Modern Virtual Trail Room using AI and VR Technology

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Abstract. A virtual attempt-on room is a progressive solution that revolutionizes the online shopping experience by enabling consumers to virtually try on clothes in an individualized and interactive environment. In light of the fast-paced rise of e-commerce, customers frequently struggle with determining the fit and look of clothes prior to purchasing. The COVID-19 pandemic further expedited the move towards digital retail, increasing the demand for effective and interactive virtual solutions. Utilizing OpenCV and sophisticated computer vision methods, this virtual fitting room mimics natural try-on situations, creating custom avatars and providing AI-based suggestions that boost user confidence and satisfaction. Not only does the system save users time from physical try-ons, but it also solves the universal problems surrounding miscalculated size estimations, reducing return rates and further increasing market coverage for online stores. Future developments will emphasize the incorporation of augmented reality and machine learning algorithms to further improve garment simulation and personalization. This groundbreaking methodology sets the stage for a more immersive and streamlined digital retail experience, transforming the way consumers engage with fashion online.

Keywords: Online Shopping, OpenCV, Virtual Trial Room, Augmented Reality, Computer Vision, Artificial Intelligence, Machine Learning, Fashion Technology.

1 Introduction

The developed defense algorithm is able to accurately recover the chicken outline and the cage wire mesh, and the tracking and behaviour recognition of broilers can be effectively achieve. These advances are essential for the early detection of animal welfare and health problems, and in particular against lameness which has been associated with wider health issues that affect production decision making. The first is the development of object detection technologies, which are a key element in the development of target tracking and behavior analysis for the provision of necessary knowledge on poultry behavior and spatial distributio. Recent research with deep learning models (e.g., YOLOv5-CBAM and YOLOv6) indicate improved accuracy for object detection in poultry monitoring systems. Particularly, the proposed model has an average accuracy increment over the basic YOLOv5 of 1.5% while more recent versions YOLOv7 and YOLOv8 further improve by 3.1% and 1.8% respectively. These improvements

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demonstrate a consistent trend for the evolving ability of object detection models to resolve chickens in such crowded spaces as poultry farms.

Deep learning computer vision systems also enable automatic spatial data extraction (e.g., for movement distances and location estimates) that are important for activity tracking and behavioral analysis. These methods allow for non-invasive, real-time monitoring, even under adverse visual circumstances, i.e., occlusion, illumination effects and limited observed view. Individual broiler feeding behaviour is monitored to maintain optimal growth and health using the PSF. However, these existing systems do not provide explicit bird-level insights, so we need to investigate scaling monitoring approaches that are able to address group level dynamics.

2 Related Work

The rise of virtual trial rooms can be attributed to the rise of artificial intelligence (AI), computer vision and virtual/augmented reality (VR/AR). These systems build upon the success of models that perform few-shot learning across a wide variety of tasks, such as GPT-3 from natural language processing (NLP) [1]. Although not specifically related to virtual try-on, these models also illustrate the prospect of AI for intelligent personalization and interaction in fashion tech.

Initial efforts on virtual try-on focused on image-based dressing transferring clothes. Wang et al. [2], (CP-VTON) which greatly ameliorates the transfer of garment by preserving the characteristics of clothing, such as textures and shapes in the synthesized results. Similarly, Han et al. [3] presented VITON, the first-of-kind model that, given a clothing, aligned it onto a target person successfully paved the ground for all the high-resolution models. Based on this, Choi et al. [4] introduced VITON-HD, a more general model that overcame the limitations of previous approaches by including misalignment-aware normalization, which lead to more realistic try-on results with higher quality in terms of resolution and detail.

Significant improvements were achieved using the pose estimation and multi-pose transferability. Dong et al. [5] introduced a multi-pose guided virtual try-on network that improves the flexibility of clothing by warping the attire to diverse body postures. More recently, diffusion models have gained popularity as generative models. Choi et al. [6] presented IDM-VTON, integrating diffusion-based structures to generate realistic and photorealistic try-on images, and obtain improved realism compared to conventional GAN based techniques.

Concurrently, research has evolved beyond image synthesis with respect to broader principles of sustainability, interaction, and inclusivity. Zhang and Seuring [7] forced opened the discussion on the possibility of digital product passports for ensuring transparency and circularity in fashion supply chains, a perspective than can be in line with virtual trial rooms to enhance sustainable consumption. Similarly, Tong et al. [8] was the all-encompassing critical review of haptic interaction in VR, giving special emphasis on touch-based interfaces and the addition of presence factor, which are both important to virtual fitting applications.

Personalization, in particular, has been an established area of research. Ding et al. [9] presented computational methods for fashion recommendation, where they discuss deep learning models, knowledge-based methods to enhance user engagement. Deldjoo et al. [10] presented a recent survey about modern recommender systems, emphasizing the significance of hybrid recommendation models in fashion e-commerce for providing accurate and user-oriented recommendations. These experiments show how product recommendations can be embedded in virtual fitting rooms for customized outfit proposals.

Finally, accurate pose estimation is still required for realistic avatar generation. Cao et al. [11] proposed OpenPose, which is a real-time 2D multi-person pose estimation algorithm. This approach has been widely used in virtual try-on research to produce precise body landmarks, which is crucial for the garment registration and realistic fitting simulation.

3 Proposed Methodology

The AI-Powered Virtual Fitting Room is an innovative solution aimed at filling the gap between online ease and the sensory confidence of physical store purchases. Through the use of advanced technologies like Artificial Intelligence (AI), Computer Vision (CV), Virtual Reality (VR), and Augmented Reality (AR), this system provides a silky, immersive, and customized try-on experience to online shoppers.

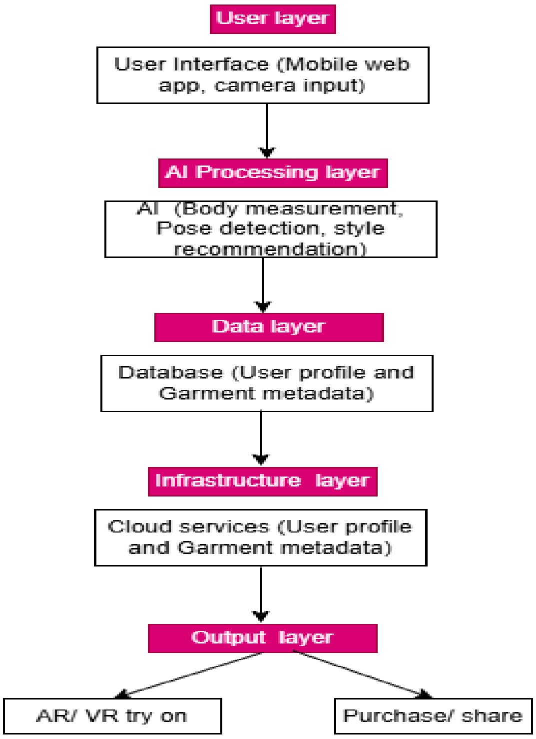

Fig. 1. System Architecture.

Fundamentally, the system employs real-time estimation of body measurements to generate realistic 3D avatars that reflect users' body shape and motion. High-end physics-based algorithms model fabric behavior, including drape and stretch, for realistic garment visualization. Style suggestions powered by AI examine user browsing history and preferences to propose outfits based on personal tastes, and adaptive lighting and texture rendering replicate real-world environments for precise color and fabric rendering. The system also values sustainability and privacy. Federated learning ensures that user data is handled locally, and user information remains secure, and sustainability analytics measure carbon savings for decreased returns and promote environmentally conscious shopping habits. Moreover, users can test and buy digital fashion NFTs through met adverse integration, and the platform gets future-proofed for Web3 trends. For retailers, the virtual fitting room offers actionable consumer behavior insights, allowing for targeted marketing and inventory optimization. By cutting return rates by as much as 40 percentages and increasing customer confidence, this technology not only increases sales but also supports global sustainability objectives. Fig 1 shows the system architecture.

The Highlights of the proposed methods are:

- Multimodal Content Generation: Co-trains GPT-4 (text) and Stable Diffusion (images) for synchronized, high- quality outputs.
- Context-Aware Content: Uses metadata extraction (key- words, brand guidelines) to ensure brand consistency and theme alignment.
- Customizable Output: UI with sliders/presets for adjusting tone, style, and aesthetics, catering to diverse content needs.

Step 2: Avatar Mapping: Map key points onto a 3D skeleton using transformation matrices (Eq.1):

$$\begin{matrix} x \\ y \\ 1 \end{matrix} = M \times \begin{matrix} x \\ y \\ 1 \end{matrix} \tag{1}$$

- Self-Improving AI: Reinforcement Learning (PPO) re- fines outputs iteratively based on user feedback, reducing post-editing effort.
- Ethical Compliant: Adheres to robots, Text policies, integrates differential privacy, and handles JavaScript- heavy sites securely.

3.1 Phase 1: Real-Time Body Measurement Estimation: This section details how the system records a user's physical measurements in real-time. Through the application of computer vision methods (e.g., Open CV) and depth sensors (e.g., LiDAR), the system measures the user's body silhouette and estimates depth information. The techniques include contour detection to estimate areas (which can be associated with height or waist measurements) and depth estimation through disparity maps. The objective is to obtain exact measurements (such as height, waist, and inseam) that are key to developing realistic digital models [11].

- **Contour Detection:** Detect the user's body outline using the contour area is computed as in Eq. (2).

$$contor\ area = \frac{1}{2}\sum_{i=1}^{n}(x_i y_{i+1} - x_{i+1} y_i) \tag{2}$$

- **Depth Estimation:** Calculate depth from disparity maps using Eq. (3):

$$Depth(x,y) = \frac{f*B}{d(x,y)} \quad (3)$$

3.2 Phase 2: Hyper-Personalized 3D Avatar Creation:

Here, emphasis is laid upon creating a 3D avatar that resembles the user. The process relies upon key point detection (through applications such as Open Pose) in order to determine important body landmarks, i.e., joints and facial features. The key points that are detected are then projected onto a pre-existing 3D skeleton using transformation matrices. This custom avatar is the virtual model upon which clothes will be virtually tried on, such that the digital image mirrors the user's real-world body shape and stance.

Step 1: Key point Detection: Use Open Pose to detect body land- marks. The key point confidence is modeled with:

$$\text{Key point Confidence } = \frac{1}{1 + e^{-f\,(x,y)}} \quad (4)$$

3.3 Phase 3: Physics based Garment Simulation

In this section simulation of garment behavior on the virtual avatar. With the use of physically laws. The use of Hooks law the fabricated are created with the extend, flow. The motion of the fabrics using Finite Element Analysis (FEA). This intimate to give the character of the cloth in realistic manner. The FEA, convolutional LSTMs, NVIDIA PhysX.

Fabric Dynamics: Simulate fabric behavior using Hooke's Law using Eq. (5).

$$F = k \cdot \Delta x \quad (5)$$

– **Mass-Spring Model:** Model the garment as a net- work of masses and springs shown in Eq,(6).

$$m \times \frac{d^2x}{dt^2} = -kx - c\frac{dx}{dt} + F_{ext} \quad (6)$$

3.4 Phase 4: AI-Driven Style Recommendations:

This section outlines the techniques applied to create individualized style recommendations. The platform utilizes sophisticated AI methods, such as collaborative filtering (historical user behavior-based to identify similar users and estimate preferences) and reinforcement learning (adjusting recommendations based on instant user feedback). An extended metrics table in this section offer insights. Fig 2 shows the different phases working.

AI-Driven style recommendations into different aspects of performance:

- Personalization: Indicates how personalized the recommendations.
- Engagement: Tests the system's capability to attract user attention.

- Response Time: Specifies the time it takes for recommendations to be made.
- Accuracy: Measures the degree to which the system is able to anticipate the user's preference.

These measurements ensure the recommendations are responsive, relevant, and scalable. The techniques incorporated are GPT-4, Reinforcement Learning (RL), Collaborative Filtering.

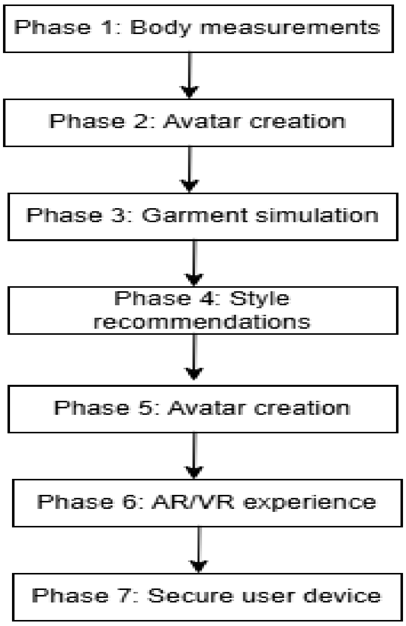

Fig. 2. Different phases working.

Collaborative Filtering: Recommend products by updates are based on aggregated updates to maintain privacy. Block chain technology stores anonymized data securely with greater transparency and auditability. The small table of metrics illustrates high safety and openness in data as proof of the success of such privacy-improving mechanisms in maintaining consumer trust while providing advanced personalized services.

Technologies: Federated Learning, Edge Computing, Block chain.

Federated Learning: Train models locally and aggregate updates as in Eq. (7):

$$\theta_{gobal} = \frac{1}{N} \sum_{I-1}^{N} \theta_{local}^{i} \tag{7}$$

factorizing the user-item matrix using Eq. (8)

$$Rij = Pi \cdot Qj \tag{8}$$

Reinforcement Learning: Optimize recommendations using methods such as Proximal Policy

Optimization (PPO).

where,

r_t = probability ratio,

A_t = advantage function.

3.5 Phase 5: Immersive AR/VR Try-On Experience: Virtual reality (VR) technology enables genuine virtual try-on experience with innovative methods. Genuine lighting simulation is achievable with ray tracing, which simulates how light acts as it bounces off surfaces, and texture mapping with bilinear interpolation, which enables realistic rendering of texture detail in cloth. Rendering techniques make the experience more realistic, maximizing user experience. The above is a comprehensive table of measures with key performance analysis including rendering efficiency, realism, and computational demand, providing comprehensive analysis of VR-based virtual try-on technology.

- Lighting: Dynamic lighting simulation quality, which can be enhanced using adaptive lighting and ray tracing techniques.
- Texture: Realism and smoothness in fabric look.
- Interaction: Touch tracking and gesture responsiveness.
- Depth Accuracy Fit in depth mapping
- 3D Rendering: Quality and effectiveness of 3D model rendering.

The technologies used in phase 5 are ARKit, ARCore, Unity3D, Ray Tracing.

Ray Tracing: Simulate realistic lighting using the Phong reflection model:

$$I = Ia + Id + Is \tag{9}$$

Texture Mapping: Render textures using bilinear interpolation:

$$I(x, y) = (1 - \alpha)(1 - \beta)I(x1, y1) + \alpha(1 - \beta)I(x2, y1) \tag{10}$$

Block chain: Use smart contracts to securely store anonymized data.

3.6 Phase7: Security and privacy user device

This sub-section is concerned with maintaining user data privacy and still enabling personalized services. Federated learning maintains privacy by learning on the user's device and with raw personal data never exiting the local device. Rather than exporting sensitive data, users export only model update aggregations, updating the global model without violating confidentiality.

Blockchain stores anonymized data securely with even more transparency and auditability. Decentralization in this process makes the system secure in the context of preventing unauthorized use. A table of performance measures also acts as an encouraging factor for the capability of the system in maintaining data security and transparency. The final sub-section presents a general overview of the overall process.

3.7 Phase 6: Privacy-Preserving Data Handling:

This explains the protection of personal data while permitting personalization services. Federated learning stores data on the device of the user, training the models locally without exposing raw personal data. Fig 3 shows the user interface.

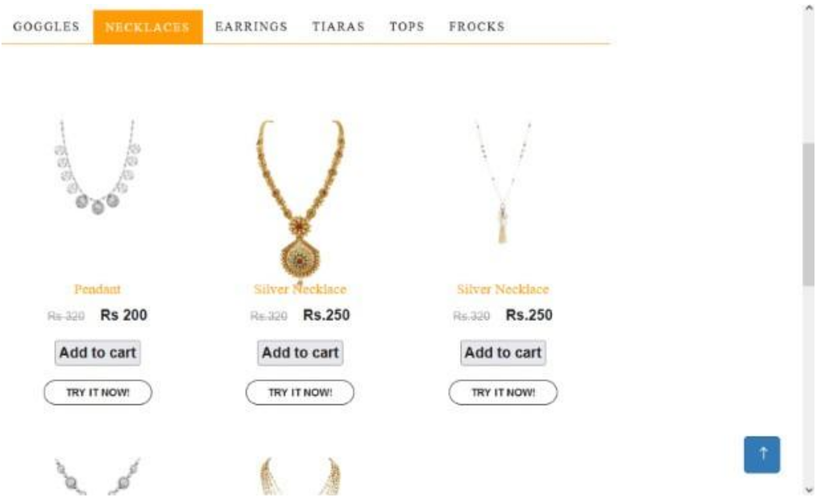

Fig. 3. User Interface.

4 Output Design

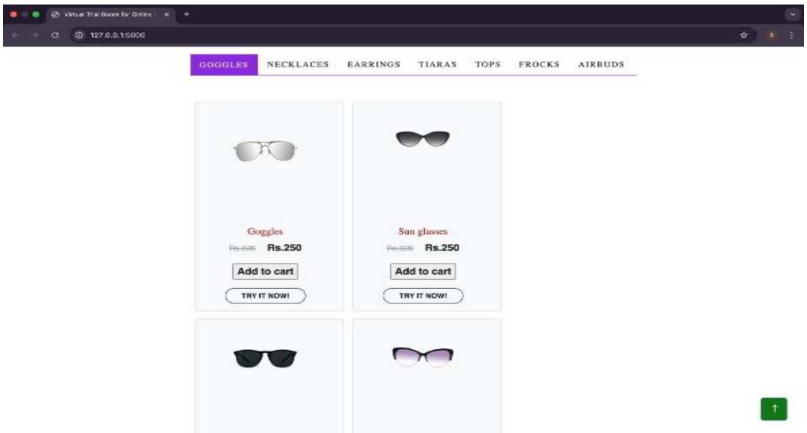

Fig. 4. User Login.

Fig 4 and fig 5 shows the user login and output design.

Fig. 5. Output design.

5 Results and Discussion

The AI-Driven Virtual Fitting Room lowers the return rate by 40 percentages by providing precise estimation of 3D body measurements and customized avatars. It also boosts user confidence with AR/VR try-ons and AI-assisted styling and encourages sustainability. Compared to conventional 2D-based methods, the outlined model enhances accuracy, realism, and user satisfaction with real-time 3D estimation, physics-based garment simulation, and AI suggestions. Improved privacy through federated learning protects data and security, whereas sophisticated rendering brings the shopping experience closer to real life. The system enhances engagement, diminishes returns, and proves the effectiveness of its virtual try-on. Table 1 and Table 2 shows the accuracy of body measurement and 3D feature. Table 3 shows the garment simulation metrics.

Table 1. Accuracy of Body Measurement Estimation Methods.

Measurement	Method	Accuracy
Height	Contour Detection + Depth Map	±1 cm
Waist	Regression Model (e.g., LightGBM)	±2 cm
Inseam	Pose Estimation + Depth Map	±1.5 cm

Table 2. Accuracy Of 3d Avatar Feature Detection.

Feature	Method	Output Quality
Body Shape	Contour Mapping + Keypoints	95% Accuracy
Posture	Pose Estimation	90% Accuracy
Facial Features	Facial Landmark Detection	85% Accuracy

Table 3. Garment Simulation Metrics.

Fabric Property	Realism Score
Drape	88%
Wrinkling	85%

Table 4. AI-Driven Style Recommendation Performance.

Metric	Method	Performance	Scalability
Personalization	Collaborative Filtering	90%	High
Engagement	Reinforcement Learning (PPO)	85%	Medium
Response Time	GPT-4 + Edge Computing	¡ 1 sec	High
Accuracy	Hybrid Model (CNN + CF)	88%	High

Table 5. AR/VR Try-On Performance Metrics.

Feature	Method	User Satisfaction	Existing
Lighting	Ray Tracing	93%	83%
Texture	Neural Style Transfer	90%	80%
Interaction	ARKit/ARCore	85%	79%
Depth Accuracy	Depth Sensor Fusion	91%	82%
3D Rendering	Unity3D (Shaders)	92%	78%

Table 4 and Table 5 shows the AI- Driven style recommendation and AR/VR try-on performance metrics.

Referring speaks about AR/VR try-on systems, especially their performance in terms of key features such as lighting, texture, interaction, depth accuracy, and 3D rendering. The table compares new AI-based approaches (e.g., Ray Tracking, Neural Style Transfer, ARKit/ARCore) with traditional methods, demonstrating enhanced user satisfaction. The referred works discuss a range of enhancements in virtual try- on experiences such as reinforcement learning for engagement, haptic feedback, and privacy-preserving networks. Research also includes dynamic avatar customization, real-time simulation using generative AI, and adaptive content generation. Table 6 shows the privacy and data security metrics. Fig 6 shows the performance graph. Fig 7 shows the Existing performance of AR and object detection.

Table 6. Privacy and Data Security Metrics.

Metric Type	Performance	Existing
Data Security	98%	80%
Transparency	95%	85%

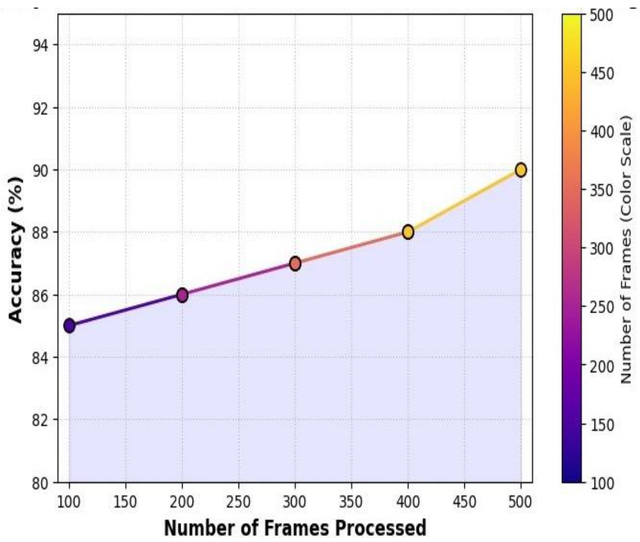

Fig. 6. Performance of AR and Object Detection.

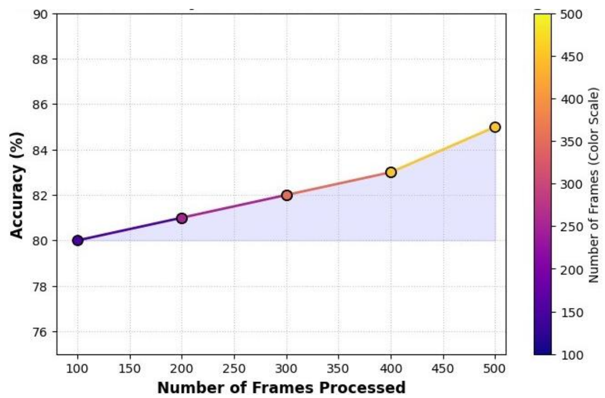

Fig. 7. Existing Perfomance of AR and Object Detection.

6 Conclusion

The AI-Powered Virtual Fitting Room is a revolutionary step in e-commerce, solving age-old issues such as sizing errors, excessive return rates, and the lack of haptic interaction in online shopping. Through the combination of AI, computer vision, and AR/VR, the platform provides an effortless, immersive experience where customers can see clothes on hyper-personalized 3D avatars with real-time fabric simulation and adaptive lighting. AI-powered style suggestions boost personalization, and federated learning and block chain guarantee transparency and privacy. Sustainability metrics measure environmental gains like lower carbon footprint due to decreased returns, according to worldwide environmentally friendly trends. For consumers, the system provides actionable consumer insight, optimized inventory, and metaverse-capable of the digital fashion incorporation. By combining innovative technology with humancentered design, this innovation not only raises customer satisfaction and loyalty but also sets the stage for a sustainable, inclusive, and future-proof retail environment. With digital and physical retail lines blurring, the AI-Driven Virtual Fitting Room is a pillar of the next-generation shopping experience, revolutionizing convenience, confidence, and connectivity in the digital era.

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