# PERSONALIZED FASHION ASSISTANT

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**ABSTRACT :**

FitGenie is an AI-powered personalized fashion assistant system designed to deliver intelligent, context-aware outfit recommendations tailored to individual users. The system integrates computer vision, machine learning, and large language models into a unified platform that functions as a smart digital wardrobe and virtual stylist. It collects user-specific attributes such as age, gender, skin tone, body type, and style preferences, and processes uploaded clothing images using a fine-tuned Vision Transformer deep learning model to extract garment category, color, pattern, and fabric attributes. The resulting feature vectors are indexed in a FAISS vector database for sub-millisecond similarity retrieval, while structured metadata is stored in PostgreSQL.

The core recommendation engine employs a Retrieval-Augmented Generation (RAG) pipeline that integrates real-time weather data, calendar event details, and current fashion trends to generate personalized outfit suggestions with natural language rationale through a Large Language Model. A virtual try-on module powered by a latent diffusion model enables photorealistic simulation of selected garments on user images through skeletal pose estimation and thin-plate spline warping. A continuous feedback mechanism updates a User Preference Matrix to improve recommendations over time, while additional features include outfit history tracking, closet gap analysis, and calendar-based scheduling.

**KEYWORDS**: Personalized Fashion Assistant, FitGenie, Computer Vision, Retrieval- Augmented Generation (RAG), FAISS Vector Database, Large Language Model (LLM), Virtual Try-On, Diffusion Model, Smart Wardrobe, Deep Learning, Context-Aware Recommendation, Generative AI, Fashion AI, PyTorch, FastAPI.

## INTRODUCTION

### 1. OBJECTIVE

The objective of this project is to create a reliable and intelligent fashion recommendation system using Python and advanced AI technologies. The system collects user profile data, processes wardrobe images through deep learning pipelines, and applies Retrieval-Augmented Generation techniques to generate personalized, context-aware outfit suggestions. The application integrates real-time weather APIs, FAISS-based vector search, and large language models to deliver outfit recommendations with natural language rationale. A virtual try-on module using latent diffusion models allows users to visualize selected outfits photorealistically before choosing them.

The system also incorporates a continuous learning mechanism through user feedback, enabling the preference model to adapt over time. Emphasis is placed on creating a scalable, modular architecture deployable across multiple user environments. Future integration with social media trend APIs and augmented reality try-on capabilities is envisioned to further enhance user experience and fashion intelligence.

### 1.2 PROBLEM STATEMENT

Fashion selection in the digital age presents a significant challenge due to the overwhelming volume of clothing choices available through e-commerce platforms and social media. Most existing fashion recommendation systems rely on generic collaborative filtering or basic content-based methods that fail to account for critical personal attributes such as body type, skin tone, and individual style preferences. Users also lack structured tools to organize and leverage their existing wardrobe effectively, leading to underutilization of owned clothing items and impulsive fast-fashion purchases.

Additionally, current platforms do not adequately incorporate contextual factors such as real-time weather conditions, seasonal trends, event type, and geographic location into their recommendation logic. The absence of feedback-driven learning mechanisms further limits personalization quality over time. Virtual try-on capabilities remain underutilized, leaving users unable to visualize outfit selections before committing to them. There is therefore a need for a comprehensive, adaptive, multi- modal AI system capable of bridging these gaps.

## 1.3 EXISTING MODELS

Several approaches have been developed to address fashion recommendation and wardrobe management. Traditional digital wardrobe applications allow users to upload and organize clothing items manually, but rely heavily on user effort and lack automation and intelligence. Basic recommendation systems use past selections and simple profile inputs to suggest outfits; however, these recommendations are often generic and fail to consider deeper personal attributes or contextual factors.

Image processing-based systems use deep learning to identify clothing attributes such as color and pattern, improving wardrobe organization but lacking deep contextual understanding. A few platforms incorporate weather or occasion-based suggestions, but these implementations remain limited in scope. None of the existing solutions effectively combine wardrobe management, context- aware recommendations, real-time trend integration, virtual try-on, and adaptive learning into a single unified platform.

## 1.4 PROPOSED MODEL

To overcome the limitations of existing systems, this project proposes FitGenie, an integrated AI-powered fashion assistant platform. The system builds detailed user profiles using personal attributes and computer vision-based image analysis. A Smart Wardrobe module automatically classifies uploaded clothing using a fine-tuned Vision Transformer model, generating 768-dimensional feature embeddings indexed in FAISS. A context-aware recommendation engine employs a Retrieval-Augmented Generation pipeline that integrates real-time weather data, calendar events, and fashion trend vectors to generate ranked outfit suggestions via a Large Language Model.

A hybrid recommendation strategy combining rule-based filtering with machine learning ranking enhances accuracy and personalization. A latent diffusion-based virtual try-on module provides photorealistic outfit previews, while a feedback mechanism continuously updates the User Preference Matrix to improve future recommendations. Additional features include outfit history tracking, closet gap analysis, and calendar- based scheduling, delivering a comprehensive, scalable, and sustainable personal fashion intelligence platform.

## LITERATURE REVIEW

**Fashion Image Classification and Attribute Prediction:**

This project builds upon the work of Liu et al. (2024), who presented a deep learning-based approach for fashion image classification using convolutional neural networks to automatically identify clothing categories, colors, and patterns. Their study demonstrated that automated feature extraction significantly reduces manual effort in fashion analysis. This directly informs the computer vision module of FitGenie, where a fine-tuned Vision Transformer extracts garment attributes from user-uploaded images with high accuracy. [1]

**Learning Fashion Compatibility with Neural Networks:**

This research draws from Han et al. (2023), who introduced a framework for learning fashion compatibility using bidirectional LSTMs. Their study demonstrated that learning compatibility relationships between clothing items improves outfit recommendation quality. The compatibility learning approach directly informs the hybrid recommendation engine in FitGenie, where outfit combinations are ranked based on learned aesthetic relationships between garment attributes. [2]

**Style Compatibility and Embedding-Based Approaches:**

This project builds upon Hsiao and Grauman (2024), who explored learning style compatibility across clothing items using visual feature embeddings. Their embedding-based approach for capturing item relationships informs the FAISS vector database architecture in FitGenie, where 768-dimensional clothing embeddings enable fast and accurate similarity-based retrieval for outfit suggestion generation. [3]

**Context-Aware Recommendation Systems in Fashion:**

This research builds on Adomavicius and Tuzhilin (2023), who examined the importance of contextual factors such as weather, location, and occasion in generating relevant recommendations. Their findings directly support the RAG pipeline in FitGenie, where real-time weather data, event type, and seasonal trends are integrated into the recommendation context to produce situationally appropriate outfit suggestions. [4]

**Virtual Try-On Using Generative Models:**

This project draws from Han et al. (2022), who discussed the application of virtual try-on systems using deep generative models. Their work demonstrates how deep learning can simulate clothing on user images to improve decision-making. The virtual try- on module in FitGenie employs a latent diffusion architecture with thin-plate spline warping and generative blending, directly inspired by these generative try-on techniques. [5]

**Retrieval-Augmented Generation for Knowledge-Intensive Tasks:**

This research draws from Lewis et al. (2020), who introduced the Retrieval- Augmented Generation framework combining information retrieval with generative language models for knowledge-intensive tasks. Their approach of dynamically retrieving external knowledge before generation directly informs the RAG pipeline in FitGenie, where fashion trend embeddings are retrieved from FAISS and injected into the LLM context window for grounded recommendation generation. [6]

**Hybrid Recommendation Systems:**

This project builds upon Burke (2022), who examined hybrid recommender systems combining rule- based and machine learning approaches. Their findings that hybrid models provide better accuracy and flexibility compared to single-method systems directly inform the recommendation engine in FitGenie, which combines rule-based color theory filters with ML-based preference ranking to enhance recommendation quality. [7]

**Feedback-Based Adaptive Learning in Recommendation:**

This research draws from Ricci et al. (2025), who highlighted the importance of continuous feedback-driven learning in improving recommendation personalization. Their work supports the feedback mechanism in FitGenie, where user ratings and interactions are captured to update a User Preference Matrix, enabling the system to continuously adapt and improve outfit suggestions based on evolving user preferences. [8]

**Wardrobe Management Using Machine Learning:**

This project builds upon Chen et al. (2025), who presented an intelligent clothing management system using machine learning for wardrobe organization. Their emphasis on structured storage, automated categorization, and intelligent retrieval directly informs the Smart Wardrobe module in FitGenie, where clothing items are automatically classified and stored in a hybrid

PostgreSQL and FAISS database architecture for efficient management. [9]

**Conversational AI in Recommendation Systems:**

This research draws from Jannach et al. (2024), who explored the integration of conversational AI in recommendation systems, demonstrating how natural language interfaces improve user interaction. Their findings directly support the chatbot interface in FitGenie, where users interact with the fashion assistant through natural language queries, receiving personalized outfit recommendations and styling advice in a conversational format. [10]

**SYSTEM SPECIFICATION**

## 3.1 Hardware Requirement

1. Processor (CPU): A minimum of an Intel Core i5 or equivalent processor is recommended to handle machine learning model inference, image processing tasks, and backend API operations smoothly. For deep learning model training, a higher-performance processor such as Intel Core i7 or AMD Ryzen 7 is preferred.

2. Random Access Memory (RAM): A minimum of 8 GB RAM is required to run the FastAPI backend, React.js frontend, and machine learning inference tasks simultaneously. For improved performance during model training and image processing, 16 GB RAM or higher is recommended.

3. Storage (SSD): A minimum of 256 GB SSD storage is required to store datasets, trained model files, wardrobe image assets, FAISS index files, and application components. SSD storage ensures faster read and write operations for real-time recommendation workflows.

4. GPU (Optional): A dedicated GPU such as NVIDIA GTX or higher is recommended to accelerate deep learning computations for Vision Transformer training, diffusion model inference, and FAISS index construction. The system can also function using CPU-based processing for smaller-scale deployments.

5. Internet Connectivity: A stable internet connection is essential for accessing real-time weather APIs, external fashion trend data, and cloud-based model deployment. Without connectivity, real- time context-aware recommendation features will be limited.

6. Display Monitor: A minimum 13-inch screen with Full HD resolution (1920x1080) is recommended for clearly

viewing the wardrobe dashboard, outfit recommendation cards, and virtual try-on previews.

## 3.2 SOFTWARE REQUIREMENT

1. Operating System (OS): The FitGenie system is compatible with Windows, macOS, and Linux operating systems. Ubuntu Linux is particularly recommended for development due to its strong support for Python-based AI frameworks and containerized deployments.

2. Programming Language (Python): Python 3.10 serves as the core programming language for backend development, machine learning model implementation, image processing pipelines, and API integration due to its extensive AI and data science library ecosystem.

3. Backend Framework (FastAPI): FastAPI is used as the high-performance web framework for developing RESTful API endpoints, handling asynchronous operations, and managing communication between the frontend, machine learning models, and databases.

4. Deep Learning Framework (PyTorch): PyTorch is used for building, fine-tuning, and deploying the Vision Transformer garment classification model and the latent diffusion virtual try-on model.

5. Computer Vision Libraries (OpenCV, PIL): OpenCV and PIL are used for image preprocessing operations including background removal, lighting normalization, resolution standardization, and body landmark detection prior to deep learning model inference.

6. Vector Database (FAISS): Facebook AI Similarity Search (FAISS) is used for indexing high-dimensional clothing feature embeddings and performing sub-millisecond kNN similarity searches for the RAG recommendation pipeline.

7. Relational Database (PostgreSQL): PostgreSQL is used for persistently storing structured data including user profiles, wardrobe metadata, outfit history, feedback logs, and recommendation results with full ACID compliance.

8. Frontend Framework (React.js): React.js is used for developing the interactive web-based user interface, including the wardrobe dashboard, outfit recommendation cards, virtual try-on preview, and chatbot interaction panel.

### 3.3 TECHNOLOGIES USED

The FitGenie system integrates a comprehensive stack of modern AI and web technologies. Python serves as the primary development language, enabling seamless integration of deep learning, image processing, and API components within a unified environment. FastAPI provides a high-performance asynchronous backend capable of handling concurrent image uploads, model inference requests, and real-time recommendation generation. PyTorch powers the deep learning backbone, including a fine-tuned Vision Transformer for garment classification and a latent diffusion model for virtual try-on functionality.

OpenCV and PIL handle image preprocessing pipelines ensuring consistent, high-quality input for machine learning models. FAISS provides efficient high-dimensional vector indexing supporting sub-millisecond similarity searches critical for the RAG pipeline. PostgreSQL manages all structured relational data with ACID compliance, while FAISS handles unstructured vector embeddings for trend and wardrobe similarity search. The Retrieval- Augmented Generation framework dynamically retrieves fashion trend knowledge and wardrobe context before LLM-based outfit generation. React.js delivers a responsive, component-based frontend interface, and Git enables version control and collaborative development throughout the project lifecycle.

## METHODOLOGY

The methodology for FitGenie follows a structured multi-phase approach integrating data collection, deep learning model training, RAG pipeline construction, recommendation engine development, virtual try-on implementation, and continuous feedback-based learning. The following steps outline the complete system workflow.

### 4.1 Data Collection

The data collection phase integrates large-scale fashion datasets and real-time user-generated content. Primary data is sourced from open-source repositories such as DeepFashion and Fashion-MNIST, providing professionally labeled images across diverse clothing categories for training the PyTorch vision models. Dynamic user data is collected through clothing image uploads via the React.js frontend, and contextual data is gathered through real-time weather APIs and geographic trend services. User interaction logs including liked outfits and feedback are stored in PostgreSQL to facilitate continuous learning.

### 4.2 Data Preprocessing

All user-uploaded clothing images undergo a preprocessing pipeline using OpenCV and PIL, including background segmentation, lighting normalization, resolution standardization to a uniform dimension, and body landmark detection. For textual and metadata inputs, preprocessing involves tokenization, lowercasing, stop-word removal, and categorical standardization mapping color synonyms to primary categories. Environmental data retrieved from external APIs is normalized into a scale suitable for the recommendation engine's heuristic filters, while timestamps are converted to uniform ISO format for calendar integration.

### 4.3 Feature Extraction and Embedding

Preprocessed garment images are passed through a fine-tuned Vision Transformer (ViT) or ResNet-based architecture, which extracts categorical attributes including garment type, color, pattern, and fabric. These attributes are stored as structured metadata in PostgreSQL, while the global feature vector is transformed into a 768- dimensional embedding and indexed in the FAISS IndexIVFFlat structure. This dual- storage strategy enables both hard filtering and soft similarity matching during recommendation generation.

### 4.4 RAG Pipeline and LLM Recommendation

When a user requests an outfit recommendation, the system constructs a situational context profile by fetching real- time weather data, parsing calendar event details, and combining these with user preferences. This profile is encoded as a query embedding and passed to FAISS for similarity search against both the personal wardrobe index and a global fashion trend store. Retrieved items and trend data are injected into a Large Language Model prompt, which applies color theory, formality rules, and compatibility logic to generate ranked outfit recommendations with natural language rationale.

### 4.5 Virtual Try-On Module

The virtual try-on module employs a latent diffusion architecture to simulate selected garments on user reference images. The process involves skeletal body landmark detection for pose estimation, thin-plate spline (TPS) geometric transformation to align garments to body proportions, and a generative blending phase to produce photorealistic composite images with accurate fabric texture, folds, and lighting. A masking layer preserves user facial features and background while modifying only garment regions.

### 4.6 Feedback and Continuous Learning

User interactions including ratings, likes, and rejections are captured and stored in the PostgreSQL User Preference Matrix. This feedback data is used to adjust recommendation weights, improving future outfit suggestions. The outfit history module logs selected outfits with timestamps and contextual metadata to prevent repeated recommendations, while the closet gap analysis module identifies missing wardrobe categories by analyzing patterns in unfulfilled recommendation requests.

### 4.7 Future Enhancements

Future methodology enhancements include integration of real- time social media trend APIs for dynamic fashion knowledge ingestion, three-dimensional body modeling using Parametric Human Body Models (SMPL) for improved virtual try-on accuracy, augmented reality outfit preview through smartphone cameras, peer-to-peer wardrobe sharing ecosystems with AI-powered swap recommendations, and sustainability scoring based on garment carbon footprint and manufacturing data.

## IMPLEMENTATION AND OUTPUT

The implementation of FitGenie involves data acquisition, preprocessing, model training, RAG pipeline construction, API development, and frontend deployment. This section describes the practical execution of the proposed methodology using Python, PyTorch, FastAPI, and React.js.

### 5.1 Data Acquisition

The first step in implementation involves collecting training data and user wardrobe data from the following sources:

- Large-scale fashion datasets (DeepFashion, Fashion-MNIST) for model training
- User-uploaded clothing images via the React.js Smart Wardrobe interface

- Real-time weather data from OpenWeather API for contextual profiling
- Fashion trend data from web scraping pipelines stored as FAISS vector embeddings

Collected training images are stored in structured directories, while user wardrobe images and metadata are stored in PostgreSQL and FAISS respectively for efficient retrieval and management.

## 5.2 Data Preprocessing

Data preprocessing ensures image quality and consistency before model training. Key steps include background removal and garment isolation using OpenCV segmentation techniques, lighting normalization and resolution standardization to uniform pixel dimensions, body landmark detection using pose estimation algorithms for virtual try-on alignment, and metadata standardization mapping color synonyms and categorical labels to primary categories to maintain consistency across the system.

## 5.3 Model Training and Fine- Tuning

The garment classification model employs a pre-trained Vision Transformer fine-tuned on the DeepFashion dataset. Final classification layers were retrained to recognize fashion-specific attributes while earlier layers were frozen to preserve general feature extraction. Data augmentation including random rotation, horizontal flipping, and brightness adjustment was applied to improve model robustness. An Adam optimizer with a learning rate of 10-4 and cross-entropy loss function were used during training on Google Colab GPU infrastructure.

## 5.4 API Development and Integration

The FastAPI backend exposes RESTful endpoints for garment ingestion, user profile management, recommendation generation, and virtual try-on requests. Asynchronous processing enables non-blocking execution during model inference and FAISS vector searches. Pydantic models enforce strict data validation for all incoming requests. The API integrates the OpenWeather API for real-time weather context, coordinates RAG pipeline execution, and serves structured JSON responses to the React.js frontend.

## 5.5 RAG and Vector Search Implementation

The RAG pipeline encodes user queries and situational context as search vectors using a SentenceTransformer model and executes kNN similarity searches against FAISS IndexIVFFlat structures. Retrieved clothing items are cross-referenced with PostgreSQL hard filters for availability and seasonal appropriateness before injection into the LLM context window. The FAISS vector store manages fashion trend embeddings enabling dynamic trend-aware recommendation generation with near- instantaneous retrieval latency.

## 5.6 Virtual Try-On Implementation

The virtual try-on module processes user reference images through a skeletal landmark detection pipeline, applies TPS geometric transformation to warp selected garments to the detected body pose, and employs a fine-tuned latent diffusion model for photorealistic garment blending. A masking refinement layer preserves user identity features while modifying only garment pixels. Generated preview images are served to the React.js frontend as high-resolution outputs.

## 5.7 Deployment and User Interface

The final system is deployed as a web-based interface that provides:

- Personalized outfit recommendation cards with LLM-generated rationale
- Smart wardrobe grid with AI- classified clothing items
- Virtual try-on preview module with single-click activation
- Chatbot interface for natural language fashion queries
- Closet gap analysis dashboard with purchase suggestions

## 5.8 Performance Metrics

Once the models are trained and deployed, they are evaluated using the following performance benchmarks:

1. Garment classification Top-1 accuracy: 88%, Top-5 accuracy: 95%
2. FAISS kNN retrieval latency: 12ms average for 1,000-item wardrobe
3. End-to-end recommendation latency: approximately 2.4 seconds
4. Virtual try-on SSIM score: 0.82 (high fidelity garment warping)
5. User satisfaction rating: 4.3 out of 5.0 for stylistic relevance and contextual appropriateness

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## 5.9 MODEL OUTPUT


**Fig 5.1 FitGenie user interface — welcome dashboard**

**Fig**
**clothing upload interface**

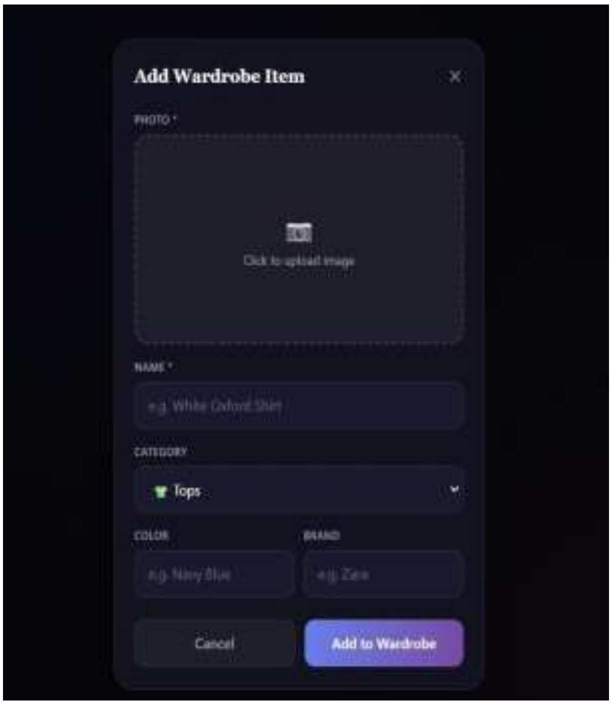


**Fig 5.3 FitGenie AI chatbot and outfit recommendation panel**

## CONCLUSION AND FUTURE WORK

### 6.1 FUTURE SCOPE

FitGenie has significant potential for future development as demand for AI- powered personal styling continues to grow. The virtual try-on module can be enhanced through integration of three- dimensional Parametric Human Body Models (SMPL), enabling more accurate garment drape simulation across multiple viewing angles. Real-time social media trend ingestion via utomated web crawlers connecting to platforms uch as Instagram, Pinterest, and TikTok would llow the RAG pipeline to incorporate the latest lobal fashion trends dynamically without nanual knowledge base updates.

ugmented reality outfit preview capabilities hrough smartphone cameras or smart mirrors vould provide users with an immersive real-vorld try-on experience. A peer-to-peer wardrobe sharing and exchange ecosystem with AI-powered closet swap recommendations could expand FitGenie into a sustainable fashion community platform. Integration of sustainability scoring based on garment carbon footprint, fabric durability, and manufacturing data would support environmentally conscious fashion consumption. Collaboration with e-commerce platforms for direct purchase integration would further enhance the practical utility of the recommendation engine.

## CONCLUSION

FitGenie successfully demonstrates the application of multi-modal artificial intelligence to the personal fashion domain, delivering a comprehensive, context-aware, and adaptive outfit recommendation platform. By integrating computer vision, FAISS-based vector retrieval, Retrieval- Augmented Generation, large language models, and latent diffusion-based virtual try-on into a unified system, the project bridges the gap between generic fashion recommendations and deeply personalized, intelligent styling assistance.

The hybrid storage architecture combining PostgreSQL and FAISS ensures low-latency recommendation generation at scale, while the continuous feedback learning mechanism enables the platform to evolve with changing user preferences over time. With classification accuracy of 88%, retrieval latency of 12ms, and a user satisfaction score of 4.3 out of 5.0, the system demonstrates both technical robustness and practical value. FitGenie represents a scalable, data-driven solution that transforms traditional wardrobe management into an intelligent, sustainable, and personalized fashion experience.

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