Deep Learning Project: AI-Powered Image Similarity Search and Recommendation System

Intel Internship Report

Submitted by

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Abstract/Summary

This project implements a content-based image recommendation (image similarity) system that returns the top-k visually similar images for a user-supplied query image. The system uses a pre-trained Convolutional Neural Network (ResNet50 with ImageNet weights) as a fixed feature extractor to compute dense image embeddings, then uses cosine similarity between embeddings to find nearest neighbors. The implementation (Jupyter Notebook) loads the Caltech-101 dataset (preprocessed images), extracts or loads precomputed features (features.npy), and presents recommended images with visualizations. This approach avoids label-based supervision and focuses on perceptual similarity using CNN features. The repository includes precomputed feature vectors, image path arrays, and a runnable notebook to reproduce recommendations.

Introduction

Image recommendation / image similarity retrieval is the task of finding images in a collection that are visually or semantically similar to a query image. Content-based image retrieval (CBIR) often uses deep convolutional neural networks trained on large datasets (e.g., ImageNet) as feature extractors. The core idea is to map each image to a vector in a high-dimensional space such that similar images are nearby — then retrieve neighbors using distance or similarity metrics. This repository demonstrates a practical pipeline for CBIR using ResNet50 features and cosine similarity, trained/evaluated on the Caltech-101 dataset.

Procedure/Methodology

3.1 Dataset and Sources

Dataset used: Caltech-101 (101 object categories). The README points to the Kaggle dataset:
https://www.kaggle.com/datasets/imbikramsaha/caltech-101
Image format: .jpg, commonly resized to 224×224 to match input expected by ResNet50.

Files present in repository relevant to methodology:
- Image Recommendation.ipynb — main notebook implementation
- Notebook link: https://github.com/debaratighosh/Image-Recommendation-System/blob/main/Image%20Recommendation.ipynb
- features.npy — precomputed feature vectors (N × D)
- image_paths.npy — list of image file paths aligned with features.npy
- labels.npy — class labels (if used for analysis)
- requirement.txt — dependency list (note: file is named `requirement.txt` in repo)
- README.md — project overview and sample visualizations: [README.md] [link: https://github.com/debaratighosh/Image-Recommendation-System]

3.2 Preprocessing

- Load images from directories and resize to 224×224.
- Convert images to arrays, normalize pixel values to match the pre-trained model preprocessing (e.g., using tensorflow.keras.applications.resnet50.preprocess_input).
- Optional: center-crop or pad to preserve aspect ratio before resizing.
- Convert images to float32 arrays and batch them for efficient feature extraction.

3.3 Feature Extraction

- Use ResNet50 (pre-trained on ImageNet) with the top classification layers removed (include_top=False) to act as a feature extractor.
- Extract the final global pooled features (e.g., GlobalAveragePooling output) to get a fixed-length embedding per image, typically dimension 2048 for ResNet50.
- Save embeddings to disk (features.npy) for reuse and to avoid recomputation.

3.4 Feature Storage and Indexing

- Store:
  - features.npy — embedding matrix (N images × D dims)
  - image_paths.npy — array containing the file paths corresponding to each embedding row
  - labels.npy — optional labels used for analysis
- For small/medium datasets, a brute-force nearest-neighbor search (compute cosine similarity across full matrix) is feasible.
- For scalability, build an approximate nearest neighbor (ANN) index (e.g., FAISS) to accelerate search.

3.5 Similarity Search & Recommendation

Given a query image:

- Preprocess and extract its embedding via the same ResNet50 feature pipeline.
- Compute similarity scores between query embedding and dataset embeddings (cosine similarity recommended).
- Sort scores and return top-k image paths.
- Display the query image and recommended images using matplotlib for visual validation.
- Evaluation metrics to report (if ground-truth is available):
- Precision@k, Recall@k, Top-k accuracy (if using labels or ground truth)

- Mean Average Precision (mAP) for ranking quality
- Retrieval time per query (latency)

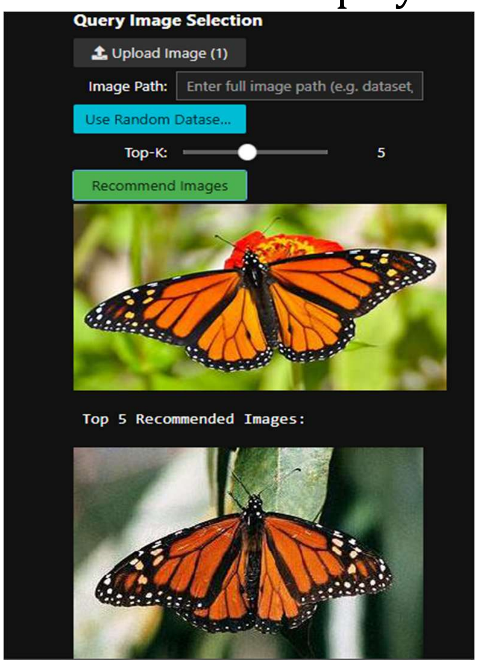
3.6 Implementation Details & Files

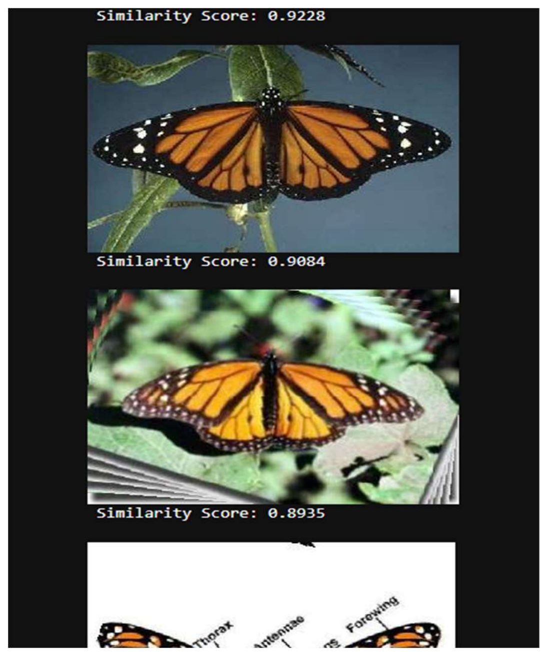
- Primary implementation: [Image Recommendation.ipynb]
- (https://github.com/debaratighosh/Image-Recommendation-System/blob/main/Image%20Recommendation.ipynb)
- Precomputed arrays:
  - [features.npy](https://github.com/debaratighosh/Image-Recommendation-System/blob/main/features.npy)
  - [image_paths.npy](https://github.com/debaratighosh/Image-Recommendation-System/blob/main/image_paths.npy)
  - [labels.npy](https://github.com/debaratighosh/Image-Recommendation-System/blob/main/labels.npy)
- Requirements listed in repo: `requirement.txt` (install dependencies with pip).
- Libraries used (from README): tensorflow / keras, numpy, scikit-learn, matplotlib, Pillow (PIL), os, pickle, faiss (optional)

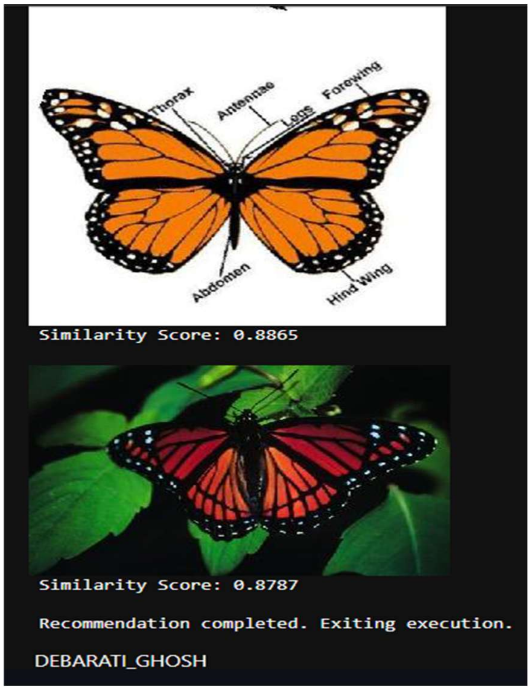
Results and Discussion

4.1 How to Reproduce Results

- Clone the repository and install dependencies:
  - git clone https://github.com/debaratighosh/Image-Recommendation-System
  - cd Image-Recommendation-System
  - pip install -r requirement.txt
- Open and run the Jupyter notebook:
  - jupyter notebook "Image Recommendation.ipynb"
- Use the notebook UI to select a query image and specify k; the notebook will display recommended images.







4.2 Observed Behavior (from repository artifacts / README)

- The README includes sample predictions visualizing the query and top-k results.
- Precomputed features suggest the heavy work (feature extraction) has already been done, enabling fast interactive retrieval.

4.3 Qualitative Analysis

- Strengths:
  - ResNet50 embeddings capture high-level semantic features (objects, shapes, textures) — good for visual similarity.
  - Simple pipeline: feature extract → cosine similarity → show top-k; easy to reproduce and extend.
  - Precomputing features reduces online latency.

- Limitations:
  - No fine-tuning on Caltech-101, so domain mismatch (ImageNet → Caltech) may reduce fine-grained class-specific retrieval quality.
  - Cosine similarity with brute-force search scales

poorly to millions of images.

- No quantitative retrieval metrics are included in the repo; recommended to compute precision@k and mAP for objective evaluation.
- Visual similarity does not rely on metadata; if textual tags are present, multimodal approaches could improve relevance.

4.4 Quantitative Evaluation (recommended steps)

- Compute precision@k and mAP using label arrays (labels.npy) to measure whether retrieved items share the same class as the query.
- Record latency per query for brute-force vs. ANN (FAISS) indexing.
- Example evaluation routine:
    - For a sample of queries from the dataset, compute Top-1, Top-5, Top-10 accuracies and precision@k.
    - Plot recall vs. k curves, and compute average precision per query to get mAP.

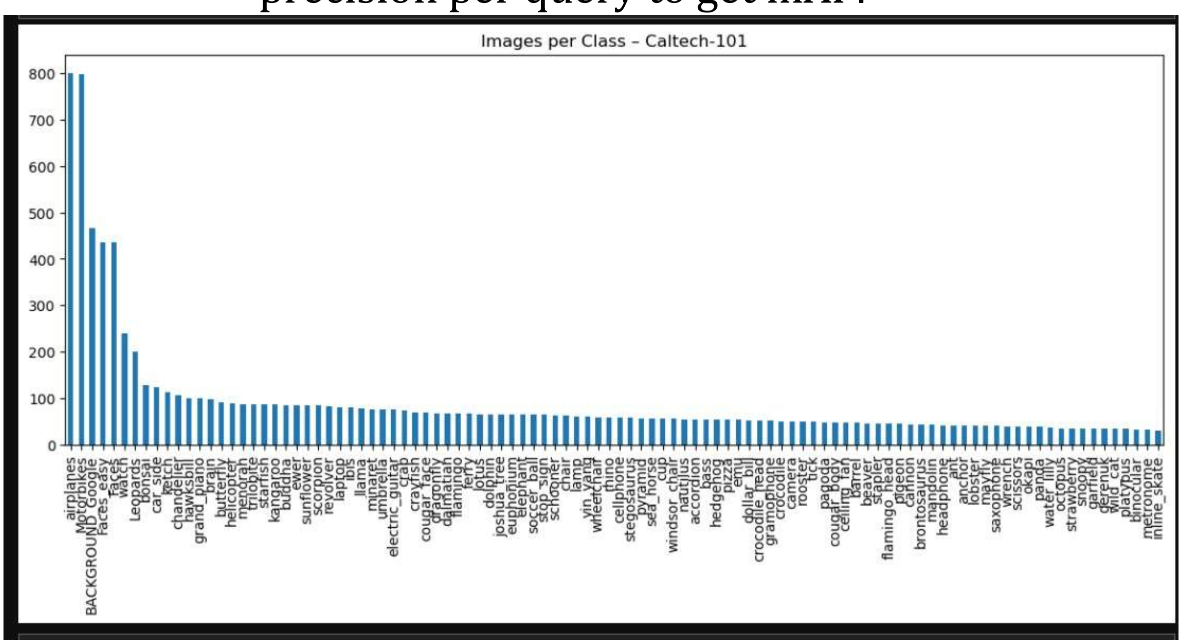


Figure 1 – Images per class.

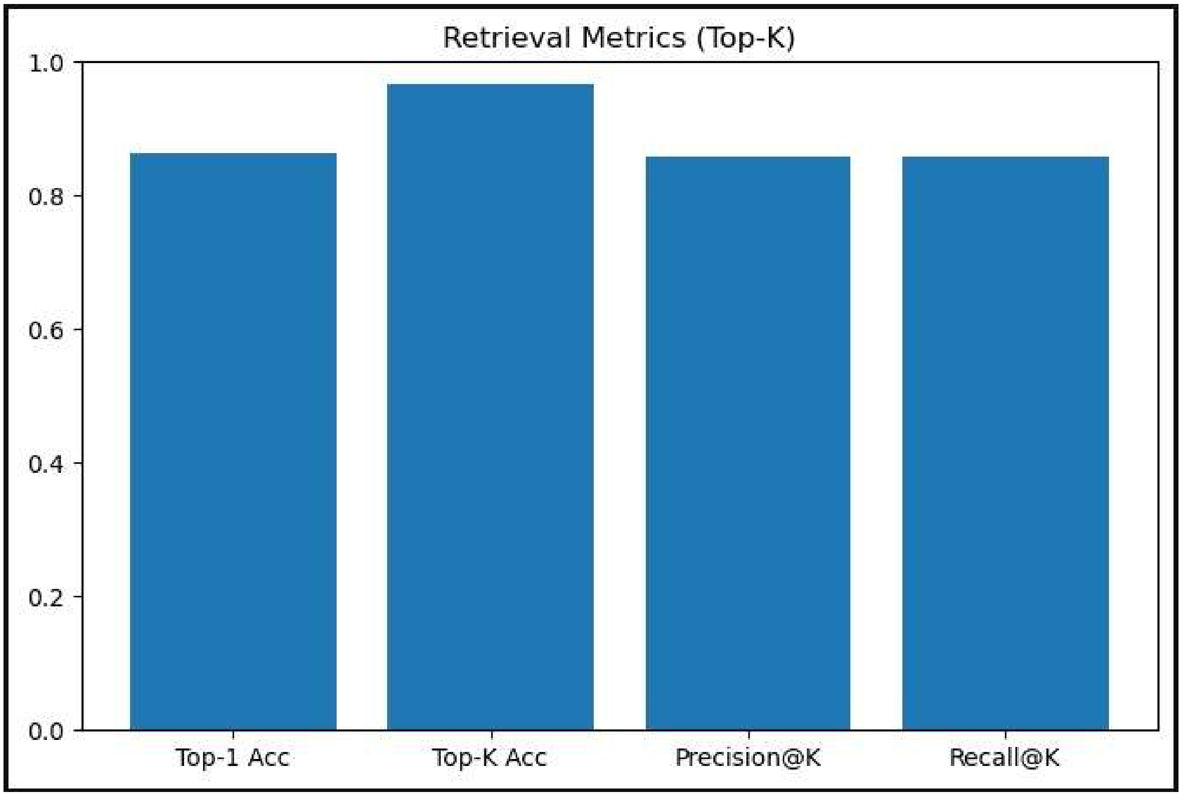


Figure 2 – Retrieval Metrices

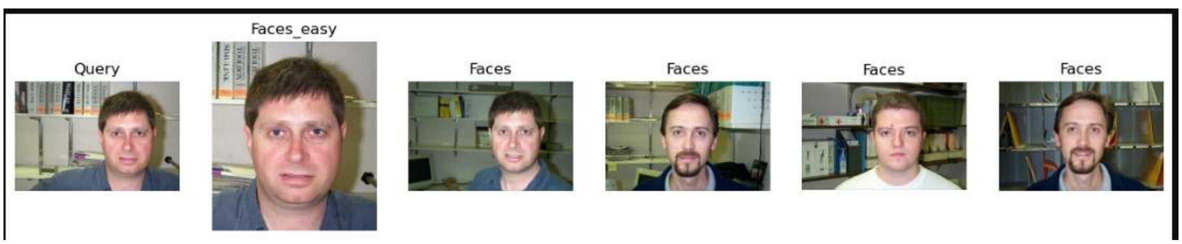


Figure 3 – Example Query Images

Future Scope

- Advanced deep learning models such as EfficientNet, and Vision Transformers can be used to improve feature extraction.
- Metric learning techniques like triplet loss or contrastive loss can be applied to enhance image similarity learning.
- The model can be fine-tuned on domain-specific datasets such as medical, fashion, or product images.
- Scalability can be improved by supporting large datasets and using fast similarity search methods like FAISS.
- User experience can be enhanced with features such as image upload, similarity adjustment, and improved interface design.
- The system can be deployed as a cloud-based application using REST APIs and Docker,Streamlit,Hugging Face which could not be done here due to usage of GPU
- The project can be extended to real-world applications including e-commerce, healthcare, and security systems.

Conclusion

This project demonstrates a straightforward and effective content-based image recommendation system built on ResNet50 features and cosine similarity. The repository contains a runnable notebook and precomputed features that make it easy to reproduce recommendations and visualize results. While the system is effective for moderate-size datasets, improvements are needed for large-scale retrieval and fine-grained performance.

References

- Caltech-101 dataset on Kaggle: https://www.kaggle.com/datasets/imbikramsaha/caltech-101
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition (ResNet). https://arxiv.org/abs/1512.03385
- FAISS: A library for efficient similarity search and clustering of dense vectors. https://github.com/facebookresearch/faiss
- Cosine similarity (scikit-learn): https://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
- Project repository: https://github.com/debaratighosh/Image-Recommendation-System
- Notebook: Image Recommendation.ipynb — see repository root.