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Final Project Report

Smart Monitoring and Automated Real-Time Visual Inspection of Sealant Application (SMART-VIStA)	
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Project Team Lead	Siemens
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MxD Contract Number	2021-01
Project Participants	Siemens, University of Cincinnati, Boeing
MxD Funding Value	N/A
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Completion Date	9/30/2022

This project was completed under the Technology Investment Agreement W15QKN-19-3-0003, between Army Contracting Command – New Jersey and MxD. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Department of the Army.

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I. EXECUTIVE SUMMARY

As a space grade solar panel manufacture, Boeing needs to assemble solar panel by gluing multiple solar cells together. A glue deposition robot deposits the glue dots at predefined positions. In current manual operation, skilled operators monitor each dot after deposition to confirm that the dot is deposited accurately in specified position with specified shape quality – no tails or connections between dots. Early detection of gradual degradation in dot quality helps an operator to modulate several process parameters in deposition module or to take corrective actions to prevent deposition of overlapping glue dots on the solar panel. This dot-to-dot high precision inspection process is a very tedious, repetitive job and could be replaced by automated visual inspection system, as has been the case in all other industries (such as automotive) to retain US employment.

In this project we propose to advance in-situ quality inspection technology named SMART-VISTA by developing a real-time adaptive solution for anomaly detection on reflective planner surface leveraging progress in recent computer vision technology. A dual feedback mechanism is developed based on visual perception (i) to refine deposition path of the robot after determining precise coordinates of the solar cells in robot frame, (ii) to tune up-stream process parameters based on dot quality inspection results so that potential quality degradation of the product can be avoided. SMART-VISTA system comprises an active image acquisition subsystem, an image processing subsystem, and a recommender subsystem with real-time control feedback. Novel image processing algorithm based on state-of-the art deep learning technology performs defect detection, classification and quantization on highly reflective planner surface. Then a Bayesian network-based advisory feedback system is developed to recommend the process parameters to be changed in up-stream process in a timely manner considering the characteristics of detected anomaly and the current context of the process. Finally, digital thread integration of the inspection data with digital twin of the inspected object helps in gaining real-time insights of the inspection process. Overall, our close loop active visual inspection system provides a complete solution not only to detect anomaly but also to prevent occurrence of future anomalies with huge market potential.

The technology is demonstrated for high quality adhesive deposition at Boeing manufacturing facility. The evaluation shows effectiveness of the technology in improving dot deposition path accuracy in terms of precise location of dots (<2 mm varaition), dot quality improvement with correct process parameter estimation (>90% accuracy). SMART-VISTA technology may yield unprecedented technological solutions in the domain of real-time in-situ automated inspection process. In such settings, the active monitoring systems works like a real-life human inspector by finding the best position to do inspection. Ability to predict future events associated with quality degradation through tracking gradual change in inspected object quality will be used to alert up-stream worker to take corrective action as required. Additionally, by anticipating the need of future up-stream parameter change, the system can not only respond more quickly (e.g., by preemptively tune the appropriate process parameter, etc.), but also better ensure the quality of the product.

SMART-VISTA software along with detailed user manual is shared with MxD.

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II. PROJECT DELIVERABLES

Table 1: MxD-20-02-07 Project Deliverables

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SOW Deliverable Names	**Deliverables as submitted**	**DESCRIPTION**	**FORMAT OF DELIVERY**
Deliverable Task 1.1 A Set of Project Requirements	Deliverable 1: Project requirements documentation	Deliverable 1 is a description document of the project requirements across all the partners.	Word Document
Deliverable Task 2.1: Image capture system: phase 1: manual/semi-automated; phase 2: following task 6.1 fully automatic	Merged into Deliverable 5: Vision-based Path Planner	Deliverable 5 is a software module for performing automatic path planning of the glue dot deposition robot by camera calibration and solar cell localization together with image capture system. This deliverable includes following software modules: (1) Cell detection and pose estimation module; (2) Module to find solar cell location w.r.t. robot; (3) Module to communicate with an industrial camera and industrial controller over OPC UA.	Code repo with readme and licensing.txt
Deliverable Task 2.2: Labeling User Interface. Labeled and cleaned image data.	Deliverable 3: Labeling User Interface	Deliverable 3 is user-interface used for performing image pre-processing operations and for labeling glue dot position and defect types.	Software Module
Deliverable Task 2.3: Meta data and storage Interface.	Deliverable 4: Meta data and storage Interface	Deliverable 4 is a storage interface to store image as well as meta data to optimize the control feedback.	Software Module
Deliverable Task 3.1: Cell detection and pose estimation algorithm.	Merged into Deliverable 5: Vision-based Path Planner	See deliverable 5	See Deliverable 5

Deliverable Task 3.2: Glue dot detection and anomaly localization.	Merged into Deliverable 5: Vision-based Path Planner	See deliverable 5	See Deliverable 5
Deliverable Task 3.3: Glue dot classification algorithm.	Merged into Deliverable 6: Inspection with Recommendation	Deliverable 6 is a software module that includes a GUI for visualizing dot inspection results along with process parameters recommendations for reducing/removing fluid deposition errors using state-of-the-art machine learning techniques. This deliverable includes following software modules: (1) Glue dot detection and anomaly localization module; (2) Glue dot classification module; (3) Glue dot quality quantification module; (4) A BDN network module for process parameter optimization; (5) A knowledge graph module representing the glue deposition process; (6) User Interface for advisory feedback analytics visualization; (7) Edge deployable software.	Code repo with readme and licensing.txt
Deliverable Task 3.4: Glue dot degradation quantification algorithms.	Merged into Deliverable 6: Inspection with Recommendation	See Deliverable 6	See Deliverable 6
Deliverable Task 4.1: A trained BDN network for process parameter optimization.	Merged into Deliverable 6: Inspection with Recommendation	See Deliverable 6	See Deliverable 6
Deliverable Task 4.2: A knowledge graph representing the glue deposition process.	Merged into Deliverable 6: Inspection with Recommendation	See Deliverable 6	See Deliverable 6
Deliverable Task 5.1: The User Interface for advisory feedback analytics visualization.	Merged into Deliverable 6: Inspection with Recommendation	See Deliverable 6	See Deliverable 6

Deliverable Task 5.2: Edge deployable software solution.	Merged into Deliverable 6: Inspection with Recommendation	See Deliverable 6	See Deliverable 6
Deliverable Task 6.1: Fully automated robotic cell for (a) Localization; (b) Deposition; (c") Capture	Merged into Deliverable 6: Inspection with Recommendation	See Deliverable 6	See Deliverable 6
Deliverable Task 6.2: Integrated Inspection evaluation and recommendation system	Deliverable 7: Demonstration of the technology	Deliverable 7 involves transfer the technologies to Boeing manufacturing research facility at Charleston for final demonstration. (1) Demonstration of the fully automated robotic cell for (a) cell localization; (b) glue deposition after path automatic refinement; (c) image capture after glue deposition. (2) Demonstration of the integrated inspection evaluation and recommendation system.	Video and Final Presentation

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III. PROJECT REVIEW

Use Cases & Problem Statement

Industrial operations have come a long way in the automation era. Unfortunately, several processes remain dependent on human input which creates variability in output and reduces final product quality. For example, human variability is problematic with (a) real-time adjustments of process parameters (often required in less than 0.5 seconds), (b) inspector fatigue, (c) inspector error, and (d) other real-time human "adjustments on the fly" required during the manufacturing process. The challenge is to eliminate human judgment and variability and replace it with scientific measurement and evaluation which approaches a 100% accuracy rate. In this proposal, the processes we automate are largely dependent on the human workers and the knowledge that they have gained with time and repetition. Replicating the "on the fly" adjustments made by an experienced operator performing the job is currently unavailable on the shop floor. The goal is to provide a real-time array of actions (through algorithm development and artificial intelligence) to be taken to prevent the repeating flaws and in some case propagating the flaw to an out of tolerance condition. Therefore, a need exists for a real-time inspection system with automated optimization of process parameters to reduce large labor costs, operator subjectivity, variation in quality inspection and corrective action, and risk associated with time loss if corrective actions are not taken timely.

Current work addresses the product quality inspection problem faced by the manufacturing partner in our team – Boeing. Boeing is the supplier of all space panels for DoD satellites and competes internationally with foreign suppliers. It currently makes the reflective space cells and then assembles them into panels for space application. One of the highest risks in the manufacturing process is automating the placement of over 10,000 dots of adhesive to bond reflective cells to the structural backboard of size 2x3 ft. Currently the event requires 14 individuals working as a team to place dots to assure each dot passes a real-time manual verification on dot location, and form factor (circular, with limited elongation). Unacceptable dots are immediately identified and reworked if possible. Operators are regularly trained and tested for dot quality and location, yet costly problems do occur, halting production and creating schedule and financial impacts.

Figure 1: Automated deposition with manual inspection.

As a solar panel manufacturer who relies on fluid deposition on planner surface, Boeing wants to automate the quality assessment with real-time feedback/recommendation so that they can take corrective measure in time which in turn would increase productivity and overall quality of the product. As an aerospace manufacturing engineer of Boeing, I want to automate the deposition of sealant dots on solar cells, so I can decrease the necessary flow time and amount of rework.

Scope & Objectives

Although Boeing has defined an automated system to perform dot location as shown in Figure 1, yet a technical gap still exists on the quality of the automated dot placement. To overcome the processing challenge, a new system employing a vision module is needed. The new system evaluates the current dot quality, and an artificial intelligence (AI) module predicts the corrective actions (if any) to take before moving to the next phase of dot deposition.

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Our overarching objective of this project is to develop **a close-loop AI inspection system** integrated with Digital Thread to provide timely, actionable insights about the quality of the current adhesive dots. The specific objectives are described below:

- **Vision-based Inspection with Limited Data:** Develop advanced deep neural networks to perform visual inspection of dot anomalies that is trainable on coarsely labeled limited defect data. This flexibility helps to overcome the challenges of limited defect data in manufacturing scenarios.
- **Close Skills Gap**: Provide the operators with real-time feedback about the current glue dot quality, type of degradation, highlighted location of degradation on Digital Twin of the solar panel, possible reasoning for the degradation, and recommendations for change in process parameters or corrective action to be taken before the next dot deposition. Thus, it helps in closing the skill gap, reducing operator variability, increasing trust on AI-system.
- **Digital Thread Benefits**: Create Digital Twins of solar panels to map real-time glue quality inspection results within possible defect sources, enabling downstream decisions through Digital Thread integration.

Planned Benefits

Our technology leads to significant quality improvements during the assembly of photovoltaic components. The technology developed within this project could be deployed to assist with sealant application and a range of Boeing's own commercial and defense programs where the need to automate the application of sealant has been identified as a goal for all programs within 10 years. The solution developed will be integrated with the existing automated glue disposal system of Boeing, allowing stakeholders to improve the overall process. This technology replaces 14 human workers currently needed in this operation with an automated system defined and designed by the Boeing Company in its Solar Panel Manufacturing company. Our proposed solution not only addresses the quality control challenges for Boeing, but it also enables the integration of AI and Vision modules in several other real-time quality inspection applications throughout the US manufacturing base, such as automated welding, painting, and soldering.

Potential benefits to MxD members are diverse: MxD members can use our unique capability for active monitoring and vision-based quality control applications. The framework will be useful for a number of applications beyond sealant deposition. A range of real-time inspection actions could be improved using this method impacting a range production processes. We anticipate increased interest in MxD membership and licensing agreements to use the capabilities of the MxD portfolio enabling MxD to have a robust ROI for this project.

IV. TECHNICAL APPROACH

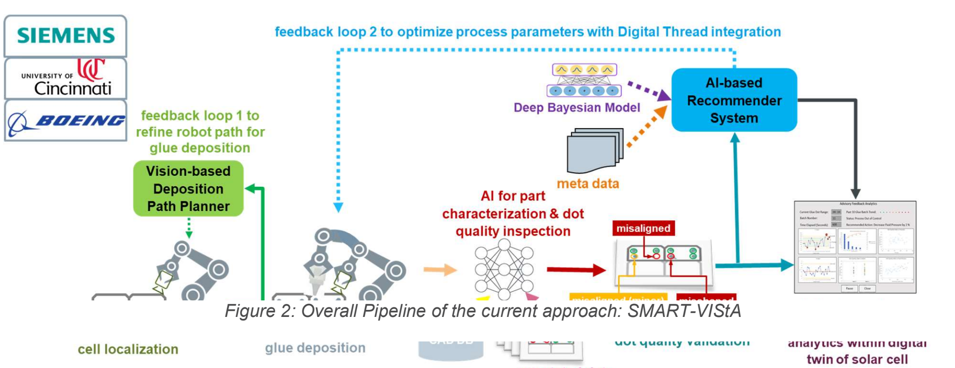

Figure 2: Overall Pipeline of the current approach: SMART-VIStA

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The quality control inspection system SMART-VIStA enables the adoption of a real-time inspection methodology for sealant deposition with AI learning from previous dots. The **dot inspection** system comprises an image acquisition and deposition path planner subsystem, an image processing subsystem, and a recommender subsystem with real-time control feedback. **Error! Reference source not found.** shows the overall pipeline of the current approach that includes a dual feedback mechanism based on visual perception. After the solar cells are placed on the planner surface, a robot with mounted camera is moved to capture images of the individual cells. As shown in **Error! Reference source not found.**, in feedback loop 1, a vision subsystem is employed to determine precise coordinates of the solar cells in robot frame to redefine glue deposition path w.r.t. actual cell positions. After the robot makes glue deposition, using feedback loop 2, the tuning of up-stream process parameters is performed for reducing/removing fluid deposition errors before depositing the next dots using state-of-the-art machine learning techniques. This avoids potential quality degradation of the product. Finally, Digital Thread integration of the inspection data with the Digital Twin model of the solar cell is done to help users gain real-time insights of the inspection process and recommendations through a graphical user interface. Our closed loop active visual inspection system provides a complete solution to detect dot anomaly and to prevent the occurrence of future faults.

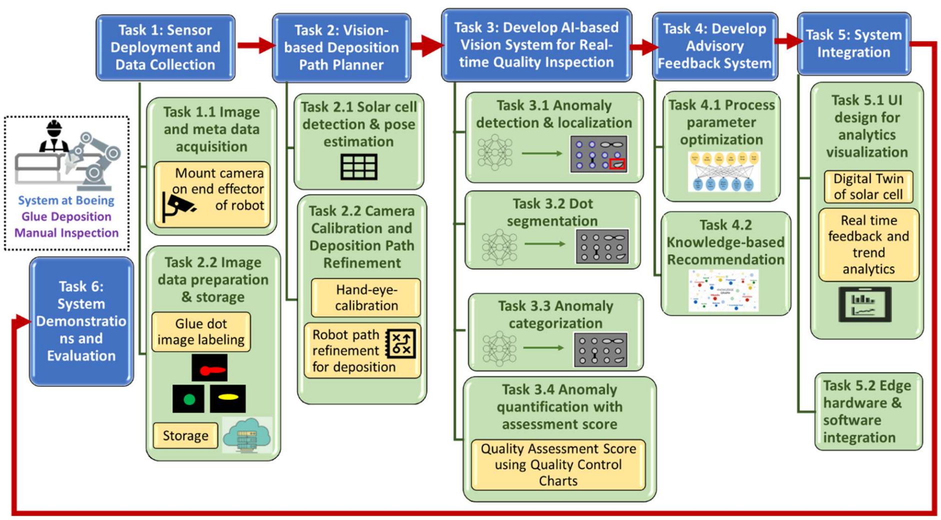


Figure 3:Task Overview diagram for SMART-VIStA framework development

Based on the real-time dot-to-dot glue deposition use case described before, we have come up with work packages for the successful execution of this project. **Error! Reference source not found.** shows the task-flow of the overall approach. These tasks were performed through collaborative efforts between the various team members.

Task 1. Sensor Deployment and Data Collection:

This task involves camera sensor deployment, and robot deposition path planning for both dot deposition and dot image data collection to perform smart inspection (Task 2 and 3). Image dataset preparation (Task 1.2) as well as process parameter collection for training of different machine learning models (Task 3 and 4) is also part of this task. Each of the modules are described in detail in the following sub-sections.

Task 1.1 Image and Meta Data Acquisition

Camera Setup: The image acquisition task is performed using a Mako 192c industrial camera. The camera was attached to the end effector of the Kuka KR 10 industrial robot, which provides the required flexibility to maneuver the camera for image capturing.

Metadata: Along with the glue dot images, associated metadata about the dot quality, manufacturing controls and process parameters (pot pressure, open time, dwell time, trigger delay, motion factor) was obtained from automated deposition system. Figure 4 Shows robot nozzle tip motion path and associated tunable motion parameters that had direct or indirect effect on got quality. By varying these parameters, different scenarios were created for experimental data collection.

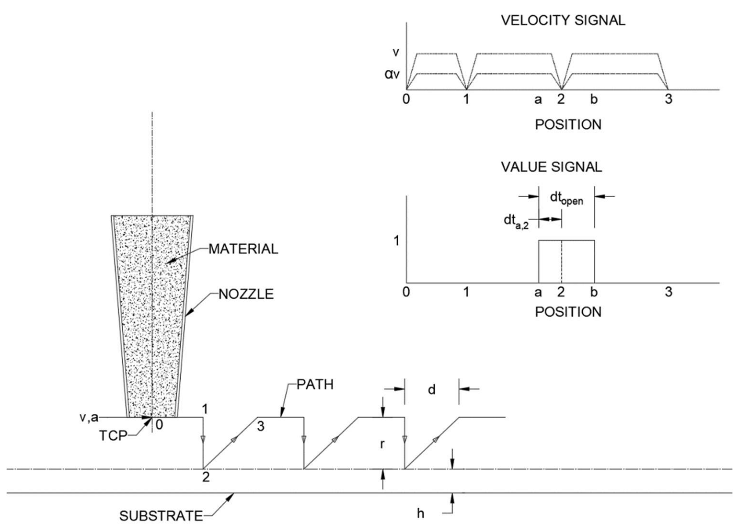
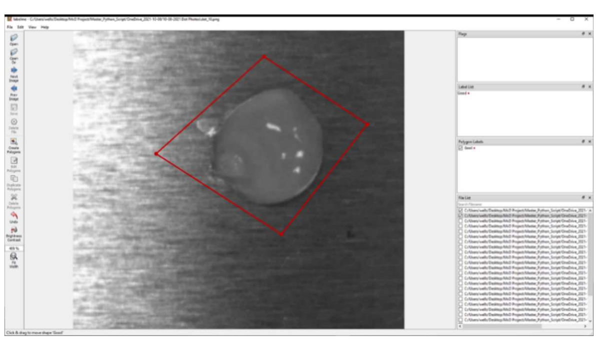


Figure 4: Glue deposition robot motion path illustration



Task 1.2 Data Preparation and Storage

After acquiring the cell and glue dot images, an open-source user-interface LabelMe[1] is used for performing image pre-processing operations and labelling the image into either one of the defect classes or as a perfect image, as shown in **Error! Reference source not found.**.

[1] *https://github.com/wkentaro/labelme*

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Data Storage: We developed a cloud storage in Amazon S3 (Simple Storage Service) to store all data to serve as input for ML model training. A well-defined version control system is set up to keep close track of the ML models and the various batch of data inputs used to train them.

Task 2. Vision-based Deposition Path Planner:

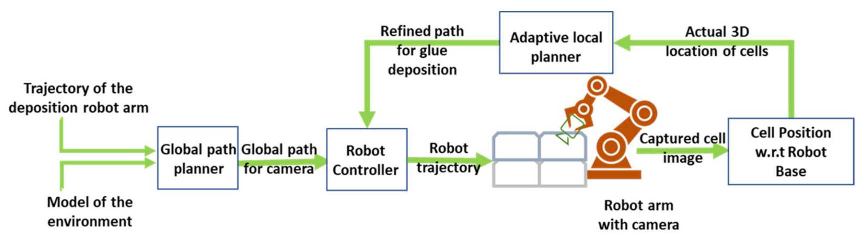


Figure 6: Path planner module workflow

The objective of this module is to determine precise coordinates of the solar cells in the robot frame. To achieve this goal, hand-eye calibration is first employed to find out the spatial relationships between a camera, robot, and cell. Then, the cell detection module (described in the next section) computes the corners of the cells in form of image pixel coordinates. These 2D pixel coordinates are then transformed into 3D robot base frame coordinates once the depth from the camera to the object is known. Figure 6 shows the workflow of this module.

Task 2.1 Cell Detection and Pose Estimation

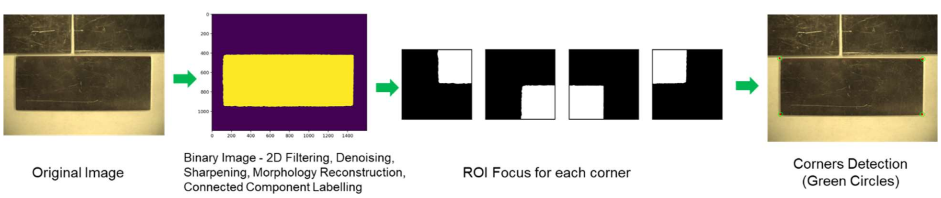
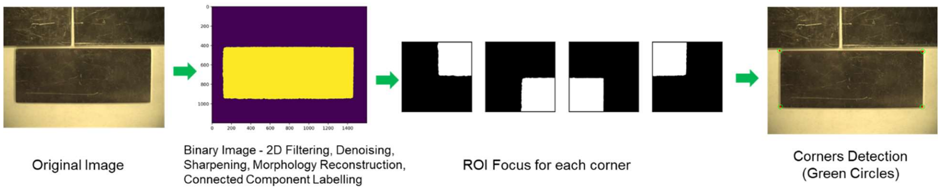


Figure 7: Steps in detecting the corners for cell plate

Cell Detection: In this module, the primary task is to detect and localize the desired cell. The top-view cell image is first binarized using OpenCV image-processing libraries. This process also ensures removal of scratches, burrs, and marks (referred to as noise) on the plate. The OpenCV algorithms include 2D filtering, denoising, sharpening, and morphology reconstruction. In the next step, connected component labeling (CCL) is implemented to filter out the region of interest (ROI) of the desired cell. Here, the CCL filters out the largest area of connected pixels to obtain the binary image of a single cell. First two images of

Figure 5: Data Labeling UI



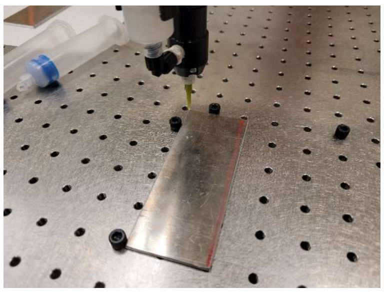


Figure 8: Eye-in-hand calibration verification by sending the tool tip to the corner of a cell

Figure 7 shows result of this stage on input image data.

Corner Detection: After finding the binary image, the cell image was observed to have a focal distortion resulting in a slight curvature around the top and bottom edges. Hence implementing commonly available open-source-based corner point detection algorithm would result in an error. To alleviate this issue, a two-step approach is implemented – first, to find approximate corners through either the OpenCV-based rectangle corner point detection or Hough Transform method and second – to focus on the ROI around these detected corners and re-apply Hough transform. The approximate corners are obtained using intersection of Hough lines (Please refer

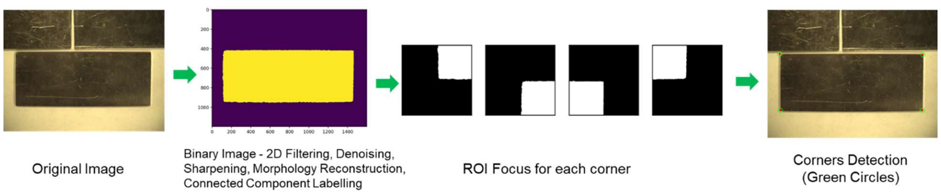


Figure 7, third image from left). While the current method is applied to detect corners for a rectangular artifact, this approach can be easily extended to detect corners for an n-sided polygon. The right most image in

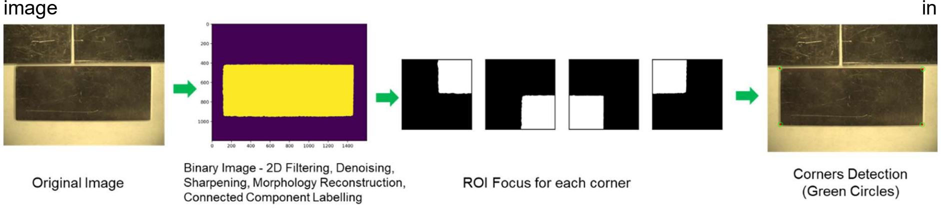


Figure 7 shows the output of this stage with detected corner highlighted in green.

Task 2.2 Camera Calibration and Deposition Path Refinement

The camera calibration is performed as an eye-in-hand calibration. This method computes the intrinsic camera parameters such as focal length, lens distortion, and camera center in addition to computing the transformation between the camera coordinate frame and the robot flange frame. It is performed by taking many images of a static calibration target (checkerboard of known square size) from different robot poses. A least-squares solver reprojects the calibration target points to the images taken using the computed eye-in-hand calibration until the reprojected points line up well enough with the actual corners of the checkerboard in the images. With the eye-in-hand calibration, it is possible to convert any image point from pixel coordinates to robot coordinates if the depth (normal distance from the camera center) of the point is known. With a calibrated camera, the depth can be computed by taking images of geometry of known dimensions. Once this is done at one height above the table that the target cells rest on, the depth can be known at any height by adjusting by the height of the known robot pose.

The 2D pixel coordinates detected from Task 2.1 are transformed into 3D robot base frame coordinates using these calibration parameters. Then this information is used to update the deposition path of the robot. The accuracy of cell localization with hand-eye-calibrated camera is tested by taking images of a cell, then commanding the robot to send the tool tip to the exact corners of the cell, or to marked locations on its surface (Please refer Figure 8). It is possible to then visually see if the tool tip lines up with the target on the cell. Any misalignment is corrected via a manual adjustment to the camera-to-flange transformation.

Task 3. AI-based Vision System for Real-time Quality Inspection:

This task involves development of Computer Vision algorithms for detecting quality of the glue dot (Task 3.1) and its position ((Task 3.2) in terms of expected shape, size and location. Anomaly in shape occurs as dot with tail, elongated, sparse, crescent as shown in Figure 9. A dot could be regarded as anomalous if the dot size is too small or too big dot. Even if the dot is not deposited in the expected location, then that off-center dot is also considered as anomalous. If a glue dot is found to be anomalous, then the dot is further analyzed to find its anomaly class (Task 3.3) and degree of degradation (Task 3.4) with a quality metric. The results of such analysis will be used for (i) up-stream process parameter optimization (Task 4.1) and (ii) integration with Digital Twin framework for real-time visualization (Task 5.1).

Task 3.1 Anomaly Detection and Localization

The objective of this task is to detect whether the current dot is anomalous or not. If it is anomalous, then highlight the location of anomaly. To achieve this goal, we apply Siemens's state-of-the-art anomaly detection framework CAVGA[2]. CAVGA is able to localize anomalies with the help of attention maps from coarsely annotated data in weakly supervised manner. Its architecture is based on variational autoencoders (VAE)[3] and guided attention mechanisms as shown in Figure 10. Along with detecting a glue dot image as anomalous, we also focus on spatially localizing the non-circular glue dot anomaly in the image. Intuitively, without any prior knowledge of the anomaly, humans look at an entire image to identify the anomalous regions. From this idea, an attention-based supervision is applied, in which a network is encouraged to generate an attention map that focuses on all normal (i.e., non-anomalous) regions of the image to reduce the need for large amount of anomalous training data. Based on this training regimen, when the network is given an image classified as anomalous, the underlying anomalous attention map will focus on the image regions considered as abnormal by the solution.

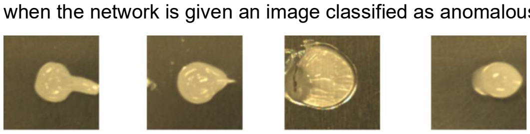


Figure 9: Different glue dot shape classes

[2] Venkataramanan, Shashanka, Kuan-Chuan Peng, Rajat Vikram Singh, and Abhijit Mahalanobis. "Attention guided anomaly localization in images." In *European Conference on Computer Vision*, pp. 485-503. Springer, Cham, 2020.
[3] *Kingma, D.P., Welling, M.: Auto-encoding variational bayes. In: Int'l Conf. on Learning Representations (2014).*

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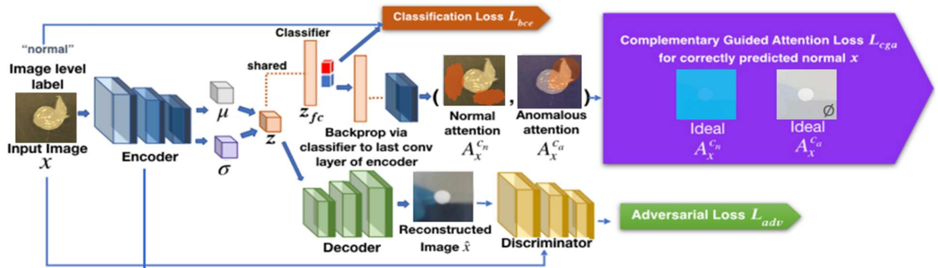
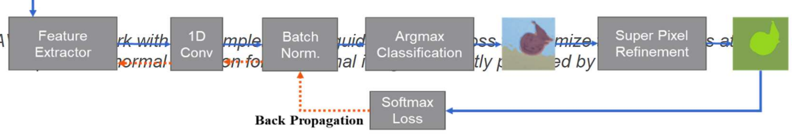
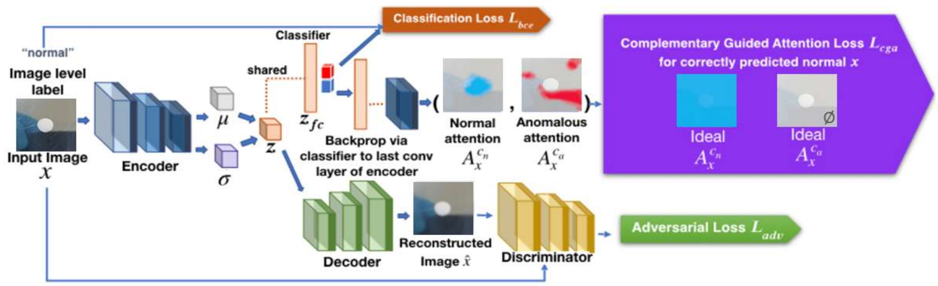


Figure 10: CA ... rk with ... mple ... uid ... ss ... mize ... s a ... and ... normal ... n fo ... al i ... tly p ... ed by





Task 3.2 Dot Segmentation

The next task is to segment the dot area for shape analysis. However, traditional supervised deep learning-based segmentation algorithms need detailed labeled data that shows the segmented dots, which is costly to acquire in industrial settings. Therefore, our aim was to develop unsupervised object segmentation algorithm that does not depend on detailed ground truth segmentation map data. We extended CAVGA for unsupervised segmentation[4]. Given an input image, the joint optimization through alternate iterations between foreground label prediction and mapping function is achieved. . We address two main objectives: (a) pixels having similar features and spatial continuity are assigned with the same label and (b) creating a significant number of unique foreground labels.

Let $\{x_n \in \mathbb{R}^p\}_{n=1}^{N}$ be a set of p-dimensional feature vectors extracted from CAVGA encoder, where N denotes the number of pixels in the input image. Cluster labels $\{c_n \in Z\}_{n=1}^{N}$ is then assigned to all of the pixels by $\{c_n = f(x_n)\}$, where $f: \mathbb{R}^p \to Z$ denotes a mapping function. Here, f is the function that assigns each x_n a cluster ID from k centroids obtained by k-means clustering. If f and $\{x_n\}$ are considered fixed, then $\{c_n\}$ could be obtained by the above equation. On the other hand, if $\{c_n\}$ is kept fixed, f and $\{x_n\}$ are trainable, then the above equation can be used for supervised classification problem.

Figure 11: Extension of CAVGA for unsupervised dot segmentation

[4] *Kim, Wonjik, Asako Kanezaki, and Masayuki Tanaka. "Unsupervised learning of image segmentation based on differentiable feature clustering." IEEE Transactions on Image Processing 29 (2020): 8055-8068.*

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Error! Reference source not found., the proposed unsupervised segmentation network is an extension of the CAVGA network with inclusion of some basic functions. Current method solves the two sub-problems alternatively: predict optimal $\{c_n\}$ keeping f, $\{x_n\}$ fixed and optimize f and $\{x_n\}$ while $\{c_n\}$ remains fixed. The first step is actually the forward process with super pixel refinement. The other step is the backward process with gradient descent. Unlike the supervised learning scenario with known target labels, here the batch normalization layer is used for obtaining multiple probable labels $\{c_n\}$ with different network parameters to achieve minimum loss. The error between the network's predicted labels and the refined cluster labels is then backpropagated to update the network parameters. We iterate this forward-backward process once after each iteration of CAVGA encoder update to obtain the final segmentation labels $\{c_n\}$.

Task 3.3 Anomaly Classification

Once the anomaly is detected and localized, it is needed to categorize them into more granular level to have better understanding of the root cause. However, the challenge is that for some of the anomaly categories, sufficient data was not present for training (less than 10 samples per categories) traditional deep learning-based classification algorithms.

The only solution in such situation is to apply Few-shot learning (FSL) or low-shot learning (LSL) strategy, where depending on data availability 1-10 samples per class would be sufficient for training. It also handles the issue of imbalanced data distribution over the number of class samples. FSL is a type of meta-learning where a learner is trained on various related tasks during the meta-training phase to generalize well to unseen tasks with just a few instances during the meta-testing phase.

Prototypical network[5] is a popular FSL approach that is employed here. It learns an embedded space where classification can be performed by computing distances to prototype centers of each class as shown in Figure 12.The training data is split into support and query set. The same encoder of CAVGA used for anomaly detection is employed for feature extraction from support and query sets. Each class prototype in the support set is computed as the mean feature vector representation of the class. The query set is then used to fine-tune the model parameters. During training, prototypical network loss refines the weights of the encoder. The final anomaly classification of the glue dot is performed by calculating the posterior probability for the query instance. We classify anomalous glue dots as size-based (small, normal, large) and shape-based (tail, elongated, sparse-with tail, and random).

Task 3.4 Anomaly Quantification with Assessment Score

Once an anomalous dot is classified, the degree of degradation is computed using the dot quality shape assessment module. We introduce a novel metric called Dot Quality Index (DQI) to measure the deviation of the dot shape from the circular shape.

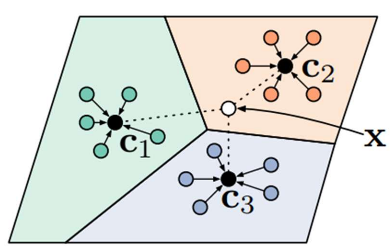

Figure 12: Prototypical Network, map images to embedding space Retrieve from: https://arxiv.org/abs/1703.05175

[5] *Snell, Jake, Kevin Swersky, and Richard Zemel. "Prototypical networks for few-shot learning." Advances in neural information processing systems 30 (2017).*

The input to this module is a segmented dot image with dot contour information. While the Hough circle fits over the dot for assessing the deviation in the circularity, the morphology segmentation can assess the actual contour region. The calculated shape metrics include (i) *eccentricity ratio, (ii) circularity, (iii) roundness, (iv) radius, (v) offset, (vi) convexity*, and *(vii) solidity*. The values for all these metrics range between 0 and 1. The final dot quality score DQI is computed based on the sum of the weighted score for each metric with a maximum value of not exceeding 10 as shown in Figure 13. On discussing with the Boeing team, the highest weightage is assigned to the eccentricity ratio (maximum deviation from the center of the circle to the desired radius of the circle). Although a specific cut-off value was not determined for a non-anomalous glue dot, it was observed that the dot quality score above 7.5 was classified as a good dot. The glue dot trends over time can be further integrated with the statistical process control charts to monitor the shape quality. In this project, the historical trends are plotted in the advisory system GUI. The DQI values are also part of the Bayesian Decision Network to correlate dot quality with glue process parameters (Task 4.1).

Task 4. Advisory Feedback System

This task involves the use of current glue inspection results obtained from Task 3 to develop the second feedback loop shown in **Error! Reference source not found.** for generating recommendations before depositing the next dot.

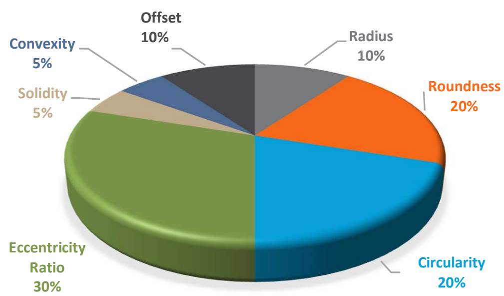

Figure 13: Pie Chart of DQI Metric with associated weightages of different descriptors

Task 4.1 Process Parameter Optimization

The objective of this module is to recommend process improvements (e.g., adjust dispense pressure, robot motion, or time parameters) to reduce the total number of glue dot defects. Bayesian Decision Network (BDN) is applied to achieve this goal.

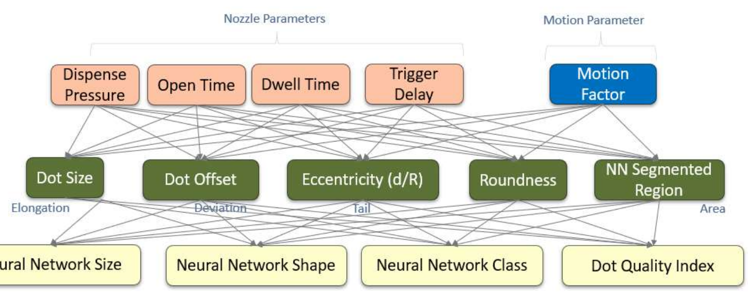

Figure 14: Overall Bayesian Decision Network structure for process parameters recommendation

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BDN is a graphical inferencing tool for calculating the probabilistic estimate of desired variables based on known observations[6] as shown in Figure 14. The BDN training was performed in five steps[7]: (i) developing the causal network, (ii) cleaning and discretizing the raw data, (iii) learning the network parameters using the conditional probability table, (iv) analyzing the network, and (v) providing inferences. Based on the experimentation at the Boeing site, some of the critical process parameters contributing to the glue dot's quality were dispense pressure, motion factors and time constants. Further, on correlating the process parameters with the quality results, it was observed that the motion factor was the most significant parameter (based on the random forest algorithm analysis).

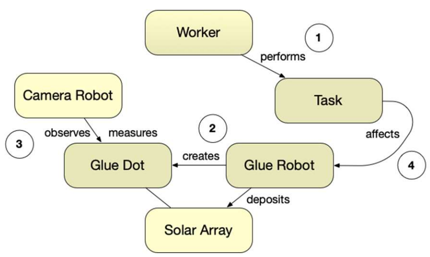
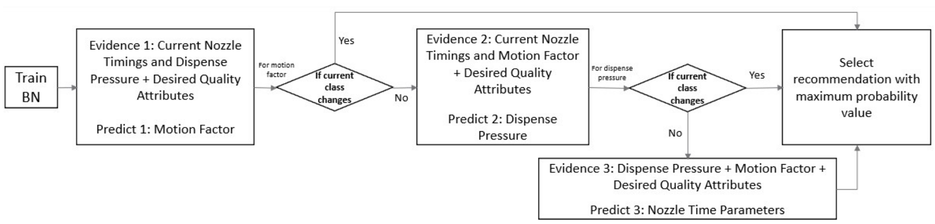


Figure 15: Recommendation strategy for improving the glue dot quality over time



Thus, to provide any recommendations, firstly, the motion factor is assessed, with the evidence such as dispense pressure, nozzle timings and user-defined quality attributes, as shown in Figure 15. If no changes are recommended for the motion factor, then the dispense pressure and time parameters are evaluated for any recommendations, in stage 2 and stage 3 respectively. During predictions, BDN produces output based on the most recent trained model. After each batch of operation, the user is provided with an option to re-train the model. In this case the model will be trained again with both existing and new data without affecting inference performance. It is also important to note that if certain threshold of glue dots in a batch are non-anomalous, then the network would not provide any recommendations.

Task 4.2 Knowledge-based Recommendation

A deterministic approach was also planned to be incorporated within the feedback system to preserve the knowledge of experienced worker. To that end, an initial framework for machine understandable representation of the glue deposition and inspection process (as shown in Figure 16**Error! Reference**

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[6] *Prediction of selective laser melting part quality using hybrid Bayesian network." Additive Manufacturing 32 (2020): 101089*

[7] *https://github.com/pgmpy/pgmpy*

source not found.Error! Reference source not found.) was developed using Semantic Technology Knowledge Graph[8].

The objective of this module is to provide recommendations for corrective actions to be taken if a deviation from normal process is identified. This recommendation will presumably take the form of an action to take, whether by a human or robotic agent. Therefore, this module is a knowledge-based rule implementation. We developed an information model to map dot inspection results to rules and return the recommendations as shown in Figure 17**Error! Reference source not found.**. In this figure the Step 2 in Figure 16**Error! Reference source not found.** is shown at (**1**), namely the ingestion of labeled data for a particular glue dot. When new data is created, the inference engine[9] (at **3**) will try to perform inferences based on the pre-defined rules (e.g., at **2**). It should be noted that rules shown in the figure are in a form of pseudocode for readability, and that rules in the context of this project are knowledge-based ones from semantic model. The reasoner tries to match the features and produces a task recommendation (at **4**, repeated from Figure 16).

This KG-based recommendation module is designed to be performed in OWL/RDFS graphs using the Topbraid Composer environment. Primary model integrations are with: (i) FONM – Functionality, Behavior, Objects, and Properties, (ii) SSF – Extensions to FONM to integrate QUDT and SSN, (iii) QUDT – Quantities, Units, and Dimensions, (iv) SOSA/SSN – Sensors and Observations, (v) W3C ORG – For manufacturers (vi) W3C PROV – Provenance. Five primary models have been constructed within the context of the Glue Dot project: (i) Glue Dot, (ii) Deposition Robot, (iii) Solar Cell, (iv) Task and Procedure.

Figure 16: Knowledge graph representing the glue deposition process

The workflows presented in Figure 17 require interaction with external services. The glue dot semantic module is implemented as a RESTful semantic web service running on an Amazon Web Services instance using the Topbraid Live Semantic Web Service. The data pipeline is implemented using SPARQL Motion[10] and SPIN Map[11], both of which are Topbraid tools. The former allows the ontologists to develop semantic application workflows, while SPIN Map allows the ontologist to map different data formats into RDF. Both of these modules are implemented using the W3C SPIN RDF library. The general data pipeline is shown in Figure 18**Error! Reference source not found.Error! Reference source not found.**. In this figure we show a single web service running on the cloud: insertSGDataToMxDGDDataAndEvaluate. This web service is used to ingest image data for a glue dot deposition into the data knowledge graph. It also performs an analysis on the glue dot by comparing the data to what is expected and returns the result.

[8] Here we describe the basic framework that was implemented at the initial phase of the project. However, later Boeing didn't want to use it, so refinement of the module was not done, and it is also not integrated with the final SMART-VISTA framework.

[9] We use the term inference engine because it is widely understood but the implementation will use a triple store's available reasoner. Most reasoners support forward/backward chaining in the same way classical inference engines would.

[10] https://www.youtube.com/watch?v=5r4mHN7KuWo

[11] https://www.topquadrant.com/spin/SPINMapRDBMS/

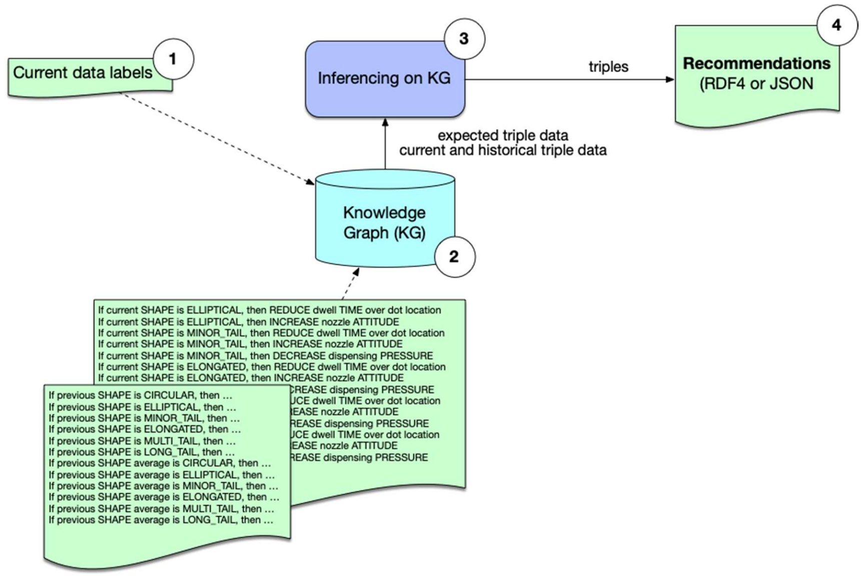

Figure 17: KG-based recommendation module workflow

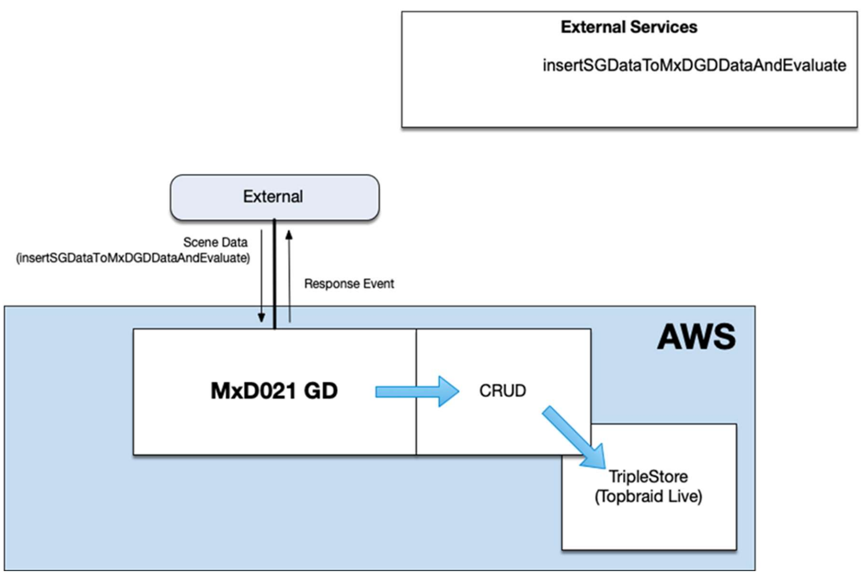

Figure 18: General semantic module data pipeline

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Task 5. Software Subsystem Integration

In this task, a User Interface for analytics visualization is implemented with different levels of integration.

Task 5.1 User Interface Design for Analytics Visualization

The objective of this module is to use the results of modules described in Task 3 and 4 to process glue dot images in real time, display the resulting quality metrics and recommendations to the user in a clear and actionable way, and save this information to a log file for potential further analysis. This task is accomplished with a GUI module that displays and logs process information, and a UI Manager module that detects new glue dot images, passes them to the processing modules, and gives the results to the GUI module to be displayed. The design of the UI will be discussed after an overview of the UI manager module's functionality.

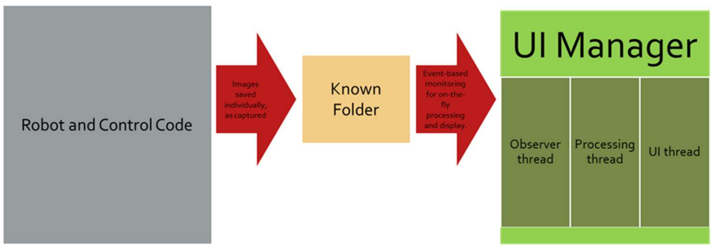

Figure 19: Overall UI workflow

Figure 19 shows the three key parts of the UI manager module and how dot images move from camera capture to the UI manager. The observation, processing and display processes occur in parallel to increase the performance and responsiveness of the UI.

Once a new image is detected in the pre-defined local folder where dot images are expected to be dumped by the camera attached to the deposition robot, Figure 20**Error! Reference source not found.** shows how the image is passed to the processing modules and how the processing modules pass their results to the Bayesian recommendation module and the GUI module.

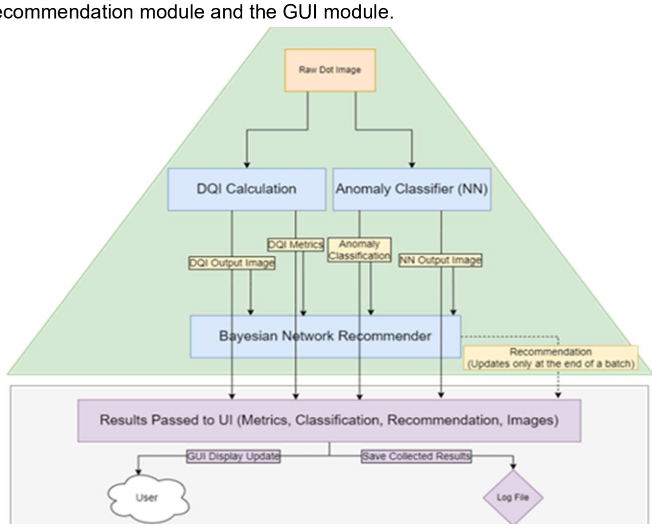

Figure 20: GUI Workflow: Processing and UI Threads

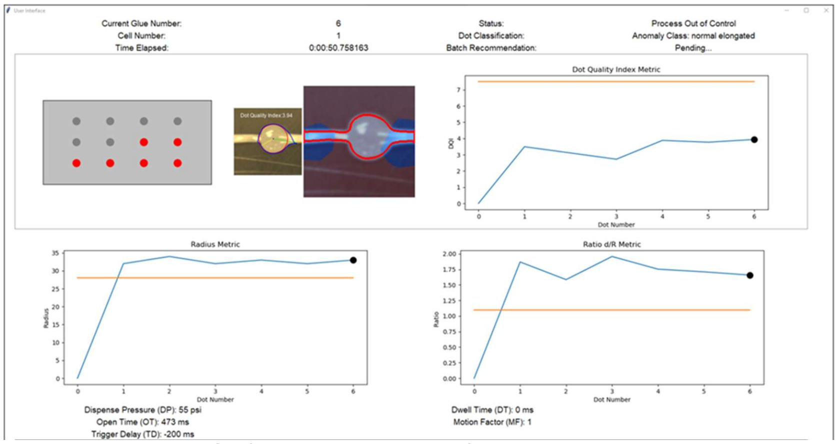

Figure 21: GUI for inspection and advisory feedback analytics visualization

As shown in Figure 19 Figure 21, the GUI is divided into three areas. Specifically, an upper section for process state and glue dot quality data, a middle section for images, and a lower section displaying the current process parameters and a help textbox. The most important information is emphasized in the upper row of the middle section so that the user can tell at a glance how well the process is performing. More specific information about the process state and what factors contributed to these primary displays of process quality are arranged above and below this emphasized row.

The key displays of current process quality (from left to right in Figure 21) include a schematic representation of the cell, the segmented dot image with highlighted anomaly area if it is a defective dot, and a plot showing the current value of the dot quality index as a continuation of its recent values. The user will be able to quickly notice a potential quality issue from the schematic representation filling in the grey spaces with red circles to represent anomalous dots, or from the segmented images highlighting problem areas, or from a decreasing trend in the dot quality index. Then, the more specific details above and below this row can be consulted to provide more information about the nature of the potential quality issue.

Once all the dot images corresponding to a cell is completed, the UI will use a popup window to show the Bayesian recommender's suggested parameter adjustment at the end of the batch as shown in **Error! Reference source not found.Error! Reference source not found.**. If the user is unclear about the meaning of any data displayed in the GUI, moving the mouse over that number or figure will cause the help textbox at the bottom of the window to display a short explanation about the nature and significance of that type of data. Figure 23 shows how our approach was effective in reducing occurrence of defective dots in the next cell batch with correct recommendation generation.

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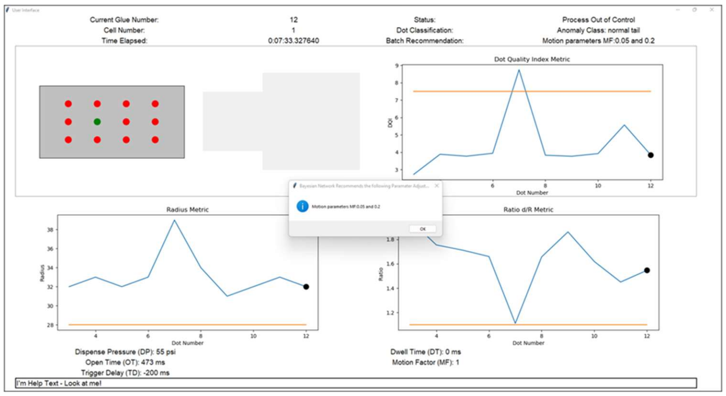

Figure 22: At the end of a solar cell batch, process parameter recommendation is shown through a pop-up window

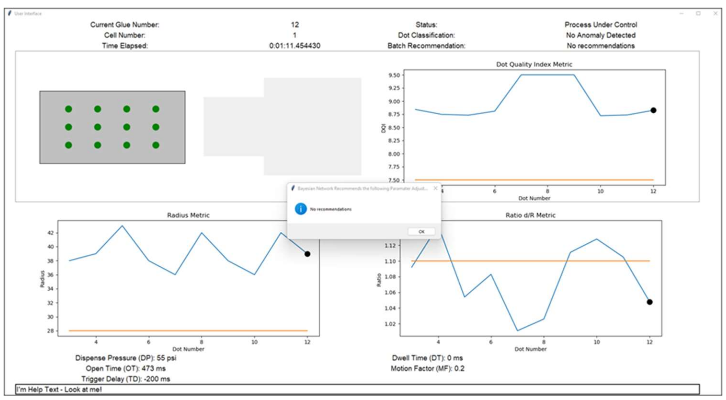

Figure 23: Effect of implementing process parameter recommendation from previous cell (shown in Figure 22): no more defective dots deposited in the current batch

V. RESULTS

Algorithm Evaluation:

Vision-based Deposition Path Planner:

For detecting the corner pixels, the traditional approach may consider shadows as part of the cell, resulting in non-accurate coordinates location. However, through filtering out the shadows and reflections, our approach was able to detect near-accurate pixel coordinates (green dots), as highlighted in Figure 24. A case study was conducted to validate the results from this algorithm. The evaluation metric was its comparison with the ground truth pixel coordinates based on user observation. The average accuracy for this case was reported to be 99.45%. The accuracy was calculated based on the deviation on the pixel coordinates in X or Y direction with respect to the image size (1600 X 1200 pixels in this case). **Error! Reference source not found.** shows the results for the pixel accuracy for four corners – top right, bottom right, top left and bottom left. Figure 25 shows the results for corners detected in varied position,

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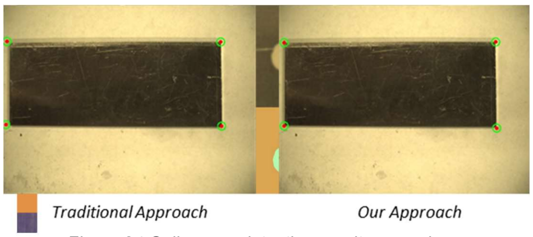

Figure 24:Cell corner detection result comparison

orientation, and shadow effects. An initial eye-in-hand calibration was performed on a checkerboard. These transforms, along with the pixel coordinates were deployed in the transformation matrix to move the robot to the desired location. The robot arm tooltip was driven to desired locations on the cells to within 4 mm of the target location. Once the additional manual was made to the camera-to-flange transform, this error was reduced to around 1 mm.

Table 1: Accuracy in corner coordinates location (2D – Pixel Units)

	Traditional Approach		Our Approach		Ground Truth		Accuracy (%)	
	X	Y	X	Y	X	Y	X	Y
Top Right	21	231	33	239	37	237	99.75	99.83
Bottom Right	12	768	33	768	37	751	99.75	98.58
Top Left	1376	234	1380	234	1380	224	100	99.16
Bottom Left	1382	771	1386	782	1381	769	99.68	98.92

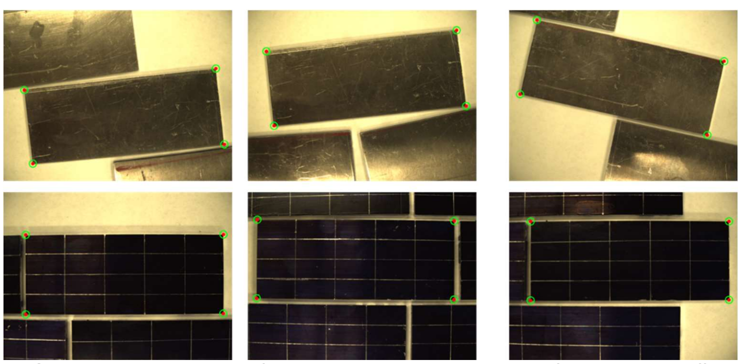

Figure 25: Cell corner detection results for varied position, orientation, type of cells, and with different shadow effects: proposed method is robust enough to handle these challenges.

AI-based Vision System for Real-time Quality Inspection:

The qualitative results for dot anomaly detection, localization, and segmentation are shown in **Error! Reference source not found.Error! Reference source not found.**. It can be observed that the anomalous dots are rightly identified with high localization accuracy. The attention based CAVGA approach helped to localize the anomalies which is useful for users to understand the defects. The second row of the figure

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also shows output of our unsupervised segmentation approach which is able to segment the dots with high accuracy.

Table 2 shows quantitative accuracy of our approach which supports the qualitative results.

Figure 27 shows qualitative results for anomaly classification. Anomaly dot are classified into different shape as well as size classes. Overall >90% accuracy was achieved for anomaly classification. The classified performed poorly when the inter-class variation in different shape or size classes is low. For example, the dot image in top right corner was falsely classified as having tail while its true ground truth class is elongated. However, the dot has properties of both the classes to some extent that confused the shape classifier.

Figure 26: Qualitative results for anomaly detection, localization, and segmentation: top show shows original dot images, middle row shows segmented dot, bottom row shows anomaly detection results where area of anomaly is highlighted in orange color

Table 2: Anomaly detection result

Total		**Predicted**	
		Acceptable Dot	Not Acceptable Dot (Anomaly)
Actual	Acceptable Dot	29.94%	03.56%
	Not Acceptable Dot (anomaly)	0.62%	65.89%

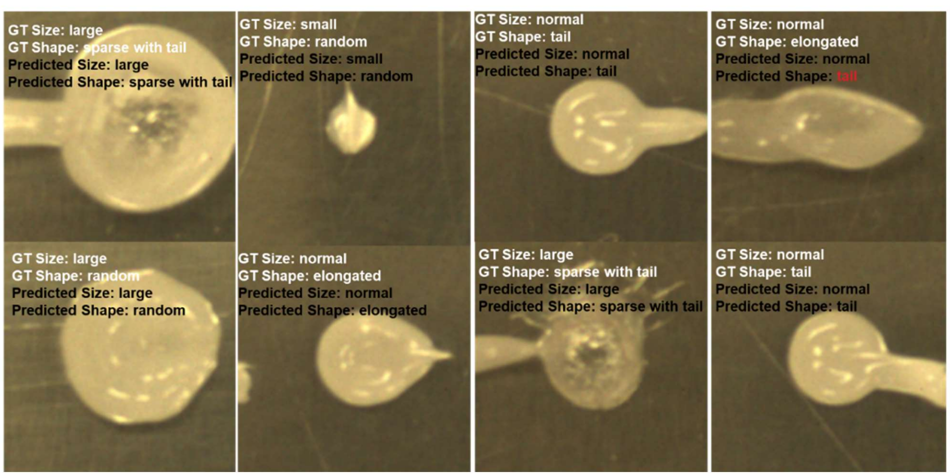

Figure 27: Anomaly classification results

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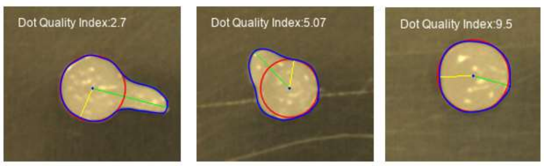
Dot Quality Assessment Score

The dot quality assessment was performed using the shape metrics discussed in Task 4.4 above. Figure 28 shows the dot quality index (DQI) calculated for different quality of glue dots. The blue outline represents the shape of the glue dot while the red circle represents the desired circular shape. The green and the yellow lines from the center of the circle represent the maximum and minimum point of the glue dot - an important parameter to calculate eccentricity. It was also observed that the results from the dot quality index were in-sync with the dot anomaly detection module. For example, the images (a) and (b) had DQI below 7.5 and were classified as anomalous, while a good quality glue dot of DQI 9.5 was classified as a non-anomalous glue dot. This metric was significant to capture the relations and uncertainties for the process parameter recommendation module.



(a) (b) (c)

Image	Dot Quality Index	Dot Anomaly Detection Class
a	2.7	Anomalous
b	5.07	Anomalous
c	9.5	Non-Anomalous

Figure 28: DQI measurement accuracy

Advisory Feedback System

Three variations in the BDN designs were evaluated to assess accuracy of recommendations –

- Design I – With DQI, NN classification and segmentation
- Design II – With DQI and NN classification only
- Design III – With DQI only

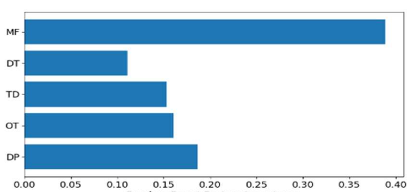


Figure 29: Feature importance for process parameters (MF – Motion Factor, DT – Dwell Time, TD – Trigger Delay, OT – Open Time and DP – Dispense Pressure)

Figure 29 shows the results for the random forest feature importance, in which motion factor is the most critical parameter for the quality. Three case studies results are reported in which the motion factor, dispense pressure, and nozzle timings are predicted with varying number evidence as shown in Figure 30-Figure 32. For the motion factor and nozzle timings, Design I shows highest accuracy as evident from Figure 31. For the dispense pressure, although Design II shows highest accuracy of 93.88%, it decreases rapidly as a greater number of evidence are removed (see Figure 30). Alternatively, the Design I shows consistent accuracy levels even with variations in the available evidence. Although Design I takes more training time, a pre-trained module can be deployed, and this model can be re-trained in the background while the process is running or when the system is idle.

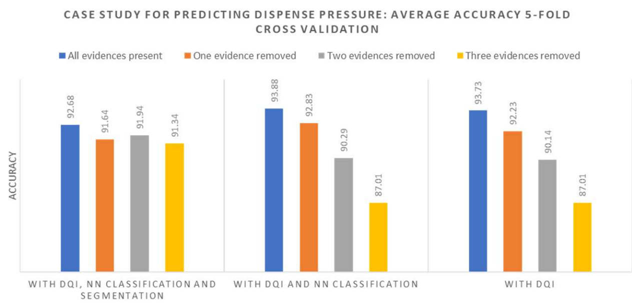


Figure 30: For predicting the dispense pressure, if all evidence is present, Design II (DQI and NN classification only) module gives highest average accuracy (93.88%). But as more evidence becomes unavailable (which may occur in certain computer vision application).

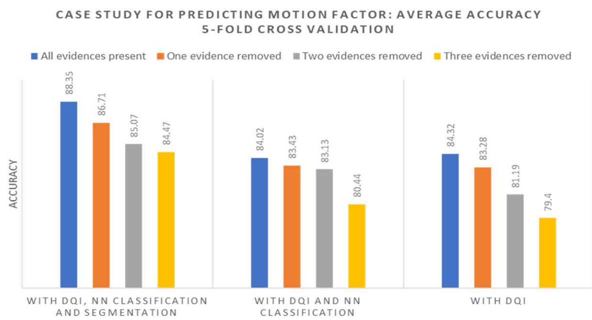


Figure 31: For predicting the motion factor, Design I (DQI, NN Classification and Segmentation) report the highest prediction accuracy when all the evidence are available.

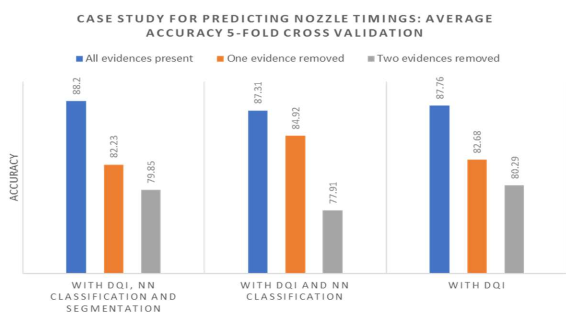


Figure 32: For predicting the nozzle timings, Design I (DQI, NN Classification and Segmentation) report the highest prediction accuracy when all the evidence are available.

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MxD-20-02-07 Project Deliverables			
#	***DELIVERABLE NAME***	***DESCRIPTION***	***FORMAT OF DELIVERY***
1	Project requirements documentation	Description of the project requirements across all the partners.	Word Document
3	Labeling User Interface	A user-interface will be used for performing image pre-processing operations and for labeling glue dot position and defect types.	Software Module
4	Meta data and storage Interface	Storage interface to store image as well as meta data to optimize the control feedback.	Software Module
5	Vision-based Path Planner	This deliverable is a software module for performing automatic path planning of the glue dot deposition robot by camera calibration and solar cell localization together with image capture system. This deliverable includes following software modules: • Cell detection and pose estimation module. • Module to find solar cell location w.r.t. robot. • Module to communicate with an industrial camera and industrial controller over OPC UA.	Code repo with readme and licensing.txt
6	Inspection with Recommendation	This deliverable is a software module that includes a GUI for visualizing dot inspection results along with process parameters recommendations for reducing/removing fluid deposition errors using state-of-the-art machine learning techniques. This deliverable includes following software modules: • Glue dot detection and anomaly localization module. • Glue dot classification module. • Glue dot quality quantification module. • A BDN network module for process parameter optimization • A knowledge graph module representing the glue deposition process. • User Interface for advisory feedback analytics visualization • Edge deployable software.	Code repo with readme and licensing.txt
7	Demonstration of the technology	Transfer the technologies to Boeing manufacturing research facility at Charleston for final demonstration. • Demonstration of the fully automated robotic cell for (a) cell localization; (b) glue deposition after path automatic refinement; (c) image capture after glue deposition. • Demonstration of the integrated inspection evaluation and recommendation system.	Video
8	User Manual	Detailed documentation to install and run all the modules of the SMART-VISTA software.	Word Document

System Overview

The goal of this project is to develop an Artificial Intelligence-based solution for sealant deposition monitoring on planner surface with real-time feedback about glue dot quality and corresponding process parameter change recommendations so that dot quality is maintained in future. The framework consists of two main modules:

- **Vision-based Deposition Path Planner Module:** This module performs automatic path planning the glue dot deposition robot by camera calibration and solar cell localization.
- **Inspection with Recommendation Module**: This module includes a GUI for visualizing dot inspection results along with process parameters recommendations for reducing/removing fluid deposition errors using state-of-the-art machine learning techniques.

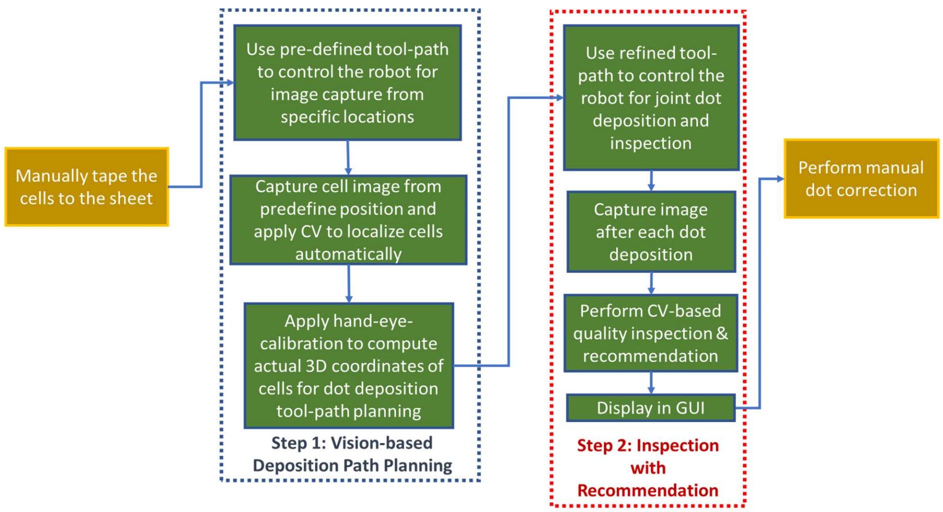

Figure 33: Overall system workflow starting from manually putting the individual cells on a sheet till the quality checked glued sheet product

Overall workflow during deployment of SMART-VISTA framework is shown in Figure 33**Error! Reference source not found.**. Yellow boxes highlight the part of the process flow that will be done manually. Parallel inspection software employing SMART-VIStA will be running in the background without hampering the normal workflow. After the solar cells are organized manually in predefined locations, the "**Vision-based Deposition Path Planner**" module is run. The goal of this module is to refine the deposition path after finding precise coordinates of the solar cells in robot frame camera.

After deposition path is automatically updated, the deposition process starts. During deposition of glue dots, the camera attached with the arm of the robot captures image of individual glue dot and saves it in local folder. **"Inspection with Recommendation"** module is run in parallel whenever new image is available in the local folder. The module performs follows tasks:

- Deep Learning-based computer vision module analyses current glue dot quality and find out if it is anomalous or not. If it is detected as an anomalous dot, the module also finds out the category of anomaly and highlights the location of degradation. This module also segments out the glue dot from background for quantitative analysis, i.e., finding Dot Quality Index.

- Deep Bayesian Network finds relationship among the glue deposition process parameters with the observed/measured dot defect metrics to recommend process improvements (e.g., clean nozzle, adjust pot pressure, etc.) to reduce the total number of defects.
- A GUI maps real-time glue quality inspection results on the Digital Twin of solar panel.

System Requirements

Hardware and software specifications of SMART-VISTA framework are noted in Table 3. The hardware set up is illustrated in Figure 34. The setup information, system goal and assumptions made during SMART-VISTA software development are described in detail in Table 4,Table 5, and Table 6, respectively.

Table 3: System Specifications

Hardware and Software Specifications	
Robot	S7 1500 (connected directly to the KUKA controller)
Robot control library	mxAutomation /Robot Integrator
Simulation Software	Process Simulate
Camera	Mako 192-C gigE
Equipment for Deposition	Techcon TS5322/TS5322D 

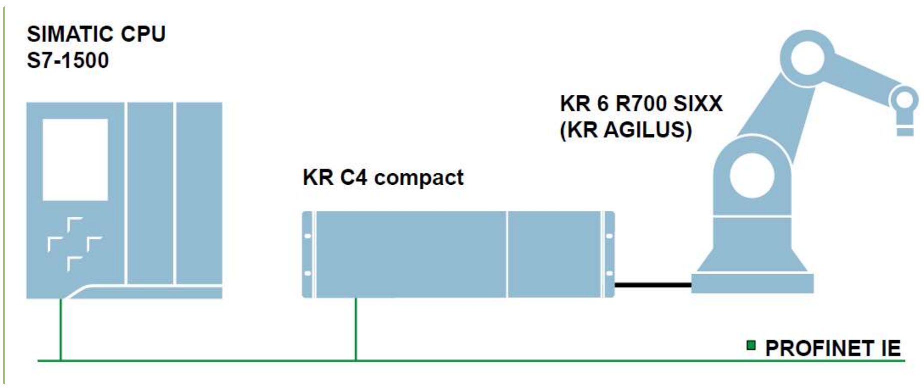

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Figure 34: Hardware setup

Table 4: SMART-VISTA setup

Setup	
Calibrate robot and camera	Establish relationship between robot and cells
Calibrate dot sizes	Calibration will be performed by weight

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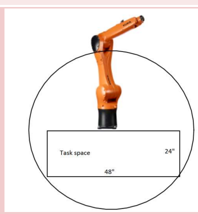
Table 5: SMART-VISTA system goals

System Goals	
Quality Goal	~1 NC dot/100
Hardware Resource Goal	Use same vision hardware for localization and classification
Time Goal	2 seconds per dot

Table 6: Assumptions made during SMART-VISTA framework development

Assumptions	
Glue Type	White silicon grease
Height of Nozzle	Fixed
Angle of Nozzle	Fixed
Amount of Glue	Fixed for both dot sizes small and large
Number of Dots per Cell	12 dots per cell
Number of Cells	3 cells
Cell Size	2” x 5”
Task Space	24” x 48” 
Dot Size Categories	Two discrete dot sizes: small and large
Dot Shape Categories	Tail, elongated, crescent, sparce with tail, random
Dot Speed Depends on:	1. Dispense time (valve open + valve closed) 2. Retreat speed 3. Break off pattern speed 4. Move to next dot spot
Dot-to-Dot Hardware Operations	1. Dispense dot 2. Take image 3. Move to next dot
Dot-to-Dot Software Operations	1. Store Image 2. Do computer vision-based quality inspection on each image 3. Generate parameters optimization recommendation 4. Display results on UI
Dot-to-Dot Operation time	2 sec cycle time
Glue Removal	After the whole sheet is done, no stopping of robot in-between.

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System Architecture

SMART-VISTA dot-to-dot inspection system comprises an image acquisition subsystem, an image processing subsystem, a recommender subsystem, and a user interface with near real-time control feedback. Figure 35 shows the overall process workflow of the system.

After the glue deposition robot makes a dot deposition, the image acquisition system uses the camera mounted on the same robot to capture image of the cell featuring one or multiple glue dots (always including the latest one). The glue deposition process starts again after the image capture.

Then, the acquired images are preprocessed to find the region of interest for detailed glue quality evaluation. The inspection system validates glue dot position, size, and shape (according to specification) and accordingly quantify dot quality. The inspection results are fed to the recommender system.

The recommender system generates up-stream process parameter tuning recommendations for reducing/removing fluid deposition errors before depositing the next dot. This avoids potential quality degradation of the product.

Finally, the inspection results along with the corresponding recommendations are displayed on a user interface to help users gain real-time insights of the inspection process.

Note that, the inspection process software will run in the background independent of the robotic operation. Thus, there is no time restriction for the SMART-VIStA operation.

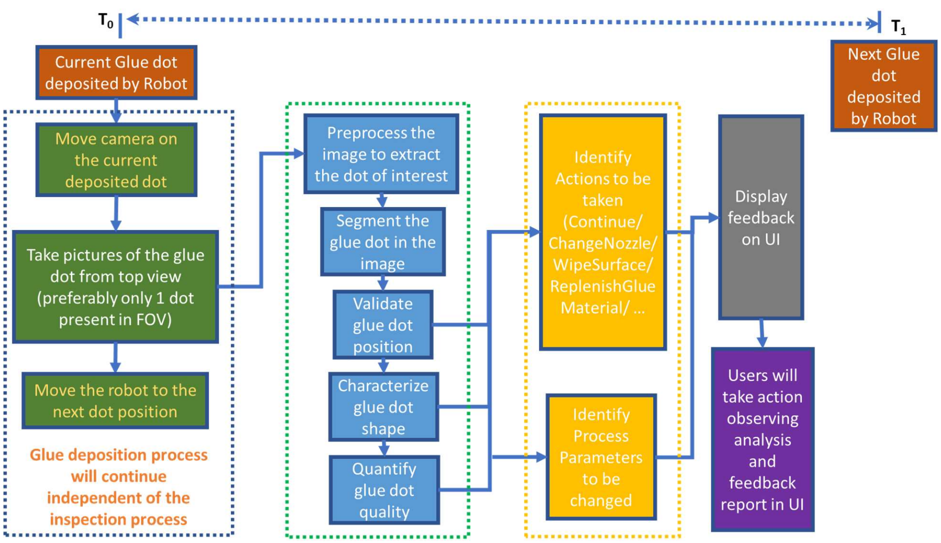

Figure 35: The SMART-VISTA inspection with recommendation system workflow

Software Installation and Usage Documentation

As mentioned before, the overall pipeline is divided into two software packages based on two primary phases: phase one is vision-based path planning and phase two is dot inspection during dot deposition. Each of these two packages are described in detail below.

Software Package 1: Vision-based Deposition Path Planner

This python package includes modules that assist in the process of robotic dot deposition, e.g., camera calibration, cell localization, and PLC communication over OPC UA. These packages were used independently for convenience but could be combined using a single python routine.

Requirements

Implemented in the programming language *Python*, the proposed tool relies on the following code libraries:

- Python >= 3.9
- Opcua
- OpenCV
- Pillow
- Yaml
- Allied Vision (Vimba)

Installation

First, Download and unzip this directory: [link]

Then, go folder root "*mxd_delivery-main/SMART-VISTA_framework/ RobotPathInitialization*" and run following commands to create Python environment:

- Create and activate Anaconda Environment

```
conda create --name boeing-ml python=3.9
conda activate boeing-ml
```

- Install Allied Vision (Vimba)

  Get vimba by installing Vimba SDK from Allied Vision. In the terminal change directory to the Allied Vision Vimba Install Directory. Navigate further to "VimbaPython\Source". It should contain "setup.py". While in this directory on the terminal, run "pip install ."up in the code.

- Install OPC UA Python Library

```
pip install opcua
```

- Install Opencv

```
conda install -c menpo opencv
```

- Install Pillow

```
conda install pillow
```

- Install Yaml

```
conda install -c anaconda yaml
```

If these steps succeed without errors, the framework is ready to run.

We now present the steps to use the tool.

1. Calibrate camera using multiple poses and associated checkerboard images using ***hand-eye-calibration.py***
2. Capture image(s) of cell(s) and deposit it into the ***"Images"*** folder
3. Run ***corner_pixel_coordinates.py*** to detect corners of the solar cell images: the pose information with associated cell image name is saved in the text file ***Localization_input.yaml***

Example content of Localization_input.yaml


```
cell_1:
      base2flange:
        A: 176.05
        B: 89.68
        C: 176.06
        X: 858.75
        Y: -151.48
        Z: 532.48
      length: 125
      width: 50.8
```


4. Run localization.py to detect corners of the solar cell w.r.t to robot base: the pose information is saved in the text file ***localization_output.yaml***

Example content of Localization_output.yaml


```
cell_1:
  base2cell:
    A: 0.5579474732615125
    B: 0
    C: 0
    X: 829.8958074220801
    Y: -108.63305998898431
    Z: 0
  base2flange:
    A: 176.05
    B: 89.68
    C: 176.06
    X: 858.75
    Y: -151.48
    Z: 532.48
  corners:
    bottom_left:
      base:
      - 829.8958074220801
      - -108.63305998898431
      - 308.10180073624883
      camera:
      - -64.64644524527064
      - 15.614584006284678
      - 268.0923139507875
      flange:
      - 224.5519528260482
      - 42.755762629105654
      - -27.61098054192751
      pixel:
        u: 97
        v: 813
    bottom_right:
      base:
      - 954.8894448949585
      - -109.85028906473116
      - 308.43186841994174
      camera:
      - 60.35232992870386
      - 16.16794194304892
      - 268.0923139507875
      flange:
```

```
    - 223.52498773762187
    - 41.560609464430755
    - 97.37908686992783
    pixel:
      u: 1442
      v: 819
  top_left:
    base:
    - 830.6281731181048
    - -58.657054928694706
    - 307.2384590250367
    camera:
    - -64.18176578365735
    - -34.37208294808501
    - 268.0923139507875
    flange:
    - 225.4304277511332
    - 92.7315605303477
    - -26.882484729084396
    pixel:
      u: 102
      v: 271
  top_right:
    base:
    - 955.6163776804847
    - -60.88860726370214
    - 307.5860725844807
    camera:
    - 60.81700939031715
    - -32.80423546058633
    - 268.0923139507875
    flange:
    - 224.38555709139678
    - 90.52208997606357
    - 98.10222803976616
    pixel:
      u: 1447
      v: 288
depth: 268.0923139507875
length: 125
width: 50.8
```


5. Use **"base2cell"** as the transform between the robot base and bottom left corner of cell. Use ***"python-com"*** to download the base2cell information to the PLC using Python.

Software Package 2: Inspection with Recommendation

An operator-friendly user interface designed to help subject matter experts with the inspection process. The GUI will display: (i) real-time inspection results overlaid on the Digital Twin of the current solar panel, (ii) recommended actions to correct anomalies and (iii) dot analytics and trends.

This software package contains the necessary resources to configure an appropriate Python environment for installing and running the SMART-VISTA user interface framework.

Requirements

Implemented in the programming language *Python*, the tool relies on the following code libraries:

- python=3.6

- scipy
- opencv
- pillow
- pytorch
- torchvision
- matplotlib
- scikit-image
- scikit-learn
- shapely
- pgmpy
- ipython
- PyYAML
- Watchdog
- easyfsl

Installation

First, Download and unzip this directory: link

Next, use following instructions to create the environment to run the software.

- Go to folder root "*mxd_delivery-main/SMART-VISTA_framework/ InspectionWithRecommendation"* and run following command to create Python environment from ***PlatformIndependedtEnvB.yml*** (or use the Anaconda package manager) and activate it.

```
conda env create -f PlatformIndependedtEnvB.yml
conda activate boeing-ml
```

- Install Easyfsl

```
pip install easyfsl
```

If all went well, the tool is now ready to be used.

To use the tool, run the following command:

- To start the UI Framework, activate its python environment and then run:

```
python UImanager.py
```

The user will be prompted to select a dot image folder. This is the folder that UImanager.py will search for pre-existing dot images and observe for new dot images on an ongoing basis. Along with the dot images, a process parameter .yml file should be present in the same folder which records the process parameter settings during the dot deposition of these images. This repository provides pre-captured test data which is placed under the folder "Test_data" that can be selected in this stage.

Next, the user will be prompted to select or create a folder for storing the "csv" log files that will be generated after processing the test data by the UI framework. For example, a folder named "CSV_data" is provided with this package that can be selected in this stage.

However, any two different folders can be specified during this stage, but it is recommended that they be descriptively named and only used by the UI framework and the module being used to capture and save dot images.

After getting these two folders' paths as input from the user, the UI window will close, and the UI framework's behavior will depend on the specific contents of the input image folder under observation.

In order to generate recommended parameter changes, information about the process parameters that were set during capturing the current dot images is necessary. Therefore, the UI framework will not start processing any dot images until a valid parameter .yml file is present in the observed image folder. Instead, it will continue to prompt the user to add a valid parameters file. If a valid parameter information file is present in the observed folder, the UI framework will start working. It will sequentially display the processed output for all the dot image files currently within the folder. When new images are added to the observed folder, the UI framework will process and display their results as they are added.

If multiple images are added at once or if a subfolder of images is added, they will be processed in the sequence in which they were captured (assuming the file naming convention used appends the capture time to the end of each image's name when they are saved initially). If process parameters are changed during new dot image capture, then add a new parameter file to the observed folder with the updated parameters. The UI will use the most recently added parameters file as the current process parameters.

The UI framework will continue to run and process new dot images added to the specified folder until the GUI is closed or the process is ended by the user.

Troubleshooting

Problem: Some files cannot be extracted from the compressed directory
Try:
-Noting which files give this error and downloading them individually from this repository

Problem: Environment won't build
Try:
-Making sure all channels listed in PlatformIndependentEnvB.yml are added to Anaconda navigator

-Change build options to allow for more permissive environment solving

-Manually add the necessary packages one at a time to a new python environment

Problem: UI launches but does nothing after the user specifies the observed folder and the log folder
Try:
-Ensure that there is a process parameters information .yml file present in the observed folder

Problem: DQI output image displays with an outline applied with incorrect rotation
Try:
-If this error occurs, edit the python environment to change the version of the scikit-image package to 0.17.2

Problem: UI Framework crashes with errors about PyTorch installation
Try:

-Verify that the environment's version of PyTorch includes CUDA

VI. DISCUSSION & ANALYSIS

Industry Impact

SMART-VIStA may yield unprecedented technological solutions in the domain of real-time in-situ automated inspection process. In such settings, the active monitoring systems works like a real-life human inspector by finding the best position to do inspection. Ability to predict future events associated with quality degradation through tracking gradual change in inspected object quality can be used to alert up-stream worker to take corrective action as required. Additionally, by anticipating the need of future up-stream parameter change, the system can not only respond more quickly (e.g., by preemptively tune the appropriate process parameter, etc.), but also better ensure the quality of the product.

Thus, SMART-VIStA improves the performance of the automated glue disposal process and reduces manufacturing costs associated with reworking the glue disposal after wiping, scrapping a low-quality glued solar panel, shipping defective products, or re-inspecting products.

The system can be adapted with minor modification for any defect assessment and real-time feedback that requires human interpretation in conjunction with a robot. It can be integrated with upstream processes for providing intelligent feedback of defects checklist through Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES).

Key Performance Indicators & Metrics

KPI	Metric	Baseline	Goal	Demonstration
Robotic system localization	Positional error	Localizing using the native robot teach methods yielded >4mm of metric error	Achieve metric error of <2mm using computer vision	Demonstrate ability to place dots onto 6 solar cells (72 dots) with an average metric error <2mm, with cell localization accuracy >99%
Glue dot quality conformance	Anomaly detection & classification accuracy	Detect metric using visual human inspection	Achieve metric accuracy >95% using computer vision	Correct, consistent and robust dot defect detection& categorization using computer vision in a production-like environment on 3 mock solar cells with >95% accuracy
Feedback accuracy	Process parameter prediction accuracy	Currently feedback is provided by human operators in an informal manner	Up-stream process parameter prediction with up-to 90% accuracy	Demonstrate process parameter prediction ability in a production-like environment

				on 3 mock solar cells with 94% accuracy
Speed of inspection and adaptive feedback	Time to perform inspection and parameter optimization	Current speed is based on subjective interpretation and knowledge of operator	Dot classification and adaptive feedback of each cell in less than 3 seconds	Demonstrate process parameter feedback ability in a production-like environment on 3 mock solar cells with 2-3 seconds processing time per cell (12 dots in a cell batch)
Visual Feedback to operators	Visual access to inspection analytics within Digital Twin	None	UI interface	Demonstrate easy to use UI for real-time dot-by-dot defect and trend analysis, recommendations within solar cell Digital Twin
Qualifying record of each dot on each cell	Defect record of each dot on each cell for traceability	Overall sheet image with dots but no record of specific defects of each dot on cell	Database of dot inspection record will be stored for future retrieval or analysis	Demonstration of storage of dot defect information and trend analysis
Deployment Cost and Training	Cost and Training Time	At least 6 weeks of training needed for the manual inspection	System that is easy to set up and ready for use within 1-2 hours.	Setup and demonstration of the system at the site in a production-like environment on 3 mock solar cells

Accessing the Technology

The software code will be shared in MxD SharePoint with detailed user manual. Members may access the software under MxD agreement. Instructions to create environment required to run the software will be provided in the user manual. However no general software support will be provided after the project duration. Anyone interested to use the software may contact Siemens to know future course of action.

Workforce Development

The algorithm development, data gathering, CNN training, implementation and integration, will be used to train students at both graduate and undergraduate levels with industry-relevant skills making them ready to join workforce upon graduation. Computer Vision and AI related topics will be integrated with several graduate and undergraduate courses at the UC. This project also served as a training platform for one M.S. student and two Ph.D. students and learning several key aspects on CV and AI for manufacturing.

Lessons Learned

Issue	What went well	What went poorly	Learning

Lighting and Background: CV algorithms require fine-tuning to adapt to specific lighting and reflective conditions.	Current algorithm works well on test data with same lighting/background characteristic as training	If lighting/background changes, finetuning of the algorithm parameters is needed	This challenge can be addressed by considering all the possible variations in images in the training pool.
Robot End Effector: Reducing the vision hardware to one image sensor requires an optimization of hardware placement.	The camera is positioned such that it can capture the solar cell and dots, which are much different sizes.	Adjusting the camera focus changes the camera intrinsic parameters, so an optimal focal plane must be chosen for the two objects. Otherwise, the camera would need to be recalibrated before each localization.	Using a separate fixed camera capable of capturing a whole array of solar cells would significantly reduce EE design challenges and improve localization performance.
Process Parameters Optimization and Recommendation	The current method considers entire cell plate to generate predictions.	For online training, the larger the training data size, the more time it takes to provide recom mendations.	In such cases, an offline trained module can be deployed for the given batch and the model can be later retrained when the system is offline. The module can be adapted to provide recommendations after every glue dot using 'Dynamic Bayesian Network' approach. The current method considers entire cell plate to generate predictions.
System Integration	Integrated system performance is satisfactory.	Integration effort was more than expected.	Plan integration at the beginning of development and revise it as needed throughout the development process.

VII. CONCLUSIONS & FUTURE WORK

The quality inspection solution SMART- VIStA could be used for other manufacturing processes that include human-in-the-loop for quality inspection. Many manufacturing companies are being asked to increase automation, but for small manufacturing operations, the cost can be prohibitive. This technology will help small and large companies examine the optimum process parameters that can be changed adaptively in response to degrading quality of the product to ensure that the company is maximizing efficiency, minimizing cost.

Next Steps & Challenges

The Siemens Technology team leading the work is the entity within Siemens who will be involved actively with other Siemens Business – such as Siemens PL, Siemens Digital Industry or Siemens Gas and Power– by demonstrating the prototype developed under this project. Siemens Digital Industry-Factory Automation (DI-FA) has shown interest in adopting the SMART-VIStA solution as a potential pilot customer to demonstrate the tool in different operational environment. They will be involved in discussions related to plans for technology transition and commercialization. The technology will be demonstrated to Siemens other business divisions such as Digital Industry-Motion Control (DI-MC) to develop and realize additional use cases. Siemens Technology has multiple teams and projects actively researching and developing technologies in related domains. We also plan to further develop the technologies by launching more research and development projects working with other entities. We will proactively pursue to insert the developed technology to the product roadmap of Siemens.

Boeing is also committed towards adoption of this technology. They are aligned with the future factory movement and aim to embed this project with other automation efforts to improve engineering processes at this site and beyond with other deployments and programs. The decision to produce this effort is particularly well timed as there are future plans to update the working environment to support automation in the near term. The design of the system will seek to deliver tools to enable workers and train them in new skills to manage and safely work around such proposed automation. The results will also benefit other AI related automation programs with the learnings for adding this functionality to Boeing's automation capabilities.

Transition Plan

Requirements to Extend the Technology for Other Organization: One of the salient features of the developed technology is the ease with which manufacturers of different sizes can customize and adapt SMART-VISTA. The core technology modules are designed to be modular so that the end-users can pick and choose the components to suit their diverse needs as follows:

- Inspection path planning for best view monitoring: To use this module, it is needed to update the definition of best view quality metric specific to the use case. Other applications could be automated welding, painting, soldering, etc.
- Deep learning algorithms for visual anomaly detection, localization and classification: This module could be adapted for other defect detection problems by retraining the modules with use case specific anomaly data. Other applications could be crack/scratch detection, leak detection etc.
- Defect quantification using shape analysis can be used for other shapes of defects.
- Process parameter optimization: This module could be applied to optimize any upstream process parameters that directly causes defect in product by retaining with use case specific data.
- Digital Twin interface for defect trend feedback/analytics: This module could be adapted to any other inspection problems with minor modifications to suit the use case.

This approach would be most beneficial for different stages of designing a manufacturing process, like, process design and fine-tuning, commissioning, or during operation.

Types of adaptations and extensions of our work: The knowledge generated from this project enables us to identify and extend the technology to further monitoring challenges and to run trials in different production environments as follows:

- Detection of weld spatter and quality issues in TIG, MIG and other welding process; feedback to welding process parameters including quality and strength of welds and aesthetics.
- Detection of defects in leather for use in car upholstery and other high-end apparel.
- Detection of defects in leather for nesting shapes and process planning in cutting stock problems for handbags, shoes and other high-end apparel. Possible reduction of scrap and optimization of material for a given master schedule.
- Detection of defects in rolled sheets (rolling process), including centerline cracking, inclusions and other defects. Adaptation in sheet metal and other industries using metal plates, sheets and foil – examples including rolling mills, automotive body panels, kitchen counter tops and appliances (Auto Manufacturers, Appliance manufacturers)
- Application for detection of anomalies in PCB or other electronic components. Possible application at Intel, AMD, NVidia.
- Defect detection and feedback in Printed Electronics (Additive Manufacturing). Possible applications at Optomec, Rockwell Collins.
- Real time process control in Powder Bed Fusion (PBFAM) and Direct Metal Deposition (DMD) Additive Manufacturing by training images of each layer with CNN for defect prediction (porosity, balling, surface roughness) and process feedback (laser power, speed, hatch pattern etc.) modifications.
- Inspection of aircraft panels for blemishes/defects in moving aircraft parts line and real time feedback of process parameters

Educational Outreach: University of Cincinnati will be responsible for the education transition and outreach of this project. The focus is to disseminate information through the university and industry community mechanisms. Project results and methods will be disseminated through conferences, papers, classwork, and presentations through MxD and other channels within the manufacturing and defense related industries. Results obtained and techniques generated from this project including computer vision algorithms, machine learning methods, inspection and process Digital Twin will be integrated into courses offered at UC. These courses include “Manufacturing Processes” offered to undergraduate Mechanical Engineering students, “Robot Control and Design,” “CAD for Manufacturing,” “Computational Methods in Additive Manufacturing,” “Precision Engineering & Computational Metrology, “Intelligent & Autonomous Mobile Robots”, and “Mathematical Models of Decision Making” offered at the graduate level. All these courses are taught by the PI or Co-PI at the University of Cincinnati. Topics related to robot hand-eye calibration, transformation and path planning will be integrated in robot control and design MECH 5131/6032. Bayesian Network aspects would be integrated in Decision Engineering class MECH 7020. All course and training materials will be made available to MxD tier 1 and 2 members.

Do you need a transition or commercialization partner? Advocating for the solution from an end-user perspective will encourage the productization at Siemens level.

The table below provides a catalog of all of the project deliverables and their respective transition routes. Deliverables can transition through deployment at an industry member’s site, as an educational reference or through a commercialization effort. Each of these transition routes are detailed below.

Table X: Deliverable Deployment Summary

#	DELIVERABLE FILE NAME	TECHNOLOGY INTEGRATION	EDUCATION	COMMERCIALIZE
1	Vision-based Path Planner	X	X	
2	Inspection with Recommendation	X	X	

Deliverable 1 – Vision-based Path Planner

- Technology Integration: Boeing will deploy Vision-based Path Planner software at their Charleston, Technology Center of Excellence to further develop a hardened production solution before working with an aerospace integrator on a production system.

- Education: Vision-based Path Planner software will be used to educate undergraduate and graduate students with integration in multiple courses so that the students get a broad perspective and applications of automation using image-processing.
- Commercialization: NA

Deliverable 2 – Inspection with Recommendation

- Technology Integration: Boeing will deploy Inspection with Recommendation software at their Charleston, Technology Center of Excellence to further develop a hardened production solution before working with an aerospace integrator on a production system.
- Education: The inspection recommendation software will be used in selective graduate level courses for providing additional insights on applications of random forest algorithm for feature importance and Bayesian Decision Network for probabilistic estimates of the process parameters.
- Commercialization: NA

Appendix B: Demos

This section should minimally include all setup instructions, bills of materials, known exceptions, and additional relevant materials to enable someone to replicate the demonstrations.

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Appendix C: Validation & Testing

This section should minimally include the project test plan, results, and exceptions to functionality/modes of operation.

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Appendix D: User Resources

This section should minimally include all installation manuals, user guides, and additional materials necessary for a user to use the technology deliverables.

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Installation Manual

The installation manual should cover how to install all technology components as an inexperienced user with no installation completed previously. Clearly state any assumptions.

User Guide

The user guide should provide enough instruction for an inexperienced user to understand how to use all modes of operation and features of the technology. The user guide should also describe any known bugs or exceptions.