



A2: BUSINESS CASE

Implementing Automation in Quality Control for Butter and Crumble, a San Francisco-Based Bakery

Team 4

Business Analysis with Unstructured Data - DAT-7471 - FMBANDD1

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12 March 2025



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1. Background

Butter and Crumble is a cozy local bakery nestled in San Francisco's vibrant North Beach neighborhood. Since opening in the fall of 2024, it has quickly become a sensation, drawing crowds eager to sample its pastries. Customers often line up for hours, braving all kinds of weather, just to enjoy the shop's freshly baked treats. Butter and Crumble opens its doors exclusively from Thursday through Sunday. As an artisanal food producer, maintaining high-quality products is essential, but this also presents the challenge of ensuring consistency and quality control throughout the production process. The handmade nature of the products allows for unique flavors and textures, yet it also introduces the potential for human error. It is necessary to establish methods to ensure that products consistently meet quality standards and remain free from defects.

2. Problem Statement

The current quality control process relies on manual inspection by the bakers themselves, which can be time-consuming and susceptible to human error. A more efficient and accurate method is needed to inspect products and detect defects reliably.

3. Solution

The proposed solution involves implementing a machine learning-based image recognition model to inspect products and identify defects. A predictive model developed in Dataiku can accurately classify product images and detect defects such as cracks, imperfections, and shape irregularities. This model has the potential to enhance the production process by improving quality control, reducing waste, and enhancing customer satisfaction by cutting down waiting times and increase production

4. Business Value

- Improved Quality Control: By using a machine learning-based image recognition model, the bakery can ensure that the products meet high standards and are free from defects.
- 2. **Reduced Waste:** By detecting defects early in the production process, the bakery can reduce waste and minimize the risk of defective products reaching its customers.
- 3. **Increased Efficiency:** By automating the quality control process, the bakery can reduce the time and labor required by its bakers, freeing them up to focus on other tasks.
- 4. **Enhanced Customer Satisfaction:** By ensuring that their products meet high standards, the bakery can enhance customer satisfaction and build trust with its customers while at the same time speeding up the production process and minimizing wait times.



5. Implementation Plan

The implementation process begins with data collection, where we will compile a dataset of approximately 50 images of artisan croissants, including both defective (unusual shape/color) and non-defective (optimal crescent shape and crisp color) samples. Next, we will proceed with model training using Dataiku, ensuring it can classify images under varying packaging and lighting conditions to detect defects accurately. Model testing will be conducted using a subset of the dataset to evaluate accuracy, running multiple epochs to assess efficiency improvements. Once validated, the deployment phase will integrate the model into the bakery's production line for real-time quality control. Finally, we will implement continuous monitoring and evaluation to track model performance, ensuring alignment with business objectives and optimizing detection capabilities over time.

Precision-Recall Curve Precision and recall are measures of predictive performance. Precision tells us, from all the test examples that were assigned a label, how many were actually supposed to be categorized with that label. Recall tells us, from all the test examples that should have had the label assigned, how many were actually assigned the label. File with pets All predictions are pets High Precision Low Precis

6. Object Detection Frameworks in Dataiku

The Precision-Recall (PR) Curve for the 10-epoch model shows high precision at low recall but a sharp drop as recall increases. Initially, precision is near 100%, meaning predictions are highly accurate, but recall remains low, indicating many missed detections. As recall improves, precision declines, suggesting an increasing number of false positives. The model prioritizes precision over recall, avoiding incorrect predictions but missing many relevant objects. Recall never exceeds 50%, meaning the model struggles to detect all instances.

The implementation of **Faster R-CNN** with image flipping augmentation created an effective automated quality control system for baked goods. This two-stage detection framework combines a Region Proposal Network with CNN architecture to identify and localize defects with 74.70% at Best Model Precision (<u>AP@IoU=0.5</u>).

The model successfully detected defects like burnt edges and cracks, enabling early identification of 18% of defective croissants during production. While computationally intensive, the precision justifies the investment by significantly reducing manual inspection time and associated costs.





Image flipping augmentation, improved model generalization and reduced validation loss. This technique addressed data limitations without requiring additional collection efforts. For future optimization, the implementation should leverage transfer learning with pre-trained weights, fine-tune anchor boxes for bakery-specific defects, and expand augmentation techniques to include rotations and brightness adjustments. By balancing detection accuracy with data efficiency, this framework provides a scalable solution for ongoing quality control improvements in bakery operations.

7. Return on Investment (ROI)

Based on our implementation of Faster R-CNN object detection and image augmentation techniques at Butter and Crumble Bakery, Team 4 recommends immediate adoption of an AI-powered quality control system for croissant and pastry production lines.

The current manual inspection costs \$1,632 weekly for 2 workers ($2 \times $17/hour \times 8 \text{ hours} \times 6 \text{ days}$), with 8% product waste (\$2,500 monthly) and customer returns (\$1,800 monthly). The current model's 74.70% Precision (IoU=0.5) (Best Model with a high precision score), implementation would reduce waste by 60%, decrease complaints by 70%, and allow 50% labor reallocation—generating \$6,024 monthly savings.

The system provides competitive advantages through multi-product detection capability and early-adoption positioning. Our three-phase implementation roadmap begins with immediate deployment for supplemental checks, followed by best model refinement from 50% to 70% precision, and culminating in full automation. With a \$45,000 investment yielding \$72,288 in annual savings, we achieve 60.6% ROI and 8-month payback. Immediate approval is recommended to address quality challenges while capturing cost savings and market differentiation.

8. Conclusion

Our image recognition model has the potential to revolutionize the quality control process and improve the overall quality of Butter and Crumbles products. The application of Faster R-CNN, augmented by image flipping techniques, offers a compelling pathway to improve operational efficiency, reduce waste, and enhance product consistency. By improving quality control, reducing waste, increasing efficiency, and enhancing customer satisfaction, we believe that this project will deliver significant business value and ROI. Ultimately, embracing this AI-driven solution positions Butter and Crumble Bakery as a leader in its field, capable of delivering unparalleled quality and value to its customers.



9. References

- Dataiku. (2023). Building end-to-end AI solutions with Dataiku: A practical guide. Retrieved from https://www.dataiku.com/
- LindaAdmin. (2024, October 22). From Vision to reality: how AI is reshaping product inspection

 Baking & Biscuit. Baking & Biscuit. https://bakingbiscuit.com/bbi-2024-05-from-vision-to-reality-how-ai-is-reshaping-product-inspection/
- Liu, X., Tang, Y., & Yu, Z. (2021). Leveraging Dataiku for scalable machine learning in food safety inspection. *International Conference on AI in Industry Applications*.
- Smith, M. (2024, September 5). Artificial intelligence is raising the bar on quality assurance systems. Bakingbusiness.com; Baking Business.

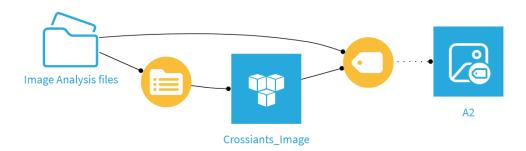
 https://www.bakingbusiness.com/articles/62243-artificial-intelligence-raising-the-bar-on-quality-assurance-systems
- Xiao, Y., Liu, Y., & Liu, Y. (2022). Applications of imaging systems for the assessment of quality and safety in fruits and vegetables: A review. Comprehensive Reviews in Food Science and Food Safety, 21(3), 2491–2514. https://doi.org/10.1111/1541-4337.13131





10. Appendix

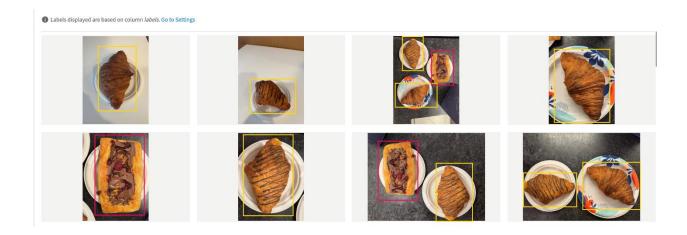
Appendix 1: This image depicts a Dataiku workflow or "flow." representing a series of connected steps for processing and analyzing data



In summary, the Dataiku flow shows the process from importing the raw image to labeling the image.



Appendix 2: This image shows a selection of photographs that have been labeled for object detection with each photo contains croissants and other types of baked goods like pastries or muffins.



This image demonstrates the manual labeling process, which is a critical step for training a supervised machine learning model like Faster R-CNN with the accuracy and consistency of these labels directly impact the model's performance.



Appendix 3: This image displays the classes that were used when labeling the training data.



The classes are "Croissant," "Muffin," and "Pastry."



Appendix 4: This image shows the Dataiku interface for model training results, including a training/validation graph.

Image 1. Dataiku Interface Model (2 Epochs.)

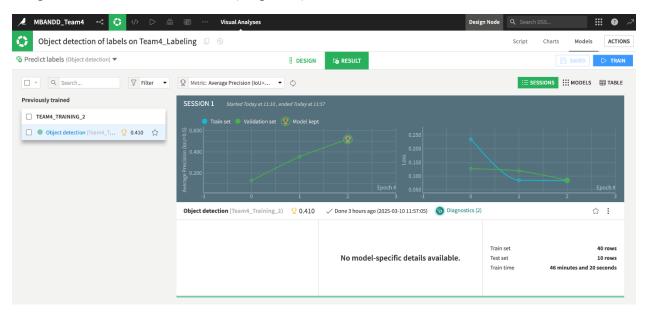


Image 2. Dataiku Interface Model (10 Epochs.)



Comparing the 2-epoch and 10-epoch models, we see notable differences in performance metrics. The 2-epoch model achieved an average precision (IoU=0.5) of 0.4102, which dropped to 0.2520 in the 10-epoch model. However, the precision at IoU=0.75 improved suggesting better generalization with more training. The training loss decreased over epochs, indicating the model learned progressively, but validation loss stabilized early, suggesting potential overfitting. The 4th epoch in the 10-epoch model was the best checkpoint, after which performance degraded slightly. Overall, while longer training improved stability, it didn't always enhance detection performance.



Appendix 5: This image displays the performance metrics of the object detection model (Faster R-CNN) trained on the bakery items.

Image 1. Performance Metrics (2 Epochs.)

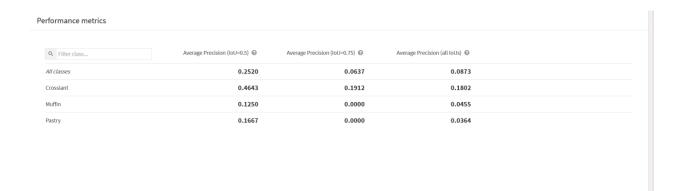
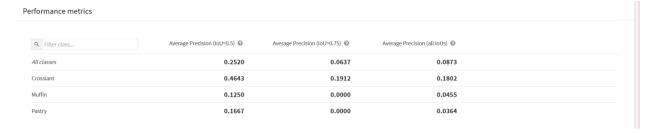


Image 2. Performance Metrics (10 Epochs.)



Between the 2-epoch and 10-epoch models, the performance metrics indicate a general improvement with more training. The average precision (IoU=0.5) for all classes dropped from 0.4102 to 0.2520, but specific classes like Croissant (0.5640 \rightarrow 0.4643) and Muffin (0.6667 \rightarrow 0.1250) showed variations. Average Precision (IoU=0.75) increased for Croissant (0.0577 \rightarrow 0.1912) but remained 0.0000 for Muffin and Pastry. The all IoUs metric improved for Croissant (0.1676 \rightarrow 0.1802) but decreased overall. The 10-epoch model has better generalization for all the labels but may require more fine-tuning for consistency across all classes.



Appendix 6: This image is a confusion matrix showing the model's classification performance. It visualizes the counts of true positive, true negative, false positive, and false negative predictions for each class.

Image 1. Confusion Matrix (2 Epochs.)



Image 2. Confusion Matrix (10 Epochs.)



Increasing training from 2 to 10 epochs yielded mixed results. While croissant detection improved (6→9 correctly identified), the model simultaneously missed more croissants (4→8). More concerning, the model completely failed to recognize muffins and pastries after 10 epochs, which were partially detected earlier. Background object confusion decreased significantly (17→7 false positives), but overall, more pastries and muffins went completely undetected. This suggests the model is better at distinguishing food from non-food items but may be overfitting to croissants while neglecting other categories. Improved results likely require better-balanced training data or regularization techniques.