

Business Insights Report

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Executive Summary

The ability to anticipate and adapt to seasonal wear trends can provide fashion retailers with a crucial competitive advantage, as demonstrated in past research (Mohapatra, 2023). In this project, I utilized Dataiku's machine learning tools to develop a model capable of identifying when consumers transition to winter clothing. The model was designed to analyze images, such as those shared on social media platforms, to detect the presence of winter-wear, thereby enabling more timely decisions across marketing, manufacturing, and distribution that align with real-time clothing trends.

Despite early challenges, the model, trained on a curated dataset of 100 images featuring individuals either wearing jackets or not, achieved an impressive precision rate of 82% after three epochs. This performance highlights the model's potential for real-world applications and commercial value, especially with further refinement.

Business Case Rationale

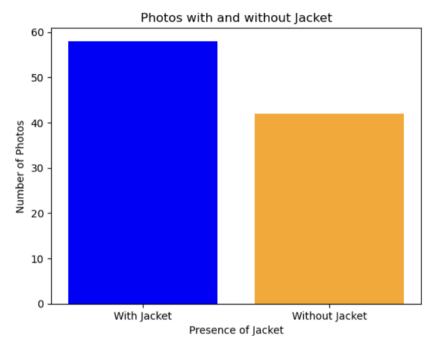
The traditional approach to trend analysis in fashion, largely based on past sales data and weather forecasts, struggles to keep pace with today's dynamic consumer behavior. In this project, I introduced a new strategy for winter-wear detection by leveraging real-time image data sourced from platforms like social media. This approach enables retailers to monitor what consumers are actually wearing as the season unfolds, offering immediate insights to guide decisions across inventory, marketing, and distribution. While full-scale manufacturing is typically planned in advance, real-time inputs still allow for rapid regional adjustments, restocking decisions, and geotargeted marketing campaigns; all of which enhance a retailer's responsiveness to emerging trends.

As illustrated by the image below, there's a clear shift in attire: shorts and T-shirts one day; jackets and layers the next. When such transitions are detected at scale through online imagery, they create a timely and actionable signal—"It's winter! Time to sell JACKETS!" This principle extends beyond winterwear and can be applied to other seasonal apparel categories such as beachwear, rainwear, or accessories. By capturing and responding to these shifts in real time, brands move from reactive forecasting to proactive engagement, aligning product decisions with live consumer behavior.



It's winter! Time to sell JACKETS!

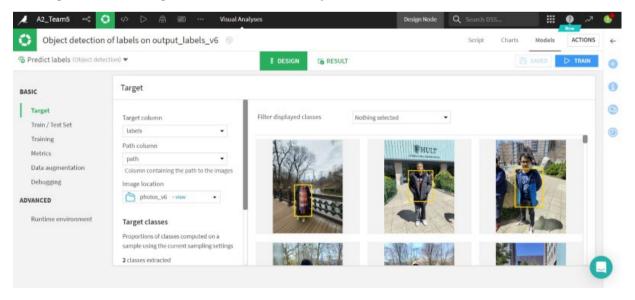
Model Setup



For this project, I used a mostly balanced dataset consisting of 58 images showing individuals wearing jackets and 42 without. I personally gathered and labeled all the images, applying essential machine learning frameworks such as image labeling and the Fastest R-CNN algorithm within Dataiku. The labeling process involved accurately tagging each image to ensure the

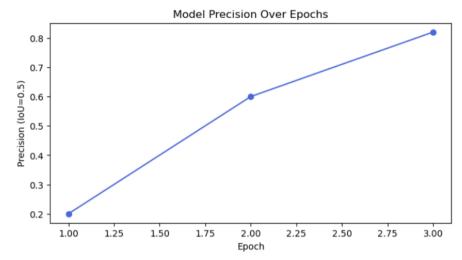
object detection model could effectively learn to distinguish between categories. This careful preparation was critical to achieving reliable classification performance.

I employed Fastest R-CNN (Region-based Convolutional Neural Networks), an advanced object detection framework known for its speed and accuracy. It integrates a region proposal network (RPN) that shares convolutional features across the entire image; this significantly enhances detection speed while maintaining high accuracy. From the outset, I also ensured diversity within the dataset by including individuals of different appearances and clothing styles, aiming to reduce bias; an issue that has historically affected computer vision models (Birhane, 2022). This combination of thoughtful dataset design and powerful modeling techniques laid a strong foundation for the analysis.



Designing of our final model

Model Results & Insights

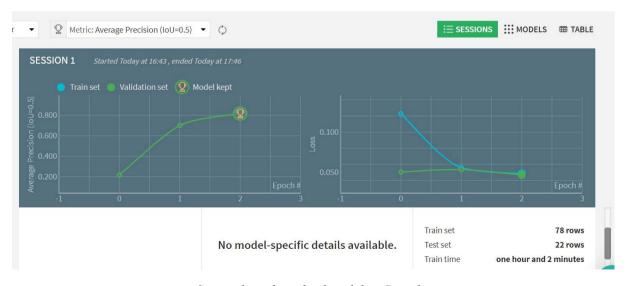


The model's precision improved significantly over the course of training—rising from an initial score of approximately 0.2 to 0.82 by the end of the third epoch. This performance gain is clearly illustrated in the graph below,

which tracks precision across training epochs. The upward trajectory reflects the effectiveness of the enhancements made, particularly the emphasis on higher-quality image inputs and refined labeling consistency.

To support this improvement, I conducted several rounds of dataset calibration. I experimented with varying image volumes—ranging from 100 to 120—and ultimately selected a clean, balanced set of 100 for final training. This approach helped minimize noise and overfitting while preserving class diversity and representativeness.

This careful and iterative process laid a strong foundation for continued optimization. As shown in the Dataiku session output below, both training and validation precision rates reached satisfactory levels, indicating solid generalization capacity. With further improvements—such as increasing data diversity, fine-tuning labels, and extending training sessions or testing more advanced model architectures—there is clear potential to further enhance performance. Even at this stage, however, the model demonstrates practical value for applications in seasonal trend detection and consumer behavior analysis.



Screenshot of our final model on Dataiku

Business Benefits Apparent

What are the business benefits of real-time winterwear detection? The fashion industry has long relied on historical sales data and generalized seasonal patterns to drive planning (Retalon, 2024; Begley et al., 2020). However, these methods lack flexibility and often lead to inefficiencies in stock management, distribution, and customer engagement. A model such as mine, capable of detecting actual shifts in seasonal wear through image analysis, enables a suite of agile business responses that go beyond traditional forecasting.

Inventory Optimization: While major inventory decisions are made in advance, real-time detection supports mid-season fine-tuning. Retailers can rebalance inventory across regions, accelerate restocks in high-demand zones, and prevent overstock in slower markets. This leads to fewer markdowns and more revenue retained.

Supply Chain Agility: Although production schedules are set early, downstream logistics remain highly flexible. Real-time trend signals can inform distribution decisions, trigger micro-batch replenishments, and optimize transportation flows between distribution centers and retail outlets.

Targeted Marketing: Detecting when and where winterwear is trending enables precise, timely marketing campaigns. Retailers can run region-specific ads, influencer activations, or flash promotions aligned with current consumer behavior, not just seasonal assumptions.

Enhanced Customer Experience: Customers increasingly expect relevant and timely product offerings. A model that reacts to actual weather-driven behavior ensures better product availability and strengthens brand loyalty.

Data-Led Decisions: With accurate trend signals, companies can confidently adjust pricing, campaign timing, and assortment strategies mid-cycle. This minimizes risk and enables smarter capital allocation.

Competitive Advantage: Being first to react to emerging trends provides a critical edge. Businesses that align with real-time signals position themselves as market leaders, capturing early demand while competitors lag behind.

Sustainability: Real-time inventory alignment helps reduce overproduction and waste; supporting environmental goals while also lowering storage and markdown costs.

In short, integrating real-time image recognition into fashion operations transforms passive planning into dynamic decision-making, positioning businesses to meet demand with greater accuracy, efficiency, and speed.

Similar Industry Examples

This approach builds upon proven industry use cases that highlight the value of AI-powered fashion analytics:

Heuritech's Trend Forecasting: Heuritech uses machine learning to analyze millions of social media images, identifying trends before they peak in popularity. This enables brands to align product collections with anticipated demand (Adegeest, 2020).

Zara's AI-Driven Supply-Chain: Zara has integrated AI throughout its production and distribution pipelines, facilitating rapid product turnarounds and demand-responsive restocking. This real-time strategy has strengthened customer retention and operational agility (AI Expert Network, 2023).

Oracle's Fashion Analytics: Oracle provides analytics tools that help retailers optimize product assortment, collection planning, and in-store execution by transforming customer behavior into actionable insights (Hickins, 2023).

These examples validate the commercial potential of real-time trend detection in reshaping how apparel brands design, market, and deliver fashion products.

Model Improvement Recommendations

To further enhance the performance and generalizability of the model, I plan to expand the dataset to include additional images captured under a wider range of lighting conditions, backgrounds, and jacket styles. Increasing demographic and phenotypic diversity will help reduce bias, while broadening the scope beyond jackets to include other winterwear items, such as scarves, boots, and gloves, will increase the model's practical utility. Extending training epochs and refining label precision should help minimize prediction noise and further improve accuracy. Additionally, exploring alternative model architectures outside of Dataiku, such as YOLO or EfficientDet, may provide the robustness and scalability required for real-world deployment. These refinements would help elevate this model from a strong academic prototype to a fully deployable industry solution.

Conclusion

In conclusion, this real-time image recognition model has the potential to usher in a new era of AI-driven fashion analytics. By detecting seasonal clothing transitions as they occur, businesses can make decisions grounded in current consumer behavior rather than relying solely on forecasts.

The results align with successful implementations by companies like Heuritech, Zara, and Oracle, demonstrating that scalable, intelligent trend detection can improve inventory accuracy, marketing precision, and customer satisfaction. This represents a critical shift—from seasonal guessing to adaptive strategy—and positions retailers to thrive in a market increasingly defined by speed, relevance, and data-driven innovation.

Appendix

Link to all of the images utilized for final model:

https://dataikufashion.s3.us-east-2.amazonaws.com/Photos.zip

References

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