Image Processing Enhancement for E-Commerce

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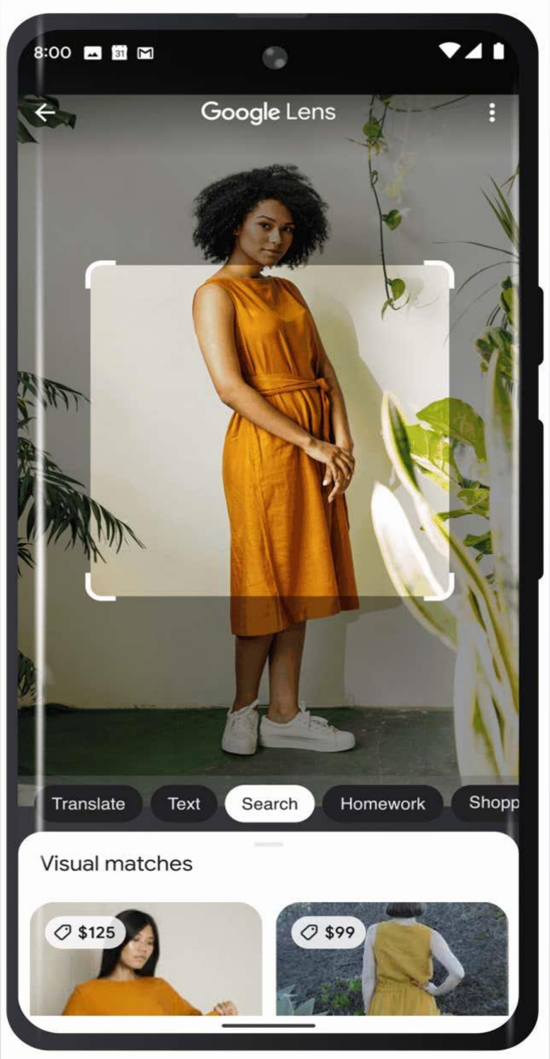
Introduction to visual similarity search

E-commerce platforms are increasingly relying on image-based search functionality to provide users with an intuitive and efficient way to find products.

Unlike traditional text-based searches, image-based systems allow users to upload photos of desired products, making the process more visual and seamless.

The approach presents significant challenges due to the variability in the quality and nature of user-uploaded images.



Fashion Product Images Dataset

- **Total Samples:** 44,072
- **Attributes:**
  - **ID:**
  - **Gender:**
  - **Master Category:**
  - **Subcategory:**
  - **Article Type:**
  - **Base Colour:**
  - **Season:**
  - **Year:**
  - **Usage:**
  - **Product Display Name:**

id	gender	masterCategory	subCategory	articleType	baseColour	season	year
The product ID assigned in the product catalog.	Clothing targeted to which gender.	Primary category.	Secondary Category.	Type of clothing	Descriptive color name.	Which fashion season is this targeted to.	Which fashion year i this from.
1163 – 60.0k	Men 50%	Apparel 48%	Topwear 35%	Tshirts 16%	Black 22%	Summer 48%	2007
	Women 42%	Accessories 25%	Shoes 17%	Shirts 7%	White 12%	Fall 26%	
	Other (3649) 8%	Other (11757) 26%	Other (21697) 49%	Other (34159) 77%	Other (29174) 66%	Other (11525) 26%	
15970	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011
39386	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012
59263	Women	Accessories	Watches	Watches	Silver	Winter	2016
21379	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011
53759	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012
1855	Men	Apparel	Topwear	Tshirts	Grey	Summer	2011
30805	Men	Apparel	Topwear	Shirts	Green	Summer	2012
26960	Women	Apparel	Topwear	Shirts	Purple	Summer	2012
29114	Men	Accessories	Socks	Socks	Navy Blue	Summer	2012
30039	Men	Accessories	Watches	Watches	Black	Winter	2016
9204	Men	Footwear	Shoes	Casual Shoes	Black	Summer	2011

Fashion Product Images Dataset

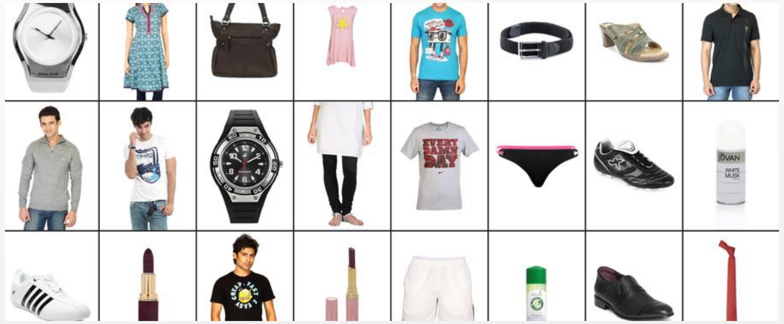
Data Explorer

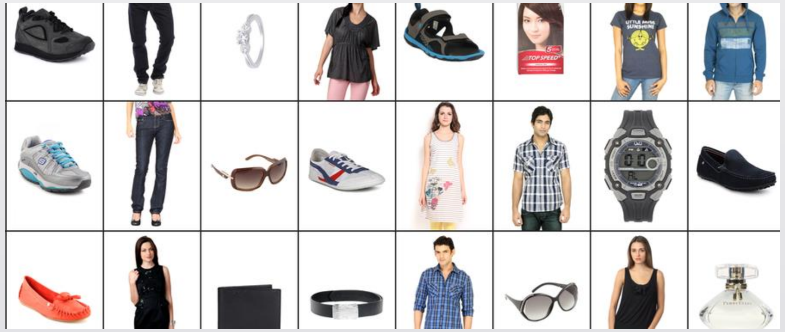
15.71 GB

- fashion-dataset
  - images
  - styles
  - images.csv
  - styles.csv

Summary

- 88.9k files
- 12 columns





Think about it?

How would instant image recognition change your shopping experience?
What if finding the perfect product was as simple as uploading a photo?
Can you imagine the impact of real-time product matching on your business?

HIGH-LEVEL SYTEM DESIGN

1. Image Quality Enhancement

Implementing filters and enhancements to normalize the lighting, background, and noise levels in customer images.

2. Reinforcement Learning Model

Developing a model that learns from each match attempt to progressively increase the accuracy of the image matching algorithm.

3.Model Deployment

Deploying the model and ensuring that the enhancements work seamlessly with the existing platform.

Low-level system design

- **Image Enhancement** (denoising, super-resolution, artifact removal)
- **Feature Extraction** (embedding generation)
- **Vector-based Product Matching** (approximate nearest neighbor search)
- **Product Management** (product metadata & lifecycle)
- **Reinforcement Learning (RL) Feedback Loop** (for continuously improving the matching policy)

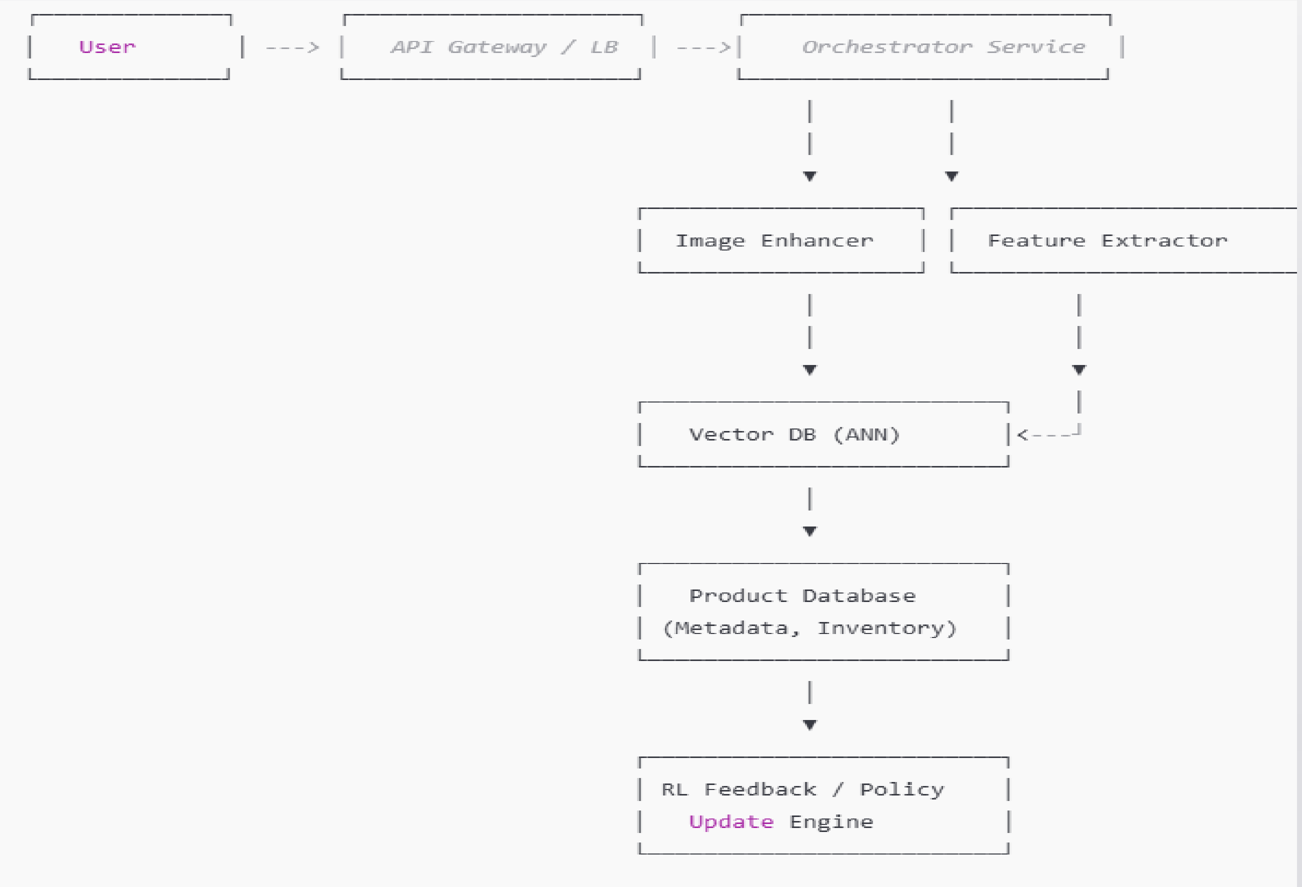


Image Enhancer

Choice of Algorithms to explore:

Real-ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) for super-resolution.

NAFNet, **SwinIR**, or **U-Net** variants for denoising and artifact removal.

If advanced, you can explore **Diffusion-based** upscalers

Role:

Enhance the user’s image to remove noise, correct artifacts, and optionally upscale resolution.

Return a processed image ready for feature extraction.

Image Feature extraction

Choice of algorithms to explore:

CLIP (OpenAI) for zero-shot feature extraction.

DINO (Facebook/Meta) ViT for self-supervised embeddings.

Swin Transformer or **ConvNeXt** for high-quality representations.

Custom Cnn: Pre-trained backbone (ResNet101, EfficientNet, etc.) + fine-tuning on domain-specific data.

Role:

Convert the enhanced image into a high-dimensional embedding

Return embeddings and store them directly in the Vector DB.

Vector Databases

Choice of Databases to explore:

Milvus (cloud-native vector database with GPU acceleration).

Weaviate (Open-source, includes semantic search and CLIP vector support).

Pinecone (SaaS vector DB, fully managed).

FAISS or ChromaDB (Open-source and small scale)

Role:

Ingest product embeddings (from product catalog images).

Provide approximate nearest neighbor (ANN) search for high-speed retrieval.

Return top-K similar products and similarity scores.

Real-time Reinforcement Learning

- Integrating Reinforcement learning to continuously improve retrieval results.

Choice of Algorithms to explore:	**Deep Q-Learning(DQN):** Simple yet effective RL approach	**Multi-armed Bandit:** Useful for optimizing reordering strategies based on limited feedback.
Role:	The RL model will learn user preferences based on feedback (e.g., clicks, ratings, or purchases).	Dynamically reorder the **top-K products** retrieved from the vector database to maximize relevance and user satisfaction.
	Continuously improve the matching policy to adapt to new trends and user behaviors.	

RL Environment

State : user embedding preferences, last recommended products, user feedback signals, etc.

Action :Re-ordering of top-K products.

Reward : Manual rating or user feedback

Estimated Plan of Action

1

Week 1-2

Choose the dataset and Begin preliminary research on existing algorithms.

2

Weeks 3-4

Develop and evaluate image enhancement algorithms.

3

Weeks 5-6

Evaluate various Feature extraction techniques and intgrate the optimal to the existing pipeline.

4

Week 7-9

Store the features on vector database and design the reinforcement learning.

5

Week 9

Model Testing and Deployment

6

Week 10

Any changes based on the company requirement.

Requirements and Questions

1. Does our project outline align with the company's requirements? If there are discrepancies, could you provide details on the expected project scope and deliverables?
2. Given our lack of access to GPUs through our college, could the company assist by providing resources or suggesting alternative solutions?
3. Are the chosen technical stack and algorithms appropriate for our project? I would appreciate any recommendations for enhancements.
4. Should the project be deployed to a server or executed locally? If deployment is necessary, can the company facilitate access to the required infrastructure?
5. Will we be working with real-time data provided by the company, or are we restricted to using only open-source datasets?

CONCLUSION

- This project revolutionizes **image-based search** for e-commerce by tackling key challenges like noise, distortion, and user variability.

- **Key Takeaways:**
  - Advanced **noise removal** and **image enhancement** ensure high-quality inputs.
  - Integration of **reinforcement learning** enables adaptive and dynamic performance improvements.
  - Real-time, **scalable processing** using Kubernetes and Apache Spark ensures robust handling of large query volumes.
  - Use of **Retrieval-Augmented Generation (RAG)** pipelines boosts matching accuracy with external data.

- **Impact:**
  - Delivers a scalable, accurate, and user-centric search system.
  - Enhances **customer satisfaction** and engagement, giving e-commerce platforms a competitive edge.

- This comprehensive solution sets the stage for future innovations in image-based search technologies, aligning with modern AI and e-commerce trends.

REFERENCES

- **Dataset:** Fashion Product Images Dataset – dataset
- Zilliz, "*Online Shopping Image Similarity Search*" - Read more here
- Microsoft DevBlogs, "*Deep Learning Image Segmentation for E-commerce Catalogue Visual Search*" - Read more here
- TensorFlow Similarity, "*Supervised Hello World*" - GitHub Notebook
- Anyscale Blog, "*Cross-modal Search for E-commerce*" - Read more here
- Medium (Akriti Upadhyay), "*Perform Image-Driven Reverse Image Search on E-commerce Sites with ImageBind and Qdrant*" - Read more here
- Kaggle Dataset, "*Fashion Product Images Dataset*" - Access dataset here
- Hugging Face Dataset, "*Fashion Product Images Small*" - Access dataset here
- Helpware Blog, "*How AI Image Recognition is Transforming E-commerce Marketplaces*" - Read more here
- Chen Delong, "*MEP-3M: A Large-scale Multi-modal E-commerce Dataset*" - View publication
- Algolia Blog, "*Visual Shopping and Discovery: How Image Search is Changing Online Shopping*" - Read more here

THANK YOU ☺