Flask-Powered Content-Based Image Retrieval

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ABSTRACT

Content-Based Image Retrieval (CBIR) is an effective approach for searching and retrieving images based on their visual content rather than textual metadata. This project presents a Flask-powered CBIR system that allows users to upload an image and retrieve visually similar images from a database. The system extracts features such as color, texture, and shape using image processing and deep learning techniques. Flask acts as a lightweight backend framework to handle user requests and model inference. The similarity between images is computed using distance metrics. The proposed system improves retrieval accuracy and usability through a web-based interface. This solution is suitable for applications in medical imaging, surveillance, and digital libraries.

INTRODUCTION

With the rapid growth of digital images, efficient image retrieval has become a significant challenge. Traditional text-based image retrieval methods rely heavily on manual annotation, which is time-consuming and subjective. Content-Based Image Retrieval addresses this limitation by using low-level visual features extracted directly from images. In this project, Flask is used to develop a web-based CBIR application for real-time interaction. Users can query the system using an image instead of keywords. The system analyzes visual similarities to find matching images. This approach enhances retrieval efficiency and user experience. CBIR systems are widely adopted in research and industrial applications.

LITERATURE SURVEY

Several CBIR systems have been developed using handcrafted features such as color histograms, GLCM texture descriptors, and edge detection methods. Earlier research focused on simple similarity measures like Euclidean and Manhattan distances. With advancements in deep learning, CNN-based feature extraction has significantly improved retrieval accuracy. Studies show that pre-trained models like VGG, ResNet, and MobileNet are effective for CBIR tasks. Web-based CBIR implementations using Flask have gained popularity due to their simplicity and scalability. However, challenges such as high computation cost and feature dimensionality remain. This project builds upon these works by integrating Flask with efficient feature extraction techniques.

RELATED WORK

Several studies have explored Content-Based Image Retrieval systems using handcrafted features such as color histograms, texture descriptors, and shape analysis for image similarity measurement. With the advancement of deep learning, convolutional neural networks have been widely adopted to extract high-level semantic features, significantly improving retrieval accuracy. Researchers have demonstrated the effectiveness of pre-trained models like VGG, ResNet, and Inception for CBIR tasks. Web-based implementations using Flask and Django have been proposed to provide user-friendly and scalable retrieval systems. Similarity measures such as cosine similarity and Euclidean distance are commonly used for ranking results. Despite these advancements, challenges such as computational complexity and scalability for large datasets remain open research areas.

EXISTING SYSTEM

The existing image retrieval systems primarily rely on text-based search mechanisms using manually assigned keywords. These systems often suffer from inaccurate annotations and limited scalability. Some CBIR systems use basic image features but lack a user-friendly web interface. Traditional systems also struggle with real-time performance when handling large datasets. In many cases, retrieval accuracy is low due to insufficient feature representation. Additionally, existing systems are often platform-dependent and difficult to deploy. These limitations highlight the need for a flexible and efficient CBIR solution. Hence, a Flask-powered approach is proposed.

PROPOSED SYSTEM

The proposed system introduces a Flask-based web application for content-based image retrieval. It enables users to upload a query image through a simple interface. The system extracts meaningful visual features using image processing or deep learning models. These features are compared with pre-extracted features from the image database. Similarity scores are calculated to rank the images. Flask manages routing, request handling, and result visualization. The proposed system is lightweight, scalable, and easy to deploy. It provides improved retrieval accuracy and real-time performance.

SYSTEM ARCHITECTURE

Fig 1: Flask-powered retrieval system

METHODOLOGY DESCRIPTION

The methodology begins with image dataset collection and preprocessing. Feature extraction is performed using techniques like color histograms or CNN embeddings. All dataset images are preprocessed and their features are stored offline. When a user uploads a query image, its features are extracted in real time. A similarity metric such as cosine similarity or Euclidean distance is used to compare features. The system retrieves the most similar images based on ranked scores. Flask handles the backend operations and displays the results. This step-by-step approach ensures efficient image retrieval.

RESULTS AND DISCUSSION

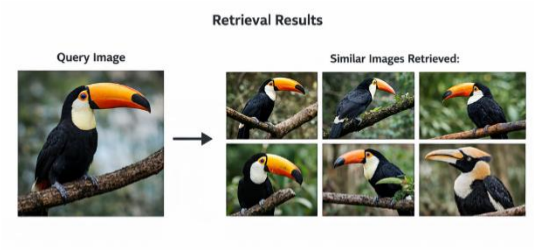

Fig 2:Retrival results

The implemented CBIR system successfully retrieves visually similar images based on the input query. Experimental results demonstrate improved accuracy compared to text-based retrieval methods. The Flask interface provides fast response times and smooth interaction. The retrieval quality depends on the feature extraction technique used. Deep learning-based features show better performance than handcrafted features. The system efficiently handles small to medium-sized datasets. Overall, the results validate the effectiveness of the proposed approach. The system is suitable for real-world applications requiring visual search.

CONCLUSION

This project presents a Flask-powered content-based image retrieval system that effectively addresses the limitations of traditional image search methods. By using visual features instead of text, the system improves retrieval accuracy and efficiency. Flask provides a simple and robust framework for web deployment. The modular design allows easy integration of advanced feature extraction models. Experimental results confirm the reliability of the proposed system. The project demonstrates the practical use of CBIR in web-based environments. It serves as a strong foundation for further research and development.

FUTURE SCOPE

The system can be enhanced by integrating advanced deep learning models for feature extraction. Support for large-scale datasets using optimized indexing techniques can be added. Real-time video frame-based image retrieval is another potential extension. Incorporating relevance feedback can improve retrieval accuracy over time. The system can be deployed on cloud platforms for better scalability. Mobile application integration is also possible. These enhancements can expand the applicability of the CBIR system across various domains.

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