TEAM 03

SNAP & CHOOSE

Smart Search for your Bottom Wear

DENIM | NON-DENIM

PixThread Boutique
(Revolutionizing your style with Snap, Shop & Wear)

Image recognition technology is revolutionizing the way we shop for clothing, particularly when it comes to finding the perfect pair of pants. By leveraging the power of visual data analysis, this technology can accurately assess body dimensions from images or videos, enabling highly personalized size and fit recommendations. This not only helps in reducing the common issue of returns due to poor fit but also ensures that customers can enjoy a better fitting pair of pants with minimal hassle. Furthermore, image recognition can facilitate quick style assessments, matching new items like pants to the shopper's existing wardrobe, thus enhancing style coherence and satisfaction (Yang, 2022).

The convenience offered by image recognition technology significantly streamlines the shopping process. Shoppers can simply use images of pants they like to find similar or identical products available for purchase, effectively bypassing the time-consuming process of manual search (Zakaryan, 2022). Additionally, by analyzing consumer preferences and shopping patterns, retailers can utilize image recognition to deliver more personalized marketing and product recommendations, ultimately enriching the overall shopping experience.
The audience for this technology in the retail clothing market is broad and diverse, but the key groups include:

- Tech-Savvy Shoppers: Younger consumers (Millennials and Gen Z), who are comfortable with technology and expect a seamless integration of digital tools in their shopping experience. They value efficiency and personalization, which image recognition technology can provide (McKinsey & Company, 2023).
- Busy Professionals: Individuals with hectic schedules who appreciate the speed and convenience of being able to quickly find and purchase clothing online.
- Fashion Enthusiasts: Those who are keen on keeping up with the latest trends and styles. Image recognition can help them find specific products or similar styles almost instantaneously, allowing them to stay fashionable without extensive searching.

Framework used in class
Framework 1: Object Detection with Faster R-CNN
The first framework involves the use of Faster R-CNN for object detection. This framework is crucial to distinguishing between denim and non-denim pants on an online retail platform, which improves the customer experience.

Its average precision (AP) scores, particularly at Intersection over Union (IoU) of 0.5, were 0.6714 for denim and 0.5597 for non-denim, as you can see in the performance metric in the appendix, demonstrating a strong ability to correctly identify items.

Business Insight: Implementing the Faster R-CNN model can significantly improve the customer search experience. Customers are more likely to find products that closely match their search intent when using high precision, lowering the likelihood of returns due to misclassified items.

Framework 2: Background Noise in Object Detection

The second framework pertains to handling background noise in object detection. Background noise refers to irrelevant information or distractions in the image that can lead to misclassification or failure to detect the object of interest.

Business Insight: In the context of an online retail platform, background noise might lead to inaccurate product tagging, frustrating customers if irrelevant goods appear in their search results or the required items are not found. Reducing background noise is consequently critical for maintaining a high-quality user experience by ensuring that buyers only see relevant product visuals. As illustrated by the confusion matrix in the appendix, the model demonstrated impressive specificity while maintaining a low false-positive rate. This specificity ensures that only relevant product photos are presented, keeping users engaged and trusting.

Model Performance

The model was trained on a small dataset with 100 photos for both denim and non-denim. The training was done using a pretrained Faster R-CNN model with a 0.80 split ratio and three epochs. The evaluation results for the model for each class are presented in the table below.

Classes	Average Precision (IoU = 0.5)*	Average Precision (IoU = 0.75)	Average Precision (all IoUs)
All classes	0.6155	0.0439	0.2125
Denim	0.6714	0.0785	0.2686
Non-denim	0.5597	0.0093	0.1565

**IoU = Intersection over Union*

Intersection Over Union (IOU) is a measure of the overlap between the predicted bounding box and the ground truth label with the same/correct class (Dataiku). With this metric, it can assess the model's accuracy for denim and non-denim detection.

Based on the results, it indicates that the model performs reasonably well at detecting objects when considering a moderate IoU threshold (0.5), but its performance decrease at increasing IoU thresholds, indicating that it struggles with precise localization of objects.
Comparing the two classes, the model performs slightly better on the "denim" class compared to the "non-denim" class, with higher AP scores across all IoU thresholds.

Precision-Recall Curve

With the IoU of 0.50, the curve shows that the optimal performance of the model achieved a recall of 0.4167, precision of 0.7143, F-1 of 0.5263, and confidence of 0.5525. The model performs

relatively well in terms of precision, indicating that when it predicts an object as denim or non-denim, it's often correct. Conversely, the recall is lower, suggesting that the model misses some denim and non-denim objects in the images.
For an online retail platform where user experience and trust are crucial, it would be important to strike a balance between precision and recall, ensuring that the model provides a reasonable number of suggestions while maintaining a high level of accuracy.
Potential improvements include collecting more data, especially for the non-denim class, and training for more epochs. Moreover, fine-tuning the model to improve recall, especially for non-denim objects, would also enhance model overall performance.

A strong argument for implementing a model for image recognition technology in online shopping platforms, specifically for selecting denim and non-denim pants, centers on the considerable reduction in product returns. This technology model enhances the precision of matching products to customer preferences by analyzing uploaded images to determine key attributes like style, color, and fit. When customers receive items that closely align with their actual preferences, the likelihood of dissatisfaction decreases significantly. (Mohmmadi &Kalhor, 2021)

This accuracy is crucial because it addresses common online shopping challenges, such as difficulty in visualizing products and uncertainty about fit factors that often lead to returns. By reducing mismatches between customer expectations and the delivered product, the platform not only minimizes the incidence of returns but also boosts customer satisfaction and trust in the brand. (Mohmmadi & Kalhor, 2021)

Moreover, fewer returns translate directly as a cost savings for the business. Logistics associated with handling returns, such as shipping, restocking, and processing, are notably expensive. Cutting down on these costs directly enhances profitability. Additionally, reducing returns helps maintain product integrity, as items are less frequently handled and shipped multiple times. (Scullard, 2023)
In the broader scope, consistently lower return rates can improve a brand's reputation, positioning it as reliable and customer centric. This reputation for reliability can attract new customers and retain existing ones, who value accurate and dependable product descriptions and deliveries. (Vestil, 2023)

To top it all, using image recognition technology to refine how customers select pants on e-commerce platforms tackles a critical pain point—returns, which is both logistically challenging and a significant cost factor. This technological integration not only improves operational efficiency but also enhances the overall customer shopping experience, leading to sustained business growth and customer loyalty. (Vestil, 2023)

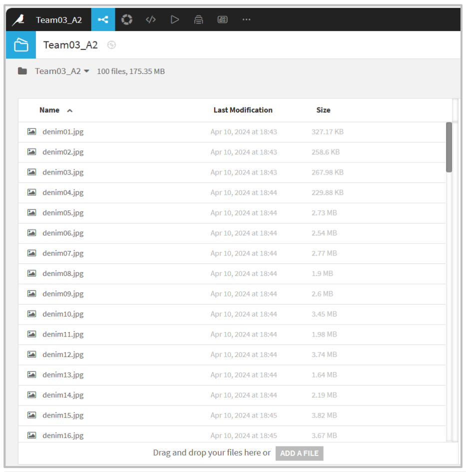
By precisely matching products to customer preferences, the Faster R-CNN model implementation for denim vs non-denim pants considerably lowers return rates in online shopping. The precision with which our model can identify these products is directly correlated with higher customer satisfaction and lower return costs and logistical burdens. The precision points to a strong basis for improved shopping experiences and operational efficiency, while the recall points to possible improvements. By lowering the carbon footprint connected with returns, adoption of this technology is a step toward environmental sustainability as well as a reduction in operating costs. Overall, our research supports the use of image recognition in e-commerce as a wise business move that could lead to long-term increases in client loyalty and competitiveness in the market.

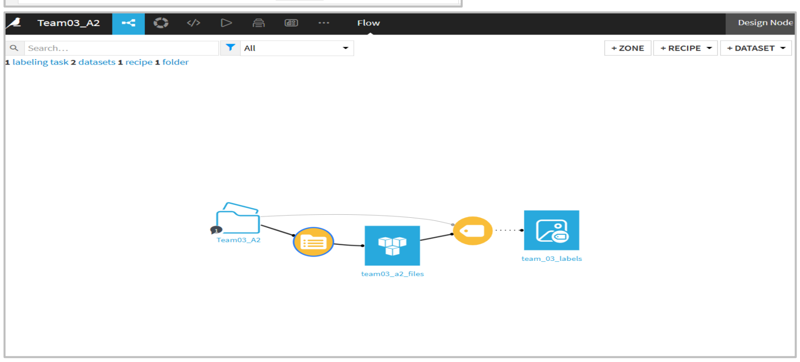
The implementation of Faster R-CNN has greatly improved product identification accuracy at PixThread Boutique, aligning products more closely with customer preferences, reducing returns, and increasing satisfaction. This precision reduces costs linked to returns and enhances the resale value of products. The technology also enriches the shopping experience by enabling personalized product recommendations through customer-uploaded images, which boosts engagement. To further enhance model performance, it's recommended to expand training data, increase training epochs, refine model parameters, and integrate user feedback. Additionally, promoting the sustainability benefits of reduced returns, integrating this technology into mobile platforms, and leveraging it for cross-selling can significantly enhance customer engagement and retention.

APPENDIX

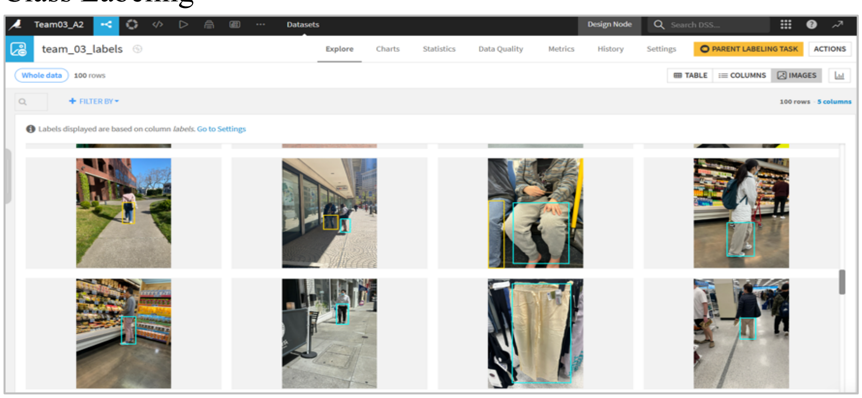
Dataiku Workflow

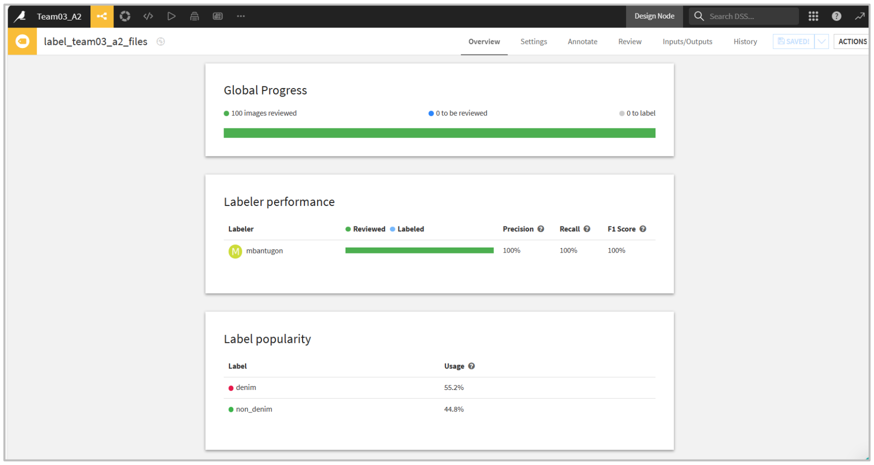
Consists of folder for photos, datasets, labeling recipes



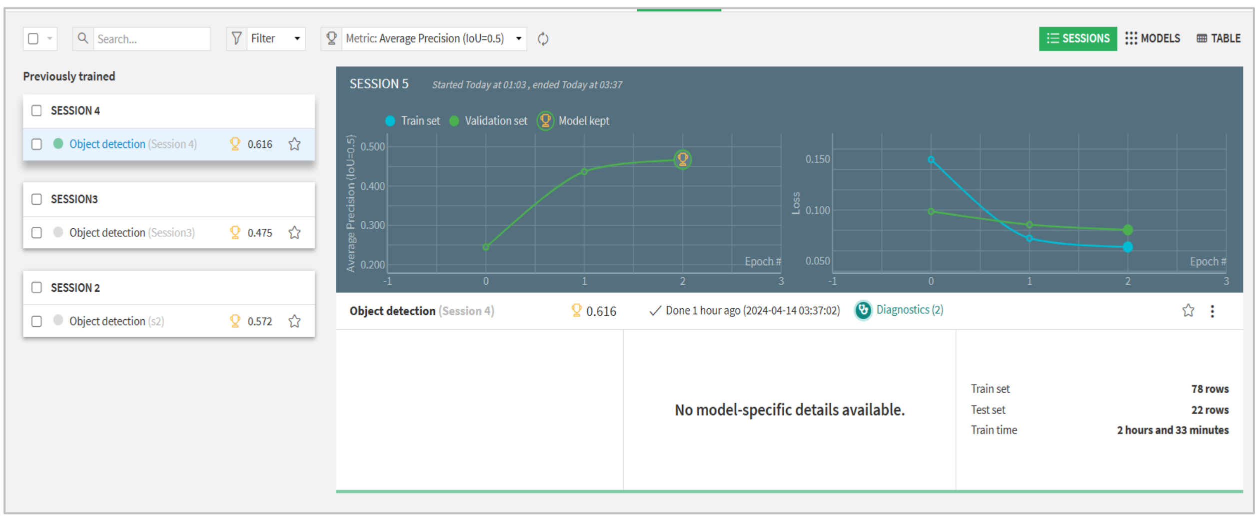


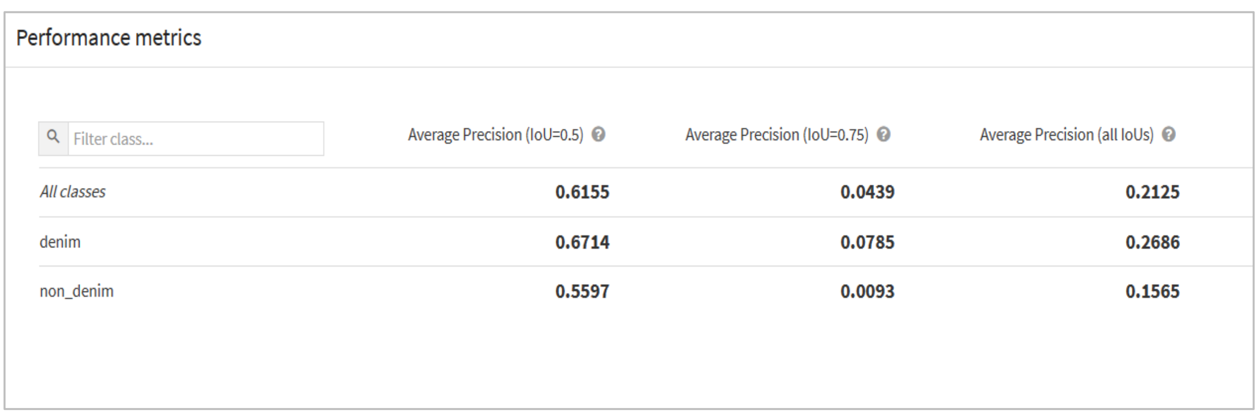
Class Labeling





Model

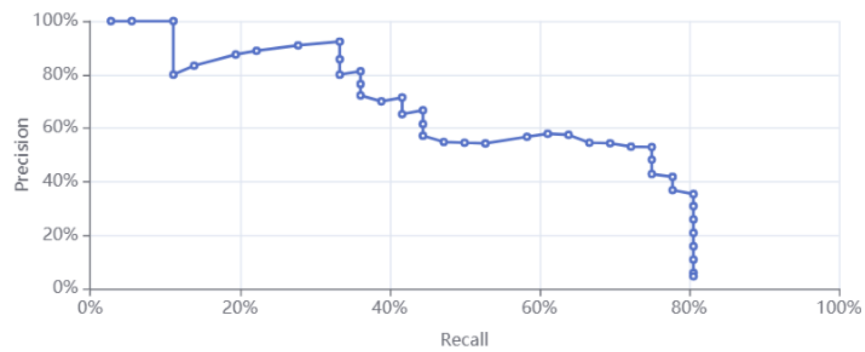




Performance metrics

Filter class...	Average Precision (IoU=0.5)	Average Precision (IoU=0.75)	Average Precision (all IoUs)
All classes	**0.6155**	**0.0439**	**0.2125**
denim	**0.6714**	**0.0785**	**0.2686**
non_denim	**0.5597**	**0.0093**	**0.1565**

Precision-Recall



Confusion matrix

IOU 0.5 — 1 0.50

Predicted

Ground Truth	denim	non_denim	Not Detected
denim	15	0	3
non_denim	0	12	6
Not an object	14	14	0

Training information

Diagnostics

Go to the design to enable/disable diagnostics

Dataset sanity checks	Training set might be too small (78 rows) for robust training Test set might be too small (22 rows) for reliable performance estimation
Modeling parameters	Nothing to report
Training speed	Nothing to report
Overfit detection	Nothing to report
Leakage detection	Nothing to report
Model check	Nothing to report
ML assertions	Nothing to report
Abnormal predictions detection	Nothing to report

Steps OPEN FULL LOGS

Loading train set	0.1s
Fine-tuning model	8,472.0s
Loading test set	0.0s
Scoring model	715.0s

Train & test sets EXPORT TO DATASET

Generated on	2024/04/11 22:16:56
Train set rows	78
Test set rows	22

Validation strategy

Mode	Train/Validation split
Split ratio	0.8

Runtime configuration

Enabled Diagnostics	Yes
Requested GPU Usage	No

Timings

Preprocessed in	0.0s
Trained in	9,188.1s

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