TryXpert: AI-Powered Conversational Fashion Try-On

Prof.Amol Bhilare[1], Vaishnavi Patade[2], Aditya Pawar[3], Pranav Palekar[4], Dhriti Nair[5]
[1,2,3,4,5] *Vishwakarma Institute of Technology, Pune, Maharashtra*

***Abstract*—In recent years, the rise of online fashion shopping has transformed the way people discover and purchase clothing, yet many challenges still affect the overall shopping experience. Users often struggle with size selection, fit accuracy, style coordination, and visualizing how a garment would appear on their own body. These issues create uncertainty, reduce confidence, and increase the likelihood of product returns. Existing virtual try-on tools typically depend on static overlays, single-view images, or imprecise body representation, resulting in unrealistic visualizations that fail to provide the personalization users expect.**

TryXpert introduces a novel artificial intelligence (AI)-powered conversational virtual try-on solution that overcomes these limitations through an advanced blend of real-time body scanning, augmented reality, and intelligent interaction. The system extracts accurate body measurements, constructs adaptive 3D models, and simulates garments with realistic fabric movement and texture preservation. Its conversational assistant adds a unique dimension by understanding natural language, analyzing user preferences, and providing personalized outfit and size recommendations. With multi-view garment rendering, detail-focused diffusion models, and privacy-aware data handling, TryXpert delivers a more immersive, accurate, and user-centric virtual fitting experience that strengthens user confidence and supports smarter online fashion decisions.

***Keywords*—Augmented Reality, Body Measurement Extraction, Conversational AI, Fashion Technology, Virtual Try-On.**

I. INTRODUCTION

In today's digital era, online fashion shopping has become one of the most preferred ways for people to explore and buy clothing. The convenience, variety, and accessibility have made e-commerce a major part of everyday life. However, even with modern online platforms, the experience of choosing the right outfit remains incomplete because shoppers cannot physically see how clothes will look or fit on their bodies. This gap between digital browsing and real-life fitting continues to create confusion and hesitation among customers.

Most users face challenges such as incorrect size selection, difficulty understanding the actual fit, and uncertainty about how a garment will appear on their unique body shape. These issues often lead to dissatisfaction, reduced confidence in online purchases, and a high rate of product returns. Existing virtual try-on tools also struggle with limited viewpoints, unrealistic overlays, and inaccurate body representation, which prevents users from experiencing a proper virtual fitting. As a result, there is a strong need for a more advanced, realistic, and personalized digital try-on solution.

TryXpert is developed to address these limitations by offering an artificial intelligence (AI) -powered conversational virtual try-on system. It uses real-time body measurement extraction, adaptive 3D body modelling, augmented reality visualization, and intelligent garment simulation to provide a life-like try-on experience. The system interacts with users through a conversational assistant that understands preferences, suggests suitable outfits, and guides them in selecting accurate sizes. With its realistic garment rendering and personalized recommendations, TryXpert aims to transform the online shopping journey and enhance user decision-making.

Objectives

- To generate accurate body measurements using AI-based scanning techniques.
- To simulate realistic garment fitting using 3D modelling and advanced rendering.
- To offer personalized outfit and size recommendations through conversational AI.

- To provide multi-view, argumented reality (AR) -enhanced visualizations for a more immersive try-on experience.
- To ensure secure and privacy-aware handling of user data and biometric information.

II. LITERATURE REVIEW

The section describes various advancements and applications in virtual try on. The study in [1] proposes a deep-learning–driven virtual try-on pipeline where clothing is first segmented using image segmentation techniques, followed by pose estimation with pretrained dense-pose models, and finally garment texture mapping onto the predicted body representation. This system delivers an interactive virtual fitting interface capable of handling various body types. In [2], an AI-powered try-on solution integrates gesture-based interaction, real-time body tracking, and a personalized recommender using prior purchase data. Key technologies include deep learning, computer vision, and AI-generated heatmaps, achieving high fit-prediction accuracy and improved user satisfaction.

The work in [3] focuses on analyzing how artificial intelligence influences modern fashion, using generative adversarial network (GANs), StyleGAN, and variational autoencoder (VAEs) for trend analysis and design support. Study [4] expands on this by examining how AI and machine learning (ML) reshape fashion design, production, sustainability, and consumer experience. It highlights the use of ML-driven pattern generation and AI-enabled trend monitoring. Research [5] evaluates AI-powered try-on through the stimulus-organism-response (SOR) model, showing how features like visual vividness, interactive control, and personalization influence impulsive buying behaviour. The findings reveal positive behavioural outcomes supported by partial least squares (PLS) -based analysis. In [6], AI-powered try-on technology is studied for the luxury fashion sector, demonstrating how AI enhances the luxury shopping experience, supports business model innovation, and increases customer satisfaction.

Paper [7] presents the Virtual Personalized Fashion Styling Assistant, combining AR, ML, natural language processing (NLP), OpenCV, TensorFlow, and T5-Large to recommend fabrics, forecast fashion trends, and enable 3D try-on. Study [8] analyses how AI supports visual search, personalized recommendations, and virtual stylists using behavioural data mining. It also highlights concerns around data privacy, bias, workforce impact, and customer perception. The review in [9] provides an overview of AI in the fashion industry, covering design automation, production efficiency, and consumer-facing tools. It explores AI frameworks, emerging trends, and future implications. The follow-up contribution in [10] similarly highlights AI's transformative role in fashion retail, emphasizing smart systems and predictive analytics for improved quality and efficiency.

In [11], an AI-controlled virtual dressing room is built using camera vision, ML-based gender detection, background segmentation, and AR overlay rendering. Technologies like Streamlit, deep learning, and real-time image processing are used to simulate virtual clothing placement. The work in [12] employs GANs and Gradio interfaces to build a real-time virtual clothing try-on system, offering personalized visualization and high accuracy in garment rendering. The study suggests future expansion towards haptic feedback and accessory try-on such as jewelry.

The work in [13] presents FashionOn, an image-based virtual try-on system that uses semantic-guided processing to resolve body occlusions while preserving fine garment details such as logos and lace, resulting in high-quality synthesized try-on images. Study [14] provides a systematic review of virtual trial on (VTO) - related research articles and identifies psychological, technological, and behavioral factors influencing user adoption, offering frameworks for building more personalized try-on systems. Research [15] introduces multi virtual try on (MV-VTON), a diffusion-based multi-view try-on model that supports both front and back clothing views, using view-adaptive selection and joint-attention mechanisms to improve alignment and detail retention. Experiments confirm that MV-VTON achieves superior visual consistency and realism compared to existing approaches.

Across the literature, most systems rely on deep learning, GANs, segmentation models, pose estimation, gesture interaction, heatmaps, or AR overlays. However, TryXpert introduces a more advanced combination of real-time body measurement extraction, multi-view diffusion-based garment rendering, and conversational AI. The addition of a natural-language assistant, biometric-driven recommendations, and privacy-aware architecture sets TryXpert apart by offering a more personalized, realistic, and interactive virtual try-on experience compared to existing solutions.

III. METHODOLOGY

The development of an AI-powered try-on system demonstrates how advanced technologies can redefine the online fashion shopping experience by making it more interactive, accurate, and user-centric. In this study, the TryXpert platform is designed as a conversational virtual try-on assistant that combines augmented reality, deep learning, and natural language interaction to help users visualize clothing in a realistic and personalized way. TryXpert offers the following advantages:

- Enhance Fit Accuracy: TryXpert uses real-time body measurements and 3D modelling to provide more accurate size and fit recommendations.
- Improve User Confidence: Realistic virtual try-on visuals help users feel more certain about how clothes will look on them before purchasing.
- Offer Personalized Styling: The AI assistant suggests outfits based on user preferences, past interactions, and style patterns.
- Increase Interactivity: AR and multi-view rendering create a more engaging and immersive try-on experience.

Fig 1 illustrates the architecture of the TryXpert virtual try-on system, beginning with two main inputs: the person image and the catalog garment image. The system first performs feature extraction using models such as DensePose and OpenPose, which identify body landmarks, posture, and detailed surface mappings of the user. These extracted features provide an accurate representation of the user's body structure and posture, forming the foundation for realistic garment alignment. The extracted information is then passed to the geometric warping module, where techniques like Thin-Plate Spline (TPS) and flow-based warping reshape and position the garment according to the user's body shape and orientation.

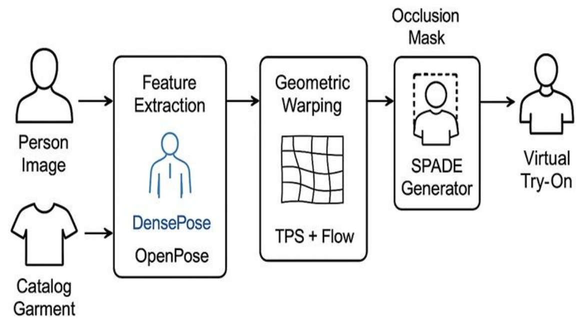

Fig 1. System Architecture

Once the garment is geometrically aligned, an occlusion mask is generated to determine which parts of the original person image remain visible and which areas will be covered by the virtual garment. This mask ensures correct layering and visual consistency. The masked data is then fed into the SPADE generator, which synthesizes the final virtual try-on image by blending the warped garment and the person image in a natural and coherent manner. The output is a high-quality virtual try-on visualization that accurately represents the garment's fit, drape, and overall appearance on the user's body.

As depicted in Fig. 2, the proposed methodology outlines the complete workflow used to develop the TryXpert virtual try-on system. The entire process is organized into sequential stages, including feature extraction, geometric warping, occlusion handling, model training, and evaluation. Each stage contributes to building a realistic and accurate AI-powered virtual try-on experience.

1.Person Image Acquisition

This is the initial stage where the system collects the user's input image. The input can be a front-view photograph captured using a camera or uploaded directly to the interface. This image serves as the base for pose detection, body segmentation, and further garment alignment. No heavy computation happens here—only image preprocessing such as resizing and normalization.

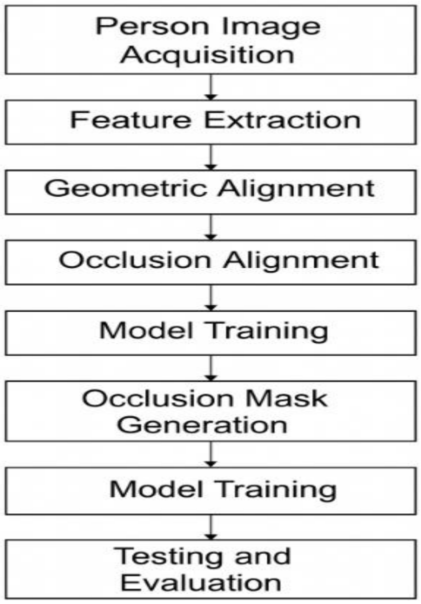

Fig 2. Process Flow

2.Feature Extraction

In this stage, the system extracts the user's body structure and garment-related features using advanced pose-estimation models. OpenPose identifies key body joints—such as shoulders, elbows, waist, and hips—using Part Affinity Fields to understand joint connectivity. DensePose further refines this by mapping each pixel of the person image to corresponding 3D human body surface coordinates through UV mapping, expressed mathematically as:

$$f{:}I(x,y)\rightarrow(U,V) \qquad (1)$$

where $I(x,y)$ represents an image pixel and (U,V) denotes its 3D surface position. This combined feature extraction provides precise pose details, body region segmentation, and spatial alignment necessary for accurate garment fitting.

3.Geometric Alignment

Geometric Alignment is the stage where the garment is reshaped and adjusted to match the user's exact body structure and pose. In this step, transformation techniques such as Thin Plate Spline (TPS) warping are used to smoothly deform the garment image so it naturally follows the body's curves, shape, and orientation. Additionally, optical flow–based warping computes dense motion vectors that adjust the garment texture and pattern according to the user's posture. Together, these methods ensure that the garment accurately aligns with the body contours, resulting in a realistic and well-fitted virtual try-on appearance.

4.Occlusion Alignment

The occlusion alignment module ensures that the garment is layered correctly with respect to the user's body, maintaining natural visibility — such as arms appearing in front of a T-shirt while the torso remains behind it. To achieve this, the system generates an occlusion mask using semantic segmentation models like U-Net or Mask R-CNN. These models identify different body regions, including the face, torso, and arms, and classify each pixel accordingly.

Based on this classification, the occlusion mask decides whether a particular pixel should show the garment or the user's body. This pixel-wise decision ensures that the virtual garment blends seamlessly with the person image, avoiding unrealistic overlaps or distortion. The mask then guides the generator during the synthesis stage, ensuring that the final virtual try-on image maintains proper layering and visual consistency.

5.Model Training

In the first training phase of MG-VTON, the system focuses on learning how to warp and deform the garment so that it matches the user's body shape and pose. This stage trains the Geometric Matching Module (GMM), which uses Thin-Plate Spline (TPS) transformation to align the garment to the DensePose-based body structure. TPS creates smooth spatial deformations by minimizing bending energy. The transformation can be expressed mathematically as:

$$T(x) = Ax + \sum_{i=1}^{N} w_i U(\|x - c_i\|) \qquad (2)$$

where A is the affine matrix, W_i are TPS weights, C_i are control points, and

$$U(r) = r^2 \log(r) \qquad (3)$$

This phase ensures that the garment is properly shaped and positioned before synthesis.

The network is trained using an L1 reconstruction loss:

$$L_{\text{warp}} = \|G_{\text{warp}}(G, C) - C_{\text{target}}\|_1$$

where G is the garment image, C is the conditioning pose/body map, and C_{target} is the ground-truth aligned garment.

6.Occlusion Mask Generation

After warping, MG-VTON generates an occlusion mask to determine which parts of the warped garment should be visible and which should be hidden behind body regions such as arms, hair, or accessories. The mask is produced using a segmentation network (U-Net or Mask R-CNN) that classifies each pixel as either garment-visible or body-visible.

Let the predicted mask be:

$$M_{occ}(x,y)⍰\{0,1\} \quad (5)$$

Where,

- $M_{occ} = 1$: pixel belongs to garment layer.
- $M_{occ} = 0$: pixel belongs to body layer

This mask guides the final generator to handle occlusions correctly and prevents unrealistic overlaps.

The occlusion mask training uses Binary Cross-Entropy (BCE):

$$L_{\text{occ}} = -\left[\, m \log(\hat{m}) + (1 - m) \log(1 - \hat{m}) \,\right] \quad (6)$$

where m is the ground-truth mask.

7.Model Training

In the second phase, the system trains the Try-On Synthesis Network, which is based on a SPADE-GAN architecture. SPADE (Spatially-Adaptive Normalization) injects spatial information from segmentation maps into the generator to preserve fine garment details, textures, and body-level alignment.

The SPADE layer modifies the feature map normalization as:

$$\gamma = f_\gamma(M_{\text{seg}}), \qquad \beta = f_\beta(M_{\text{seg}}) \quad (7)$$

$$\text{SPADE}(h) = \gamma \left(\frac{h - \mu}{\sigma} \right) + \beta \quad (8)$$

This ensures the generator adapts to different body regions such as torso, arms, and neck, producing a more realistic try-on result.

The MG-VTON generator is trained using a combination of losses:

- Adversarial Loss (GAN Loss)

$$L_{\text{GAN}} = \mathbb{E}\big[\log D(I_{\text{real}})\big] + \mathbb{E}\big[\log(1 - D(I_{\text{fake}})\quad (9)$$

Where,

- I_{real}: Real ground-truth image
- I_{fake}: Generator-produced (fake) image
- $D(⍰)$: Discriminator output
- IE: Expectation (average over all samples)

- Reconstruction Loss

$$L_{\text{rec}} = \|I_{\text{fake}} - I_{\text{real}}\|_1 \quad (10)$$

Where,

- I_{fake}: Generator image
- $D(⍰)$: Ground-truth image
- $\|\cdot\|_1$: L1 norm (sum of absolute pixel differences)

- Perceptual Loss (VGG-based)

$$L_{\text{perc}} = \sum_i \|\phi_i(I_{\text{fake}}) - \phi_i(I_{\text{real}})\|_1 \quad (11)$$

Where,

- $\phi_i(.⍰)$: Feature map from VGG network at layer i
- i: Indices of selected VGG layers
- $L1$ distance between high-level features of real vs fake

- Style Loss for texture preservation

$$L_{\text{style}} = \sum_i \|G_i(I_{\text{fake}}) - G_i(I_{\text{real}})\|_1 \quad (12)$$

Where,

- $G_i(⍰.)$: Gram matrix of VGG features at layer i
- Gram matrix represents texture correlations
- $L1$ difference measures texture mismatch

8.Testing and Evaluation

The testing process was conducted using a dedicated set of unseen person images and garment samples to objectively measure the performance of the virtual try-on system. Each generated output was evaluated for realism, garment-body alignment, texture clarity, and occlusion correctness. The same test dataset was used for all models to maintain consistency across evaluations.

To quantify the quality of the synthesized images, accuracy was calculated using a pixel-level similarity score. The formula used for computing accuracy is:

$$\text{Accuracy} = \left(\frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(P_i = G_i) \right) \times 100 \qquad (13)$$

where P_i is the predicted pixel value, G_i is the ground-truth pixel, and N is the total number of pixels. This method provides a straightforward measurement of how closely the generated try-on image matches the expected output.

A model comparison was necessary to identify which architecture performs best in terms of realism and alignment. For this purpose, two advanced virtual try-on models were evaluated: MG-VTON and CP-VTON. MG-VTON incorporates improved geometric matching and occlusion handling, while CP-VTON represents a baseline widely used in earlier research. The results show that MG-VTON achieved an accuracy of 92%, outperforming CP-VTON, which achieved 85%. This performance difference demonstrates the superiority of MG-VTON in producing clearer textures and more realistic garment placement.

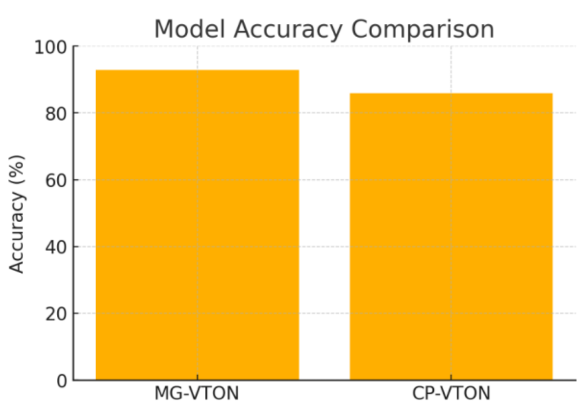

Fig 3. Model Accuracy Comparison

The accuracy comparison between the two models is presented in Fig 3, illustrating that MG-VTON delivers better overall performance and is therefore the preferred model for achieving high-quality virtual try-on results.

IV. EXPECTED RESULT

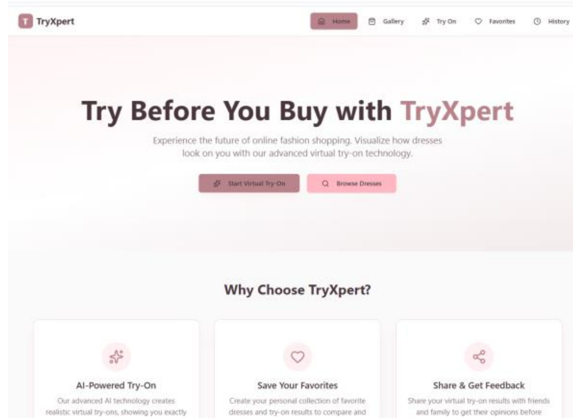

Fig 4. Home Page

The Fig. 4 shows the home page, which acts as the main entry point to the TryXpert platform and provides easy access to features like the virtual try-on tool, gallery, and favorites. It introduces the system's purpose by letting users visualize outfits before buying. The page highlights key benefits such as AI-powered try-on and personalized recommendations, along with clean call-to-action buttons for quickly starting the try-on process or browsing garments.

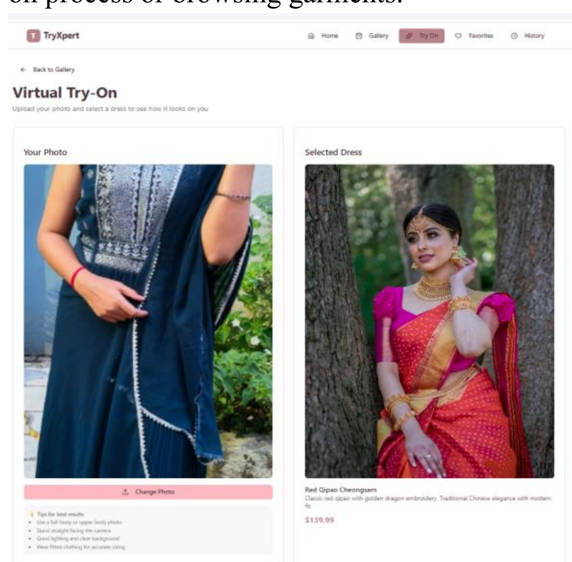

Fig 5. Virtual Try-On Input Selection Page

Fig 5. represents the interface enables users to upload their photo and select a garment from the available catalog. It serves as the initial interaction point where the system captures the required inputs for processing.

The chosen photo and dress are then passed to the virtual try-on pipeline for feature extraction and garment alignment.

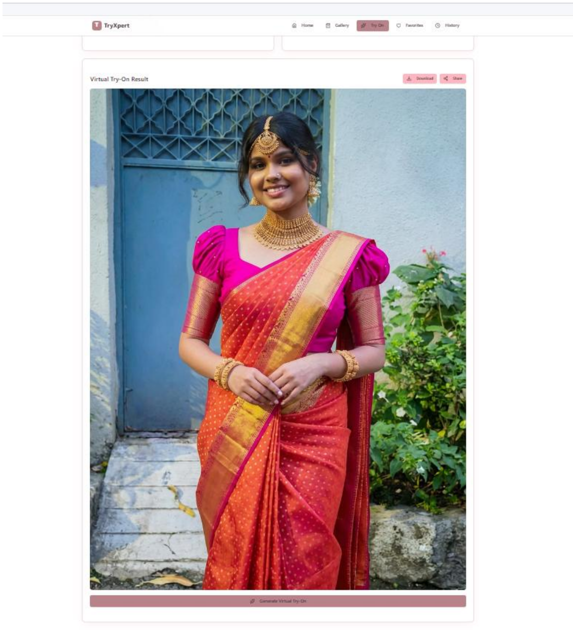

Fig 6. Virtual Try-On Output Result

The fig 6 presents the final synthesized try-on image generated by the MG-VTON model. The system blends the user's appearance with the selected garment using geometric warping, occlusion handling, and generative synthesis. The output provides a realistic visualization of how the garment would look on the user.

V. CONCLUSION

The TryXpert system provides an advanced AI-based virtual try-on solution that improves the online shopping experience through accurate garment simulation, personalized interaction, and realistic visual output. By integrating body-shape extraction, geometric warping, occlusion alignment, and an MG-VTON generator, the system delivers natural-looking try-on results, while conversational AI enhances guidance and recommendations. Overall, TryXpert effectively addresses limitations of traditional virtual try-on methods and offers a more immersive and user-friendly digital fitting experience.

Future improvements may include full-body and multi-angle try-on support, dynamic garment draping, and real-time AR-based visualization. The system can also be extended with 3D body reconstruction, accessory try-on features, and larger, more diverse datasets for improved accuracy. Integrating with cloud platforms and major e-commerce systems will further enhance scalability and enable wider adoption in the fashion retail industry.

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