



GEORGE BROWN COLLEGE
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Applied A.I. Solutions Development

FULL STACK DATA SCI. SYSTEMS
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AI Powered Smart Try On

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Introduction to the Smart Try On

Online shopping has revolutionized the retail industry, offering consumers unparalleled convenience and access to a vast array of products from the comfort of their homes. However, despite its many advantages, online shopping presents unique challenges, particularly in the fashion and apparel sector. One of the most significant issues faced by online shoppers is the difficulty in visualizing how clothing will fit and look on them without the ability to try it on physically. This challenge not only creates uncertainty and hesitation during the purchase decision-making process but also contributes to a high rate of returns. Many customers find themselves dissatisfied when the item they receive does not meet their expectations in terms of fit, style, or color. This disconnect between online presentation and physical reality leads to increased operational costs for retailers, who must manage returns, and can also negatively impact customer loyalty and trust. As a result, addressing the gap between virtual shopping experiences and physical expectations has become a critical focus for improving customer satisfaction and reducing return rates in the online fashion industry.

Problem Statement

In the rapidly expanding online fashion industry, a significant challenge for consumers is the inability to try on clothing before purchase, leading to uncertainty about fit, style, and appearance. This uncertainty often results in hesitation during purchase decisions and a high rate of returns, which are costly for both consumers and retailers. To address this issue, there is a pressing need for innovative solutions that bridge the gap between virtual and physical shopping experiences. Developing a virtual trial room that allows users to digitally try on clothes offers a promising solution. By enabling customers to visualize how garments will look and fit on their bodies, a virtual trial room can reduce the need for physical fittings, lower return rates, and enhance the overall online shopping experience. This technology not only improves customer satisfaction but also provides retailers with a competitive edge, fostering more confident purchasing decisions and increasing customer loyalty.

Market Demand: The demand for a virtual trial room is driven by the growing online fashion market, where consumers increasingly seek convenience without compromising on the assurance of fit and style. With the rise of e-commerce, the inability to physically try on clothes remains a major pain point, contributing to high return rates and customer dissatisfaction. As online shopping continues to expand, there is a clear market need for solutions that replicate the in-store experience digitally. A virtual trial room addresses this demand by offering a personalized and interactive shopping experience, allowing consumers to visualize how garments will fit and look on their bodies. This not only enhances customer confidence in purchasing decisions but also reduces returns, making it a valuable tool for retailers aiming to improve customer satisfaction, operational efficiency, and brand loyalty in an increasingly competitive market.

Social Impact: The development of a virtual trial room has significant social impact by making online shopping more inclusive and accessible to a diverse range of body types, reducing the stigma associated with size and fit discrepancies. It empowers consumers to make more informed and confident purchasing decisions, thereby decreasing the frustration and financial burden of returns. Additionally, this technology promotes sustainability by reducing the carbon footprint associated with shipping and handling returns. By enhancing the online shopping experience, it fosters greater consumer satisfaction and trust, ultimately contributing to a more equitable and environmentally responsible retail ecosystem.

Past Available Project Overview

One of the early attempts to address the challenge of online clothing fit was the development of a virtual fitting tool called Virtusize, which was integrated into various online retail platforms. Virtusize aimed to assist customers in making more informed purchasing decisions by allowing them to compare the measurements of garments they were considering buying with those of clothes they already owned. This tool operated on a 2D comparison model, where users could input the dimensions of their existing clothing items and compare them with the product dimensions listed online.










Technology

The technology behind Virtusize was relatively straightforward, relying on 2D measurement comparisons without the integration of advanced technologies such as artificial intelligence (AI) or 3D modeling. While this approach provided a basic level of fit guidance, it was limited in its ability to offer a truly immersive or accurate representation of how the clothing would fit on the user's body. The lack of 3D modeling meant that Virtusize could not account for the nuances of different body shapes or provide a realistic visual representation of the garment on the user's figure.

Outcome

While Virtusize succeeded in offering basic size recommendations and helping some users avoid sizing issues, it fell short in delivering a comprehensive fitting experience. The tool's limitations in providing a realistic visualization of how clothing would fit led to continued uncertainty among customers, who still had to rely on guesswork. As a result, while Virtusize was a step forward in the evolution of virtual fitting tools, it highlighted the need for more sophisticated solutions that could provide a more accurate and personalized shopping experience. The tool's outcomes underscored the importance of integrating advanced technologies like AI and 3D modeling to enhance the realism and effectiveness of virtual fitting rooms.

ML Canvas

<div></div> <div>PREDICTION TASK</div> <div>Type of task? Entity on which predictions are made? Possible outcomes? Wait time before observation? Type of task? Image classification, object detection, and virtual fitting. Entity on which predictions are made? User's body measurements, clothing items, and body poses. Possible outcomes? Accurate virtual fit, mismatched fit, or no match available. Wait time before observation? Real-time processing, ideally within a few seconds to maintain user engagement.</div>	<div></div> <div>DECISIONS</div> <div>How are predictions turned into proposed value for the end-user? Mention parameters of the process / application that does that. How are predictions turned into proposed value for the end-user? The ML model predicts how well a clothing item will fit a user's body in real-time and displays the virtual trial results. The application interface shows the user a realistic virtual fitting experience, suggesting the best size or highlighting potential fitting issues. Parameters of the process/application: User measurements, clothing dimensions, fabric flexibility, and posture data are analyzed to generate the visual fitting results.</div>	<div></div> <div>VALUE PROPOSITION</div> <div>Who is the end-user? What are their objectives? How will they benefit from the ML system? Mention workflow/interfaces. Who is the end-user? Online shoppers, retail customers, and fashion brands. What are their objectives? To try on clothes virtually before purchasing, ensuring the right fit and style without the need to physically visit a store. How will they benefit from the ML system? The end-user can see a realistic preview of how clothes will look and fit, reducing return rates and enhancing customer satisfaction with online shopping.</div>	<div></div> <div>DATA COLLECTION</div> <div>Strategy for initial train set & continuous update. Mention collection rate, holdout on production entities, cost/constraints to observe outcomes. Strategy for initial train set & continuous update: Use a dataset of labeled images containing various body types, clothing items, and poses. Continuously update the model with user feedback and additional data from different demographics. Mention collection rate holdout on production entities cost/constraints to observe outcomes. Data can be collected through user inputs, fashion brand partnerships, and crowdsourced images, ensuring diversity in the dataset while considering user privacy and data storage constraints.</div>	<div></div> <div>DATA SOURCES</div> <div>Where can we get (raw) information on entities and observed outcomes? Mention database tables, API methods, websites to scrape, etc. Where can we get (raw) information on entities and observed outcomes? Publicly available datasets like DeepFashion, user-submitted photos, clothing brand catalogs, and e-commerce websites. Mention database tables, API methods, websites to scrape, etc.: APIs from fashion brands, image scraping from online stores, and user-uploaded photos via the application.</div>
<div></div> <div>IMPACT SIMULATION</div> <div>Can models be deployed? Which test data to assess performance? Cost/gain values for (in)correct decisions? Fairness constraint? Can models be deployed? Yes, models can be deployed in a cloud environment for scalability and real-time processing. Which test data to assess performance? A test set containing various body shapes, clothing types, and poses to ensure the model's generalization. Cost/gain values for (in)correct decisions? Correct decisions enhance user experience, reduce returns, and boost sales, while incorrect decisions might lead to customer dissatisfaction and increased return rates. Fairness constraint: Ensure inclusivity across different body types and demographics to avoid bias in the virtual fitting experience.</div>	<div><div></div><div>MAKING PREDICTIONS</div></div> <div>When do we make real-time / batch pred? Time available for this + featurization + post-processing? Compute target? When do we make real-time/batch predictions? Real-time predictions during user interaction with the virtual trial room. Time available for this + featurization + post-processing? Less than a few seconds to ensure smooth user experience. Compute target? Cloud-based GPU or TPU instances for real-time processing.</div>		<div><div></div><div>BUILDING MODELS</div></div> <div>How many prod models are needed? When would we update? Time available for this (including featurization and analysis)? How many prod models are needed? One main model for real-time fitting with possible variations for different clothing types. When would we update? Regularly, based on new data inputs and user feedback. Time available for this (including featurization and analysis)? Continuous, with a pipeline for regular updates.</div>	<div><div></div><div>FEATURES</div></div> <div>Input representations available at prediction time, extracted from raw data sources. Input representations available at prediction time extracted from raw data sources: User body measurements, clothing images, user-uploaded photos, and pose data.</div>

Model Benchmarking

Technology Components

1. **Distance()**: This function computes the Euclidean distance between two points in a Cartesian coordinate system. It is essential for measuring the spatial separation between keypoints on the body or between various features in the image, facilitating accurate alignment and fitting of garments on the 3D model.
2. **Shrink()**: This function crops the image to eliminate unnecessary transparent areas around the primary subject. By focusing only on the relevant portions of the image, it optimizes processing efficiency and enhances the quality of subsequent image manipulations, such as overlaying clothing items.
3. **Validatex() and Validatey()**: These functions are used to validate the coordinates of detected keypoints. **validatex()** ensures that the x-coordinates of keypoints fall within acceptable ranges, while **validatey()** performs a similar function for y-coordinates. These validations are crucial for maintaining the accuracy and reliability of body part detection and pose estimation.
4. **Overlay_image_alpha()**: This function overlays one image on top of another using an alpha mask for transparency. It allows for the seamless integration of clothing images onto the 3D body model by managing the transparency levels and ensuring that the clothing appears natural and appropriately aligned with the user's body.
5. **Changecolor()**: This function modifies the color of the clothing image based on specified color rules. It enables users to visualize garments in different colors or patterns, enhancing customization options and allowing for a more personalized shopping experience.

Model Utilization

The script utilizes two key pre-trained models:

- **ssd_512_mobilenet1.0_coco**: This model is employed for detecting people within images. It leverages Single Shot Multibox Detector (SSD) with MobileNet architecture, offering efficient and accurate detection of human figures.
- **simple_pose_resnet18_v1b**: This model is used for pose estimation, leveraging the ResNet-18 architecture to identify and map key body points. It plays a critical role in determining the user's posture and body orientation, which is crucial for accurately rendering clothing on the 3D model

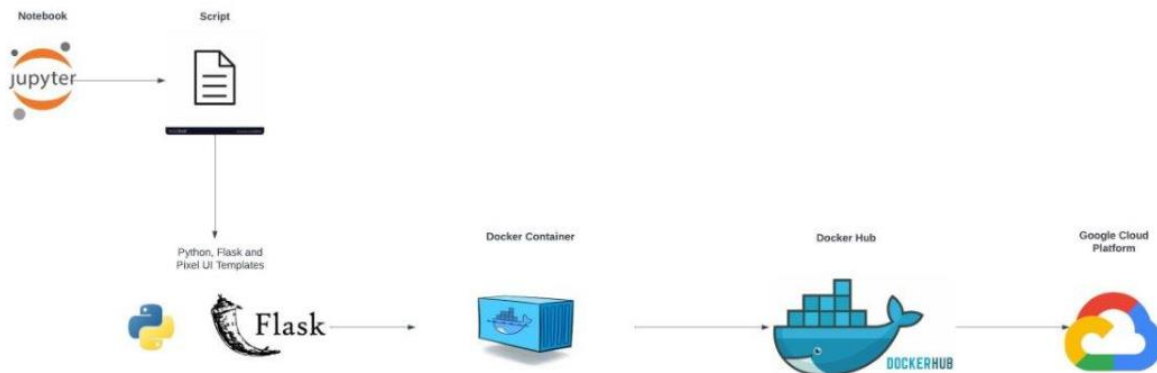
Model Deployment

Model deployment follows a straightforward procedure:

1. Training on of model on Jupyter Notebook.
2. Transforming the model into a script that can be reuse in python.
3. Integration and implementation of the model in a Python, Flask environment

4. Containerization of the project
5. Uploading the project into Docker hub
6. Preparing the Google Cloud instance and deployment of the container

Below an image representation of our deployment process.



Demo

