We have been tasked to define an AI strategy for a midsize manufacturing firm CSI, and create business value for them using a value creation framework. In this presentation, we will discuss the problems we worked on in Workshop 1 and Workshop 2, the data and models we used, and the benefits our solutions provide to CSI. I will also analyze the value creation perspective, organization and execution perspective, and industry environment perspective to create additional value for CSI. Finally, additionally we will discuss the key lessons we have learned while working on the project and outline future directions.

From workshop 1 our focus is the wet fill process we propose a data-driven solution for optimizing product yield and reducing waste in manufacturing using logistic regression models.

Our solution involves leveraging historical data on product weight, color, and fluid dispensing ratios to train a logistic regression model that can predict the likelihood of a failed product being salvageable through rework.

Read in the liquid fill data then isolate the failures.

We first read in the entire data set and then reduced it to isolate all the liquid filled records.

Then from that reduced data set we further reduced the outcome to include only failures.

From there we split the failures into fill station 3

A further reduction is to isolate the data that had weight failures.

Separate the data that did not pass inspection and build the split and training test data set 80/20

Fit logistic regression model.

Build a confusion matrix.

The Confusion matrix for the test set in this case shows that there were 28 true positives, 1 false positive, 74 true negatives, and 0 false negatives.

This means that the model correctly identified 28 vials that failed visual inspection and 74 that passed, while misclassifying only one vial that passed as a failure. The absence of false negatives in this matrix indicates that the model did not miss any vials that failed visual inspection.

The confusion matrix showed that the model correctly predicted 98% of the negative outcomes (no failure) and 30% of the positive outcomes (failure). The ROC curve showed that the model's performance was above chance, but it could be improved with a higher true positive rate at low false positive rates

The results suggest that the model could benefit from additional variables or more sophisticated machine learning methods. Further analysis is necessary to improve the model's performance and optimize the inspection process.

In conclusion, this logistic regression model provided a moderate level of accuracy in predicting the outcomes of visual inspections of liquid fill vials

The AI strategy for utilizing logistic regression algorithms and computer vision for liquid level detection in an automated fill station environment would involve the following steps:

Identify the specific business problem: The specific business problem here is to reduce product waste and improve overall efficiency in an automated fill station environment.

Define the AI solution: The AI solution would involve utilizing logistic regression algorithms and computer vision to detect the liquid level in real-time and automatically adjust the filling process to reduce product waste and improve efficiency.

Collect and preprocess data: Data on liquid level measurements and filling process parameters will need to be collected and preprocessed to ensure accuracy and consistency.

Train and validate the model: The logistic regression algorithm will need to be trained and validated using the preprocessed data to ensure accurate and reliable liquid level detection.

Implement and integrate the solution: Once the model is trained and validated, it can be implemented and integrated into the existing automated fill station system.

Monitor and optimize the solution: The solution will need to be continuously monitored and optimized to ensure it is achieving the desired ROI by reducing product waste and improving overall efficiency.

Overall, the AI strategy would focus on maximizing ROI by reducing product waste and improving efficiency in an automated fill station environment using logistic regression algorithms and computer vision for liquid level detection.

From a value creation perspective, the use of logistic regression algorithms and computer vision for liquid level detection in an automated fill station environment has the potential to create significant value for CSI by:

Reducing product waste: By accurately detecting the liquid level and automatically adjusting the filling process, the AI solution can help reduce product waste, which in turn can reduce the costs associated with wasted product.

Improving overall efficiency: The AI solution can also help improve overall efficiency by reducing the time and resources needed to manually adjust the filling process. This can result in increased productivity and throughput, which can improve overall profitability.

Enhancing product quality: By accurately detecting the liquid level, the AI solution can help ensure consistent and accurate filling, which can improve product quality and customer satisfaction.

Enabling data-driven decision-making: The AI solution can generate valuable data on liquid level measurements and filling process parameters, which can be used to inform data-driven decision-making and optimize operations further. Overall, the use of logistic regression algorithms and computer vision for liquid level detection in an automated fill station environment has the potential to create significant value for CSI by reducing product waste, improving overall efficiency, enhancing product quality, and enabling data-driven decision-making.

From an industrial environment perspective, the use of logistic regression algorithms and computer vision for liquid level detection in an automated fill station environment can help CSI stay competitive in an increasingly automated and data-driven industry. Specifically, it can:

Improve safety: Automated fill stations can help reduce the risk of injury or accidents associated with manual filling processes, which can improve safety in the workplace.

Increase efficiency: The use of AI can help streamline and automate the filling process, which can increase overall efficiency and reduce costs associated with manual labor.

Enhance quality control: Accurate liquid level detection can help ensure consistent and accurate filling, which can enhance quality control and reduce the risk of product defects.

Enable predictive maintenance: By generating data on filling process parameters, the AI solution can enable predictive maintenance, which can reduce downtime and maintenance costs.

Overall, the use of logistic regression algorithms and computer vision for liquid level detection in an automated fill station environment can help CSI stay competitive in an increasingly automated and data-driven industry by improving safety, increasing efficiency, enhancing quality control, and enabling predictive maintenance.

From an organization and execution perspective, the use of logistic regression algorithms and computer vision for liquid level detection in an automated fill station environment requires careful planning and execution to ensure successful implementation and adoption. Specifically, it requires:

Cross-functional collaboration: The successful implementation of the AI solution requires cross-functional collaboration between various departments, such as engineering, data science, operations, and maintenance.

Data infrastructure: The AI solution requires a robust data infrastructure to support data collection, processing, and analysis. This infrastructure should be designed to handle large volumes of data and ensure data accuracy and consistency.

Training and education: Employees who will be working with the AI solution need to be trained and educated on its use, benefits, and limitations. This training should be ongoing to ensure continued adoption and improvement.

Performance metrics: To ensure the ROI of the AI solution is being achieved, performance metrics should be established and tracked regularly. These metrics should align with the specific business problem being addressed and provide a clear picture of the solution's impact on productivity, efficiency, and product waste reduction.

Continuous improvement: The AI solution should be continuously monitored, optimized, and improved to ensure it is meeting the evolving needs of the business and delivering maximum value.

Overall, the successful implementation of the AI solution requires cross-functional collaboration, a robust data infrastructure, training and education, performance metrics, and continuous improvement.

AI can help optimize lean manufacturing processes: Lean manufacturing aims to eliminate waste and improve efficiency in production processes. AI can assist with this by analyzing vast amounts of data in real-time and identifying areas where production can be improved. By using machine learning algorithms to analyze historical data and identify patterns, AI can help manufacturers identify inefficiencies, reduce lead times, and improve product quality.

AI can improve decision-making in lean manufacturing: One of the key principles of lean manufacturing is continuous improvement. This requires making data-driven decisions based on real-time information. AI can help manufacturers by providing real-time insights into production processes, allowing managers to make informed decisions quickly. For example, AI-powered predictive maintenance can detect equipment failures before they occur, enabling manufacturers to take preventative action and avoid costly downtime. Additionally, AI-powered quality control systems can detect defects in products before they leave the factory, reducing the risk of product recalls and improving customer satisfaction.

Key lessons learned while working on this project include:

Data quality is crucial: The success of any AI project heavily depends on the quality of data used to train the models. Therefore, it's essential to have a solid understanding of the data sources, data quality, and the potential biases in the data.

Iterative approach is key: Developing a successful AI solution requires an iterative approach. Starting with a minimum viable product (MVP) and continuously refining and improving the solution based on feedback and data is critical to ensure the solution meets the business needs.

Collaboration is essential: Collaboration between different teams is crucial for the success of any AI project. It's important to foster a culture of open communication, where teams can share their expertise and work together to overcome any challenges.

Future directions for this project include:

Expand the solution to other types of liquids: The current solution focuses on detecting the liquid level of a specific type of liquid. Expanding the solution to work with different types of liquids can increase the potential ROI and value created for CSI.

Incorporate predictive maintenance: The solution can be extended to incorporate predictive maintenance capabilities. By using AI to analyze data on the filling process, the solution can predict when maintenance is required, reducing downtime and maintenance costs.

Integration with other systems: The solution can be integrated with other systems used by CSI, such as production planning and scheduling systems. This integration can provide a holistic view of operations and improve decision-making.

Continuous improvement: The solution should be continuously monitored, evaluated, and improved to ensure it remains aligned with the evolving needs of CSI and delivers maximum value.

In summary, while working on this project, we learned that developing a successful AI solution requires a solid understanding of the data sources and data quality, an iterative approach, and cross-functional collaboration between different teams. We also identified future directions to expand the solution to work with different types of liquids, incorporate predictive maintenance, integrate with other systems, and continuously improve the solution to ensure it remains aligned with the evolving needs of the business. Overall, this project highlighted the potential of AI to create value for CSI by reducing product waste, improving efficiency, enhancing quality control, and enabling predictive maintenance, and underscored the importance of careful planning and execution to ensure successful implementation and adoption.

A value creation framework is a structured approach to identifying, defining, and measuring the value created by an organization. It provides a systematic way to understand how an organization creates value for its stakeholders, including customers, employees, shareholders, and society.

The framework typically involves a series of steps, which may include:

Defining the organization's mission, vision, and values: This involves defining the organization's purpose, the impact it aims to make, and the principles that guide its actions.

Identifying the organization's value drivers: This involves identifying the key factors that contribute to the organization's ability to create value, such as its products and services, processes, technology, people, and culture.

Understanding customer needs and preferences: This involves understanding the needs and preferences of the organization's customers and stakeholders, and how they perceive the value created by the organization.

Mapping the organization's value chain: This involves identifying the key activities and processes that contribute to the creation of value, and how they are connected and integrated across the organization.

Measuring and monitoring value creation: This involves developing metrics and KPIs to measure the value created by the organization, and monitoring performance against these metrics to ensure continuous improvement.

Overall, a value creation framework provides a structured way to align an organization's activities and resources with its goals, and to ensure that it creates value for all of its stakeholders.