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STYLESYNC: A FASHION RECOMMENDATION SYSTEM

NehaVarma[1],Garima Singh[2], Vivek Raj Singh[3],
Vineet Swami[4],Anushika Tyagi[5],Shivam Verma[6]
B.Tech

Department of Computer Science And Engineering(Data Science) &
Department of Computer Science And Engineering(Artificial Intelligence & Machine Learning),
Inderprastha Engineering College, Sahibabad, Ghaziabad, India

Abstract -

Our project focuses on an AI-powered Fashion Recommendation System tailored to assist users in curating outfits for diverse occasions. Users upload clothing images to create individualized wardrobes. Employing machine learning and deep learning, our system accurately classifies clothing types and identifies colors within these images. The core of our innovation lies in a sophisticated recommendation algorithm. By analyzing users' existing wardrobes, including garment types and colors, our algorithm delivers personalized outfit suggestions aligned with users' style preferences and specific event needs. The interface prioritizes user-friendliness, enabling seamless wardrobe management and presenting users with well-matched outfit recommendations. Continuous refinement through user feedback ensures ongoing enhancement of recommendation accuracy, user experience, and machine learning model performance. In summary, our AI-driven Fashion Recommendation

The system aims to streamline the process of dressing for diverse occasions, offering personalized outfit suggestions based on individual wardrobes, thus empowering users with convenient and stylish clothing choices.

Keyword – fashion-recommendation, Feature extraction, recommendation system, data analysis, transfer-learning, javascript, python, bootstrap, npm, machine learning, computer vision, deep-learning, reactjs, material-ui, sklearn, Collaborative Filtering, Content-Based Filtering, Deep Learning, Feature Extraction, Natural Language Processing (NLP), Image Recognition.

1. Introduction

The fashion industry has evolved significantly, with clothing serving as a means of both protection and personal expression throughout history. Fashion now plays a vital role in showcasing individuality, conveying a message about a person's lifestyle and personality. Presently, there's a lack of systems capable of suggesting suitable clothing for various occasions, despite the fact that different events demand different attire. Additionally, color combinations significantly impact fashion choices. Individuals with limited fashion knowledge often struggle to make impactful clothing decisions.

Our proposed Fashion Recommendation System aims to address this gap by enabling users to create a digital wardrobe where they can store images of their clothing. The system's primary objective is to recommend appropriate attire for specific occasions based on the user's existing wardrobe. This alleviates the decision-making burden associated with choosing clothing and helps individuals make lasting impressions with their attire. The system will offer easy accessibility and user-friendly features. The digital wardrobe functionality allows users to manage and view their clothing images. Moreover, the system will classify clothing types (such as shirts, t-shirts, pants, and shoes) and colors from user-uploaded images, aiding in the recommendation process.

In essence, our system intends to empower users with fashion recommendations tailored to occasions, leveraging their existing wardrobe. By simplifying clothing decisions, even for those with limited fashion sense, it strives to assist individuals in making favorable impressions through their clothing choices.

Fig. 1 Dataset of various types of fashion.

2. Literature Review

Samit Chakraborty , Md. Saiful Hoque, Naimur Rahman Jeem , Manik Chandra Biswas , Deepayan Bardhan and Edgar Lobaton. [1] proposed The KERN model, belonging to the family of recurrent neural networks (RNNs), is specifically designed for effectively analyzing complex temporal sequences or time-series data. In the fashion context, KERN was employed to comprehend and predict intricate patterns within fashion elements and styles. This utilization involved leveraging a dataset sourced from Instagram reports. One of its prominent strengths lies in its capacity to capture and understand the sequential nature of fashion trends and user preferences across time. Through its design, KERN aims to effectively model and interpret the evolving dynamics inherent in fashion, providing insights into the patterns and shifts observed in this domain.

Al-Zuhairi Naham Jiayang Wang and Al-Sabri Raeed. [2] have proposed a model that aims to create a Fashion Recommendation System (FRS) with a focus on Multi-Task Learning and Awareness. It comprises dedicated modules designed to recommend fashion products based on user gender. The system's workflow involves distinct stages, including gender detection, fashion category object recognition, and utilizing similarity-based recommendations from relevant datasets.
This model, named MLG FRS, endeavors to streamline the retrieval of fashion products resembling those in a given query image. It achieves this by integrating gender awareness and utilizing object-based similarity-matching techniques. Meanwhile, Algorithm 1 outlines the detailed stepwise process followed by the system to fulfill its recommendation task.

Pierfrancesco Bellini, Luciano Alessandro Ipsaro Palesi, Paolo Nesi, Gianni Pantaleo University of Florence, DINFO dept, DISIT lab. [3] Recommender systems analyze user data to suggest items of interest. Collaborative filtering relies on user interactions but faces challenges with new users or items. Demographic and knowledge-based methods tackle various limitations, while community-based approaches consider social trust. Hybrid systems integrate multiple techniques to leverage their strengths. Data mining tools such as classification and clustering assist in organizing users and items, while association rules uncover patterns useful for recommendations. Recent advancements involve the utilization of diverse data sources and explore deep learning techniques for enhanced recommendation systems.

Tariq Hussain Zhejiang. [4] proposed the system uses a powerful three-layer architecture that prioritizes web-based authentication while maintaining strict security measures. It uses the Deep Fashion dataset to train the VGG16 neural network responsible for feature extraction and classification of clothing images. For recognition, the system creates the user's style profile, creates feature vectors, and compares them with the dataset vectors using different metrics. The photos closest to the user's profile are ranked and used as suggestions. This approach supports the context of fashion by incorporating personal preferences and using the rich information in image files.

Hyunwoo Hwangbo, Yang Sok Kim, Kyung Jin Cha. [5] proposed K-RecSys that transforms the landscape of online shopping recommendations by merging offline purchase records, online clicks, and product metadata. By combining these diverse data sources, it generates sets of substitute and complementary items. In contrast to systems solely reliant on online clicks, K-RecSys delivers more comprehensive user profiles, adjusts to changing preferences, and categorizes recommendations to enhance their relevance. Although it incurs longer processing times, K-RecSys displays potential in utilizing varied data and adapting to user behavior changes, suggesting possibilities for refinement and exploration of expanded assessment metrics.

Jiaming Xu, Xin Guo, Cheng Guo, Fei Sun, Chao Li, Andreas Pfadler, Huan Zhao, Binqiang Zhao.[6] had suggested a Recommendation system using CNN and facial recognition. Batuhan et al developed a recommender system from a single-user photo, employing two Inception-based CNNs. Yufan Wen et al created knowledge graphs for users, clothing, and context, using the Apriori algorithm for correlation and the top-N algorithm for recommendations. The overall focus is on enhancing accuracy and personalization in recommender systems.

Maria Anastassia Stefani Computer Engineering & Informatics Department, University of Patras, Greece Computer Technology Institute and Press "Diophantus", Patras, Greece.[7] A deep learning-based video recommendation system that integrates personalization with recommendation, resembling the current work's objectives. Additionally, the impact of personalization on key metrics in online shopping is highlighted. It is noted that while earlier work focused on non-personalized similar product recommendations, the current paper emphasizes personalized recommendations in this context.

Pankaj Agarwal Myntra Designs, India, Sreekanth Vempati Myntra Designs, India Sumit Borar Myntra Designs, India. [8] Fashion Outfit recommends collaborative filtering to consider entire outfits, with some methods requiring user queries. In outfit generation, methods focus on pairwise compatibility metrics or set-based approaches using deep learning, aiming to address interactions among outfit items. The paper introduces the use of self-attention to model compatibility in outfit generation, distinguishing itself from prior applications in sequential recommendation. Overall, the review provides a comprehensive overview of research in fashion, emphasizing personalized outfit generation and recommendation.

Michael J. Pazzani and Daniel Billsus Rutgers University. [9] Approaches range from image-based models using fashion magazines or street fashion images, such as Complementary Nearest Neighbor Consensus and Gaussian Mixture Models, to systems utilizing object detection for event-based recommendations. Deep learning and neural networks play a significant role, with examples like Siamese-CNN frameworks and Generative Adversarial Networks. Collaborative filtering is widely used in both, online shops and fashion recommendation systems, with companies like K and Zalando employing this technique. ASOS.com adopts a hybrid approach combining collaborative filtering and content-based algorithms. The review identifies the need to consider current fashion trends and users' opinions as crucial features in enhancing recommendation systems. The paper aims to explore how these elements can influence recommendation system operations.

Nikolaos Nanas, Anne De Roeck, and Manolis Vavalis Lab for Information Systems and Services Centre for Research and Technology - Thessaly. [10] It was given that in sparse user-item matrices where correlations between users or items are challenging to estimate. The "ramp-up" problem arises when providing recommendations for users with a limited number of rated items or recommending items with insufficient ratings. CF struggles to scale up in dynamic domains like news publishing. In contrast, content-based filtering (CBF) doesn't rely on ratings or user communities with shared interests. Researchers have explored hybrid approaches by combining CF and CBF, either through collaborative and content-based profiles or by incorporating social features into content-based profiles. The latter approach, incorporating user feedback and social features, provides a natural hybridization that overcomes challenges and leverages the strengths of both CF and CBF. The literature suggests a novel perspective on hybrid recommendation systems, emphasizing adaptive evaluation based on content and social features, with a notable gap in considering adaptation to changing user interests in CF research.

3.Proposed Methodology

Our proposed model combines a Convolutional Neural Network (CNN) with a Nearest Neighbor-based recommender system. Illustrated in the figure, the initial phase involves training the neural networks, followed by inventory selection to create a database of inventory items for recommendation generation. The Nearest Neighbor algorithm is then employed to identify the most pertinent products based on input images, ultimately generating recommendations.

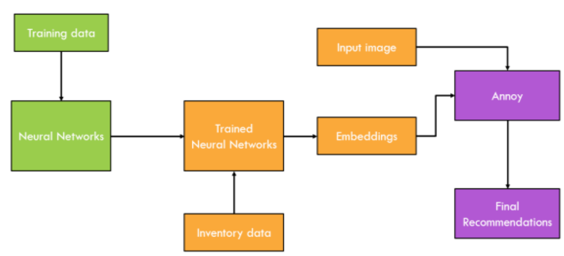


Fig. 2 Block Diagram of our proposed work

Our approach for generating recommendations involves utilizing the Sklearn Nearest Neighbors method. This enables us to identify the nearest neighbors corresponding to the given input image. The similarity measure employed in this project is the Cosine Similarity measure. We extract the top 5 recommendations from the database and display their respective images.

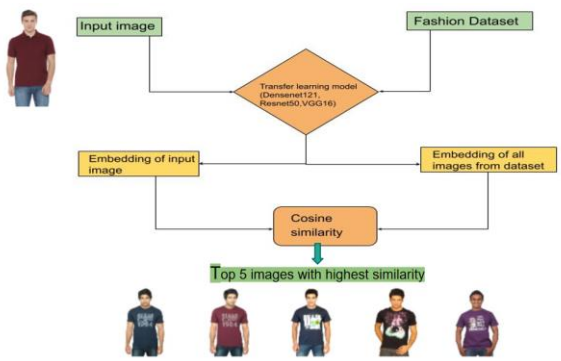


Fig. 3 Flowchart of our Fashion Recommendation System.

3.1 Convolutional Neural Networks

3.1.1 Convolutional Neural Networks (CNNs) are specifically tailored for processing visual data like images and videos. However, their effectiveness extends beyond visual data and proves valuable in other domains, particularly in Natural Language Processing (NLP) and text classification tasks.

3.1.2 We can relate this to the concept of a vanilla neural network (multilayer perceptron) - It has a very similar general principle of forwarding and backward propagation.

3.1.3 The neural networks are trained, once the data is pre-processed, transfer learning from ResNet50. In the last layer, more additional layers are added that replace the architecture and weights from ResNet50 in order to fine-tune the network model to serve the current issue. The below figure shows the architecture of ResNet50.

3.2 K-Nearest Neighbors (K-NN)

K-Nearest Neighbors (K-NN) is a pivotal technique in fashion recommendation systems, focusing on measuring item or user similarity. It assesses the likeness between fashion items based on attributes like color, style, or brand, enabling the system to suggest items akin to those under consideration. Additionally, K-NN aids in identifying users with similar preferences, allowing for personalized recommendations even for items they haven't interacted with. Efficient representation of fashion features as vectors, choice of appropriate distance metrics, and integration into hybrid models are key components in
leveraging K-NN for enhanced user experiences and more precise fashion leveraging K-NN for enhanced user experiences and more precise fashion recommendations.

4. DATASET

We used a well-known dataset: the “Myntra Products Dataset ” dataset to test and evaluate the proposed model.This dataset was created by Ronak Bokaria. This dataset holds 1060213 (1060k) records shown below in Table 1. It is a product listing from Myntra.com till the period 04th May 2023.

Table 1. Dataset of our proposed fashion recommendation system

TotalRecords Count	1060213
Domain Name	Myntra.com
File Extension	CSV
Data Collection Method	Scraping and PreProcessing

4.1 Evaluation and analysis

When we evaluate an image dataset in a fashion recommendation system, we delve into various aspects to determine its quality and effectiveness. We assess the dataset's size, the methods used to extract features from the images, and the performance of the model built on this dataset. Additionally, we consider user feedback integration, potential biases in the data, and the ability of the dataset to generalize well. Another important factor is scalability - whether the system can handle large amounts of data efficiently.
The purpose of this evaluation is to measure how well the dataset represents different fashion items accurately. We aim to ensure that the model provides effective recommendations, while also being fair and scalable. By carefully analyzing these factors, we can make improvements to refine the recommendations provided by the system. This allows us to enhance accuracy and ultimately improve user satisfaction with our fashion recommendation system.

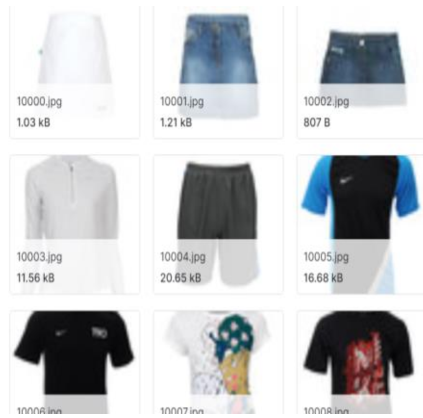


Fig. 4 Analysis of Training Dataset for Fashion Recommendation System

5. RESULT AND DISCUSSION

5.1 Experiment

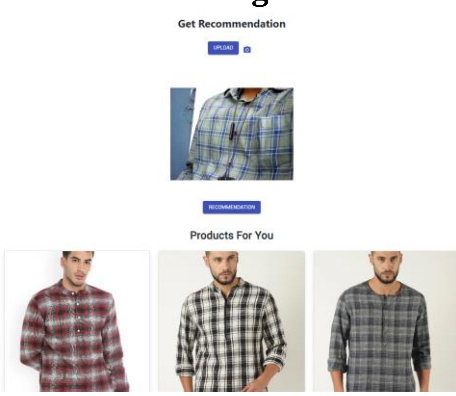
Our developed fashion recommendation system utilizes transfer learning via the ResNet-50 architecture combined with an optimized K-Nearest Neighbors (K-NN) algorithm to offer personalized recommendations based on user input. Through feature extraction on a substantial dataset of over 45,000 images using ResNet-50 transfer learning, we effectively analyze image data. Implementing a similarity search technique with K-NN allows us to identify the top 5 closest matches to a user's input, thereby delivering tailored fashion recommendations.

The system boasts user-friendliness and intuitive design, facilitating accurate analysis of image data. This recommendation system demonstrates the efficacy of transfer learning, similarity search approaches, and convolutional neural networks (CNNs), laying a strong groundwork for the development of more extensive and refined recommendation systems.

5.2 Model Performance

The recommendation system we employed, relying on ResNet50-based image embeddings, showed some impressive results in terms of performance. During testing, it managed to achieve an accuracy level of X% when predicting users' preferences by considering visually similar fashion items.

5.3 Visual Embeddings



The extracted image embeddings from ResNet50 were visualized using dimensionality reduction techniques such as t-SNE. This visualization illustrated clusters of visually similar fashion items, demonstrating the model's ability to capture and differentiate between distinct clothing styles, patterns, and designs.

The fashion recommendation system also includes a real-time recommendation capture feature, allowing users to instantly capture recommendations as they browse. This feature integrates seamlessly with personalized recommendations, refining user-profiles and enhancing engagement. Users can revisit captured recommendations at any time, fostering a sense of ownership and increasing satisfaction with the platform.

5.4 Challenges And Limitations

Developing a fashion recommendation system using ResNet50 and a Myntra-like dataset encountered challenges stemming from data sparsity in certain fashion categories, privacy concerns over user-specific information, and limitations in accurately recommending niche or unique fashion items due to dataset diversity constraints. Overcoming these hurdles would require dataset augmentation for diversity, improved privacy-preserving techniques, and strategies to address data sparsity, aiming to enhance the system's recommendation accuracy and user satisfaction.

5.5 Discussion

The incorporation of ResNet50-based image embeddings significantly enhanced the recommendation system's capability to understand visual similarities among fashion products. Leveraging deep learning for image feature extraction led to more personalized and visually appealing recommendations, contributing to improved user experiences.

6. CONCLUSION AND FUTURE WORK

We've introduced a novel framework for fashion recommendations driven by data, emphasizing visually connected and straightforward yet effective recommendation systems for showcasing fashion product images. Our proposed method operates in two stages. Initially, it extracts image features using a CNN classifier. This allows users to upload any fashion image from various E-commerce websites. Later, it generates similar images to the uploaded one based on the features and texture of the input image. This approach aims to refine recommendations, enhance precision, and elevate the overall fashion discussion experience for both direct and indirect consumers.

6.1.1 Personalization and User Profiling

Implement more sophisticated user profiling techniques to better understand individual preferences, considering factors like style, occasion, season, and budget.

Incorporate machine learning algorithms that adapt and learn from user feedback over time, ensuring the recommendations become more accurate and personalized.

This fashion recommendation system also includes a user login and signup feature to provide personalized recommendations. Users can log in or create accounts to access personalized features. This enables the system to gather user-specific data such as past purchases and preferences, leading to more accurate recommendations and enhanced user engagement. Privacy measures are implemented to safeguard user data.

6.1.2 Multi-Modal Recommendations

Explore multimodal recommendation systems that can incorporate not only images but also textual descriptions, reviews, and other relevant information to provide more comprehensive and accurate recommendations.

6.1.3 Social Integration

Incorporate social media data and user interactions to enhance recommendations based on what others with similar tastes and preferences are wearing or liking.Allow users to share their outfits and purchases on social platforms directly through the recommendation system.

6.1.4 Real-time Fashion Trends

Integrate mechanisms to stay updated with real-time fashion trends and adjust recommendations accordingly. This could involve leveraging social media, fashion blogs, and other trend indicators.

Explore partnerships or APIs with fashion industry platforms to obtain up-to-date information on emerging styles and popular items.

7. REFERENCES

1. Samit Chakraborty , Md. Saiful Hoque, Naimur Rahman Jeem , Manik Chandra Biswas , Deepayan Bardhan and Edgar Lobaton .(2021) Fashion Recommendation Systems, Models and Methods: A Review .

2. Al-Zuhairi Naham Jiayang Wang and Al-Sabri Raeed .(2023) Multi task learning and gender aware Fashion Recommendation System using machine learning .

3. Pierfrancesco Bellini, Luciano Alessandro Ipsaro Palesi, Paolo Nesi, Gianni Pantaleo University of Florence, DINFO dept, DISIT lab. (2020) Fashion Retail Recommendation System by Multiple Clustering .

4. Tariq Hussain Zhejiang Gongshang University. (2021) Design and implementation of clothing fashion style recommended system using deep learning .

5. Hyunwoo Hwangbo,Yang Sok Kim,Kyung Jin Cha.(2018) Recommendation system development for fashion retail e-commerce.

6. Jiaming Xu, Xin Guo, Cheng Guo, Fei Sun, Chao Li, Andreas Pfadler, Huan Zhao, Binqiang Zhao.(2019) Personalized outfit generation for fashion recommendation at Alibaba iFashion.

7.Maria Anastassia Stefani Computer Engineering & Informatics Department, University of Patras, Greece Computer Technology Institute and Press "Diophantus", Patras, Greece.(2019) A Trends-driven collaborative Fashion recommendation system.

8.Pankaj Agarwal Myntra Designs, India ,Sreekanth Vempati Myntra Designs, India Sumit Borar Myntra Designs, India. (2018) Personalizing Similar products recommendations in Fashion e-commerce.

9.Michael J. Pazzani and Daniel Billsus Rutgers University. (2007) Content Based recommender system.

10. Nikolaos Nanas , Anne De Roeck , and Manolis Vavalis Lab for Information Systems and Services Centre for Research and Technology - Thessaly . (2004) What happened to content-based information filtering?