e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:10/October-2024 Impact Factor- 8.187 www.irjmets.com

REVOLUTIONIZING VIRTUAL WARDROBE MANAGEMENT WITH3D TECHNOLOGY AND GEMINI AI

Prof. Yogeshri Chaudhary[*1], Jyoti Rangu[*2], Sakshi Malve[*3], Ritik Urkude[*4], Vedant Patel[*5]

[*1,2,3,4,5]Information Technology KDK College Of EngineeringNagpur, India.

DOI: https://www.doi.org/10.56726/IRJMETS62555

ABSTRACT

The proposed application seeks to engage customers and offer a unique experience of fashion retailing through a 3D wardrobe solution. This feature utilizes Gemini AI for fashion recommendation where application users are provided with recommendations on outfits based on their choices. Clothing and accessory design do so using the PIFuHD model for 3D modelling garments and accessories for high-end avatars. For improving the user interaction, face & body shape recognition technologies are included in the system with the help of Artificial Intelligence and Machine Learning that will provide the best fit and natural look. Thefront-end part is created with Flutter; the UI remains adaptive and engaging The main back-end services are established in Flask and PostgreSQL, the API is developed for data handling and enlarging.Here, fashion and technology meet East and West as the latest in AIand 3D modelling create a unique and engaging shopping experience.

Keywords: Gemini AI, Pifuhd, Flask, Postgresql, 3D Modelling, Fashion Recommendation, Body Shape Estimation.

I. INTRODUCTION

Style era has undergone substantial transformation in latest years, pushed with the aid of advancements in artificial intelligence (AI), device learning (ML), and laptop imaginativeand prescient. those technologies have enabled the development of programs that provide personalized fashion guidelines, digital strive-on experiences, and complex second to 3-D human reconstruction. as the demand for customized style experiences grows, the integration of those technologies allows users to discover clothing tailor-made to their man or woman preferences, body kinds, and characteristics.

Personalized style recommendation systems utilize deep mastering and herbal language processing (NLP) to analyze user records, frame shapes, and style alternatives, enabling more correct outfit guidelines. additionally, virtual try-on technologies offer users with an immersive revel in where theycould visualize outfits, hairstyles, and colorings before creatinga buy. This greatly enhances user self belief and satisfaction oftheir style choices.

The improvement of those applications entails multi-layer neural networks, coarse-to-wonderful frameworks for three-D human modeling, and integration with structures like Flutter andFlask for seamless cross-platform capability. the ones technological upgrades not most effective simplify the technique of favor exploration however moreover pave the way for extra interactive and custom designed person stories. This paper explores the methodologies and technology that power those upgrades, addresses the demanding situations of accuracy and scalability, and examines the destiny possibilities of integratingaugmented fact (AR) and sensitive algorithms to in addition beautify the fashion era panorama.

The style industry, historically driven by using layout and tendencies, is now closely prompted by using way of data-driventechnologies that personalize the individual revel in. machine reading (ML) fashions have emerged as effective tools for stylerecommendation systems, using complicated algorithms to analyze seen and textual functions from person alternatives. theones models take a look at beyond user behaviors, choices, and body metrics to generate garments that resonate with man or woman tastes. With the upward push of customized style, ML- based totally structures offer customers with hints that decoratestyle exploration whilst minimizing the attempt required to picknew outfits.

Moreover, the incorporation of digital attempt-on opinions has notably reshaped the web buying panorama. by means of utilizing augmented reality (AR) and 3D human reconstruction strategies, the ones programs allow clients to "attempt on" garments, hairstyles, and add-ons in a digital vicinity. PIFuHD,a pioneering 2nd to 3-d reconstruction method, makes use of immoderate-choice inputs to create correct and positive fashions of the human frame. This technique no longer simplest complements the visual accuracy of virtual strive however additionally improves consumer engagement with the aid of creating a quite immersive revel in that mimics in-person shopping.

Every other key innovation is the integration of cross- platform frameworks together with Flutter and Flask, which streamline the improvement of real-time, responsive fashion applications. Flutter, particularly, enables developers to create move-platform apps that paintings seamlessly on each Android and iOS, making sure consistency in person revel in. Coupled with backend technology like Flask, which helps actual-time statistics handling and processing, those systems allow for clean updates in user preferences, recommendations, and virtual strive-on functionalities, making the apps tremendouslyresponsive and adaptable.

No matter those advancements, several demanding situationspersist in optimizing fashion technology. ensuring the accuracy of digital try-ons throughout diverse frame sorts, perfecting tips based on complicated consumer inputs, and improving the seamless integration of ML fashions pose significant technical hurdles. future developments ought to consciousness on refining ML algorithms, enhancing the precision of AR features, and integrating AI-pushed personalization to provide exceedingly tailored, immersive buying studies.

Furthermore, the incorporation of digital try-on experiences has appreciably reshaped the net buying landscape. via using augmented truth (AR) and three-D human reconstruction strategies, those packages allow customers to "try on" garments, hairstyles, and accessories in a virtual area. PIFuHD, a pioneering 2d to 3-d reconstruction approach, uses excessive- decision inputs to create correct and detailed models of the human body. This method no longer only enhances the visible accuracy of virtual strive-ons but also improves consumerengagement by way of developing a noticeably immersive revelin that mimics in-person purchasing.

Skin tone detection and material popularity are a number of the advanced techniques being explored to beautify thepersonalization of style evaluations. thru leveraging AIalgorithms that look at pores and skin tones, customers can getkeep of recommendations on colorings and styles thatsupplement their specific features. This presents some other layer of customization, making the shopping revel in more intuitive and aligned with man or woman choices. fabric popularity, instead, aids in identifying the maximum appropriate substances for customers based totally on weather, consolation, and event, including in addition intensity to the style recommendation systems.

As the style employer maintains to encompass era, future innovations are possibly to attention on mixing tool mastering with other rising era like augmented truth (AR) and virtual fact(VR). these era, whilst incorporated with AI-powered personalization, can provide customers with fully immersive virtual shops in which they could discover entire collections and experiment with one-of-a-type appears in real-time. moreover, optimizing algorithms for quicker processing and enhancing statistics protection in these packages may be key inmaking sure a continuing and comfy experience for clients. The evolution of favor technology, driven via way of these innovations, guarantees to revolutionize now not just how customers shop however how they interact with fashion as a whole.

II. RELATED WORK

There has been a growing interest in fashion recommendation systems particularly in the areas of e-business and customization. Major e-commerce websites have continued to experience an increase and fashion recommendation systems have emerged as a key component to improve user experience and loyalty. This section briefly discusses the related work and technologies that are important for the creation of outfit suggestion systems using ML[2].

In the past, there have various fashion recommendation systems, which included the basic collaborative filtering and content-based systems. Much like collaborative filtering, this approach identifies individual tastes and provides outfits that have been preferred by other users. Su and Khoshgoftaar (2009)note that user-based and item-based collaborative filtering are very effective in providing personalized results to users. Content-based approaches, on the other hand, pay attention to the characteristics of articles of clothing, including color, fabric type, and style, with similar outfits being suggested (Lops et al., 2011). New developments in hybrid recommendation systems integrate both collaborative and content-based filtering approaches to increase recommendation precision. According to Burke (2002), hybrid systems help avoid the shortcomings of each method and produce recommendations that are more individualized and varied[2].

Recommendation systems have benefited from computer vision techniques where the visual components of clothing havefacilitated the outfit suggestions. Some recommendation systems for fashion images like 'Dressify' (Kim et al., 2019) employ computer vision to evaluate the coordination of differentgarments. Furthermore, the application of deep learningtechniques, especially the convolutional neural networks (CNNs) has provided a deeper level of feature extraction on the clothes images thus giving more details on aspects of styles and texture[2].

Today, silhouette alignment is one of the crucial steps in the process of personal styling, which aims to match the client withclothes that fit her or him the best. Technologies such as 3D body scanning have materialized, which provide accurate body measurements to improve the efficiency of the fashionrecommendations. According to Jinyan et al. (2019), image processing is a valuable tool for determining body shapes and forms but does not require contact with the patient. In addition, virtual try-on applications (Zanotto et al., 2015) based on augmented reality help users imagine how specific clothes maylook on them, improving the overall experience. New developments, like the incorporation of generative adversarial networks (GANs), has enabled the advancement of fashion recommendation systems. 'StyleGAN' (Karras et al., 2019) is the first to generate realistic fashion images that could complement current datasets and open up new possibilities in fashion suggestions[2].

There has been a great progress in modeling human shapes from digital 2D images to 3D through the recent introduction ofdeep learning methods. One such outstanding model is PIFuHD(Pixel-Aligned Implicit Function for High-Resolution 3DHuman Digitization), which is instrumental in creating virtual wardrobe systems and more. [1].

Traditional approaches to 3D human shape reconstruction from images struggled to balance global context and high- resolution detail. Earlier models typically used low-resolution images to predict 3D structures, resulting in coarse, less accurate reconstructions. PIFuHD addresses these limitations by utilizing a multi-level framework that reconstructs detailed 3D human models from high-resolution images, allowing for the recovery of fine features such as clothing folds and facial details(PIFuHD 2d to 3D).[1]

PIFuHD builds upon the foundation of the Pixel-Aligned Implicit Function (PIFuHD) architecture, but extends it tohandle much larger image resolutions, up to 1024x1024 pixels,making it especially effective for high-fidelity 3D reconstructions needed in fashion applications(PIFuHD 2d to 3D). This is achieved through a coarse-to-fine architecture, where a lower-resolution model captures the overall structure, and a fine-resolution model incorporates detailed geometry. This multi-level approach provides a more accurate and contextually aware reconstruction, particularly in areas where details are crucial, such as clothing fit and texture(PIFuHD 2d to 3D).[1]

Specifically, due to the need for increase of personal approach in e-commerce, the idea of fashion recommendation systems has emerged. These systems are designed to help select clothes that can be worn together, which in the past, would have involved hiring stylists. undefined com's GORDN system actually solves the problem of providing scalable and automated outfit suggestions. It uses multi-modal deep learning to represent fashion items in a style space where similar items can be recommended.[3]

Undefined Outfit Recommendation Systems The firstattempts at outfit recommendation relied on data inputs from fashion experts on possible good matches for outfit combinations. The ASOS study presents a system for teaching the neural networks the visual and textual characteristics of styles to establish compatibility and generate outfits automatically. Undefined All these modes are trained and embedded in a shared space in which products from each category are grouped according to their companionship in the Fashion category, e. g., shirts and trousers. The recommendation system of GORDN, based on neural networks, utilizes textual descriptions, visuals, and types of products to get the most accurate result on the recommended outfit.[4]

Undefined Training with Real-world Data The ASOS dataset containing more than 586,000 outfits was used fortraining the model. It is one of the largest annotated fashion datasets; it contains both women and men wear; thus, theeffectiveness of the system is evident in different types and usage settings.[5]

Undefined Evaluation Testing of the system was done through A/B testing where it was 21% better than a baseline model for generating outfits that were preferred by the users forwomen's wear, while for men's wear it was 34% better. This proved the effectiveness of the model in producing outfits thatcould be worn in real

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:10/October-2024 Impact Factor- 8.187 www.irjmets.com

life.[6]

III. METHODOLOGY

This research paper offers an elaborate depiction of the steps to undertake to accomplish sentiment analysis with emphasis onthe flow of information. Starting with data ingestion by uploading the CSV file, we move on to textual data preprocessing, incorporation of analytical models, andvisualizing the sentiment analysis. Here we give a clear description of each phase to give a clear understanding of how sentiment analysis system handle the data flow and how to lay down a good ground for good the sentiment analysis implementation as shown by the figure 1.

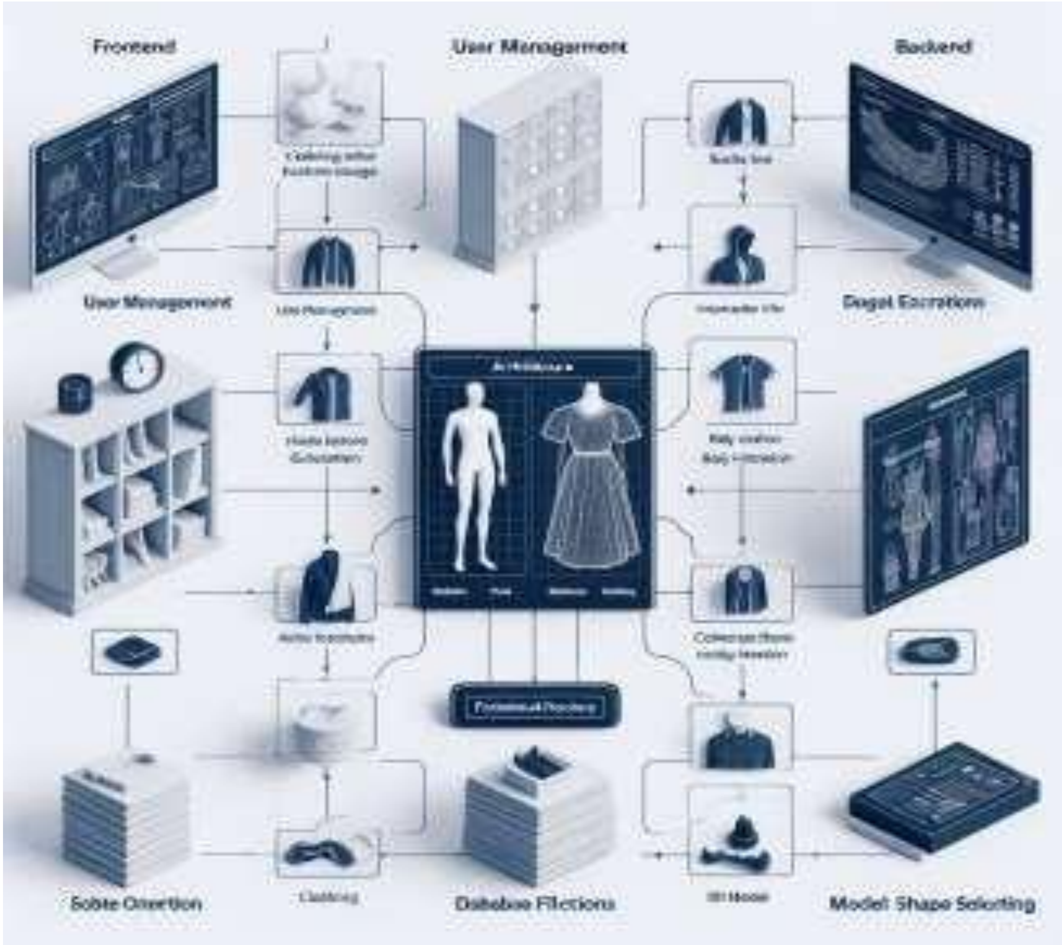

Fig. 1. System Architectures Diagram

1. Data Collection and Storage

The data, including fashion-related attributes such as body measurements, item images, and descriptions, was collected from various sources. Key sources include online fashion datasets and user input for personalization. This data is stored in a PostgreSQL database for efficient querying and management. Each clothing item and user data is structured toinclude:

- **Clothing attributes:** style, color, size, material, and fit.
- **User attributes:** body shape, preferences, and previous outfit interactions.
- **3D model data:** garments and user avatars generated using PIFuHD Model.

2. Backend Architecture (Flask and PostgreSQL)

The backend is developed using Flask, a lightweight Python framework, to serve the ML models, handle API requests, and manage communication between the frontend and database. The primary functionalities include:

- **User Management:** Authentication and profilemanagement.
- **Data Processing:** Handling requests for outfit suggestions based on user preferences and past data.

- **Database Operations**: Performing CRUD operations on the PostgreSQL database to store and retrieve clothing and user data. Flask also acts as an intermediary to call the Gemini API for advanced 3D model generation and manipulation.

3. **Machine Learning Model for Outfit Suggestions**

The core ML model is built using body shape analysis to recommend outfits that best suit individual users. Techniquessuch as computer vision and deep learning are utilized for:

- **Image Feature Extraction:** Clothing items are analysed using image processing techniques to extractvisual features (style, colour, texture).
- **Body Shape Analysis:** User body shape data is compared to the available outfit data to generate personalized recommendations.
- **Collaborative Filtering:** Suggesting outfits based on user preferences and interactions, as well as what similar users have preferred.

4. **3D Model Integration (Gemini API and PIFuHD)**

The Gemini API and PIFuHD are used to generate and display 3D models of clothing items and outfits. These models are tailored to the user's body shape, providing an interactive virtual try-on experience. The process involves:

- **Model Generation:** Using the PIFuHD API to createaccurate 3D models of clothing and user avatars.
- **3D Rendering:** Gemini API handles the rendering of clothing in real-time, adjusting to the user's body proportions and selected items.
- **Real-Time Visualization:** The rendered models are sent to the Flutter frontend for real-time display and user interaction.

6. Frontend Development (Flutter)

The frontend interface is developed using Flutter, providing a seamless and interactive user experience across devices. It includes:

- **User Dashboard:** Displays personalized outfitrecommendations and 3D models.
- **Interactive 3D View**: Users can view and interact with3D models of the outfits, enabling virtual try-on.
- **Outfit Selection:** Users can select, customize, andsave outfits directly from the 3D interface

7. **Evaluation**

The system was evaluated based on user satisfaction and system performance. The key performance metrics include:

- **Model Accuracy:** The effectiveness of outfitrecommendations based on user preferences.
- **Rendering Speed:** The speed and responsiveness of the3D model generation.
- **User Engagement**: Feedback collected from users interacting with the 3D interface and virtual try-on feature.

8. System Workflow

- The user inputs data (body measurements, preferences)via the Flutter app.
- The Flask backend retrieves data from the PostgreSQLdatabase and processes it using ML models for outfit recommendations.
- The Gemini API and PIFuHD generate 3D models ofselected outfits.
- The results, including the interactive 3D model, aredisplayed on the Flutter app.

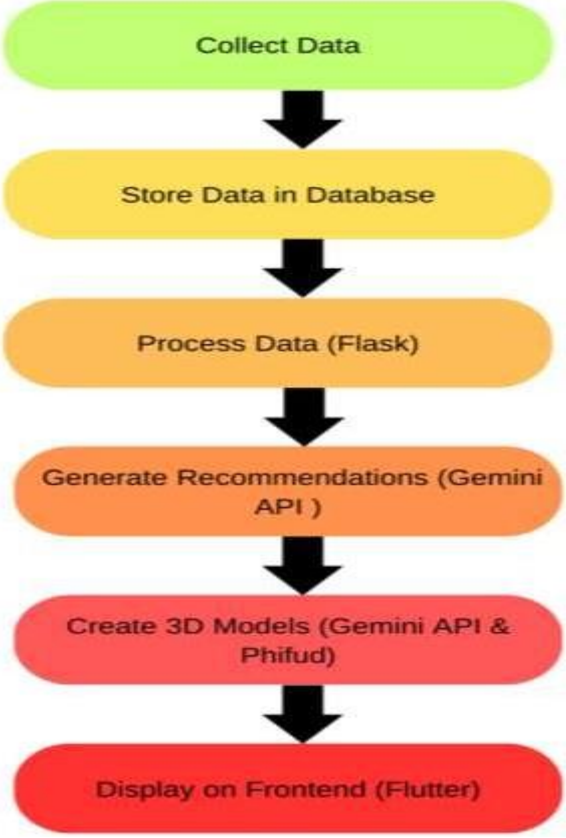

Fig. 2. Data Flow Diagram

IV. RESULT AND DISCUSSION

The insights presented in the paper mimic the proposition that incorporating the Galaxy AI and PIFuHD technology into the virtual wardrobe administration highly improves the online fashion e-commerce. The following are the accomplishment obtained by the application; Additionally, PIFuHD also enhances the interactive portions of clothing and accessories bybeing able to model 3D avatars more realistically existing as a key point for creating an enhanced shopping experience. Userssay that it results in a higher satisfaction with the virtual try-on,as it reflects the actual appearance and fit of the garments one might want to purchase.

Secondly, Gemini AI properly comprehends the user's inclination and the dimensions required to make preferable fashion recommendation. These AI-based recommendations are more focused towards user preferences and their body shapes, contributing to a more personalized shopping experience. Moreover, compared with facial recognition and body shape recognition technologies for garment identification, it also improves the accuracy of fitting. This leads to avatars that are closer to the users in terms of body shape and size, thuscreating a realistic and ultimately more satisfying virtual fittingexperience.

Moreover, these technologies are well integrated in theapplication of the proposed system. The front-end, built with Flutter, provides the adaptive and engaging UI, while the back-end services based on Flask and PostgreSQL provide efficient data processing and accommodating scalability. This smooth integration helps in maintaining coherent and effective functioning of the applications. Furthermore, the application helps to break cultural barriers by incorporating modern technology with latest fashion trends and offering an exclusive shopping experience that meets the individual needs of users.

V. CONCLUSION

By incorporating Gemini AI and PIFuHD to a virtual wardrobe, the fashion retail industry takes a leap forward with the WDM. Besides, this approach improves the involvement of users with the utility of 3D modeling in enhancing the fashion suggestions in a more individualized manner. The application of face and body shape recognition technologies assures a better and more genuine fitting experience solving one of the major issues of online fashion selling.

The flexibility of the developed application as a mobile application employing Flutter technology and the API backend using Flask and PostgreSQL, offer a solid and scalable solution. This combination of technologies provides a groundbreaking solution to organizing virtual wardrobes which defined new standards for online clothing shopping.

VI. REFERENCES

[1] Shunsuke Saito, Tomas Simon, Jason Saragih, "PIFuHD: Multi-Level Pixel-Aligned Implicit Function for High-Resolution 3D Human Digitization" IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) in 2020.

[2] Elaine M. Bettaney and Stephen R. Hardwick, "Fashion Outfit Generation for E-commerce"., ·Preprint, March 2019, 2019. ACM ISBN.

[3] Chandrakant D. Kokane , Aadit Rode "ML–Based Outfit Suggestion System " at International Journal of Scientific Research in Computer Science, Engineering and Information Technology ISSN : 2456-3307

[4] Andreas Veit, Balazs Kovacs, Sean Bell, Julian Mcauley, Kavita Bala, and Serge Belongie. 2015. Learning Visual Clothing Style with Heterogeneous Dyadic Co-occurrences. In IEEE International Conference on Computer Vision. 4642–4650.

[5] Xuemeng Song, Fuli Feng, Xianjing Han, Xin Yang, Wei Liu, and Liqiang Nie. 2018. Neural Compatibility Modeling with Attentive Knowledge Distillation. In SIGIR Conference on Research & Development in Information Retrieval. 5–14.

[6] Tong He and Yang Hu. 2018. FashionNet: Personalized Outfit Recommendation with Deep Neural Network. (2018), 1–9.