Liquid Level detection group 1 Final Report

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Automated fill stations are widely used in various industries for filling up containers with liquids such as fuel, chemicals, and beverages. Accurately detecting the liquid level in these containers is crucial to prevent overfilling or underfilling, which can lead to safety hazards, product loss, and environmental damage. Traditionally, level detection is performed using sensors that rely on physical contact with the liquid, which can be prone to errors and require regular maintenance.

Recent advancements in computer vision technology have paved the way for non-contact liquid level detection, offering a more accurate, reliable, and cost-effective solution. By using machine learning algorithms, computer vision systems can process images or videos captured by cameras placed above and around the fill station and accurately determine the liquid level in the container in real-time.

In this report, we will explore the benefits of using computer vision AI for liquid level detection in an automated fill station environment, including improved accuracy, reduced maintenance, and increased safety. We will also discuss the key components of a computer vision system, the training and testing process of the machine learning algorithm, and the challenges and limitations of this technology.

Furthermore, the goal of implementing computer vision AI for liquid level detection in an automated fill station environment is to maximize the return on investment (ROI) by reducing product waste and improving overall efficiency. By accurately detecting and bypassing the vials that are either overfilled or underfilled to a rework station, these vials can be inspected and corrected, making them a part of the properly filled vial population. This ensures that only high-quality products are delivered to customers, while minimizing the amount of product waste and reducing operational costs associated with rework and disposal. Therefore, the use of computer vision AI not only enhances the accuracy and reliability of liquid level detection but also contributes to the overall success of the automated fill station process.

The implementation of a computer vision system for liquid level detection in automated fill stations requires several key components, including cameras, lighting, image processing software, and machine learning algorithms. The cameras capture images or videos of the containers passing through the fill station, which are then processed by image processing software to extract features such as the liquid level. Machine learning algorithms are then trained using labeled data to recognize the liquid level and make accurate predictions in real-time.

However, there are several challenges and limitations associated with the implementation of computer vision in the context of automated vial filling stations. One significant challenge is the variation in lighting conditions and reflections on the containers, which can affect the accuracy of the liquid level detection. Moreover, the presence of bubbles or froth in the liquid can also cause errors in detection. Another challenge is the need for extensive training data to train the machine learning algorithm effectively, as the system needs to account for various liquid types and container sizes. Additionally, the high-speed nature of the fill station requires real-time processing, which can be a bottleneck for traditional machine learning algorithms. To overcome these challenges and limitations, researchers have proposed several solutions, such as the use of advanced imaging techniques, such as hyperspectral imaging and polarization imaging, to improve liquid level detection accuracy. Additionally, the use of deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown promising results in reducing errors and improving real-time processing speed. However, the effectiveness of these techniques still depends on the quality and quantity of the training data and the specific characteristics of the liquid being filled.

Our group has 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 report, 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. We 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.

**AI strategy**

The specific business problem here is to reduce product waste and improve overall efficiency in an automated fill station environment. Our AI solution will 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. Data on liquid level measurements and filling process parameters were collected and preprocessed to ensure accuracy and consistency. The solution will need to be continuously monitored and optimized to ensure it achieves the desired ROI by reducing product waste and improving overall efficiency.

**Industry environment perspective.**

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 filling 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.

**Value creation perspective.**

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.

**Organization and execution perspective.**

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 meets the evolving needs of the business and delivers maximum value.

**Problem definition - workshop 1**

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.

**Data for workshop 1**

Read in the liquid fill data then isolated 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 just weight failures.

**Model for workshop 1**

* 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.

**Confusion matrix from workshop 1**

* The Confusion matrix in this case shows that for our test set had 1 true positive and 2 true negatives, and 0 false negatives and false positives.
* This means that the model correctly identified every vial that failed visual inspection. The absence of false negatives in this matrix indicates that the model did not miss any vials that failed visual inspection.

**Summary and conclusions for workshop 1**

* The confusion matrix showed that the model correctly predicted the outcomes (no failure). An 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.
* In conclusion, this logistic regression model provided a moderate level of accuracy in predicting the outcomes of visual inspections of liquid fill vials.

**Problem definition - Workshop 2**

Following up workshop 1 we utilized computer vision AI (image data analysis) to verify and reinforce the predictive power of our original logistic regression models.

We chose to examine two different computer vision models one is a binary case (pass, fail) while the other is a tertiary case (under fill, correct level and overfilled).​

**Data for workshop 2**

* Images from both recipe 1 vials and recipe 3 vials were used.
* Wrote code to sort images based on weight into overfill, under fill, and proper fill.
* Weight data turned out to be flawed so we visually inspected to manually classify images. Cropped images to isolate just the vial and reduce background for the image classifier using photo editing software to apply the cropping consistently across all images. A picture containing text, beverage, alcohol

  Description automatically generated A picture containing indoor, wall, kitchen

  Description automatically generated

**Model for workshop 2**

* Loaded images into Custom vision application.
* Used small number of samples from the properly filled set so that training data would be balanced.
* Cropped photos worked to help the model isolate relevant feature increasing accuracy from 75% to 100%

**Summary and conclusions for workshop 2**

* The model was able to correctly predict over-fill under-fill and proper fill from test images.
* Had some confusion with properly filled recipe 3 vials being classified as likely underfilled.
* A larger training set would likely result in more precise classifications even determining the ranges for how underfilled or overfilled the product is.
* Has ability to catch leaking or damaged containers even if they initially passed inspection.

**Idealized Project**

* With more data, project 1 could be improved to allow rework of a broader set of failed products.
* Using the visual inspection RGB data, a classifier could be made to indicate what ingredient is missing or overfilled for vials that do not pass visual inspection.
* Custom vision models from project 2 could also be improved to classify leaking or broken containers that might have passed inspection but are no longer properly filled so they don’t go out to customers.
* The vision model could also be fine-tuned to determine more precisely how much the vials are over/under filled.

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.

In conclusion, the implementation of computer vision AI in automated vial filling stations offers several advantages, including increased accuracy, reduced maintenance, and improved efficiency. However, the challenges and limitations associated with this technology need to be addressed to ensure its effectiveness in real-world applications.

Items(deliverables) included with this report are:

1 - Final report

2 - PPP presentations – workshop 2 and final

Python code used for workshop 1 and 2, CNN code that was not implemented.

References:

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Weng, C., Jiang, H., & Wang, X. (2021). Deep learning for liquid level detection: A review. Measurement, 183, 109-123.