



Jyothy Institute of Technology

Department of Artificial Intelligence and Machine Learning

Project Phase 2 Seminar(18AIP23)

Title:

Complementary Fashion Recommendation
using Compatibility Modeling

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ABSTRACT

In the rapidly evolving eCommerce landscape, fashion retailers are confronted with the task of engaging customers virtually amidst unprecedented online spending. This project aims to address this challenge by introducing a specialized recommendation system focused on suggesting complementary items to complete outfits. By harnessing image style embeddings, the model predicts compatible products across diverse categories, providing retailers with a solution that doesn't necessitate extensive customer data.

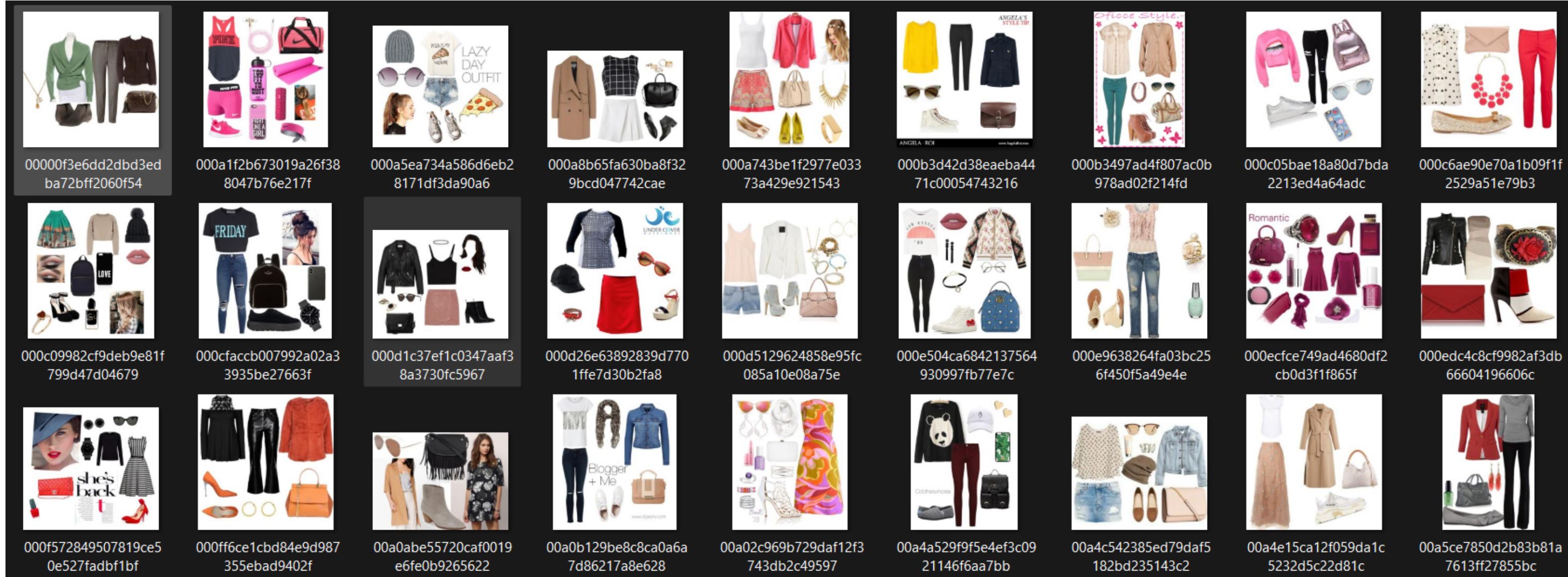
INTRODUCTION

This project addresses the challenge of suggesting complementary items to complete outfits within the rapidly evolving digital retail landscape. The objective is to enhance the virtual shopping experience for fashion retailers and their customers. By leveraging compatibility modeling, retailers are empowered to offer curated selections that harmonize seamlessly. This approach minimizes reliance on historical customer data, providing a tailored solution to the evolving dynamics of digital retail.

METHODOLOGY

Department of AIML, Jyothy Institute of Technology, Bengaluru

DATASET



Step 1: Style Embedding Extraction for the Entire Image Database:

- The project initiates by extracting style embeddings from the entire image database. This process utilizes a Modified ResNet18 model to analyze each image and produce style embeddings.
- These embeddings act as concise representations of each product's visual style, cataloged for efficient retrieval during the recommendation process.

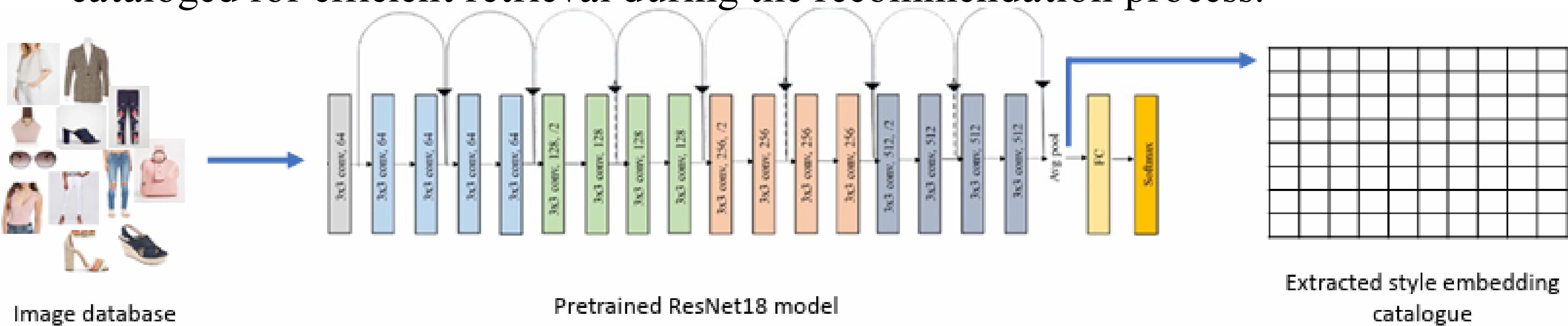


Image database

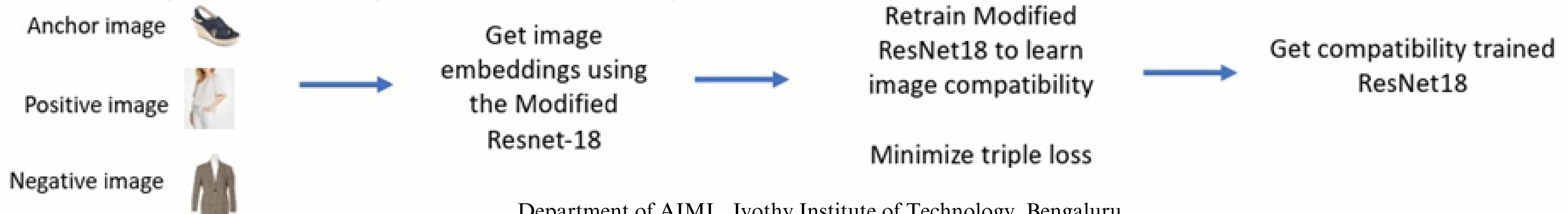
Pretrained ResNet18 model

Extracted style embedding catalogue

Step 2: Model Training Using Triple Loss

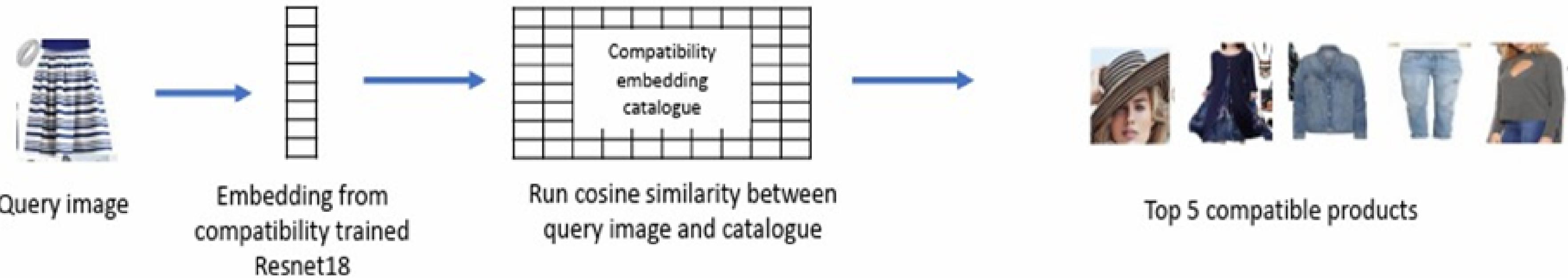
During this phase, the model learns image compatibility through training:

1. Anchor Images: We start with a reference anchor image.
2. Positive and Negative Images: Images with similar and dissimilar styles to the anchor are selected.
3. Image Embeddings: Each image undergoes processing to create embeddings using the Modified ResNet18 model.
4. Retraining: The model adjusts its parameters to minimize the triple loss, aiming to bring embeddings of similar images closer together.

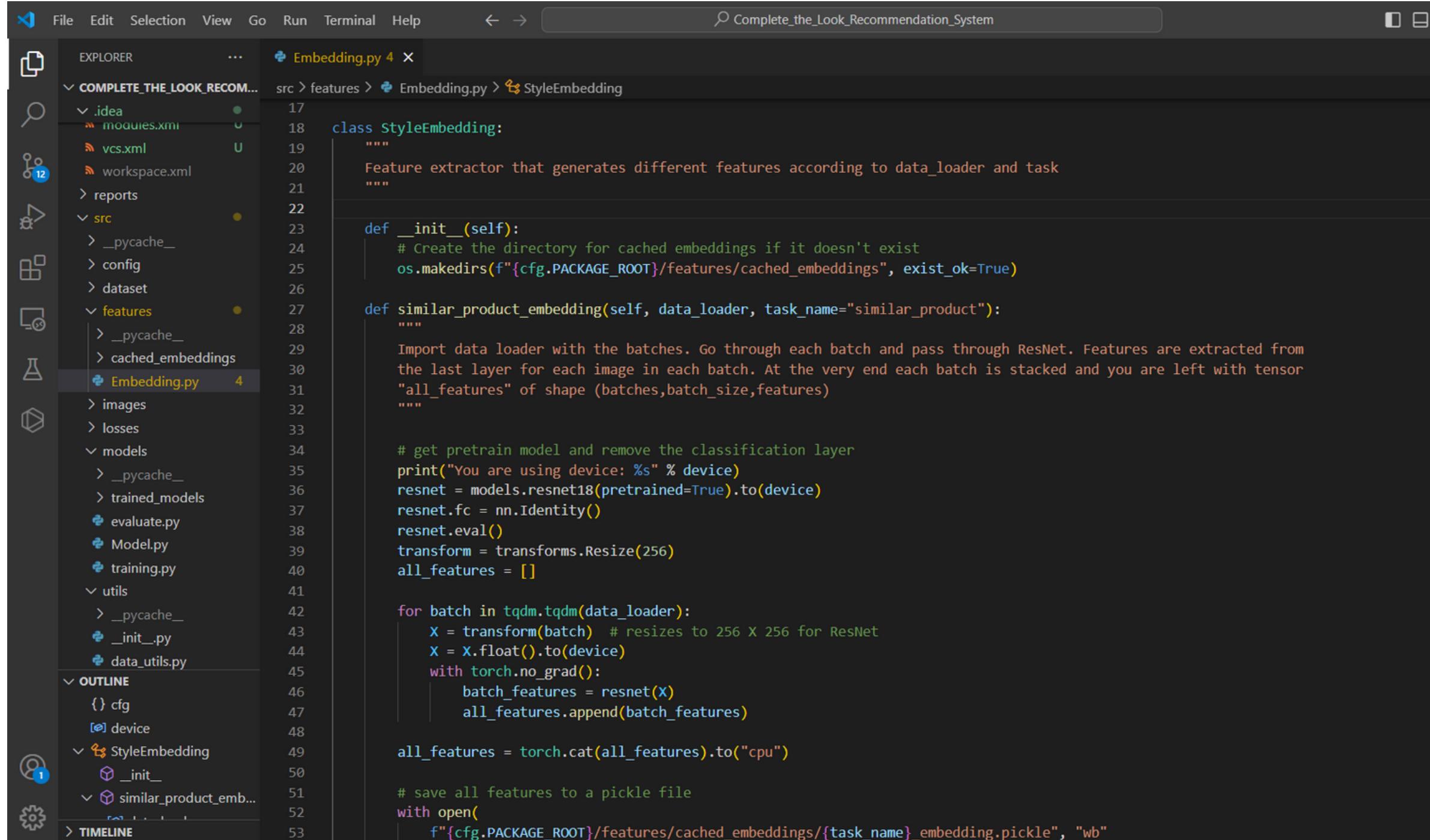


Step 3: Matching Query Image with Database

- **Query Image Embedding:** We extract the embedding of the user's query image using our Modified ResNet18 model.
- **Comparison:** This query image's embedding is then compared with the embeddings cataloged in step one.
- **Cosine Similarity:** We measure the similarity between the query image's embedding and the cataloged embeddings using cosine similarity.
- **Results:** The top 5 compatible images/products are retrieved from the database.



Code Implementation



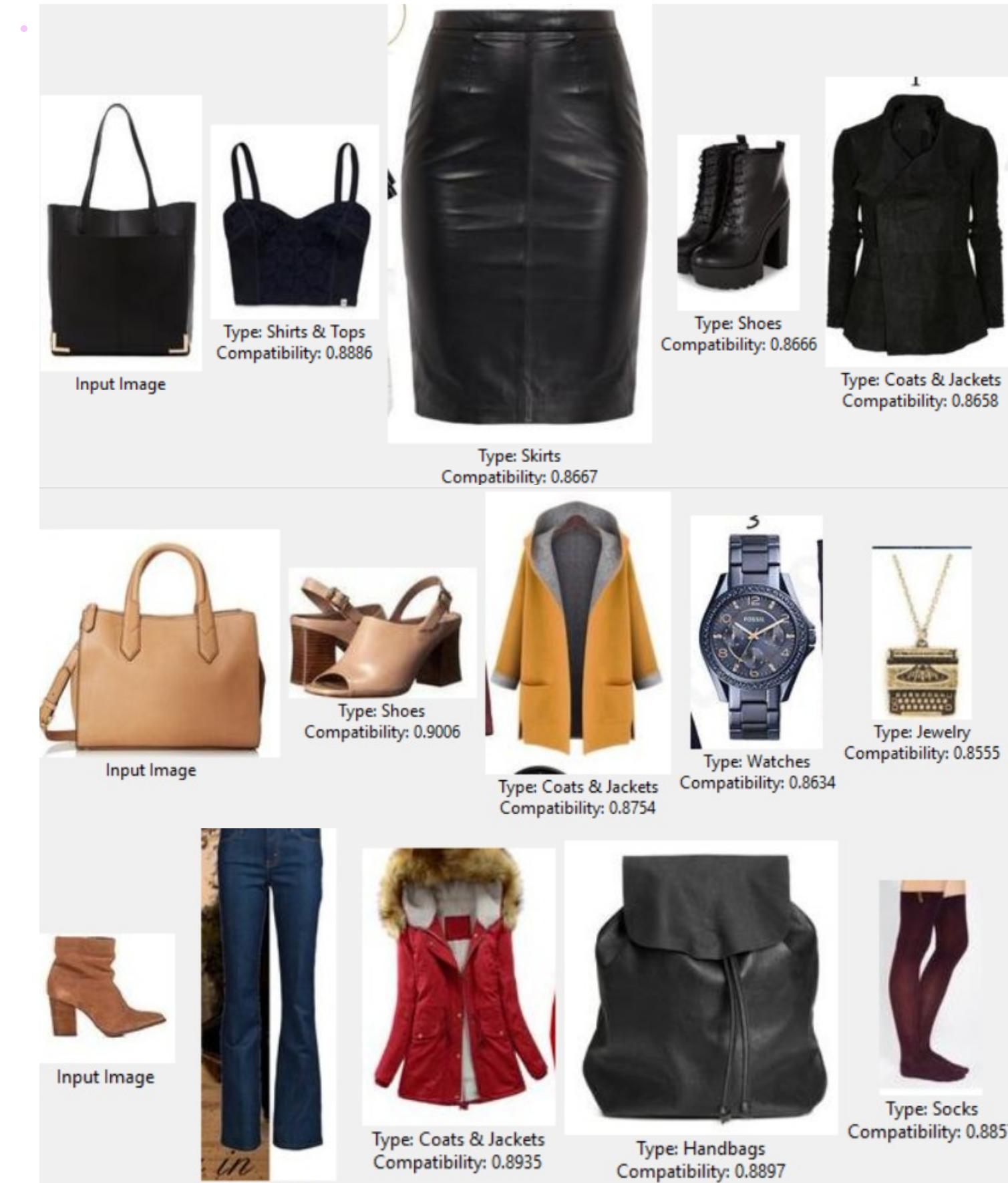
The screenshot shows a code editor interface with a dark theme. On the left is the Explorer sidebar, which displays the project structure:

- COMPLETE_THE_LOOK_RECOM... (expanded)
- .idea
- src (expanded)
 - features (expanded)
 - Embedding.py
 - images
 - losses
 - models (expanded)
 - evaluate.py
 - Model.py
 - training.py
 - utils (expanded)
 - data_utils.py
- OUTLINE
- device
- StyleEmbedding
 - _init_
 - similar_product_emb...
- TIMELINE

The main editor area shows the content of `Embedding.py`:

```
17
18 class StyleEmbedding:
19     """
20         Feature extractor that generates different features according to data_loader and task
21     """
22
23     def __init__(self):
24         # Create the directory for cached embeddings if it doesn't exist
25         os.makedirs(f"{cfg.PACKAGE_ROOT}/features/cached_embeddings", exist_ok=True)
26
27     def similar_product_embedding(self, data_loader, task_name="similar_product"):
28         """
29             Import data loader with the batches. Go through each batch and pass through ResNet. Features are extracted from
30             the last layer for each image in each batch. At the very end each batch is stacked and you are left with tensor
31             "all_features" of shape (batches,batch_size,features)
32
33
34         # get pretrain model and remove the classification layer
35         print("You are using device: %s" % device)
36         resnet = models.resnet18(pretrained=True).to(device)
37         resnet.fc = nn.Identity()
38         resnet.eval()
39         transform = transforms.Resize(256)
40         all_features = []
41
42         for batch in tqdm.tqdm(data_loader):
43             X = transform(batch) # resizes to 256 X 256 for ResNet
44             X = X.float().to(device)
45             with torch.no_grad():
46                 batch_features = resnet(X)
47                 all_features.append(batch_features)
48
49         all_features = torch.cat(all_features).to("cpu")
50
51         # save all features to a pickle file
52         with open(
53             f"{cfg.PACKAGE_ROOT}/features/cached_embeddings/{task_name}_embedding.pickle", "wb"
```

Output

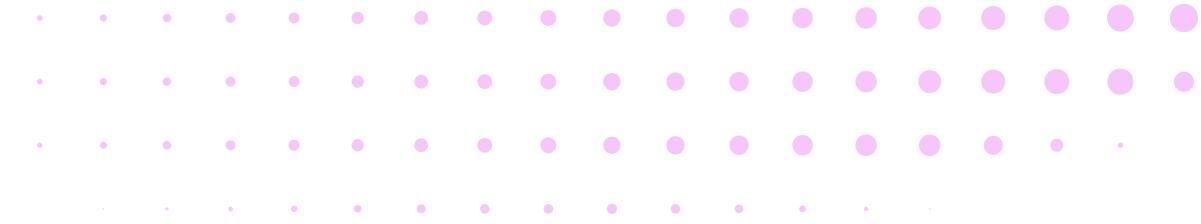


Next Phase Implementation

1. Frontend Development: Incorporate user-friendly interfaces to interact with the recommendation system.
2. UI/UX Enhancement: Refine the user experience by improving navigation and visual presentation.
3. Implement User Input: Allow users to input preferences or refine search criteria to enhance recommendations.
4. Fine-Tuning Algorithm: Refine the recommendation algorithm based on user feedback and testing results.

References

- [1] [https://www.forbes.com/sites/johnkoetsier/EFEF/F\\"E/covid-\"d-accelerated-e-commercegrowth-X-to-\\" years/?sh=\aXadc\f\FFF](https://www.forbes.com/sites/johnkoetsier/EFEF/F\\)
- [2] Z. Liu, P. Luo, S. Qiu, X. Wang and X. Tang, "DeepFashion: Powering Robust Clothes Recognition and Retrieval with Rich Annotations," EF"\ IEEE Conference on Computer Vision and Pattern Recognition (CVPR), EF"\, pp. "Fd\ ""FX, doi: "F.""Fd/CVPR.EF"\."EX.
- [3] Y. Shin, Y. Yeo, M. Sagong, S. Ji and S. Ko, "Deep Fashion Recommendation System with Style Feature Decomposition," EF"\d IEEE dth International Conference on Consumer Electronics (ICCE-Berlin), EF"\d, pp. VF"-VFI, doi: "F.""Fd/ICCE-BerlinXNdXX.EF"\d.Hd\EEH.
- [4] Eileen Li, Eric Kim, Andrew Zhai, Josh Beal, Kunlong Gu, "Bootstrapping Complete the Look at Pinterest", arXiv:EFF\."FNdE, June EFEF
- [5] Mahamudul Hasan, Shibir Ahmed, Md. Ariful Islam Malik, and Shabbir Ahmed, "A comprehensive approach towards user-based collaborative filtering recommender system," DOI:"F.""Fd/IWCI.EF"\.NH\FVIHDecember EF"\



Thank You

