

A background image of an industrial machine, likely a vision inspection system. It features a large, black camera lens with a gold-colored ring, mounted on a black metal frame. The machine is positioned over a dark, reflective surface. In the background, there are various mechanical components, including a white metal bracket and a black cable. The image is overlaid with several semi-transparent blue hexagonal shapes.

TECHNICAL BRIEF

AI Vision Inspection Process Overview

Automation NTH

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INTRODUCTION

AI-driven vision inspection systems are reshaping quality control in modern manufacturing. These technologies expand the possibilities of automated inspection by offering adaptability, scalability, and the ability to recognize complex patterns beyond the reach of traditional rule-based systems. At Automation NTH, our AI vision integration solutions are engineered to deliver highly accurate and consistent inspection capabilities tailored to our customers' specific production requirements.

Because AI models learn from visual examples, the quality and structure of the development process are crucial. Just as a human operator improves with experience in identifying defects, AI models must be trained, validated, and deployed through a systematic and well-managed approach. This whitepaper outlines Automation NTH's methodology for successfully executing AI vision projects—from initial goal definition through development, deployment, and continuous improvement—ensuring value and reliability for our customers.

DEFINING INSPECTION GOALS AND REQUIREMENTS

A successful AI vision project begins with a clear and detailed definition of inspection goals. While this process shares similarities with traditional vision systems, AI development introduces new considerations. A well-defined scope and criteria help prevent inconsistencies in training data, which can otherwise impact performance, timelines, and cost.

Customers should understand that AI inspection requirements can differ significantly from standard vision systems. Below are key considerations when developing a User Requirements Specification (URS) for an AI vision project:

Inspection Requirements

- Start by documenting work instructions for what a trained operator looks for during visual inspection, as a foundation for requirements. Include example images, if possible. These can be exemplary and not online production images.
- Identify the visual features that distinguish pass/fail conditions. This includes specific defect criteria, pass/fail conditions and/or thresholds, along with acceptable tolerances.
- Confirm lighting and part handling constraints before system design and evaluation.
- Detail any additional product or environment constraints that can affect the pass/fail conditions. For instance, are certain blemishes or anomalies only defective on specific portions of the product?

Sample Images/Product

- Provide representative images (or product) of both acceptable and defective parts. See section on Data Collection and Preparation for details.
- Include samples that are fully representative of product and condition variance for lighting, product appearance, and defect types and presentation.
- If sufficient image or product samples are unavailable upon project commencement, AI inspection evaluation may not be fully vetted and may result in additional project costs and risks. If similar inspections cannot be presented, a Proof of Principle investigation will be required to quantify AI inspection effectiveness.

ASSUMPTIONS AND CLARIFICATIONS

1. Training & Sample Dataset

- AI vision performance depends on the quality and quantity of the sample dataset provided.
- The customer must supply a representative set of images covering acceptable and defective parts for AI model training.
- If insufficient samples are available, additional training may be required, impacting timeline and cost.

2. Performance & Accuracy Expectations

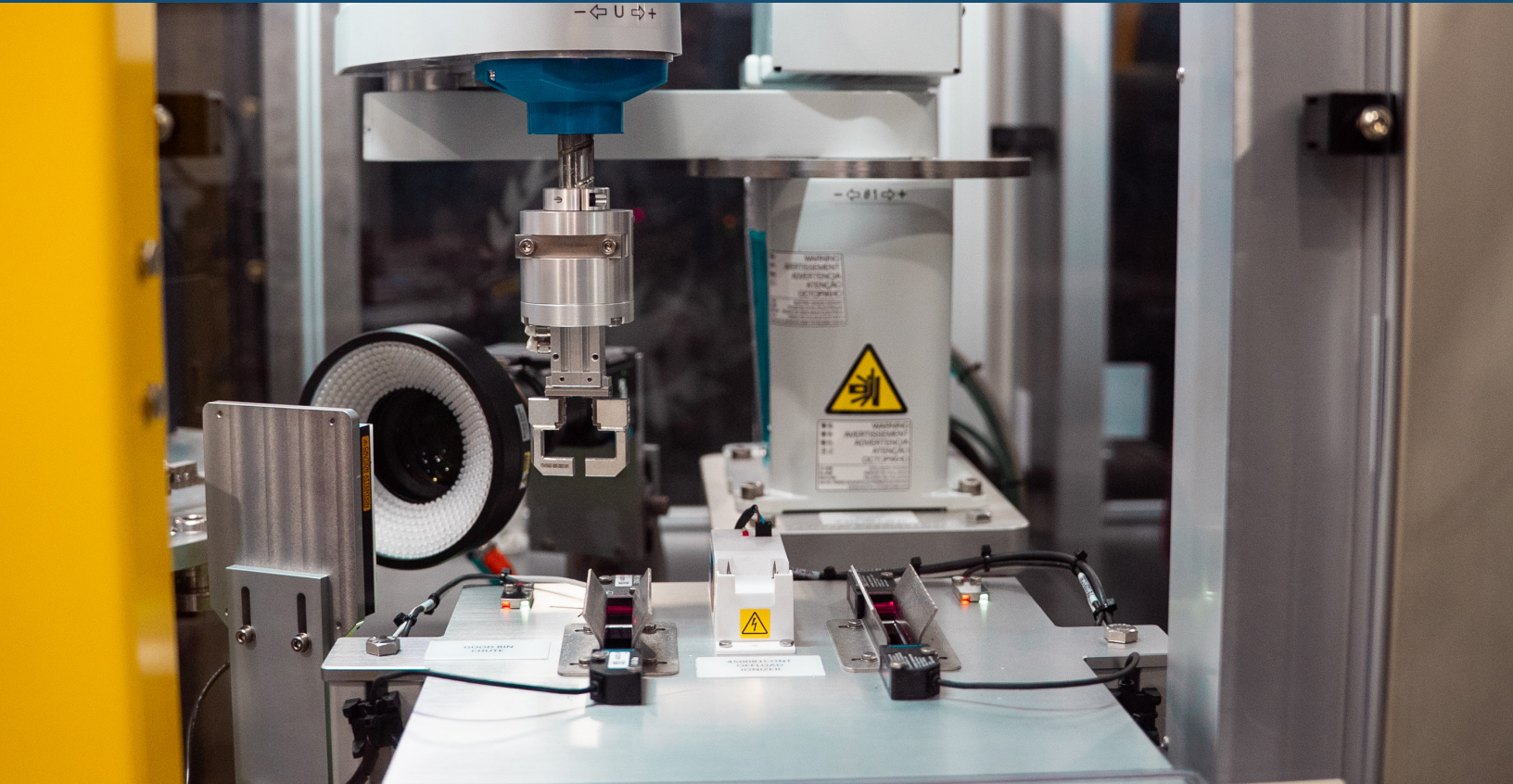
- AI vision is probabilistic, not deterministic; results may have some variance based on presentation of defect conditions.
- Expected accuracy levels must be defined upfront (e.g., detection rate, false-positive/negative tolerance).
- Final accuracy depends on lighting, part variability, and environmental conditions.
- The customer is considered the expert in product evaluation and should be available for labeling and reviewing of AI training data.

3. Environmental & Part Variability Considerations

- AI models require stable lighting and consistent part presentation for optimal performance.
- Any variations in materials, surface finishes, or positioning outside the trained dataset may impact performance.
- Changes to part design, color, or defects beyond the trained model scope may require re-training at an additional cost.



ASSUMPTIONS AND CLARIFICATIONS



4. AI Model Training & Validation

- Initial model training will be conducted with provided samples; additional training may be required if results do not meet expectations.
- Validation testing will be conducted with customer-provided samples before deployment and after each training update.
- Customers are responsible for reviewing and approving vision inspection criteria before final implementation.

5. Limitations & Ongoing Support

- AI models may require periodic retraining due to product/process drift or new defect anomalies.
- Additional retraining, reprogramming, or process modifications beyond initial scope will be quoted separately as a Change Notice (C/N).
- Post-deployment support, customer training and AI model tuning beyond the proposed durations are available via support contract as needed.

SOLUTIONS

Accurate and consistent data collection is foundational to effective AI model training. At this stage, assumptions about part consistency, environmental stability, and defect variability must be clearly documented and understood by AI developers.

Guidelines for Data Collection:

- Gather images under conditions that reflect actual production environments as closely as possible.
- Include all known defect types and natural variations in part materials.
- Ensure that the data covers edge cases and borderline examples.

AI Performance Considerations:

- AI performs best with stable, consistent parts and lighting.
- The more complex or variable the application, the larger and more diverse the dataset required.

Measurement Limitations:

AI vision systems are not well-suited for high-tolerance dimensional measurements. While they can match or exceed human judgment for visual estimation, they are not designed for tasks that require micrometer-level precision. If precise measurements are essential, consider combining AI with traditional vision tools or metrology solutions. In such cases, a proof-of-principle evaluation is recommended to validate feasibility and accuracies before full implementation.

Key Takeaway:

Well-prepared, diverse, and accurately labeled image datasets significantly increase the likelihood of AI model success and reduce development iterations. The minimum image requirements vary based on numerous factors, with 500–1,000 images generally requested for common defects and over 2,000 images required challenging cases. Means of bulk testing validation images is critical! Insufficient sample data or post-training model testing can lead to misclassification of defects, increased false positives, and compromised inspection precision.

MODEL SELECTION AND TRAINING

Once data has been collected, the next step is to select and train the appropriate AI model architecture. The chosen model type depends on the inspection task, part characteristics, and expected output (e.g. processing and decision logic, detection, segmentation).

Model Training Workflow:

1. Pre-process data and annotate training images.
2. Choose a model architecture (e.g., classification CNN, object detection network).
3. Train the model using curated datasets.
4. Validate performance using separate test data.
5. Iterate as needed to improve generalization.

Training Objectives:

- Achieve high sensitivity (detecting actual defects).
- Maintain high specificity (avoiding false positives).
- Ensure robustness to normal variations in parts or lighting.

Models must not only perform well during testing but must generalize reliably to real-world production data.



DEPLOYMENT AND INTEGRATION

Once a model has been trained and validated, it must be integrated into the production line. This includes:

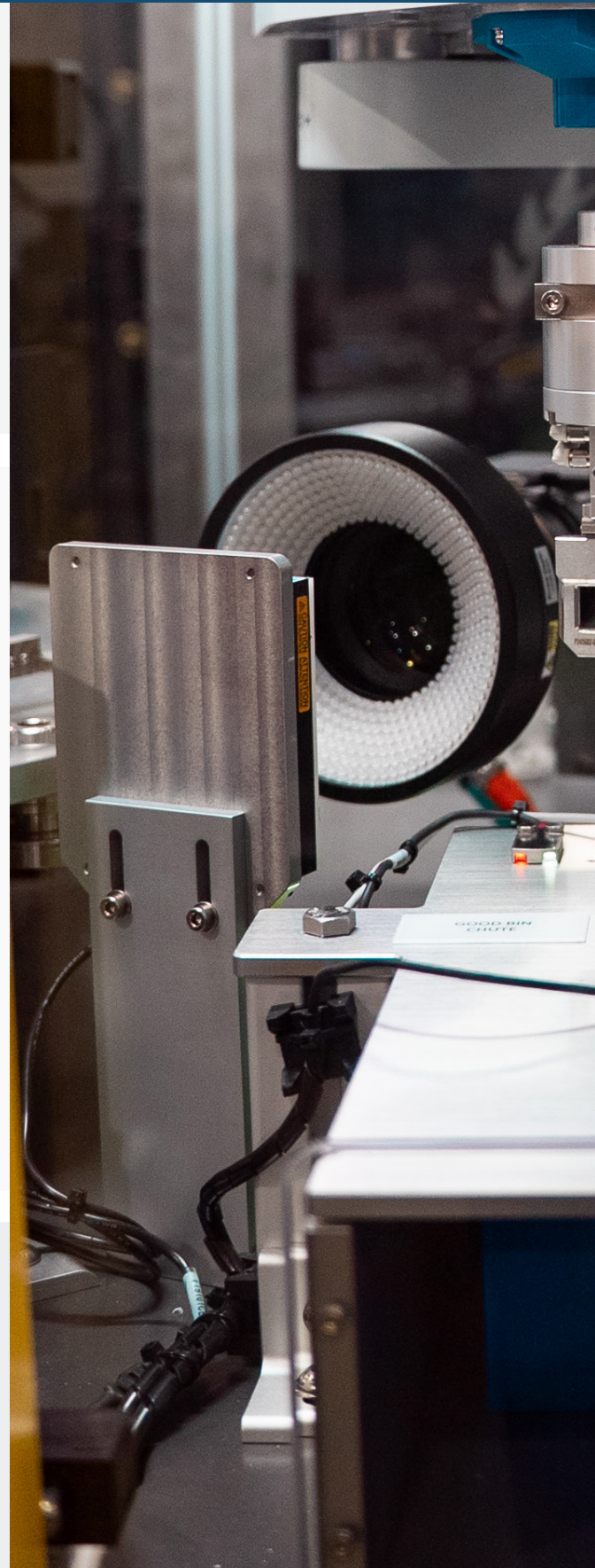
- Camera and lighting hardware integration
- Triggering and timing coordination with automation systems
- Processing and decision logic along with reject handling
- Communication of inspection results to line control systems
- Process result recording and raw image labeling and storage

Considerations During Deployment:

- Validate model performance in production-like settings.
- Establish pass/fail logic thresholds and alarm conditions.
- Monitor real-time performance and accuracy.

Key Takeaway:

Seamless integration with existing automation infrastructure is critical to the success of an AI vision inspection solution. All processed images should be categorized and stored for an agreed to duration for potential system review and retraining.



MAINTENANCE AND CONTINUOUS IMPROVEMENT

AI vision systems are dynamic and benefit from regular monitoring and tuning. Over time, part designs, materials, or process variables may change—necessitating updates to the model.

Best Practices for Maintenance:

- Implement logging/recording of inspection results for analysis.
- Regularly review edge cases and mis-classifications.
- Schedule periodic model retraining with updated image data.

Revalidation Procedures:

To maintain regulatory or quality standards, formal revalidation procedures should be in place when model updates are made. Golden product/images should be maintained for minimal, exemplary requirements validation after every model retraining

CONCLUSION

AI-based vision inspection offers significant advantages in flexibility, defect detection, and scalability. However, success depends on thoughtful planning, high-quality data, and a structured development process. At Automation NTH, our approach ensures that every stage—from requirements definition to deployment and improvement—is aligned with your operational goals. By following this process, customers can be confident that the developed AI vision solution enhances product quality, reduces development and maintenance costs, and unlocks long-term value from intelligent automation.

About NTH

Founded in 1999, Automation NTH is a trusted partner in automation for manufacturers, with our headquarters located just outside of Nashville, TN and additional offices in San Diego, CA. Our expertise transforms your manufacturing operations from manual processes to semi-automated and fully automated production. Whether scaling up from individual work cells or introducing fully integrated production lines, we deliver solutions that drive cost savings, enhance efficiency, and minimize risks. With a strong focus on robotics and controls, we ensure timely delivery of projects with strict adherence to budget.

Key markets we serve include:



Medical
Diagnostics



Drug Delivery
Systems



Wearable
Devices



Therapeutic
Devices



Vascular
Technologies

Our innovative approaches improve production capacity, product quality, and enable operator autonomy.

Our Solutions:

- Customized Automation: Scalable production solutions for complex products.
- Proof of Principle Creation: Validating manufacturing processes before full automation.
- Scalable Production: From semi-manual cells to full automation.

Services We Provide:



Custom Automation



Automation Consulting



Equipment Optimization

Engineering Your Edge, Together!

Contact Us today at sales@automationnth.com