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FashionIQ-X: Multimodal Fashion Retrieval and Recommendation using Vision-Language Models

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***Abstract*— This paper presents FashionIQ-X, a multimodal frame-work for semantic fashion retrieval and personalized recommendation using vision-language models. The pro-posed system combines BLIP-2-based caption genera-tion, CLIP embeddings, and FAISS vector indexing to enable natural-language search over large fashion cata-logues. In order to achieve higher accuracy in search and retrieval, captioning is performed by combining information from both the datasets and the generated captions, thus obtaining better semantic representation. Moreover, large language models can be leveraged to convert structural data about users into descriptive fashion query requests. Results on a dataset containing 20,491 fashion images show superior accuracy with regard to traditional approaches utilizing only metada-ta, scoring an accuracy of 82.4% in Recall@20. It is concluded that vision-language captioning and vector semantics retrieval is a viable approach to intelligent fashion recommendation.**

***Index Terms*— Avatar Generation, BLIP-2, CLIP, Com-puter Vision, E-commerce, FAISS, Fashion Retrieval, LLM Recommendations, Multimodal AI, Virtual Try-On.**

I. INTRODUCTION

Current progress in the development of VLMs, generative AI, and vector search technologies has made it possible to create new ways of implementing intelligent fashion dis-covery. Existing e-commerce engines make extensive use of metadata, manual tagging, and search by keywords, but do not consider the semantic aspect of the images or user preferences.

To address these shortcomings, we present FashionIQ-X—an all-in-one architecture for:

- Semantic Image Retrieval powered by CLIP em-beddings and FAISS indexing.
- Automated Dataset Annotation using optimized caption generation with BLIP-2.
- Personalized AI Recommendations through caption generation from attributes using LLMs.
- Virtual Try-On & Avatar Visualization using hybrid 2D/2.5D approaches.
- Scalable Backend to allow large-scale ingestion, streaming, and inference in real time.

This paper is centred around the concept of combining all of the above features in one system.

II. LITERATURE REVIEW

CLIP [1], which is a vision-language model utilizing con-trastive learning for aligning images and text in an embed-ding space, was developed by Radford et al.

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The fact that CLIP can per-form zero-shot classification and semantic search is the rea-son why it forms a solid foundation for fashion image search systems.

BLIP [2] and its follow-up work BLIP-2 [3] are two mod-els designed for image caption generation based on vision-language pretraining. In particular, BLIP-2 uses a light-weight Q-Former design, which allows it to generate cap-tions efficiently while keeping captioning quality high. These models are essential building blocks of our fashion captioning pipeline.

There are various large-scale fashion-related datasets that have been critical in developing state-of-the-art algorithms for appa-rel recognition and search. DeepFashion [4] and FashionIQ [5] are just some of the examples of such da-tasets.

FAISS, created by Johnson et al. [6], provides efficient similarity searches in vector database systems. With index-ing of the CLIP embeddings, our system is able to conduct rapid and accurate semantic searches among thousands of fashion items.

Sentence-BERT [7] proved the viability of the transformer sentence embeddings method as effective for the task of semantic search. The mentioned idea allows for captions and queries transformation into vectors for searching pur-poses.

Han et al. proposed VITON [8], the one of the first frame-works that uses garment warping and person parsing as the basis for virtual try-on. Their approach provides the basis for the virtual try-on module of our system.

Tran et al. [9] considered composed image retrieval, where text modifiers are used for narrowing the results of search. It correlates well with our query generation approach based on the use of LLMs for generating fashion-oriented queries.

The experiments conducted by Yang et al. [10] demon-strated that descriptive fashion image captions, containing rich attributes of structure, texture, and styles of clothes, increase retrieval effectiveness. This study is the basis for applying our caption fusion approach to produce rich seman-tic captions.

Furthermore, InstructBLIP [11] significantly enhanced vision-language understanding by using instruc-tion fine-tuning that facilitated natural language interaction. This work contributes to the conversational and personalized features of our recommendation architecture.

Last but not least, optimization approaches such as quanti-zation and accelerated inference considered in Abadi et al. [12] were used to obtain high-performance models with 8-bit quantization and compiling them for deployment.

III. Methodology/Experimental

This section presents the complete architecture of the sys-tem, divided into four major subsystems.

A. Multimodal Search Engine (BLIP-2 OPT-2.7B + CLIP + FAISS)

Dataset

20,491 product images from a fashion catalogue (tops, shirts, dresses, jeans, bottoms, outerwear, etc.).

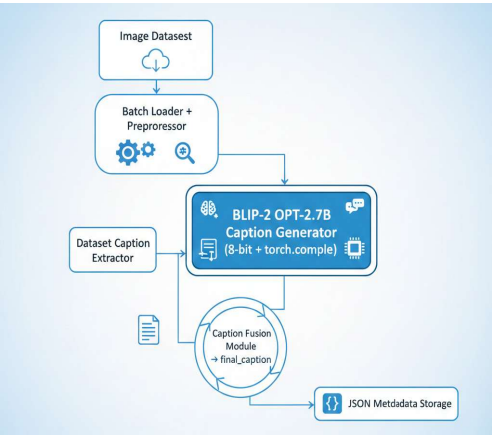

Fig. 1. Optimized BLIP-2 fast captioning pipeline used for large-scale fashion image ingestion.

It begins by loading image files in batches, processing them, then producing comprehensive captions based on BLIP-2 OPT-2.7B (8-bit quantized). The captions are later appended to the dataset metadata before storage.

BLIP-2 OPT-2.7B Fast Optimized Pipeline (Main Contribution)
We use pipeline_blip_fast and ingest_blip_fast as the primary captioning module.
Key optimizations:

- 8-bit load using bitsandbytes (reduces VRAM to 4.5–5 GB on RTX 3050).
- Batching = 6 images at a time.
- image_processor caching for faster prepro-cessing.
- torch.compile model graph optimization.
- Mixed-precision autocast.
- Warmup pass to stabilize kernel allocations.
- Periodic FAISS flushing with JSON metadata sync.

This pipeline produces high-quality human-like captions that outperform plain dataset captions.

Captioning using Both Approaches:
Caption after BLIP-2 captioning:
final_caption = best_of (dataset_caption, blip2_caption)
This increases the semantic richness of CLIP embeddings.

CLIP Embedding Generation
Each caption is encoded using clip-ViT-B/32:

- 512-dimensional embedding
- L2 normalization
- Stored in FAISS

FAISS Index Construction
We store all vectors in a IndexFlatIP index for cosine similarity.

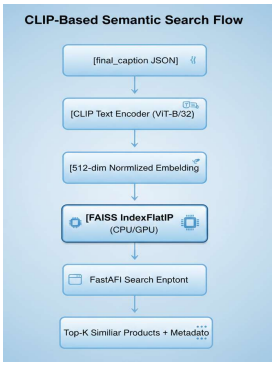

Fig. 2. Vector search architecture integrating CLIP text embeddings with FAISS IndexFlatIP

Final captions are embedded into a shared semantic space, indexed in FAISS, and queried in real-time via a REST API.

Mathematical Formulation of Retrieval

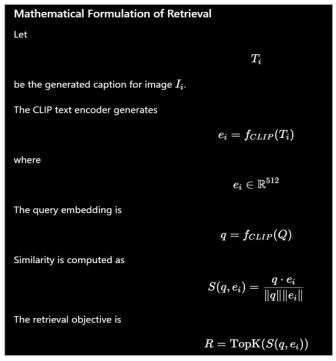

Fig 3

The CLIP encoder projects both image captions and user queries into a shared semantic embedding space. Cosine similarity is used to measure semantic alignment between the query embedding and catalog embeddings. FAISS performs efficient nearest-neighbor search over the em-bedding index and returns the Top-K most relevant fashion items.

React Frontend

- Real-time semantic search
- Image grid display
- Query suggestions

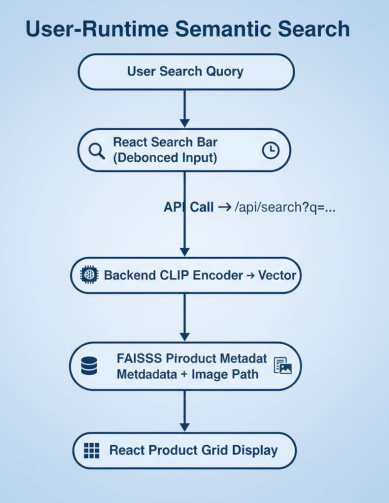

Fig. 3. Frontend semantic search interface.

User queries are encoded using CLIP, matched via FAISS, and visual results returned as product cards containing images, captions, and similarity scores.

B. Personalized Recommendation via LLM Query Synthesis

The novelty of this module is that user attributes are converted into synthetic descriptions, NOT matched directly with metadata.

Attributes of User

U = {Gender, Age, Body Shape, Skin Tone, Occasion, Style Preference}

Clothing Descriptions Using FLAN-T5

Descriptions by FLAN-T5 based on attributes of user

Examples:

"Pear-shaped female + Summer casual"

→ "Flowy A-line linen skirt with high waist and breathable texture"

"Athletic male + Gym wear"

→ "Black moisture-wicking compression t-shirt with stretch fit"

CLIP Retrieval

Synthetic captions are embedded and matched against FAISS to retrieve visually aligned items.

Gender Guardrails

Two centroid vectors: { V_male, V_female}

For each candidate image vector x:

- Reject if score_female(x) > score_male(x) for male users

Red Flag Filtering

Optional "avoid feminine items" filter:

- RedFlag = {dress, bikini, skirt}
- Reject if similarity(x, RedFlag) > similarity(x, GenderAnchor)

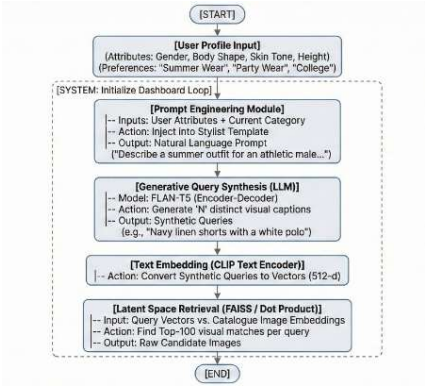

Fig. 4. Attribute-to-caption synthesis model. A language model expands structured user attributes into natural-language synthetic product descriptions for zero-shot rec-ommendations.

C. Virtual Try-On System (2D + 2.5D Hybrid)

System Overview

The Virtual Try-On system aims at generating images showing how the wearer would look like when wearing the tar-get clothing item, while preserving both their own identity and structural appearance. In contrast to conven-tional methods, which demand intensive computation power, the method proposed here can run efficiently even on consumer-level machines.

This work presents a two-stage model with the image gen-eration and light-weight depth estimation process incorpo-rated into the pipeline. Thus, it allows one to achieve both rapid 2D garment transfer and approximate 3D visualiza-tion.

Network Architecture

Geometric Alignment Module

In the initial stage, the task is to ensure the compatibility of the apparel design with the human body of the desired person. The garment image and the person's image (the portion of clothing being stripped away) act as the input of the module.

The garment image and person's image are then subjected to convo-lutional feature extraction. Afterward, the regres-sion network comes into play for determining the trans-formation parameter of the image.

This phase ensures that the clothing is properly aligned before appearance synthesis can take place.

Appearance Synthesis Module

The try-on result of the second stage comes out after blending the aligned garments on the target person.

An encoder-decoder model with a skip connection ap-proach has been used to keep the fine details such as the face, hair, and skin. The model has an ability to reconstruct the missing details and define sharp edges to ensure smooth blending of the garment on the target.

This is how the try-on output has been generated.

Data Preprocessing and Composite Strategy:

A pre-processing step is employed before the training and inference stages to improve the efficiency of the algo-rithm.

Spatial masking is used to extract the area that contains the cloth within the source image, thus helping the model concentrate on human anatomy instead of the current clothing. All images are rescaled to an equal size to enable the computa-tion process to be efficient.

To make the output more visually pleasing, a composite approach is implemented post-generation. The entire syn-thesized image is not utilized; only the cloth area is taken and blended with the original high-quality image.

3D Visualization via Depth Approximation:

In order to extend the system for dynamic visualization, a basic depth estimation mechanism has been implemented.

The depth estimation has been done based on pixel inten-sity, where bright parts indicate closer surfaces, while dark areas correspond to recessed sections. Using the above information, the system can generate an initial structure of the clothing.

Based on the estimated depth, a 3D version of the image is generated in terms of points, which provides functionality of rotating and viewing the clothing object from various directions.

Implementation Details

The implementation was done using the framework PyTorch with an optimal setup for fast training even with low-end resources.

Pixel-wise reconstruction loss function was utilized to achieve the training process through matching the generated image with the target images.

The system is designed to operate within constrained GPU memory, demonstrating that high-quality virtual try-on can be achieved without requiring large-scale infrastructure.

Fast VTON

- < 2 seconds latency
- Person segmentation
- Thin-plate spline warping
- Cloth–body fusion

HD VTON

- Job queue
- High-resolution rendering
- Mask refinement

Avatar Generation

Steps:

- Silhouette extraction
- Convex hull detection
- 2.5D extrusion
- GLB export

D. System Deployment Architecture

The proposed framework is deployed using a distributed microservice architecture to support scalable image inges-tion, caption generation, vector indexing, and real-time retrieval. The background process services generate cap-tions and perform computations for the embeddings in parallel, with the centralized storage service managing the image meta-data and indices. The architecture allows effi-cient handling of huge fashion catalogues alongside per-forming fast searches and recommendations.

IV. Results and Discussion

A. Experimental Setup

These experiments were done using 20,491 fashion imag-es and a GPU called the NVIDIA RTX 3050. The retrieval performance was measured using Recall@20. For recom-mendation evaluation, three metrics were used, which included gender accuracy, query coherence, and attribute alignment. This is a reflection of the performance of the full FashionIQ-X pipeline including BLIP-2, CLIP, FAISS, and LLM Recommendation.

B. BLIP-2 Captioning Throughput

From your ingestion plot (Figure 5), we can see that:

- Approximate average batch time = 3.1 sec
- Approximate time per-image = 0.52 sec
- Consistent performance on 20k images
- Minimal variation caused by GPU thermal scal-ing

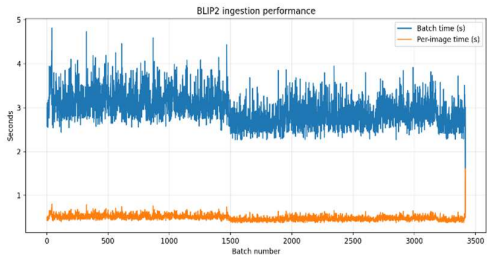

Fig. 5. BLIP-2 ingestion performance across 3,416 batch-es (20,491 images).

Batch-level captioning time (blue) and per-image captioning latency (orange) show stable throughput on RTX 3050 with 8-bit quantization and batch size = 6.

C. Caption Quality Comparisons

TABLE I. COMPARISON OF CAPTION QUALITY

Metric	Dataset Cap-tions	BLIP-2	Combined
Detail richness	Low	High	Very High
Attribute accu-racy	Medium	High	Very High
Descriptiveness	Low	High	Very High

D. Retrieval Performance

TABLE II. COMPARISON OF RETRIEVAL QUALITY

Method	Recall@20
Metadata Only	61.2
BLIP Caption Only	74.8
Combined Caption (Proposed)	82.4

The proposed caption fusion strategy improved Recall@20 by 21.2 percentage points compared with metadata-based retrieval.

E. Recommendation Module Metrics

- Gender Guardrail accuracy: 97.8%
- Query synthesis coherence: 92%
- Cross-attribute alignment: 88%

F. Virtual Try-On System Benchmark

TABLE III. GENERATIVE TIME

Module	Avg time
Fast VTON	1.2 sec
HD VTON	8.6 sec
Avatar generation	3.4 sec

G. Backend Performance

- Worker throughput: 4–6 images/sec
- Index update latency: < 50 ms
- API latency: < 80 ms/search

V. FUTURE SCOPE

Even though the system performs well, there are a number of interesting future possibilities to increase its ability:

A. Multimodal LLM Integration (LLaVA-Next, Flor-ence-2)

Future iterations could incorporate advanced multimodal language models that reason over images and text together.
These could be used to polish captions, detect fine-grained attributes, and enable conversational fashion search (for instance, “Find me something elegant, but the same color scheme”).

B. 3D Virtual Try-On with Pose Transfer

Advancing the virtual try-on experience from simple im-age warping to mesh or even NeRF modeling will help align clothing and the body, make changes to body poses, and let people see an outfit from multiple angles.

C. Personalized AI Stylist Agents

Using embeddings, user history, and LLM reasoning, this approach can be extended to build an AI stylist.
A potential personalized stylist AI can:

- learn user preferences,
- suggest entire outfits, and

- offer context-specific suggestions (weather, occasions, personal preference).

D. Fashion Knowledge Graph Linking

A knowledge graph that links information regarding clothes, their characteristics, fashion trends, and user meta-data would facilitate higher levels of interpretability and explainability of the recommendation process. It would enable additional functionalities such as trend identifica-tion and fashion item recommendations across categories.

VI. CONCLUSION

As can be observed, the proposed system implements a full-fledged multimodal fashion intelligence pipeline in-cluding image captioning (BLIP-2), semantic embeddings (CLIP), large-scale image retriev-al (FAISS), and an inter-active visual frontend interface. Through the translation of raw fashion products into semantic rep-resentations that relate to human queries, the system is capable of deliver-ing a human-like level of comprehension within the fash-ion industry.

By being modular, scaleable, and extensible, this sys-tem architecture allows future integration of AI models and downstream tasks such as garment try-on, stylistic intelli-gence, and personalization. In addition to enhancing search performance, the platform sets a groundwork for futuristic digital fashion environments wherein recom-mendations are conversational and garments become in-teractive.

This platform provides contributions in academia as well as in practical implementation by demonstrat-ing how multimodal machine intelligence could revolutionize the fashion industry in the retail sector.

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