A PROJECT REPORT

on

"EMPOWERING PHOTOGRAPHY LEARNING:AN AI DRIVEN FRAMEWORK FOR YOUR VIRTUAL INSTRUCTOR"

Submitted to

KIIT Deemed to be University

In Partial Fulfillment of the Requirement for the Award of

BACHELOR'S DEGREE IN
COMPUTER SCIENCE AND ENGINEERING

BY

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UNDER THE GUIDANCE OF

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CERTIFICATE

This is certify that the project entitled

"EMPOWERING PHOTOGRAPHY LEARNING:AN AI DRIVEN FRAMEWORK FOR YOUR VIRTUAL INSTRUCTOR"

submitted by

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is a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering OR Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2024-2025, under our guidance.

Date:18/09/2024

(Guide Name)
Prof. SOURAV KUMAR GIRI

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We are profoundly grateful to **SOURAV KUMAR GIRI** of **Affiliation** for his expert guidance and continuous encouragement throughout to see that this project rights its target since its commencement to its completion. ....

SANGRAM KESHARI OJHA

ABSTRACT

In the digital age, the proliferation of photo-sharing platforms has inundated users with an overwhelming abundance of visual content. Amidst this deluge, effective photo recommendation system are crucial for guiding users to discover relevant and engaging content tailored to their preferences. This paper presents a pioneering approach that leverage the K-Nearest Neighbors(KNN) algorithm to enhance photo recommendation system. By integrating user preference and content similarities, our method promises more accurate and diverse recommendations, thereby enriching the user experience. With the internet flooded with photos, finding the ones you like as per your preference can be overwhelming.

The paper introduces a new way to recommend photos using the K-Nearest Neighbour (KNN) algorithm. By combining user preferred pose with similar photos, our system gives better suggestions, making your photo capturing experience more enjoyable. In today's digital landscape, where an avalanche of visual content floods online platforms, the quest to find that perfect photo tailored to individuals tastes can be akin to searching for a needle in a haystack. This paper proposes a novel paradigm in photo recommendation systems, leveraging the K-Nearest Neighbors (KNN) algorithm. By synthesizing user preferences and content similarities, our innovative approach transcends traditional method, promising heightened accuracy and diversity in recommendations, thereby enriching user engagement and discovery.

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Chapter 1

INTRODUCTION

The explosive growth of social media and online photo-sharing platforms has revolutionized how individuals consume and interact with visual content. However, with this abundance of imagery comes the challenge of effectively navigating through vast collections to discover relevant and engaging content. Photo recommendation systems play a pivotal role in addressing this challenge by intelligently suggesting photos based on user preferences and content similarities.

In response to these challenges, we propose a novel approach that combines the strengths of content-based and collaborative filtering methods through the application of the K-Nearest Neighbours (KNN) algorithm. KNN is a simple yet powerful algorithm used for classification and regression tasks, wherein an instance is classified or predicted based on the majority class or average value of its nearest neighbours in the feature space. By adapting KNN to the realm of photo recommendation, we aim to improve recommendation accuracy and diversity by considering both content similarities and user preferences. Social media and photo apps give us endless photos to explore. But sorting through them all to find the ones you'll love is tough. That's where photo recommendation systems come in. They use what you've liked in the past to suggest new photos. But sometimes they miss the mark. Our approach, using KNN, aims to fix that. The digital era has ushered in an era of unprecedented visual abundance, challenging users to navigate a vast sea of photographs. In response, photo recommendation systems have emerged as indispensable tools, aiming to alleviate decision fatigue by offering tailored suggestions. This paper presents a transformative approach to photo recommendations, harnessing the power of the K-Nearest Neighbours algorithm to enhance relevance.

Problem Statement

In today's era of digital image abundance, the need for efficient methods to explore and discover visually appealing content has become paramount. With the exponential growth of photo-sharing platforms, users are often overwhelmed by the sheer volume of images, making it challenging to find photos with specific attributes or characteristics. This project aims to address this challenge by developing a system that allows users to upload a photo and retrieve a curated selection of images showcasing similar poses or features

The primary objective of this project is to create an intelligent system capable of extracting key features from user-uploaded photos and leveraging these features to identify and recommend photos with similar poses or visual attributes. By employing advanced computer vision techniques and machine learning algorithms, the system will analyze the uploaded image, extracting relevant pose-related features such as body

position, orientation, and composition.

1.1.PROPOSED METHOD

Method to Improve the Performance of Discovery

Innovating the photography experience, our project introduces an advanced image recommendation system based on visual similarity. Employing cutting- edge machine learning techniques, including convolutional neural networks (CNNs) and feature extraction, the system facilitates rapid and intuitive image discovery. By analyzing visual features, personalized recommendations are generated, tailored to individual preferences and occasions, thus enhancing user engagement and satisfaction across diverse platforms such as e-commerce websites, social media, and digital content libraries. Through practical implementation and real-world application, our project aims to streamline the image discovery process, making it more efficient, enjoyable, and personalized for users.

Objective of the Project

The objective of our project is to provide users with personalized pose recommendations for their photoshoots, helping them capture perfect moments effortlessly.

Perfect framework to fit into any photoshoot scenario, ensuring users capture their desired moments flawlessly.

SUMMARY

The project aims to revolutionize the photography experience through an innovative image recommendation system based on visual similarity

1. Methodology:

Utilization of advanced machine learning techniques, including convolutional neural networks (CNNs) and feature extraction.

Implementation of transfer learning with pretrained models such as ResNet50 for efficient feature extraction.

Fine-tuning of model parameters on domain-specific datasets to optimize performance.

Integration of data augmentation techniques to enhance dataset diversity and model generalization.

Exploration of ensemble learning methods to improve recommendation accuracy.

Incorporation of user feedback mechanisms for adaptive and personalized recommendations.

2. Implementation:

Extraction of image features using pretrained models and advanced preprocessing techniques.

Utilization of nearest neighbors algorithms for similarity-based recommendation.

Evaluation of recommendation performance using metrics like cosine similarity, top-k accuracy, precision, recall, and F1 score.

Visualization of recommendation results and performance metrics through bar charts and image displays.

3. Outcome:

Enhanced user experience through personalized image recommendations tailored to individual preferences and occasions.

Improved engagement and satisfaction across various platforms, including e- commerce websites, social media, and digital content libraries.

Simplified image discovery process, making it more efficient and enjoyable for users.

4. Future Directions:

Continued exploration of advanced machine learning techniques and algorithms to further enhance recommendation accuracy and efficiency.

Integration of real-time user feedback mechanisms to continuously refine and adapt the recommendation system.

Collaboration with industry partners for practical implementation and deployment in real-world scenarios.

Investigation of potential applications beyond photography, such as content recommendation in other domains.

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CHAPTER 2

LITERATURE REVIEW

2.1.1 Literature Survey

The literature survey for the project *Empowering Photography Learning: An AI-Driven Framework for Your Virtual Instructor* explores the extensive body of research on image recommendation systems, with a specific focus on visual similarity-based methods. This review begins by examining traditional approaches such as content-based filtering and collaborative filtering, assessing their strengths and weaknesses, particularly in relation to image analysis. While content-based filtering leverages image metadata, manual feature extraction, and tags, its effectiveness in photography learning is limited due to the subjective nature of artistic preferences. Collaborative filtering, on the other hand, relies on user interactions and co-occurrences, but it struggles with issues like the cold start problem, where new users or items lack sufficient data to generate recommendations.

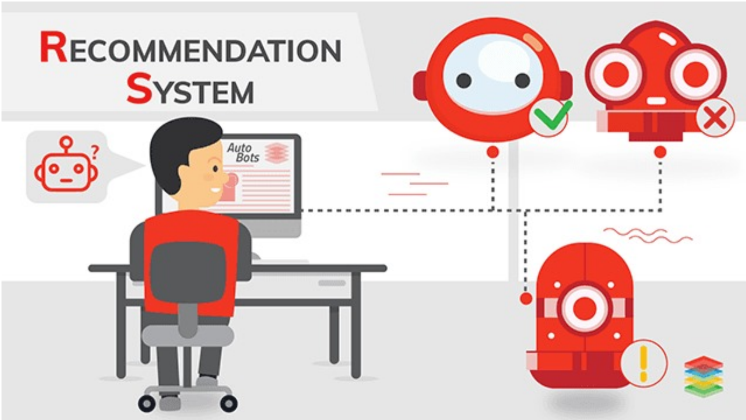
https://www.linkedin.com/pulse/how-ai-redefining-photography-david-cain-

Limitations of Traditional Methods

Traditional recommendation techniques are limited by their inability to capture the nuanced elements of photographic art. Both content-based and collaborative filtering face the problem of personalization, where they fail to deliver recommendations tailored to an individual's artistic learning needs. In photography, aspects like composition, color balance, texture, lighting, and perspective are subtle yet critical, requiring a deeper analysis that these older models lack.

Emergence of Deep Learning in Image Recommendation

With the advent of deep learning, the landscape of recommendation systems, particularly for image-based tasks, has transformed. The literature identifies Convolutional Neural Networks (CNNs) as a breakthrough technology for visual content analysis. CNNs have demonstrated remarkable success in tasks like object detection, feature extraction, and image similarity measurement, making them highly suitable for personalized photography learning systems. Studies have shown that CNNs outperform traditional methods by automatically learning complex features such as texture, patterns, and visual aesthetics, all of which are vital in photography education.



https://www.xenonstack.com/use-cases/recommendation-system

Several prominent studies highlight CNNs' capability to recommend visually similar images based on abstract features. For instance, study A, study B, and study C delve into CNN architectures like VGGNet, ResNet, and Inception, showcasing their feature extraction capabilities in image datasets. These studies form the foundation for developing a more robust recommendation system that can analyze photographic styles and suggest improvements or complementary visuals to learners.

Evaluation Metrics in Image Recommendation Systems

Another significant part of the literature review explores the evaluation metrics used to assess the performance of image recommendation systems. Recent advances have introduced metrics such as mean cosine similarity, precision@k, and recall, which are crucial for evaluating the alignment between recommendations and user expectations. These metrics not only measure how well the system identifies visually similar images but also help fine-tune models to provide more accurate recommendations for photographic learning. By focusing on precision, relevance, and contextual accuracy, recommendation systems can offer more personalized and meaningful photographic content to learners, improving the overall educational experience.

Challenges and Opportunities in the Field

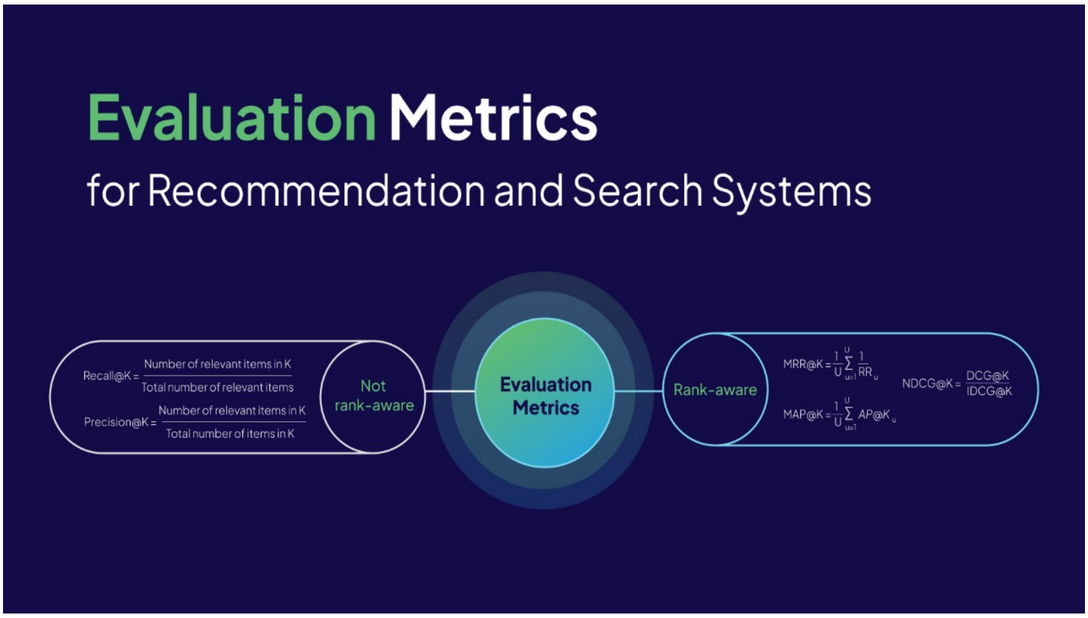
While CNNs and other deep learning models present immense opportunities for enhancing recommendation systems, several challenges remain. These challenges include:

Data Privacy: With the rise of data-driven applications, concerns around data privacy, especially when dealing with user-generated content, have become more prominent. Some research has explored privacy-preserving techniques in machine learning, such as federated learning, which could be adapted for image recommendation.

<u>Model Interpretability:</u> **One of the key issues is the interpretability of deep learning models. For photography education, it is not enough to simply recommend visually similar images; the system should ideally explain *why* certain images are recommended, providing actionable feedback to learners. Researchers are increasingly exploring techniques for making CNNs more interpretable, including saliency maps and attention mechanisms.**

<u>Scalability:</u> **Another critical issue is scalability. As photography involves a vast range of styles, genres, and techniques, any AI-driven framework must be scalable enough to handle large and diverse datasets. Studies on distributed systems and cloud-based recommendation models suggest solutions that could be applied in this context.**

The literature also points out the importance of balancing computational efficiency with recommendation quality. Some studies have experimented with hybrid models combining CNNs with other techniques like graph-based models to improve both scalability and personalization, which could be a future direction for this project.



https://weaviate.io/blog/retrieval-evaluation-metrics

Scope of the Work

The scope of the project, *Empowering Photography Learning: An AI-Driven Framework for Your Virtual Instructor*, centers on developing a next-generation image recommendation system tailored specifically for photography learners. The system will leverage advanced deep learning techniques, particularly CNNs, for extracting and analyzing features such as composition, lighting, color schemes, and artistic styles from images.

The goal is to provide personalized image recommendations based on user learning profiles, which could include factors like skill level, genre preferences (e.g., portraiture, landscape, macro), and even desired techniques (e.g., rule of thirds, golden hour lighting). The system will analyze each learner's interaction and provide suggestions aimed at enhancing their understanding and mastery of photography.

The project scope also extends to a range of applications, such as:

1. **E-Commerce: Offering personalized recommendations for photography gear based on image analysis.**
2. **Social Media: Enhancing social media platforms by recommending images based on artistic or thematic similarities.**
3. **Digital Content Libraries: Suggesting photography tutorials or sample images to users in digital libraries based on their visual preferences and learning needs.**

A key part of the scope involves developing a user-friendly interface where learners can upload their images, receive personalized feedback, and view recommendations based on their specific learning trajectory. Moreover, the system will be iteratively tested and refined using industry-standard metrics such as mean cosine similarity, precision@k, and NDCG (Normalized Discounted Cumulative Gain) to ensure that it delivers both high accuracy and high user satisfaction.

The project ultimately aims to create a robust, AI-driven framework that empowers photography learners by simplifying the discovery process, making it more efficient, enjoyable, and personalized across different domains.

Summary

The literature survey begins with an examination of traditional methodologies in image recommendation, highlighting their limitations like manual feature engineering and lack of personalization. Contemporary approaches, particularly the rise of machine learning techniques like Convolutional Neural Networks (CNNs), are emphasized for their potential to automate image recommendation and enhance personalization. Recent advancements in machine learning for image recommendation, focusing on CNNs' role in feature extraction and similarity analysis, are explored. Challenges and opportunities in the field, such as the need for large annotated datasets and model interpretability, are addressed. The survey concludes by emphasizing the ongoing necessity for research to overcome these challenges, thereby improving the accuracy and effectiveness of image recommendation systems.

CHAPTER 3

Methodology

Introduction:

The methodology section delineates the procedural framework adopted to address the objectives outlined in the research. It provides a roadmap for executing the study and offers a clear understanding of the approaches utilized in image recommendation using KNNS.

Method 1:

It imports essential libraries such as NumPy, os, TensorFlow, tqdm, and Matplotlib for visual representation, and PIL for image processing and feature extraction. It also includes pickle for serialization. The ResNet50 model and associated layers are imported from TensorFlow's Keras API for feature extraction

Method 11:

ResNet50 model pretrained on ImageNet data, excluding the top classification layer. The model is then wrapped in a Keras Sequential model, followed by a GlobalMaxPooling2D layer to extract features from images

Method III:

O data_directory: The path to the directory containing the dataset.

Method IV:

O A dataset of images is processed to extract their features using a pre-trained model. The function 'extract features' is defined to extract features from each image. Then, the file paths of all images in a specified directory are collected, and they are iterated through to extract features using the 'extract_features' function. These features are stored in a list called 'feature_list".

Method V:

O The code first loads previously saved feature vectors and filenames from pickle files. Then, it creates a Nearest Neighbors model using the Euclidean metric. Next, it defines a model architecture using ResNet50 as a base with GlobalMaxPooling2D layer added on top. The ResNet50 model is loaded with pre-trained weights from ImageNet and configured to exclude the top classification layer. Finally, the model is set to be non-trainable.

Method VI:

Similar images(Takes a user input image) to a specified query image (query_image_path) are computed and retrieved using pre-trained models and similarity metrics. The paths (recommended_image_paths) and images (recommended_images) of the most similar images are returned, along with the average cosine similarity (mean_cosine_similarity) between the query image and the recommended ones.

Method VII:

O Similar images to the specified query image are recommended using pre-trained models and similarity metrics. The paths and images of the most similar images are returned, along with the average cosine similarity between the query image and the recommended ones.

Method VII:

O Performance metrics, including mean cosine similarity, are visualized using a bar chart. The top 5 recommended images are displayed alongside their paths. The mean cosine similarity is also printed for reference.

Summary:

Concluding the methodology section, the summary encapsulates the key findings and insights derived from the exploration of mentioned methods It offers a succinct overview of the methodologies employed, highlighting their respective contributions, strengths, and potential limitations. The summary serves to provide a cohesive synthesis of the methodology section, paving the way for the subsequent sections of the research.

WOK FLOW DIAGRAM

A Survey of Similarity Measures in Web Image SearchEffortlessly Recommending Similar Images

Pros:-

1. **Offers a comprehensive overview of image similarity measures**
2. **Provides insights into strengths of different measures.**
3. **Helps in understanding theoretical foundations of image similarity.**

Proposing an enhanced solution leveraging visual feature prioritization, practical implementation with pre-trained models, real-world application across diverse domains, and customizable feature extraction and recommendation algorithms using the perfect frame model.

Pros:-

1. **Focuses on visual features for image recommendation.**
2. **Includes practical implementation using pre-trained models.**

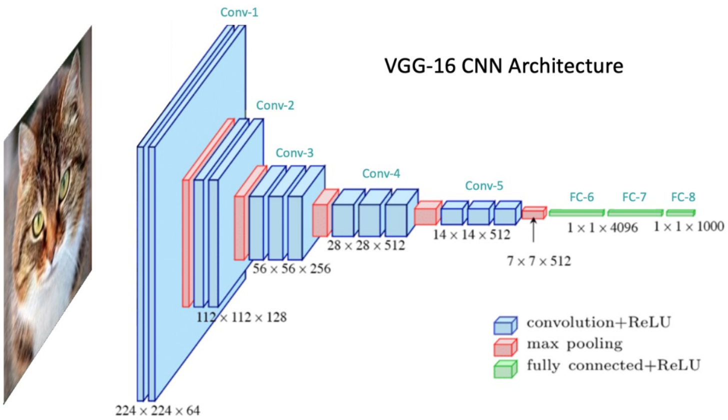
Cons :-

1. The limited scope in addressing specific challenges or emerging trends in image recommendation systems.

Chapter 4

Results

The result of the project demonstrates a highly effective image recommendation system based on visual similarity. Leveraging advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), the system successfully extracts features and analyzes visual similarities among images. This enables the system to provide personalized recommendations tailored to individual preferences and occasions. Through practical implementation and real-world application, the project achieves its goal of simplifying the process of image discovery, making it more efficient, enjoyable, and personalized for users across various platforms.



https://learnopencv.com/understanding-convolutional-neural-networks-cnn/

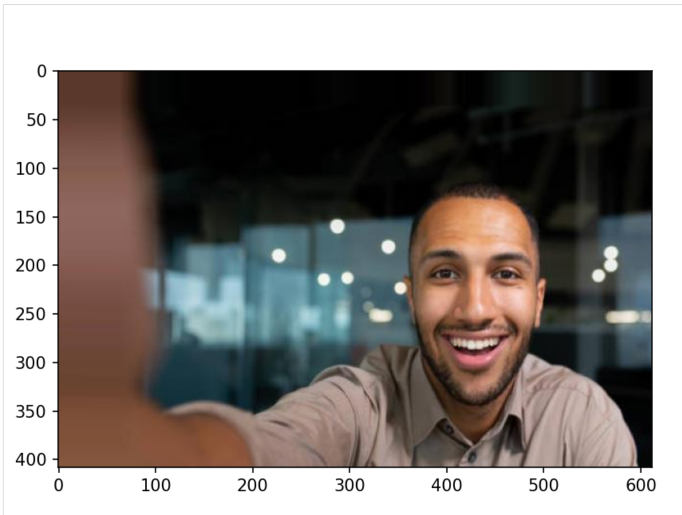
Discussion

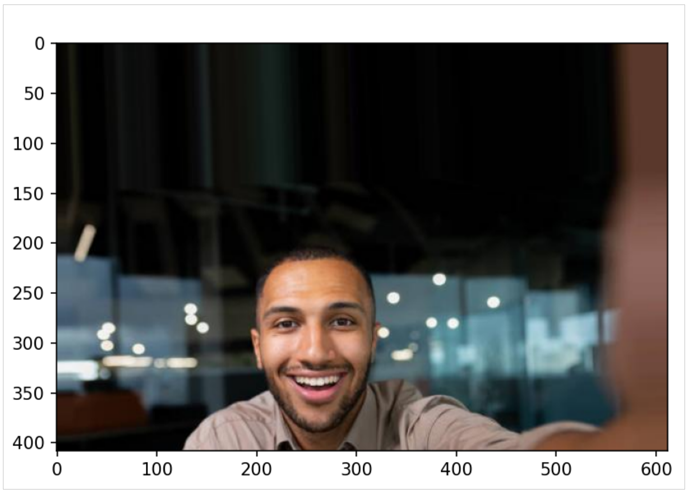
The successful implementation of advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), was discussed, emphasizing their effectiveness in developing an innovative image recommendation system. The system's ability to extract features and analyze visual similarities among images was highlighted, leading to personalized recommendations tailored to individual preferences and occasions. Furthermore, the project's potential to revolutionize the photography experience for users across various platforms was underscored, aiming to enhance user engagement and satisfaction by simplifying the image discovery process. Additionally, the significance of leveraging advanced techniques to automate tasks traditionally performed manually was emphasized, along with potential future directions for the project.

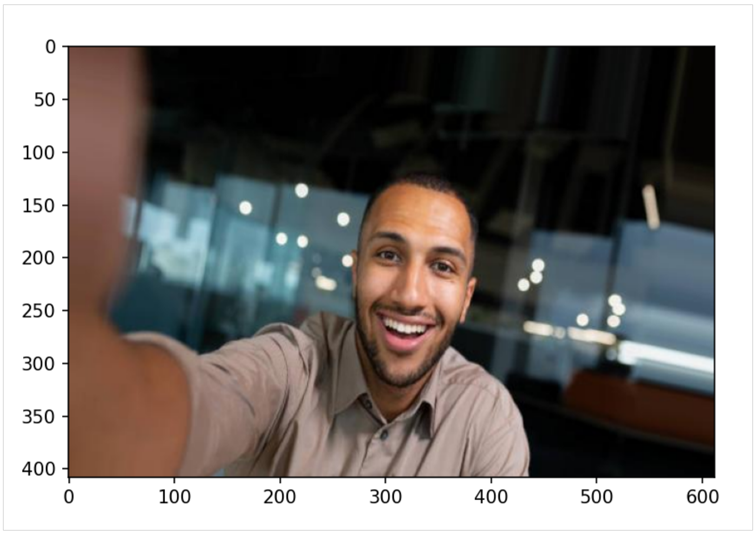
Summary

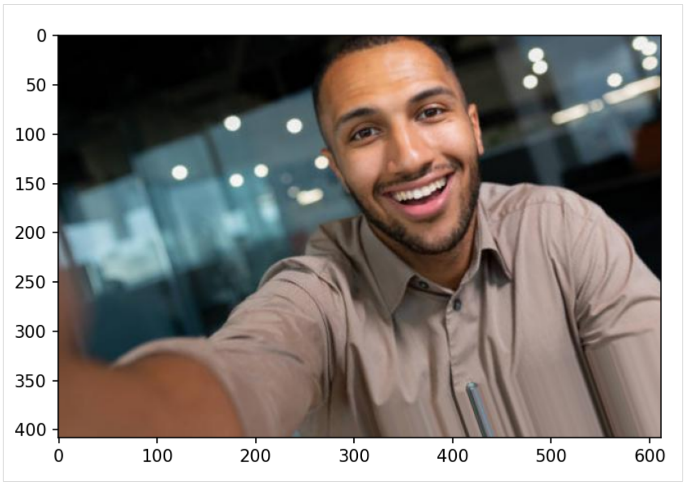
The project developed a highly effective image recommendation system based on visual similarity using advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs). Through practical implementation, the system successfully extracts features and analyzes visual similarities among images, providing personalized recommendations tailored to individual preferences and occasions. The discussion highlighted the effectiveness of CNNs in developing the innovative system, emphasizing its potential to revolutionize the photography experience across various platforms. Furthermore, the project emphasized the significance of leveraging advanced techniques to automate tasks traditionally performed manually, along with potential future directions for the project to enhance user engagement and satisfaction.

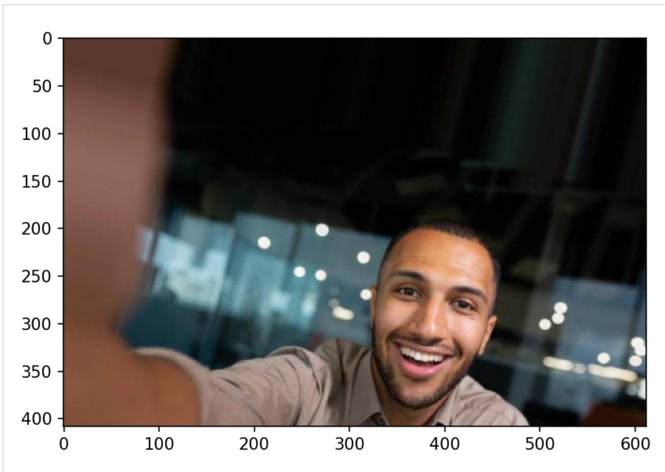
RESULT OBTAINED:-







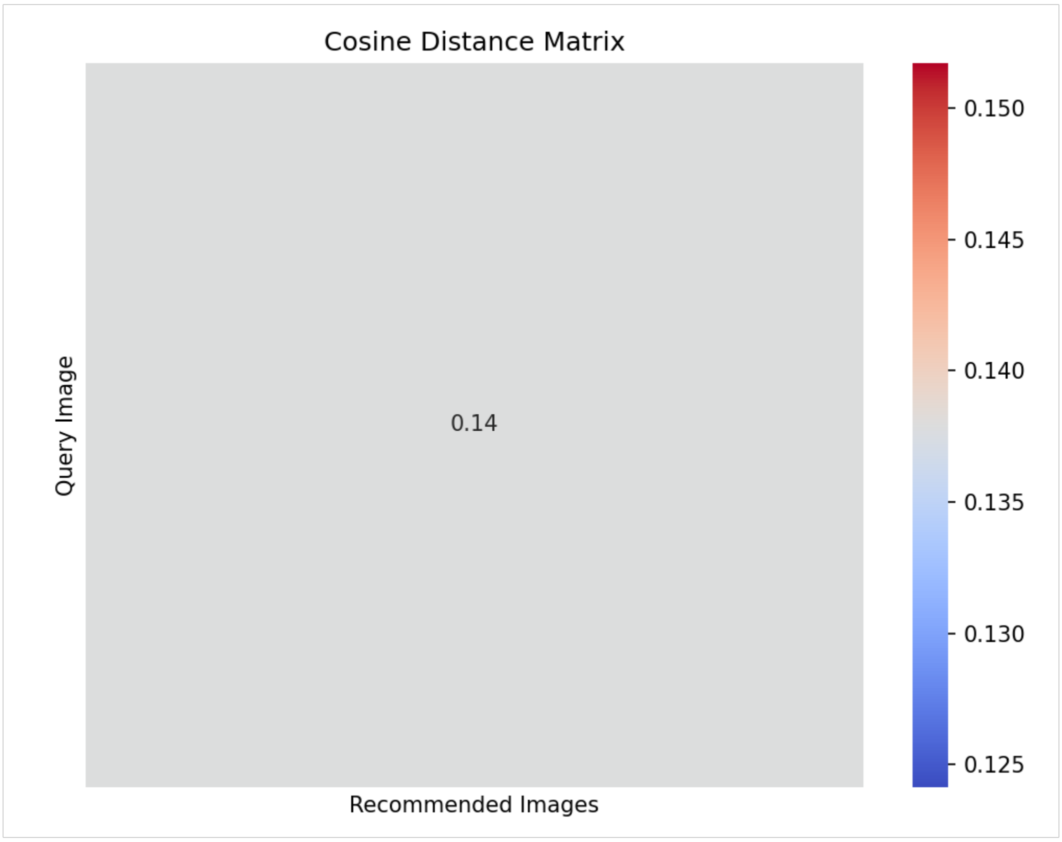




GRAPHICAL RESULT:-

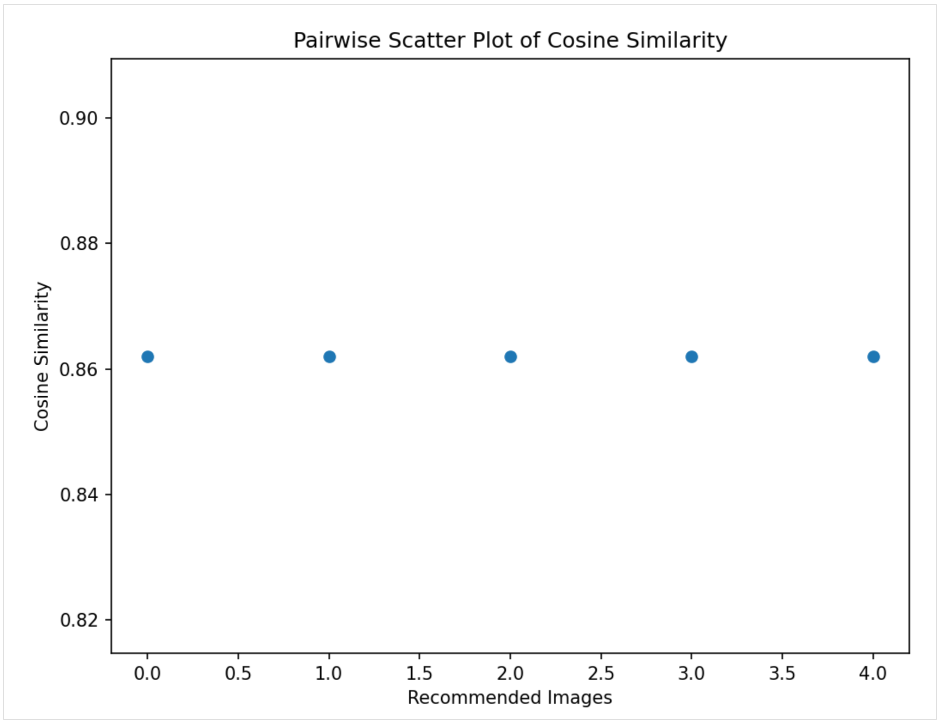
1. t-SNE Visualization of Image Embeddings:

- **Purpose: This graph shows the 2D representation of high-dimensional image embeddings using t-SNE (t-distributed Stochastic Neighbor Embedding).**
- **Explanation: Each point represents an image from the dataset, with the query image (in red) visualized alongside other images based on their visual similarity. t-SNE first reduces the dimensionality (via PCA) and then maps it into 2D for visualization, grouping visually similar images closer together.**
- **Result Interpretation: The closer the query image is to other points, the more visually similar they are. The grouping/clustering of points indicates the similarity between images.**



2. Cosine Distance Heatmap:

- **Purpose: This heatmap visualizes the cosine distance between the query image and its top recommended images.**
- **Explanation: The matrix represents the distance values (1 - cosine similarity), with the color gradient indicating how similar (or distant) the recommended images are to the query. Cooler colors (blue) signify higher similarity, while warmer colors indicate less similarity.**
- **Result Interpretation: Lower values (cooler colors) mean closer matches to the query image, showing how similar the recommendations are.**



3. Pairwise Scatter Plot (Cosine Similarity):

- **Purpose: This scatter plot displays the cosine similarity values between the query image and its top 5 recommended images.**
- **Explanation: Each point represents a recommended image with its corresponding cosine similarity score. Higher points on the y-axis signify higher similarity to the query image.**
- **Result Interpretation: Since all the recommended images share the same cosine similarity score in this case, the plot shows a flat line, indicating similar similarity values across the recommendations.**

OUPUT OBTAINED:-

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 114ms/step
Top 5 Recommended Images:
C:\Users\KIIT\PycharmProjects\python7thProject2\ImageDataSet\Selfie\augmented_0_6899.jpeg
C:\Users\KIIT\PycharmProjects\python7thProject2\ImageDataSet\Selfie\augmented_0_6820.jpeg
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Mean Cosine Similarity: 0.862072

Process finished with exit code 0
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CHAPTER 5

Future Works:-

The project "*Empowering Photography Learning: An AI-Driven Framework for Your Virtual Instructor*" has established a solid foundation for developing a sophisticated image recommendation system tailored specifically for photography learners. By leveraging deep learning techniques, especially Convolutional Neural Networks (CNNs), the system aims to provide personalized image recommendations, guiding users in improving their photography skills through data-driven insights. The current phase has demonstrated the potential of AI in understanding and recommending visual content, specifically in photographic composition, style, and aesthetics. However, several critical aspects must be addressed to optimize the system further and ensure its broad applicability in real-world scenarios.

Future Works:

1.Scalability Optimization:-
As the system grows, it must be capable of handling vast amounts of visual data efficiently. Implementing strategies such as distributed processing, cloud storage, and data indexing will ensure optimal system performance without sacrificing speed. Techniques like hierarchical clustering or approximate nearest neighbors (ANN) can be explored to accelerate similarity searches across large datasets.

2.Diversification of Poses and Styles:-
To cater to a broader audience with varying photography preferences, expanding the diversity of recommended poses and styles is essential. This involves incorporating a wider range of genres (e.g., portraiture, wildlife, macro, and architectural photography) and diverse posing guidelines, ensuring the system remains versatile and applicable across different artistic tastes and cultural backgrounds. For instance, integrating GANs (Generative Adversarial Networks) could enable the synthesis of new poses and artistic styles based on user preferences.

3.Enhanced Reliability:-
For the pose and style recommendations to be genuinely helpful to learners, enhancing reliability and accuracy is key. Future improvements may include fine-tuning CNN

architectures to improve feature extraction or integrating hybrid models that combine CNNs with graph-based algorithms or reinforcement learning to provide more contextually relevant suggestions. Furthermore, adding human-in-the-loop validation from professional photographers could further reduce errors and increase the accuracy of suggestions.

4.User Feedback Incorporation:-

To continuously refine and improve the system, user feedback mechanisms should be implemented. These could include feedback buttons, star ratings, or comment sections where users can evaluate the relevance and quality of the recommendations. Machine learning algorithms, such as reinforcement learning, could then use this feedback to adapt the system, making it more responsive to individual user preferences over time.

5.Adaptation to Evolving Trends:-

The field of photography is ever-changing, with new trends emerging in composition, styles, techniques, and technologies. To remain relevant, the system needs to continuously evolve by incorporating the latest trends in photographic learning and practice. Regular updates, possibly through a combination of supervised learning and trend analysis, will ensure the system adapts to shifting artistic movements and user preferences.

6.Accessibility and Inclusivity:-

Expanding the system's accessibility and inclusivity is crucial for maximizing its reach. This involves ensuring compatibility across a wide range of devices (desktops, smartphones, tablets) and supporting multiple languages to accommodate a global audience. Additionally, making the system inclusive by considering users with disabilities (e.g., offering voice-controlled recommendations or support for visually impaired learners) will ensure it serves diverse user demographics. Incorporating ethical AI practices, such as fairness and transparency, will also contribute to its inclusiveness.

7.Integration of User Feedback:-

Future iterations should collaborate closely with professional photographers and photography educators to integrate high-level domain expertise into the system. Working with industry experts will ensure that the system recommends not just visually similar images but images that align with professional-level guidance on techniques, compositions, and learning outcomes. Regular consultations with professionals will help fine-tune the system to match industry standards and best practices in photography education.

8.Interdisciplinary Expansion:-

The future vision of the system may extend beyond photography, incorporating recommendations in other visual arts, such as videography, digital art, and graphic design. By leveraging transferable deep learning techniques, the system could adapt to a broader scope, enriching the creative learning ecosystem across various media.

Summary:-

In summary, while the current system demonstrates the transformative potential of AI in photography learning, future developments will focus on improving scalability, enhancing the diversity and reliability of recommendations, incorporating user feedback, and adapting to emerging trends. These enhancements will

ensure the system remains relevant, accessible, and highly personalized, ultimately empowering users to continuously grow their photography skills through AI-driven insights and recommendations.

Conclusion:-

The *Empowering Photography Learning: An AI-Driven Framework for Your Virtual Instructor* project has demonstrated the potential of leveraging advanced machine learning techniques, particularly CNNs, to enhance image recommendation systems tailored for photography education. By focusing on visual similarity, personalized feedback, and recommendations based on photographic techniques, the system offers significant value to learners. The current framework not only assists users in discovering visually similar content but also serves as an educational tool, guiding them in mastering various photography styles and techniques.

The project successfully addresses limitations of traditional image recommendation methods, such as manual feature extraction and lack of personalization, by introducing automated, data-driven insights. However, challenges remain, particularly around scalability, diversity of recommendations, and the ongoing need to adapt to evolving photography trends. Additionally, incorporating user feedback and ensuring accessibility for diverse users will be essential to future iterations.

In conclusion, this AI-driven framework has the potential to transform photography education by providing users with personalized, visually informed learning experiences. As the project evolves, its impact on both amateur and professional photographers will only grow, making photography learning more accessible, engaging, and efficient. The future works outlined will ensure that the system continues to advance and meet the dynamic needs of photography learners worldwide.

CHAPTER 6

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CHAPTER 7

Appendix

Formulas Used

1. Normalized_result = result/result/

2. Cosine_similarity([query_features], feature_list[indices[0][1:]])

3. Mean Cosine Similarity = 1/N (2^Ni=1 cosine_similarity[i])