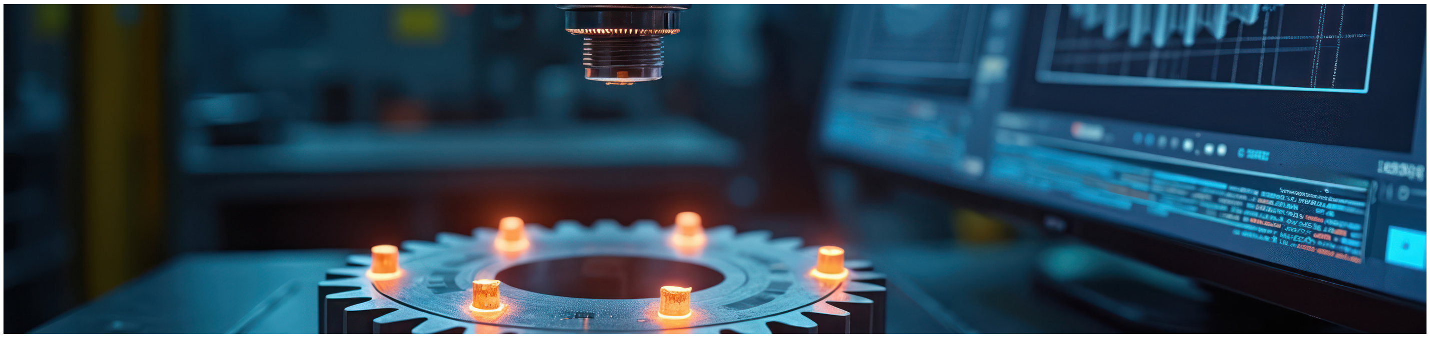
In this way, safety is not treated as a secondary benefit of automation. It becomes a central design principle for the entire inspection workflow.

From Manual Observation to Structured Insight

The project also introduces a more structured approach to inspection. Measurements are no longer treated only as one-time observations made under time pressure. Instead, they can become repeatable, reviewable, and comparable across time and conditions.

This is particularly important in industrial environments where small changes may indicate early signs of wear, misalignment, or degradation. When inspection data can be compared across multiple frames, multiple videos, or repeated inspection cycles, teams can begin to identify patterns that may be missed through isolated manual observation.

The early pipeline developed through this project brings together detection, segmentation, tracking, image processing, and measurement logic. This creates the foundation for inspection workflows that are not only faster, but also more transparent and easier to review.



Impact

Technical Progress Through Real Testing

The project made progress across several areas of AI-enabled visual inspection. The team tested multiple detection and segmentation models, implemented a tracking pipeline, explored post-processing workflows, and began early work on image stitching. The team also expanded model development for multiple component classes and continued a second training phase to improve accuracy and robustness across scenarios.

Several technical insights emerged through the project's testing process.

In one comparison scenario, measurements derived from different video resolutions showed noticeable variation. This reinforced the importance of calibration, capture quality, and consistency in inspection conditions.

In another case, selecting different frames from the same video produced different measurement outputs. By comparing multiple frames and identifying more stable reference points, the team began reducing this variation and improving confidence in the results.

The team also resolved several pipeline errors as the workflow became more automated and integrated. This allowed for faster experimentation cycles and more consistent testing across different approaches.

These findings helped the team clarify a critical principle: the value of AI in safety-critical inspection is not simply automation. Its value lies in creating a process that can be trusted.

For this reason, the team moved away from asking only whether the system could detect an object or feature. Instead, the project began asking whether the system could produce a result that was consistent, explainable, and useful for inspection decision-making.

Impact

Professional Learning insights

This project changed how the team understood AI in industrial systems.

At the beginning, much of the focus was on model performance. The central question was whether the model could detect the relevant feature. As the work progressed, the team came to understand that detection was only one part of the challenge.

The deeper professional learning came from recognizing that AI used in safety-critical environments must be held to a higher standard. It is not enough for the system to produce an answer. The process behind that answer must be traceable, testable, and explainable.

The team learned that:

- AI in safety-critical environments must be designed with transparency and accountability in mind
- measurement logic matters as much as model accuracy
- data quality, camera positioning, lighting, and capture conditions significantly affect results
- validation against known physical measurements is essential for trust
- repeatability is central to responsible use in industrial contexts
- human expertise remains necessary for interpretation, judgment, and final decision-making

The project also highlighted the value of collaborative inquiry. Faculty leadership, student researchers, technical contributors, and project partners worked together through regular technical reviews, shared model evaluation, feedback, and iterative model training cycles. This created a shared understanding of the full system rather than a narrow focus on isolated technical tasks.

For the student team, the project created an applied learning experience in computer vision, AI model development, segmentation, tracking, spatial measurement, and systems thinking. Team members gained hands-on experience working with larger AI models, scaling datasets across multiple component classes, troubleshooting pipeline errors, and evaluating performance across different testing scenarios.

Impact

Professional Learning insights

What Worked Well

- **Pipeline-based thinking:** The team moved beyond a single-model mindset and began developing a repeatable process for visual measurement.
- **Rapid experimentation:** Access to the **Dell Pro Max with GB10** environment enabled quick iteration by combining GPU-accelerated model training with high-throughput video processing. The team used the Dell Pro Max with GB10 as a dedicated AI workstation to retrain models, refine the visual inspection pipeline, and repeatedly process large video datasets, turning it into the core platform for rapid experimentation and performance tuning.
- **Technical collaboration:** Regular technical reviews and shared evaluation helped the team refine models, troubleshoot issues, and improve the inspection pipeline.
- **Real-world problem framing:** The project remained grounded in a practical inspection challenge rather than treating AI as a standalone technical exercise.
- **Human-centered positioning:** The team consistently framed AI as a tool to support inspector expertise, not replace it.

What Can Be Improved

- **Measurement accuracy** is still sensitive to camera positioning, viewing angle, perspective distortion, frame selection, and video resolution. Additional validation against physical measurements is needed to confirm the reliability of outputs across different environments and conditions.
- **Segmentation accuracy** also requires continued improvement, particularly as the system expands across multiple component classes and more complex visual scenarios. Image stitching and 3D spatial mapping will need further refinement to support more robust measurement from multiple camera feeds.
- **Real-time performance also requires further optimization.** For the system to be useful in active inspection workflows, it must be able to process visual information quickly while maintaining accuracy and explainability.
- The team also identified the **need for standardized data capture protocols**. Without consistent capture practices, even strong models can produce inconsistent results. Future work will need to define expectations for camera placement, resolution, reference markers, lighting, and acceptable measurement thresholds.
- Perhaps most importantly, the team recognized that **building trust in AI systems requires more than accuracy.** It requires transparency. In safety-critical settings, users must be able to understand how an output was generated, what conditions influenced it, and when human review is required.

Going Forward

The next phase of this work will focus on moving from experimentation to validation and deployment readiness.

The team will continue refining the system to improve real-time performance, expand measurement capabilities, validate results against physical benchmarks, and strengthen robustness across different inspection conditions.

Future work will also focus on developing practical guidance for responsible implementation. This may include data capture protocols, calibration procedures, validation checklists, and documentation to support explainable use in safety-critical environments.

Key next steps include:

- improving segmentation accuracy
- training and evaluating larger models
- improving image stitching and post-processing workflows
- expanding the range of measurable inspection features
- validating AI-derived measurements against manual and physical benchmarks
- evaluating accuracy and repeatability across different scenarios
- strengthening performance across varied camera angles, resolutions, and lighting conditions
- developing standardized data capture protocols
- documenting the conditions under which the system performs reliably
- defining points where human review and sign-off are required

The long-term vision is to support a shift in how safety-critical inspection is performed.

From manual, exposure-dependent workflows to remote, data-driven inspection systems, this project points toward a future where inspectors can make better-informed decisions while spending less time in hazardous spaces.

This project is not simply about applying AI to inspection. It is about redefining the relationship between human expertise, visual data, and safety. By turning video into measurable and structured information, the system creates a new layer of insight that supports the inspector’s judgment.

It enables safer working conditions, more consistent measurements, and scalable inspection workflows. Most importantly, it lays the foundation for a future where inspection is not limited by physical access, but enhanced by intelligence, evidence, and human expertise.