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# FASHION RECOMMENDATION SYSTEM

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***Abstract*— he fashion industry has witnessed significant growth, driven by the innate human attraction towards visually appealing aesthetics. With the emergence of recommender systems across various domains, retail industries are embracing technological advancements to enhance their business models. Fashion, an integral part of human culture for centuries, continues to evolve, attracting increased attention, particularly from women who are closely associated with fashion and style.**

## I. INTRODUCTION

The fashion industry has undergone a rapid transformation in recent years, driven by technological advancements and changing consumer behavior. With the proliferation of e-commerce platforms, consumers now have access to a vast array of fashion choices, making the decision-making process increasingly complex. However, the abundance of options has also created challenges for consumers, who often struggle to find clothing items that match their personal style and preferences .To address this challenge, there is a growing need for personalized recommendation systems that can help consumers navigate the overwhelming landscape of fashion choices available online. Traditional recommender systems that rely solely on user history and preferences may not always provide accurate recommendations, particularly when users are seeking specific clothing items based on visual cues.

In this case study, we propose a personalized Fashion Recommender System that leverages advanced technologies such as Convolutional Neural Networks
(CNNs) and transfer learning to provide consumers with personalized recommendations based on input images prov

## II. LITERATURE REVIEW

Fashion recommender systems have gained significant attention in recent years due to the growing popularity of online shopping and the increasing complexity of the fashion market. These systems aim to assist users in finding clothing items that match their personal style and preferences, ultimately enhancing the overall shopping experience. Traditional recommender systems rely on user history and preferences to generate recommendations, but they may not always provide accurate suggestions, particularly when users are seeking specific clothing items based on visual cues.Content-based recommendation systems analyze the features of items and users' preferences to generate recommendations. In the context of fashion, these systems extract features such as color, pattern, style, and fabric from clothing images to recommend similar items. Research in this area has focused on developing algorithms that can accurately extract and analyze visual features from fashion images, enabling the generation of personalized recommendations based on users' preferences.Image-based recommendation systems leverage advanced technologies such as Convolutional Neural Networks (CNNs) to analyze fashion.

## III. Existing System

Fashion recommender systems have become increasingly popular in recent years, driven by the growing demand for personalized shopping experiences and the expansion of the online fashion market. Several existing systems employ different approaches to recommend clothing items to users based on their preferences and browsing behavior Content-based recommendation systems analyze the features of items and users' preferences to generate recommendations. In the context of fashion, these systems extract features such as color, pattern, style, and fabric from clothing images to recommend similar items. One example of a content-based fashion recommendation system is the one proposed by Chen et al. (2018), which utilizes deep learning techniques to extract visual features from fashion images and generate personalized recommendations for users.

**DRAWBACKS:**

- Limited Diversity in Recommendations:
  Since the recommendations are solely based on visual similarity, the system may fail to consider other important factors such as brand, style preferences, and user context. As a result, the recommendations may lack diversity and fail to cater to the user's specific needs and preferences.

- Dependency on Image Quality and Composition:
  The effectiveness of the recommendation system heavily relies on the quality and composition of the input image. Images with poor quality, improper framing, or complex backgrounds may result in inaccurate recommendations.

- Limited Contextual Understanding:
  The system lacks the ability to understand the context in which the fashion items are being worn. It does not consider factors such as occasion, weather, or user preferences, which are crucial for making appropriate fashion recommendations.

- Cold Start Problem:
  The system may face difficulties when dealing with new or rare fashion items that are not well-represented in the dataset. In such cases, the

## IV. Proposed System

- In our proposed Fashion Recommender System, we aim to leverage the strengths of multiple deep learning models to enhance recommendation accuracy. Specifically, we have assembled two widely used models, ResNet50 and VGG16, to create a more robust and accurate recommendation system. By combining these models, we can capture a wider range of visual features from fashion images, resulting in more accurate and personalized recommendations for users.
- The neural networks are trained using transfer learning from ResNet50 and VGG16. Additional layers are added to fine-tune the network models, ensuring optimal performance for the current task. By combining the features learned by ResNet50 and VGG16, we can create a more comprehensive representation of fashion images, which improves the accuracy of our recommendation system.
- Images from the Kaggle Fashion Product Images Dataset are used to create an inventory. The images are run through the ResNet50 and VGG16 models to classify and generate embeddings. The output from both models is then combined to create a more comprehensive representation of the inventory items. This combined representation allows us to generate

more accurate recommendations by capturing a wider range of visual features from the inventory items.

- To generate recommendations, our proposed approach uses a combination of the embeddings generated by ResNet50 and VGG16. We employ Sklearn Nearest Neighbors to find the nearest neighbors for the given input image using the combined embeddings. The similarity measure used in this project is the Cosine Similarity measure. By combining the embeddings from ResNet50 and VGG16, we can generate more accurate and personalized recommendations for users.

## ADVANTAGES:

- Personalized Recommendations:
  The system provides personalized fashion recommendations based on the visual characteristics of the user's input image. By analyzing the visual features of the input image, the system identifies similar fashion items from a large dataset, ensuring
- Wide Range of Fashion Items:
  The system can recommend a wide range of fashion items including clothing, shoes, and accessories. This ensures that users can find recommendations for various fashion needs, allowing them to explore and discover new styles easily.
- Efficient and User-Friendly Interface:
  The system offers a simple and intuitive interface for users to upload their images and receive recommendations quickly. The use of Streamlit provides a seamless and interactive experience, allowing users to navigate the system effortlessly.
- Utilization of Pre-trained Deep Learning Models:
  By leveraging pre-trained deep learning models such as DenseNet121, ResNet50, and VGG16, the system can extract high-level features from fashion images efficiently. This allows for accurate and reliable feature representation, leading to more precise recommendations.

V. MODEL DESIGN

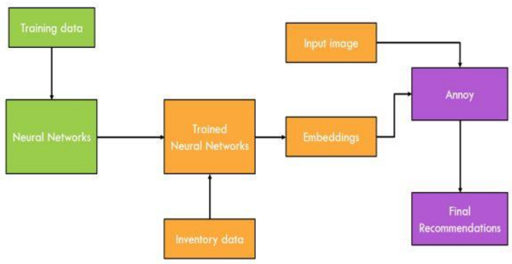



**Figure 1.** Block diagram of proposed system

## HARDWARE REQUIREMENTS:

- CPU: Intel Core i7 or equivalent
- GPU: NVIDIA GPU with CUDA support
- RAM: 16GB or higher
- Storage: 500GB SSD

## SOFTWARE REQUIREMENTS:

- Operating System: Windows, macOS, or Linux
- Python Environment: Python 3.7 or higher
- Development Environment: Anaconda
- Other Tools: Git for version control (optional)
- Additional Requirements: CUDA Toolkit

VI. RESULT AND DISCUSION

## RESNET50:

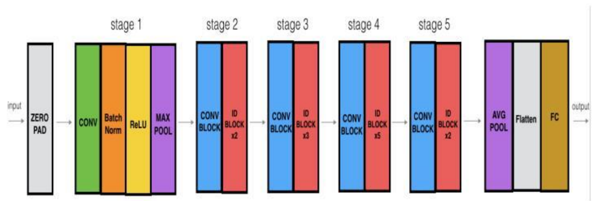
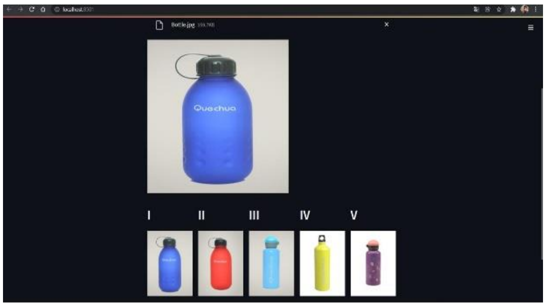
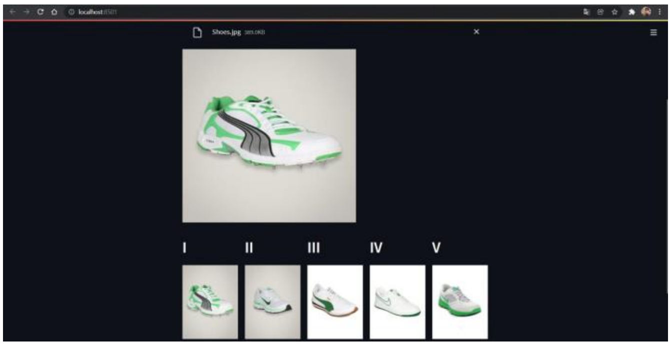



**Figure 2.** ResNet50 architecture

ResNet50, short for Residual Network with 50 layers, is a deep convolutional neural network (CNN) architecture that has proven to be highly effective for various computer vision tasks, including image classification, object detection, and feature extraction. Developed by Microsoft Research, ResNet50 is an extension of the original ResNet architecture, which introduced the concept of residual learning.

**RESULT:**




## VII. CONCLUSION

In this project, we have presented a novel framework for fashion recommendation that is driven by data, visually related and simple effective recommendation systems for generating fashion product images. The proposed approach uses a two-stage phase. Initially, our proposed approach extracts the features of the image using CNN classifier ie., for instance allowing the customers to upload any random fashion image from any E-commerce website and later generating similar images to the uploaded image based on the features and texture of the input image. It is imperative that such research goes forward to facilitate greater recommendation accuracy and improve the overall experience of fashion exploration for direct and indirect consumers alike.

## VIII. REFERENCES


- Sean Bell and Kavita Bala. 2015. Learning Visual Similarity for Product Design with Convolutional Neural Networks. ACM Trans. Graph. 34, 4, Article 98 (July 2015), 98:1–98:10 pages.
- Lukas Bossard, MaŠ hias Dantone, Christian Leistner, Christian Wengert, Till ‹ ack, and Luc J. Van Gool. 2012. Apparel Classi€ cation with Style. In Proc. ACCV. 321–335.
- Y-Lan Boureau, Francis Bach, Yann LeCun, and Jean Ponce. 2010. Learning Mid-Level Features for Recognition. In Proc. CVPR.
- Gal Chechik, Varun Sharma, Uri Shalit, and Samy Bengio. 2010. Large Scale Online Learning of Image Similarity Œrough Ranking. J. Mach. Learn. Res. 11 (March 2010), 1109–1135.
- Huizhong Chen, Andrew C. Gallagher, and Bernd Girod. 2012. Describing Clothing by Semantic AŠ ributes. In Proc. ECCV. 609–623.
- TensorFlow and Keras Documentation: [TensorFlow Documentation](https://www.tensorflow.org/guide)
- Streamlit Documentation: [Streamlit Documentation](https://docs.streamlit.io/library)
- 3. Deep Learning Models: [DenseNet121 Documentation](https://keras.io/api/applications/densenet/#densenet121-function)
- 4. Image Similarity Calculation:[Cosine Similarity in Python](https://scikitlearn.org/stable/modules/generated/sklearn.metrics.pairwise.cosine_similarity.html)
- 5. Fashion Datasets: [Fashion Product Images Dataset (Kaggle)](https://www.kaggle.com/paramaggarwal/fashion-product-images-dataset)
- 7.GitHub Repositories: [Fashion Recommendation System using Deep Learning](https://github.com/marco-willi/fashion-recommendation-system)