

Technical Report: Fingerprint Generation and Similarity Comparison using CNN

Introduction

In this report, I present a methodology for generating fingerprints from images using a custom-trained convolutional neural network (CNN) model and comparing the similarity between these fingerprints. The CNN was trained on a dataset comprising 2000 images, which include variations in contrast, noise, zoom, and rotation. The goal is to demonstrate the effectiveness of the custom-trained CNN in capturing image features for fingerprint generation and similarity assessment.

Methodology

Model Training

I trained a CNN model from scratch on a dataset consisting of 2000 images, which include variations in contrast, noise, zoom, and rotation. This approach ensures that the model learns robust features that generalize well to diverse image conditions.

The CNN architecture was designed using TensorFlow/Keras, with convolutional layers, pooling layers, and fully connected layers. The model was trained using stochastic gradient descent with momentum and categorical cross-entropy loss function.

Fingerprint Generation

To generate fingerprints for images, I utilized the trained CNN model. Given an input image, the model extracts features from intermediate layers, effectively generating a feature vector representing the image.

The trained CNN has learned to capture relevant features from images, including those with variations in contrast, noise, zoom, and rotation.

Similarity Comparison

I compared the similarity between fingerprints using the Euclidean distance metric. Euclidean distance measures the straight-line distance between points in space.

The Euclidean distance metric provides valuable insights into image similarity, capturing the magnitude of differences between fingerprints.

Results

The custom-trained CNN model achieved satisfactory performance in generating fingerprints for images with variations in contrast, noise, zoom, and rotation.

Similarity comparison using Euclidean distance showed promising results, indicating the effectiveness of the generated fingerprints in capturing image similarities across diverse conditions.

Further analysis of the Euclidean distances between fingerprints revealed meaningful patterns in image similarity, demonstrating the robustness of the CNN features.

Conclusion

The methodology presented demonstrates the effectiveness of a custom-trained CNN in generating fingerprints from images with diverse conditions and assessing their similarity using Euclidean distance.

The robustness of the CNN features indicates its potential applicability in various image-based tasks, including image retrieval, classification, and similarity assessment.

Further research can explore advanced CNN architectures and training strategies to enhance the performance and scalability of the proposed approach.