Image Retrieval and Audio Summarization for Blinds

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Baseline Results- Report

Project Github Link:
https://github.com/lakshay22037/CSE508_Winter2023_Project_11

Problem Statement

Image Retrieval and Audio Summarization for Blinds. The project aims to address the challenge encountered by individuals with impaired vision when browsing the internet, particularly in the context of visual media.

Literature Review

At present, there are a few platforms that help us to retrieve similar images, or get an audio description of the image. But we plan to build a user-friendly platform, especially for blinds, which does both together.
There are no such live platforms available that can help a blind person understand the given image and also check out some similar images if the idea is not clear with the given image. Combining such features and also working on building a user experience design specific to blinds, will help us to make a product for solving a social problem.

Some References of papers that are based on this similar topics are:

- A Decade Survey of Content Based Image Retrieval using Deep Learning
  This Paper summarizes a decade-long CBIR (Content Based Image retrieval) method used in IR systems.
- Content-Based Image Retrieval by Clustering
  This paper also reviews the development of content-based image retrieval (CBIR) techniques from the early years to the present and discusses the current state-of-the-art in the field.
- Deep Learning for Image Retrieval: What Works and What Doesn't
  This paper presents a comprehensive study of deep learning methods for content-based image retrieval, including a detailed review of various deep learning architectures and their performance on standard benchmark datasets.
- Teena Varma, Stephen S Madari, Lenita L Montheiro, Rachna S Pooojary, 2021, Text Extraction From Image and Text to Speech Conversion, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) NTASU – 2020 (Volume 09 – Issue 03)

Our Approach

From our Literature Review, we found that Autoencoders and Deep CNN Classifiers are commonly used to extract embeddings from image data. Autoencoders use a bottleneck layer to create compressed representations of the original input, while Deep CNN Classifiers use neural codes containing activation of convolutional layers to extract powerful features.

For our project, we will combine both the latent space and neural code features to create a hybrid vector representation of the input image. We will generate these hybrid embeddings for all images in our database and use PCA to reduce the dimensionality of the embeddings.

Overall, this approach will enable us to efficiently and accurately represent images in our project, which will be used further to do similarity matching with the query image. This will help people who are blind or visually impaired access the audio descriptions of those related images and gain insight into what the image wants to say.

In conclusion, our system stands out from others in two ways.

A. It offers a more accurate and scalable image retrieval system with audio summarization.
B. It provides a user-friendly web interface that seamlessly interacts with the information retrieval system.

Methodology

1. Firstly, we will extract the embeddings from our image dataset using various methods and store them as a CSV file. This will enable us to represent the images in a compressed format that captures their important features.
2. We will then perform clustering on these embeddings to group similar images together. This will help us to organize our dataset and identify images that are similar to each other.
3. Next, we will build a unigram inverted index using the cluster centers as terms and the corresponding embeddings of each cluster as postings. This index will enable us to efficiently search for images that are similar to a given query image.
4. Finally, we will evaluate the search performance of our system with test queries which will be evaluated using metrics such as mean average precision and also try to optimize the time and space required for the retrieval system. These metrics will help us to understand how well our system is able to retrieve relevant images in response to user queries.

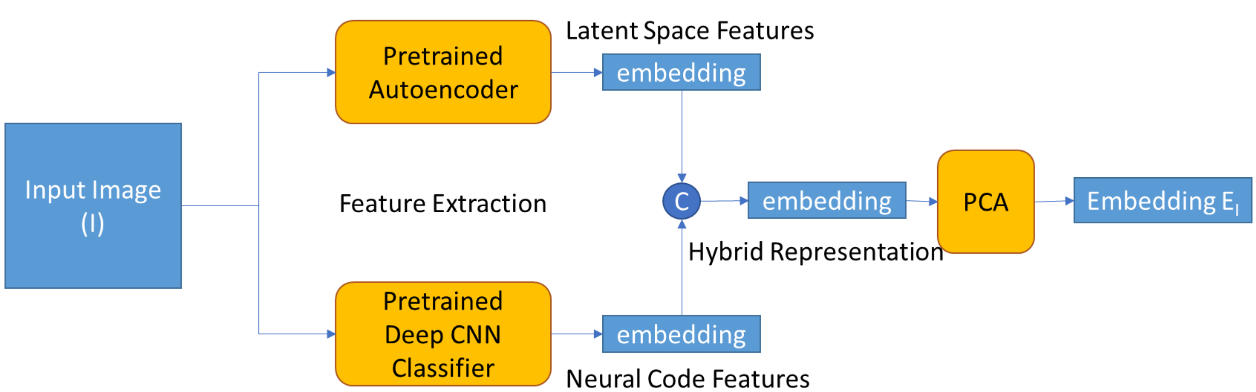


Fig 1 - Embedding extraction

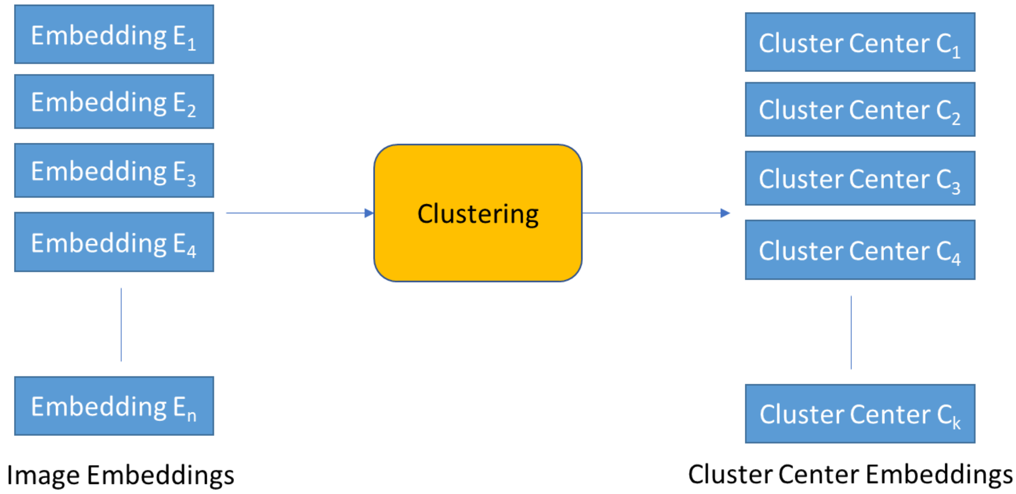


Fig 2 - Clustering the embeddings

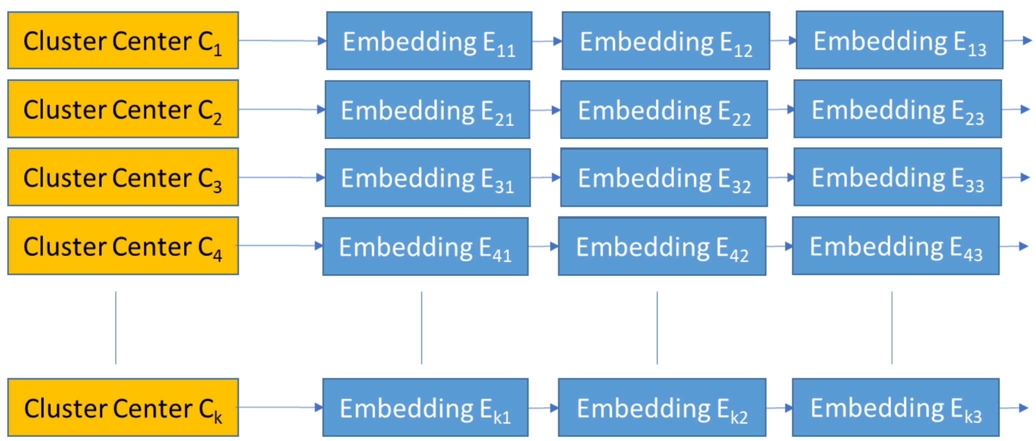


Fig 3 - The inverted embedding index

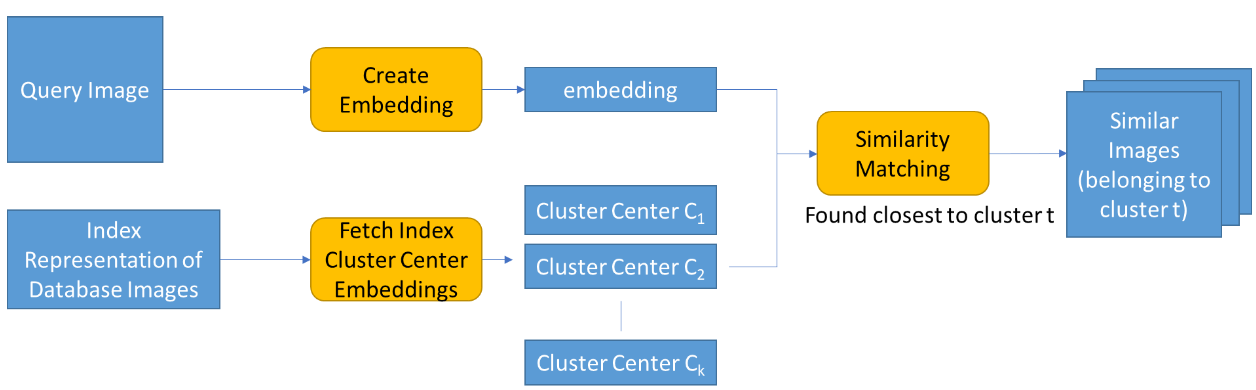


Fig 4 - Processing a test query image

Baseline Results

A baseline inverted index was built using the embeddings extracted from the CIFAR 100 dataset. A pre-trained EfficientNet-B0 architecture was used for the same. The pretrained weights are available at this link.

Note -

a) K-Means clustering was used for finding the cluster-centers and corresponding labels on the train and test image datasets
b) For similarity score, cosine similarity was used to map a given query embedding to the closest term in the inverted index dictionary.

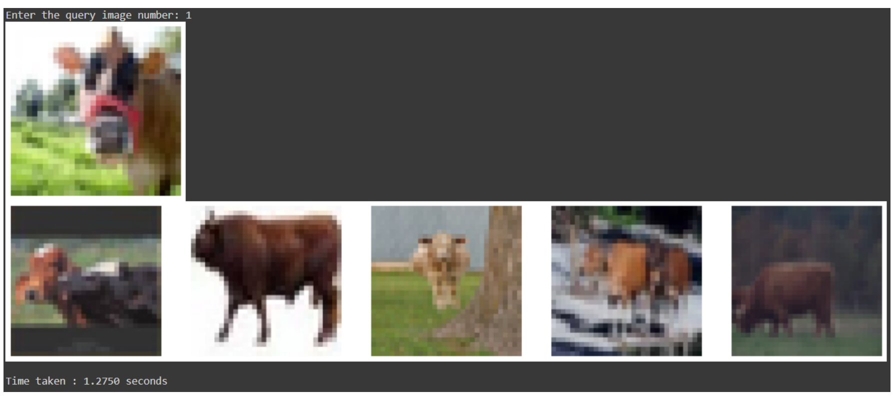
Specifications -

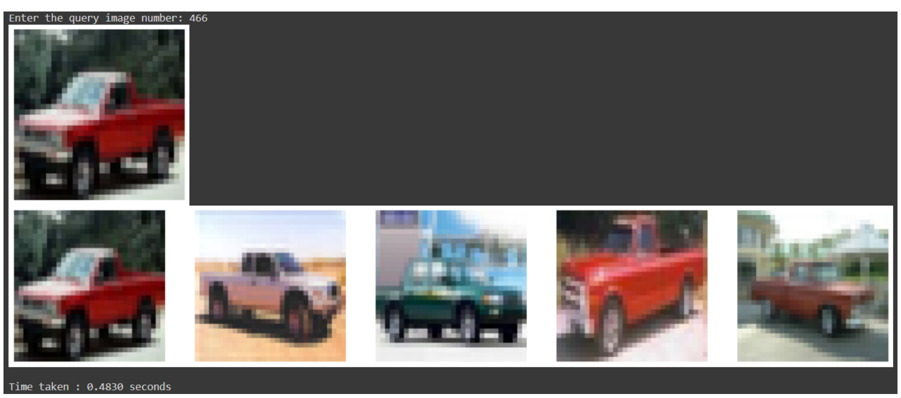
Train Images : 50000
Image Size : 32x32x3
Embedding Size : 1280 (compressed from 3072 features)
Clusters found : 100
Size of Inverted Index: 491 Megabytes

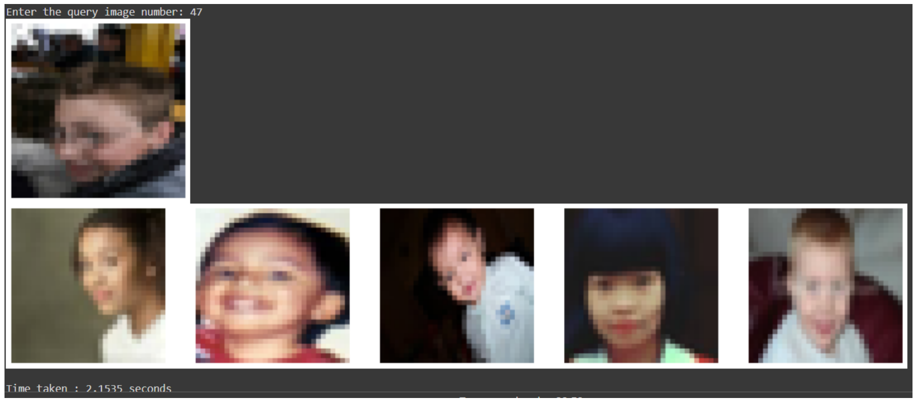
Results -

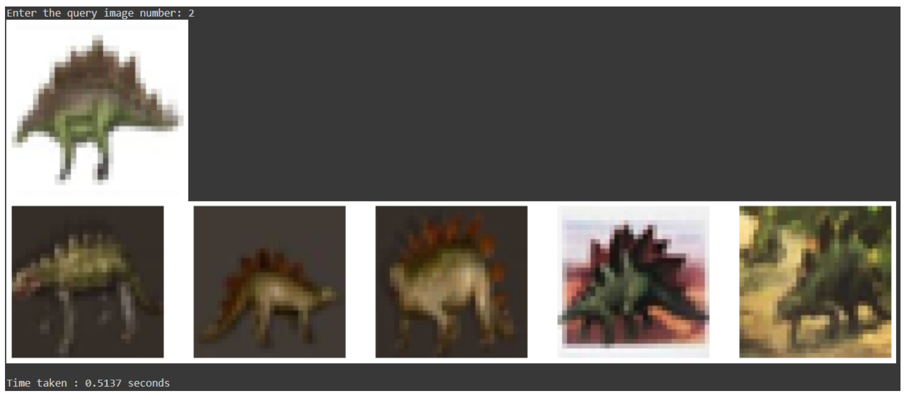
Test Images : 10000
Mean Average Precision : 92.09%

Sample Queries -









Future Work

We will also incorporate latent feature embeddings from autoencoders and try to improve the performance of the hybrid inverted index for the image retrieval system. Finally we will also integrate image summarization and audio output using text to speech services.