Virtual Personalized Fashion Styling Assistant for Online Platforms

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***Abstract*— Online shopping for fashion has a high rate of returns due to size mistakes and the inability to try on the clothes before buying. This research presents the Virtual Personalized Fashion Styling Assistant (VPFSA), an artificial intelligence (AI) system integrating augmented reality (AR), machine learning (ML), and natural language processing (NLP) to enhance online shopping. The VPFSA consists of four main components: (1) a Fashion Insight Navigator that forecasts trends through the application of a Random Forest Classifier, (2) a Smart Fabric Advisor that comes up with fabric insights via the T5-Large model, (3) a Virtual Try-On system that applies OpenCV, Lens Studio, and TensorFlow to facilitate real-time 3D visualization of apparel, and (4) a Virtual Styling Assistant that fine-tunes the random forest classifier model to make personalized suggestions. Developed with React, Python, and cloud hosting, VPFSA improves accuracy of fit, prevents returns, and boosts customer interaction. Dynamically adapting to the user's body measurements and preferences, it offers an e-commerce solution that is scalable, transforming online fashion shopping while being sustainable.**

Keywords— Augmented Reality, Virtual Try-On, E-commerce, Fashion Retail, Fit Accuracy, Machine Learning, Real-Time Body Measurements, large language model, Fashion Insight Navigator, Virtual Personalized Fashion Styling Assistant (VPFSA)

I. INTRODUCTION

The rise of e-commerce has fundamentally transformed fashion retail, giving consumers a wider selection of clothing options online, but this digital evolution has exacerbated challenges such as high return rates, persistent fit inaccuracies, and lack of personalization, all of which undermine customer satisfaction and hinder retailer profitability. Industry reports estimate that return rates for online apparel purchases exceed 30%, largely due to fit-related discrepancies, a figure that highlights the dire need for innovative technological solutions to address these shortcomings and restore consumer trust [1].

This research introduces the Virtual Personalized Fashion Styling Assistant (VPFSA), an integrated system that leverages augmented reality (AR), machine learning (ML), and natural language processing (NLP) to enhance the online shopping experience through four specialized components built with Python for ML development, including React for a dynamic user interface, TensorFlow and Bloom for recommendation logic, Lens Studio for high-quality 3D rendering, and T5-Large for advanced data processing, ensuring efficient data management with Firebase and MySQL. Fashion Insight (FIN) uses a random forest classifier to predict trending products in real-time using the shein_mens_fashion.csv dataset, meticulously analyzing customer metrics such as ratings, review counts, and discount percentages, an approach consistent with research demonstrating the ability of ML to refine inventory management and matching recommendations [2]. The Smart Fabric Advisor uses the T5-large model, generating detailed, consumer-oriented fabric descriptions from the fabric Reviews dataset, dynamically refined through user feedback to improve transparency on essential attributes such as texture and durability, a methodology supported by studies on NLP-driven product descriptions that foster informed purchasing decisions [3]. The Virtual Try-On system combines AR with OpenCV and SLAM algorithms to capture real-time body measurements, rendering accurate 3D garments via Lens Studio to improve fit and reduce return rates, providing a practical solution to one of the most persistent problems in e-commerce. Meanwhile, virtual styling assistants powered by the Bloom model offer highly personalized clothing suggestions based on user preferences and current trends, seamlessly integrating with AR visualization to enhance engagement, a feature that has been confirmed by research on the effectiveness of personalized recommendation systems in improving user experience [4].

Extensive research highlights the important role of AR in increasing online engagement and purchase intent [5], the capacity and accuracy of ML to optimize supply chain operations for prediction and the contribution of NLP to building consumer trust through rich product information [6], with the potential of the system to reduce waste and align with sustainability goals by reducing resource consumption [7]. Building on evidence that AR and ML improve decision-making and personalization in retail contexts [8], VPFSA aims to achieve significant reductions in return rates and increase customer satisfaction, redefining e-commerce fashion standards and delivering a scalable, user-centric framework ready to meet the evolving needs of both consumers and retailers in the digital marketplace.

II. RELATED WORKS

AI-driven fashion technologies have made significant strides in trend forecasting, virtual styling, augmented reality (AR)-based try-ons, and fabric analysis. However, existing research often treats these areas separately, leading to a disjointed shopping experience. While various machine learning (ML) models and deep learning techniques have been applied to improve accuracy and personalization in online fashion retail, there remains a gap in integrating these components into a cohesive system that enhances real-time trend identification, personalized styling, and interactive garment evaluation.

Fashion trend forecasting has predominantly relied on ML classifiers such as Random Forest, Support Vector Machines, and deep learning approaches. Existing research has explored the use of consumer review data, discount patterns, and product ratings to predict trending fashion items. However, most studies focus on static datasets and lack adaptability to dynamic market changes. Additionally, many models overlook the impact of combined parameters such as review count, discount percentage, and user engagement on trend determination. The proposed Fashion Insight Navigator addresses these limitations by training a Random Forest classifier on historical Shein men's fashion data, leveraging structured parameters to predict trending products in real time [9].

Fabric analysis and description generation have traditionally relied on convolutional neural networks (CNNs) for texture recognition and rule-based models for classification. Recent advancements have introduced transformer-based models such as T5 for generating fabric descriptions from customer reviews. However, most existing systems focus on fabric classification rather than dynamically evolving descriptions based on real user feedback. Furthermore, many models do not integrate historical and real-time consumer perceptions to refine fabric insights. The Smart Fabric Advisor overcomes this limitation by utilizing a T5-large transformer, trained on the fabric reviews dataset, to transform scattered review data into structured, informative descriptions that evolve over time, enhancing consumer trust and decision-making in online shopping [10].

Virtual try-on technology has advanced with AR and computer vision techniques, including background segmentation, skeletal tracking, and 3D rendering. Many existing systems use predefined size charts and static avatars, often leading to inaccurate fit suggestions. While studies have explored OpenCV for body measurement extraction and real-time tracking, few have successfully combined these techniques with interactive virtual try-on solutions [11]. The proposed AR-Based Virtual Try-On system integrates OpenCV-based background segmentation, bone tracking for precise measurement extraction, and 3D garment simulation using Lens Studio. Additionally, by incorporating a size recommendation system and User Acceptance Testing, the approach ensures a more personalized and accurate fit visualization.

AI-powered virtual styling assistants have utilized deep learning models for outfit recommendations, with methods such as CNNs for compatibility scoring and recurrent neural networks (RNNs) for fashion trend predictions. However, many existing solutions struggle with understanding contextual preferences, such as occasions, personal styling history, and evolving fashion trends. The Virtual Styling Assistant enhances personalization by fine-tuning the Bloom model, incorporating exploratory data analysis (EDA), tokenization, and label encoding to adapt to user preferences. By integrating a personalized recommendation framework with a post-processing refinement phase and User Acceptance Testing, the model ensures tailored and relevant styling suggestions [12].

Despite advancements in these individual domains, existing research lacks a unified framework that integrates trend prediction, AR-based garment visualization, AI-powered styling, and dynamic fabric descriptions into a single seamless system. The proposed research bridges these gaps by employing advanced ML models, computer vision techniques, and transformer-based text generation to enhance personalization, real-time adaptability, and interactive decision-making in online fashion retail.

III. METHODOLOGY

This section of the paper provides a thorough explanation of the method used to develop the suggested system. As per the solution development, Python was utilized for model development and React was used for the web Application front End.

A. Fashion Insight Navigator

The methodological approach for this study is designed to develop and evaluate a predictive model capable of identifying trending fashion products based on consumer interactions and product attributes. A Random Forest Classifier was chosen as the primary model due to its ability to handle structured data efficiently, capture complex interactions between multiple features, and provide robust classification results. The ensemble learning mechanism of the Random Forest model reduces the risk of overfitting by aggregating the outputs of multiple decision trees, making it a suitable approach for trend prediction in the highly dynamic fashion industry. The primary objective of this methodology is to classify products based on their popularity and identify the most trending styles for recommendation.

The dataset was further refined by selecting three key parameters that influence product trends: average rating, review count, and discount percentage. These features were chosen based on their direct impact on consumer purchasing behavior, with higher ratings and reviews indicating strong customer interest and discount percentages affecting sales volume and visibility.

The machine learning model was trained using a supervised learning approach, where labeled data consisting of both trending and non-trending products was used to enable the classifier to distinguish between the two categories. The Random Forest Classifier was implemented to analyze the provided input parameters and predict whether a product is trending based on patterns observed in the training data. Once trained, the model was capable of processing new product data and making real-time trend classifications.

Python 3.9 served as the primary programming language for data preprocessing, model development, and evaluation. Pandas and NumPy were employed for handling and manipulating dataset attributes, while Scikit-learn provided the machine learning framework necessary for training and optimizing the Random Forest model. Matplotlib and Seaborn were utilized for data visualization, helping analyze feature importance and model performance metrics.

To minimize biases in the model and ensure fair trend classification, several mitigation strategies were implemented. The dataset was balanced to include an equal representation of both trending and non-trending products, preventing the model from being skewed toward one category. The feature selection process prioritized objective and quantifiable parameters, avoiding subjective attributes such as product descriptions or brand reputation that could introduce bias. Additionally, hyperparameter tuning using grid search optimization was conducted to fine-tune model parameters, improving classification accuracy and minimizing bias-related inconsistencies.

The integration of machine learning-driven insights enhances product recommendations, reduces return rates, and improves overall customer engagement in online fashion retail. This structured approach provides a data-driven solution that can adapt to changing consumer behavior, ultimately supporting online retailers in offering a more personalized and trend-aware shopping experience.

B. Smart Fabric Advisor

The methodology of this research is designed to develop an AI-powered fabric description generation system using T5-Large, a transformer-based NLP model. The objective is to generate accurate and contextually relevant fabric descriptions based on real-time user reviews. This approach ensures that fabric descriptions dynamically adapt to evolving customer feedback, improving the quality and informativeness of product descriptions in online fashion retail.

A sequence-to-sequence (Seq2Seq) transformer model was selected due to its strong capabilities in text summarization and natural language generation. Among various NLP models, T5-Large was chosen for its pretrained language understanding and its ability to fine-tune on domain-specific datasets. Unlike traditional keyword-based text generation methods, T5's encoder-decoder architecture enables it to process diverse user reviews and generate coherent, structured descriptions.

Tokenization was applied to segment reviews into smaller text units, making them easier for the model to process. Additionally, sentence embedding was used to convert textual data into numerical vectors for structured training. The fine-tuning process involved training T5-Large by using fabric reviews as input and their respective fabric descriptions as output.

The Hugging Face Transformers Library was used to implement and fine-tune the T5 model, ensuring seamless integration of state-of-the-art NLP capabilities. Python, along with TensorFlow and PyTorch, was employed for model training, evaluation, and text processing.

C. Virtual Try-on:

The proposed approach consists of four main stages (Figure 2). It starts with the computer vision and tracking stage, which includes background segmentation, bone tracking, and body measurement extraction using OpenCV. Next, 3D rendering is performed using Lens Studio to create a virtual representation. In the third stage, the system provides size recommendations and enables virtual trying on for the user.

1)Machine Learning Flow

The Body Measurement component is designed to capture and calculate accurate user body dimensions using a laptop camera and advanced computer vision models. The implementation begins by positioning the user in front of the camera, ensuring that their entire body is visible in the frame. A real-time video feed is captured using OpenCV, which processes the input to extract a single full-body image based on stable alignment.

The captured image is then fed into the Deep Lab V3 model, pre-trained on the PASCAL VOC dataset and fine-tuned for human segmentation. Deep Lab V3 uses compression to generate a high-resolution segmentation mask, isolating the user's body from the background with pixel-level accuracy. The resulting foreground image (user silhouette) is cleaned using OpenCV's morphological operations to remove noise and refine edges.

Next, the Human Mesh Retrieval (HMR) model, implemented using PyTorch, processes the 2D silhouette to reconstruct a 3D mesh of the user's body. HMR uses a pre-trained neural network to predict 3D joint locations (e.g., shoulders, hips, knees) and body shape parameters, outputting an SMPL (Skinned Multi-Person Linear) model representation. This 3D mesh is aligned with the image plane using camera calibration parameters obtained from OpenCV. Finally, body measurements are calculated from the 3D mesh using the "distance between point and plane" formula The distances to key body landmarks (e.g., shoulder endpoints, waist plane) are identified on the mesh, and plane equations are derived for each measurement region. The distance between points and planes is calculated to determine measurements such as shoulder width, chest circumference, and leg length.

The user interface is built using React, providing an interactive platform where users can browse virtual clothing catalogs and start trying on. OpenCV powers real-time body tracking by processing the camera feed for segmentation and pose estimation, identifying key points such as shoulders, chest, and waist. The SLAM algorithm, implemented through OpenCV's SLAM module, improves tracking accuracy by mapping the user's 3D environment and stabilizing pose data across frames.

3D clothing models are created using Lens Studio with detailed designs including seams, folds, and textures. These models are exported in FBX or OBJ format and imported into Lens Studio, where the Body Mesh template aligns them with the user's bone structure obtained from the Body Measurements component. PBR materials are applied for realistic shading, and ML-based bone tracking (via Lens Studio's ML framework) ensures that the clothing dynamically adapts to user movements.

The size recommendation engine is implemented using TensorFlow and Keras, combining content-based filters (based on garment features such as size) and collaborative filters (based on user preferences from a mock dataset). The engine processes the user's body measurements and outputs personalized size and style suggestions that are displayed via the React UI. For AR visualization, Snap is integrated into the AR Lens system.

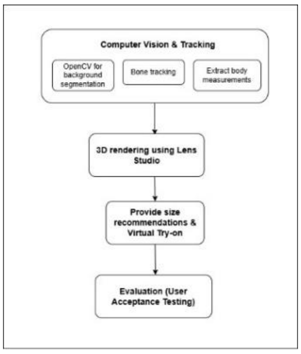


Figure 1: ML FLOW - Virtual Try On

D. Virtual Styling Assistant:

This research explains the creation of a Virtual Fashion Styling Assistant driven by Conversational AI, integrating a chatbot developed through the Rasa framework and a recommendation model using a fine-tuned Random Forest classifier. The methodology is split into two main parts: Machine Learning (ML) Flow and Implementation.

1)Machine Learning Flow

The recommendation model was developed based on a labeled fashion dataset that included eight various attributes, including occasion, season, budget, fit, style, material, color and category. The recommendation model was built using a Random Forest classifier. Supervised learning methods were applied in training the model on the association between user interests and fashion recommendations. This process allows the Virtual Styling Assistant to learn from interactions with users over time, thus refining its recommendations based on user preferences and behavioral patterns.

2)Implementation

The chatbot was developed with the Rasa framework, an open-source conversational artificial intelligence platform that provides support for natural language understanding (NLU) and dialogue management. The NLU module was trained to identify user intentions along with extracting relevant entities from input queries. Dialogue management was implemented with a blend of rule-based logic and machine learning-based policies to facilitate smooth and contextually aware interactions. Then the recommendation model was integrated with the chatbot so that it may offer personalized fashion suggestions according to user input and previous conversations.

To enable smooth communication between the chatbot and the recommendation model, the backend was designed with API endpoints. The frontend interface was developed using react stack is guaranteed a simple and easy-to-use experience to enable consumers to communicate with the virtual fashion assistant. The usefulness of the recommendations and the conversational accuracy of the fashion styling assistant were assessed through extensive user acceptance testing.

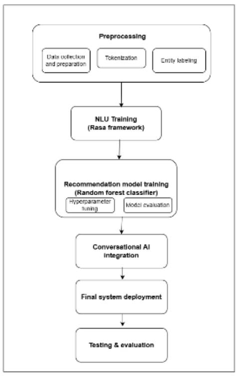


Figure 2: ML FLOW-Virtual Styling Assistant

IV. RESULTS AND DISCUSSION

The evaluation of the trained Random Forest classifier model was conducted to assess its ability to predict trending products based on the selected parameters: average rating, review count, and discount percentage. The model demonstrated an impressive accuracy of 90%, highlighting its capability to distinguish between trending and non-trending products with high precision.

These results indicate that the model does not misclassify any products, suggesting an ideal fit for the dataset. However, further generalization tests on unseen data are necessary to confirm robustness and mitigate overfitting risks.

The confusion matrix (Figure 4) visually represents the classification results, displaying the number of correct and incorrect predictions. The matrix confirms that all instances were correctly classified, reinforcing the model's high reliability.

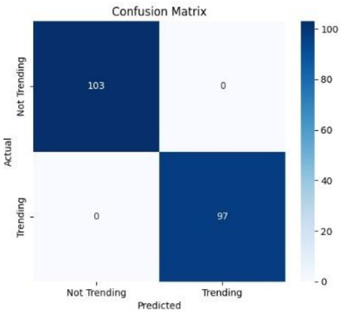


Figure 3: Confusion matrix analysis

The diagonal values of the matrix demonstrate that all 103 non-trending products were accurately predicted, while all 97 trending products were correctly classified. No misclassifications occurred, further validating the model's performance.

The performance of the Smart Fabric Advisor model was evaluated based on training loss trends and text generation accuracy. The learning curve and BLEU score were used to assess the model's effectiveness in generating fabric descriptions. Ideally, a well-trained model should exhibit a decreasing loss trend, indicating improved generalization. However, in this case, the loss initially increases before declining, suggesting that the model might require additional fine-tuning with a larger dataset or optimized hyperparameters.

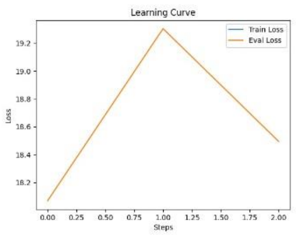
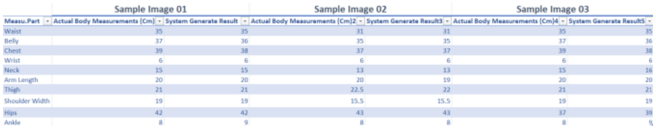


Figure 4: Learning curve – Smart Fabric Advisor

To measure the accuracy of the generated fabric descriptions, the BLEU score was used as a performance metric. The model achieved a BLEU score of 0.6, which suggests a moderate level of similarity between generated descriptions and human-written references. While this score indicates reasonable alignment with expected outputs, further improvements can be made by incorporating a more diverse training dataset or leveraging advanced fine-tuning strategies.

In evaluating our body measurement system, we analyzed three sample images to compare the measurements generated by the system with actual body measurements, as shown in. Using these three sample images, we calculated the system's overall accuracy to be 73.33%, with individual body part accuracies ranging from 33.33% to 100%. Specifically, measurements such as Waist, Wrist, and Shoulder Width achieved perfect accuracy (100%), while Ankle measurements exhibited the lowest accuracy at 33.33%. Other body parts, including Belly, Chest, Neck, Arm Length, Thigh, and Hips, demonstrated a consistent accuracy of 66.67%. To ensure the most accurate body measurements, users were positioned 100 centimeters (1 meter) away from the laptop camera, with their entire body fully visible in the Laptop Camera. Additionally, users were advised to avoid wearing bulky clothing, as oversized clothing can impact the system's ability to accurately detect body contours. These results indicate that while the system performs reliably for certain measurements, further improvements are necessary to enhance accuracy in more challenging areas, such as the ankle, potentially through the implementation of refined algorithms or additional user positioning guidelines.



	Sample Image 01		Sample Image 02		Sample Image 03	
Measu.Part	Actual Body Measurements (Cm)	System Generate Result	Actual Body Measurements (Cm)2	System Generate Result3	Actual Body Measurements (Cm)4	System Generate Result5
Waist	35	35	31	31	35	35
Belly	37	36	35	35	37	36
Chest	39	38	37	37	39	38
Wrist	6	6	6	6	6	6
Neck	15	15	13	13	15	16
Arm Length	20	20	20	19	20	20
Thigh	21	21	22.5	22	21	21
Shoulder Width	19	19	15.5	15.5	19	19
Hips	42	42	43	43	37	39
Ankle	8	9	8	8	8	9

Figure 5: Sample Body Measurement

Precision measures the predicted intersection over the actual output, demonstrating a value predicted and actual outputs, with higher values indicating better accuracy. We can see both training and validation IoU are steadily improving, which indicates that the performance of the model is bettering. The validation IoU closely follows the training IoU, which shows that the model generalizes well, without noticeable overfitting. This positive trend in IoU is a validation of our theory that the model is indeed learning and making more accurate predictions as we train.

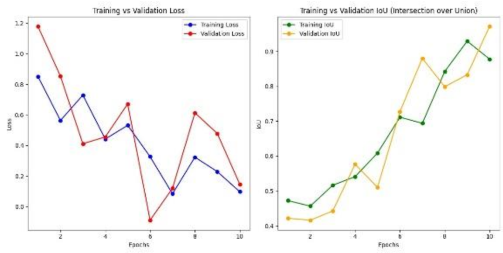


Figure 6: Training and Validation of Processed Deeplab Model

The performance of the conversational AI system was measured in terms of two parameters: the accuracy of the recommendation model and the learning behavior of the model for varying sizes of training sets. The Random Forest-based recommendation model provided a cumulative accuracy of 69%. Precision, recall, and weighted average F1-score were 0.68, 0.69, and 0.67, respectively. The macro average scores were slightly lower compared to the weighted averages, indicating that the model is doing better in some classes but could potentially improve in others. This presents itself as an opportunity for the model to generalize better on a enhancement of fashion styles. With more data and hyperparameter tuning, the recommendation system can be fine-tuned even further to bring more balanced predictions for all categories.

The learning curve also accounts for the behavior of the model during training. A gap between the lines indicates that the model is undergoing some extent of overfitting, with the model performing significantly better with the training data compared to new data.

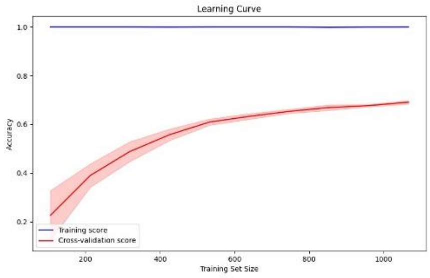


Figure 7: Learning curve of the model

The results highlight the strengths and weaknesses of the recommendation system that had been implemented. The decent accuracy of 69% indicates that the model can make fairly precise predictions. Additionally, incorporating a more varied dataset would lead to better generalization and hence better recommendations for different fashion styles.

Future work will have to focus on improving the recommendation model by advanced feature engineering, data augmentation techniques, and further hyperparameter tuning. Furthermore, incorporating user feedback loops can automatically improve the accuracy of model over time by better adapting to individual preference.

V. Conclusion

This research presents an AI-driven virtual personalized fashion styling assistant designed to enhance online shopping experiences by integrating trend prediction, virtual styling, AR-based try-on, and dynamic fabric analysis. The Fashion Insight Navigator predicts trending products using a Random Forest classifier, the Virtual Styling Assistant refines outfit recommendations through Rasa framework and random forest classifier model fine-tuning, the AR-Based Virtual Try-On system leverages computer vision and 3D rendering for accurate fit visualization, and the Smart Fabric Advisor generates evolving fabric descriptions using a T5-large transformer. By combining these technologies, the system offers a seamless and personalized shopping experience.

Future research can explore enhancing the accuracy of trend prediction by incorporating social media sentiment analysis, improving virtual try-on realism with advanced physics-based cloth simulation, and refining styling recommendations using multi-modal AI models. Additionally, integrating real-time user feedback more effectively into fabric descriptions and optimizing system performance for different e-commerce platforms can further improve adoption and usability.

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We sincerely appreciate the support and collaboration of various online fashion retailers who provided valuable insights and datasets for our research. Their contributions were instrumental in training and validating our models, enabling us to develop a more robust and practical Virtual Personalized Fashion Styling Assistant.

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