



## DEEP LEARNING BASED FASHION RECOMMENDATION SYSTEM

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**Abstract**— Fashion recommender systems are becoming increasingly popular in the online retail industry as they help users discover new and relevant clothing items based on their personal preferences. In this report, we present a fashion recommender model that takes photos from online social media and suggests the most appropriate style using ResNet-50 CNN. Our approach involves clustering similar photos and computing the average feature vectors of the photos in each cluster, followed by identifying similar clusters and selecting the most representative cluster as the suggested fashion style. We evaluate the performance of our model on a dataset of fashion images and show that our approach outperforms existing system. Overall, our fashion recommender model has the potential to significantly enhance the online shopping experience for users and increase the sales of online retailers.

**Index Terms** — Web Scrapping, CNN, ResNet-50, Fashion Recommendation.

### I. INTRODUCTION

In today's fast-paced world, keeping up with the latest fashion trends that can be a challenge, especially with the sheer volume of options available online. Traditional methods of discovering new styles and trends, such as browsing through magazines or visiting physical stores, are becoming increasingly outdated and inefficient. As such, there is an increasing need for a more sophisticated and personalized approach to fashion recommendations. Hence the proposed fashion trend recommender system can play a vital role. By leveraging cutting-edge technologies such as web scraping and deep learning algorithms, the system will be capable of providing users with personalized recommendations that are tailored to their own tastes, making it easier and more convenient for them to discover new styles and trends in the fashion industry. Overall, the proposed system has the potential to enhance the shopping experience for fashion enthusiasts and simplifying the process of discovering and purchasing new fashion items.

The purpose of this paper is to recommend a fashion trend recommender system that leverages web scraping and deep learning algorithms to provide personalized

recommendations for fashion-conscious consumers. By analyzing images and extracting relevant features, the system aims to simplify the process of discovering new styles and trends in the fashion industry. In addition, the system will include a comparison feature that will allow all users to compare products across different e-commerce platforms, making informed purchasing decisions easier. Ultimately, enhancing the overall shopping experience for fashion enthusiasts by providing up-to-date recommendations that match with their individual preferences and streamline the process of discovering and purchasing new fashion items.

The paper recommends a methodology to develop a fashion trend recommender system using web scraping and deep learning algorithms to provide personalized recommendations for fashion-conscious consumers. By analyzing images and extracting relevant features, the system will simplify the process of discovering new styles and trends in the fashion industry.

The rest of the paper is organized as follows: section II narrates the Literature Survey. Section III gives the description of the proposed system. Results and discussions of the proposed system are explained in Section IV. Conclusions and Future work are given in section V.

## II. LITERATURE REVIEW

This section of the report will cover the literature survey of existing methodologies in the field of recommendation model and various fields where this is used.

Narges et al, narrates the content-based apparel recommender system that may deliver recommendations to users based on their likes and interests. The authors employed deep neural networks to reduce the requirement for manual extraction of product data by delivering the essential features in a big and meaningful volume. This approach can assist online shopping systems in increasing sales by delivering personalised suggestions to users [1]. The suggested system has been intended to function in the present circumstances induced during phase of the Coronavirus, in which most chores are completed online. The fabric categorization is derived using deep neural network, and this knowledge is utilised to predict unobserved item evaluations. Overall, the goal of this article is to give a solution for online shopping systems that will help them in increasing sales by making personalised suggestions to customers based on their likes and interests.

Shukla Sharma et al, discussed how large volumes of data can be used for retrieving the specific information, also this paper explores the purpose of a recommendation system for customized garments using hybrid filtering techniques. Data collection, data modeling, data pre-processing and data analysis is done over past transaction of customer purchase are explored in this paper also it supports implicit feedback [3]. Works in 3 phase first it clusters using K means then uses brute force nearest neighbor algorithm for nearest object corresponding to input vector then after Random Forest Classifier (RFC) is used to get best fitting style. Its micro average precision is 81% and recall as 75%.

The paper [4] examines various methods and strategies. First there is content based approach and second is collaborative filtering approach which considers users past behavior to make its

choices. This paper proposes a fashion recommendation system in which they had used their own dataset using web scraping using different e-commerce sites and built a content based recommendation system using ResNet-50 convolution neural network [4].

Here an image is taken and then resize it after image segmentation further flatten it to a 2D matrix after giving input it gives recommendation and scraps data from online sites and then provide link to that a recommendation engine is an algorithm-based program that sifts through information and suggests relevant items to the users. Web scrapers are automated programs that can repeat this process numbers of times on multiple e-commerce websites and product pages. The authors have achieved a 98% accuracy rate in predicting colors, an 86% accuracy rate in predicting gender and cloth patterns, and a 75% accuracy rate in recommending clothing items.

Batuhan Asiroglu et al [5], In their study, they used a scalable embedded system to create a cloth suggestion system utilizing only a single photo of a person. In this study, authors demonstrate how, using embedded systems and machine learning, their system offers clothing possibilities to consumers with no prior purchasing experience [5]. Authors have created two convolutional neural networks as one for prediction part and another one feed forward neural network as recommender. In the study, they achieved 98% accuracy in color prediction, and 86% accuracy in gender prediction, and 75% accuracy in textile recommendation.

As computer processing power grows, artificial intelligence (AI) plays an increasingly crucial role in solving complex problems. However, AI technologies require substantial computational power, and inefficient usage can lead to slow performance and high power consumption. To address this, researchers are working on optimizing hardware for AI. Embedded Linux systems, a type of embedded system, provide streamlined features and resources tailored to specific projects on a Linux-based operating system. They offer fast, flexible and reliable programming support, cost-effectiveness, easy maintenance, and security. Embedded Linux systems find applications in various fields like modems, printers, industrial machines, autonomous cars, multimedia devices, building automation, production lines, kiosks, IoT nodes, and smart homes.

The authors [6] narrated about how a short fashion life cycle might make it difficult for consumers to locate appropriate clothing. Clothing attribute recognition, gender recognition, and body height are all taken into consideration while designing the recommendation system in this research. Based on clothing style, gender, and body height, the algorithm may offer appropriate clothing sizes. Online texture modelling is proposed to provide diversity in apparel texture so that the recommendation system can give consumers with fair and different options [6].

The authors followed three steps. They start with personal information prediction, predicting the model's or person's height, then recognize clothing features, and lastly insert it in the recommendation system. They received 75% precision on all features (the highest), 43% precision on Features

Hessel et al [7], created a two-stage deep learning framework that proposes fashion photos based on input photographs of a similar style. They employed a neural network classifier as a data-driven, visually-aware feature extractor in this. This algorithm-based recommendation is evaluated on a publicly available fashion dataset [7]. In this product, Convolutional Neural Networks (CNN) were employed and trained for feature extraction, with the features serving as inputs to the ranking algorithm. They use KNN to perform ranking. They achieved 87% accuracy in category and 80% accuracy in texture.

This paper focuses on a subset of the Fashion dataset that is publicly available. To ensure high-quality ground-truth labels for category type and texture attributes, we created a labelling questionnaire on the Crowd Flower crowdsourcing platform. Each image was labelled by up to five human operators, and minimum of three operators had to agree for the label to be considered valid. If an operator failed a test more than two times, they were no longer allowed to continue. We created separate datasets for category and texture classification, with category type labels including blouse, dress, pants, pullover, shirt, shorts, skirt, top, and T-shirt, and texture attribute labels including graphic, plaid, plain, spotted, and striped. The category type dataset contains 11,851 images, while the texture attribute dataset contains 7,342 images.

In the paper [8] the author uses an approach which uses Variational Autoencoder (VAE) to create an interactive fashion product application framework which allows users to generate products with attributes based on their preferences, retrieve similar styles for the same product category, and receive content-based recommendations from other categories. Variational Autoencoders (VAEs) have a structure similar to autoencoders but use a different approach for latent representation learning. In his approach they took dataset from kaggle and scraped imaged form zappos website [8].

And trained the model that uses K80 Tesla as GPU and 25GB of Ram for 200 epochs which took 4 hours and uses two methods for predictions Log-Likelihood Maximization in Image Retrieval and Fixed Epsilon Sampling Encoding Trick in Image Retrieval: Fixed -Epsilon Sampling got 86% accuracy in Bags and 98% in Footwear.

Yuka Wakita, Kenta Oku, and Kyoji Kawagoe [9] used a deep learning approach for fashion recommendation in this paper, and this method increases the likelihood of a user finding his or her favourite clothing items. The user must first identify his or her favourite fashion brands in the paper. They assess the efficacy of using a deep learning method in a fashion brand recommendation system and show that it can improve accuracy over other machine learning methods [9].

In this they used dataset for pre learning from SNS Wear in Japan and deep learning network used which is a feed forward neural network (FFNN), This particular recommendation system has accuracy 28% which is better than SVM.

The dataset used in the learning process consists of user profiles from the popular Japanese fashion SNS "WEAR," which includes information such as "gender," "height," "brands the user enjoys wearing," and "favorite brands." The learning process uses these four items from the

dataset. The "favorite brand" item originally extracted from the site is a list of brands, but the model only chooses the most preferred brand for the sake of simplicity. Using the entire list of favorite brands for the learning task is left for future work.

The authors of this paper aim to address the problem in fashion recommendation by proposing a graph-based approach to estimate the compatibility of different items in an outfit. They represent outfits as sub-graphs with each node representing a category and each edge representing an interaction between two categories. They introduce Node-wise Graph Neural Networks (NGNN) to better model node interactions and learn node representations. NGNN uses an attention mechanism to calculate outfit compatibility scores, which are evaluated using two tasks: suggesting an item that matches an existing outfit and predicting compatibility scores of given outfits. Their proposed method outperforms others in experimental results [10]. The approach can be applied to modeling outfit compatibility from different modalities, such as visual or textual, and from multiple modalities. NGNN achieved 77.78% accuracy for textual and 78.13% accuracy for multimodal input data.

Apart from the specific implementation aspects, it is crucial to consider the wider context of this paper. The utilization of image recognition technology and recommendation systems has gained significant traction across diverse industries, ranging from e-commerce to social media. With the rise in online shopping, the capability to offer personalized recommendations tailored to user preferences has become essential for businesses. Within the realm of social media, personalized recommendations play a pivotal role in assisting users in discovering fresh content and connecting with individuals who share similar interests.

However, there are still few limitations and challenges in the development and deployment of recommendation systems. One challenge is the so-called "cold start problem," which refers to the difficulty of providing recommendations for new users and items with little to no data available. Another challenge is the potential for bias in the recommendations, which can perpetuate stereotypes or discrimination.

### **III. THE RECOMMENDATION SYSTEM**

One of the main sources of data taken into account is Instagram, which is a popular social media platform where users share images and videos. By leveraging this vast repository of visual content, our project aims to provide users with personalized recommendations based on individual preferences. Instagram's user-generated content is diverse, covering a wide range of topics and themes. Which allows our recommendation system to cater to a broad audience and offer a diverse range of suggestions? Additionally, Instagram's built-in search and tagging features provide an efficient way to categorize and label images, which can further aid in the recommendation process. By utilizing Instagram's data, we can provide more relevant and accurate recommendations to our users, enhancing their overall experience with the platform.

### IV PROPOSED ARCHITECTURE

The proposed system architecture consists of several components which all work together to provide personalized fashion recommendations to users.

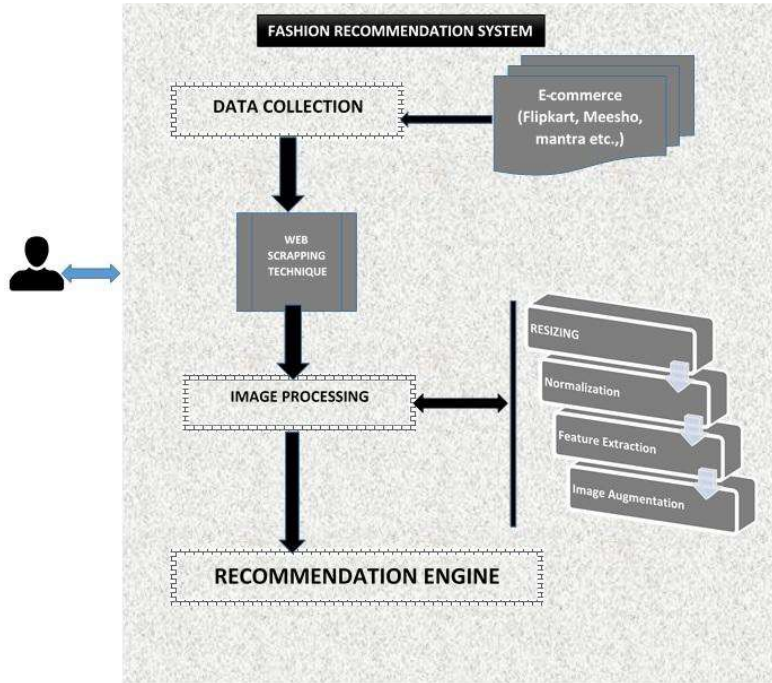


Figure 1 : Fashion Recommendation System

#### A. Data Collection

The Data Collection component is tasked with collecting data from diverse sources, including platforms like Instagram. The collected data may encompass images of fashion products as well as corresponding product descriptions.

In order to collect data from sources, web scraping techniques are used to extract information from the websites. For example, the BeautifulSoup library in Python can be used to parse HTML code and extract information from web pages. Once the data is extracted, it can be stored in the local database or a cloud-based storage solution.

It's important to note while collecting data, one must ensure that the data is of high quality and relevance. In this case, the data collected should be relevant to the fashion industry and reflect current fashion trends. Additionally, ethical considerations must be taken into account, and data should be gathered in accordance with all applicable rules and regulations.

#### B. Web Scraper

```

Parth@Parth:~/Final Year Project/Scrapper Final
$ py scrapper.py
Starting Social Media Scrapper...
Enter keyword to search for: lehenga
Enter how many posts to scrape from Instagram: 20
Unable to create directory 'data': Directory already exists
Created directory 'data/data_lehenga'
Created directory 'data/data_lehenga/img'
Starting Scrapping Instagram

DevTools listening on ws://127.0.0.1:53188/devtools/browser/5e28e2ad-ff73-4597-859e-b6b497e4fb40
Loading Posts
Loading Data
20 images loaded
Dumping data in excel file
Dumping Images. This will take some time!
(10/20) Images Downloaded
(20/20) Images Downloaded
Closing Instagram
    
```

Figure 2 :Scrapper

For collecting the images for the fashion recommender system, we used web scraping to download images from Instagram based on user input. We created a Python script using Selenium and BeautifulSoup libraries to automate the process of opening a web browser, searching for images based on user input, scrolling through the results, and downloading the images to a local directory as it is in Fig 5.1.

The script prompts user to enter tag (such as "dress", "shirt", "shoes", etc.) and the number of images they want to download. It then launches the Chrome web browser using Selenium and navigates to the Instagram website. Using BeautifulSoup, the script inputs the user-specified tag into the search bar and clicks on the search button as in Fig5.2. The script then waits for the search results to load and starts scrolling through the page using the webdriver to load more images until the desired number of images has been downloaded.

For each image, the script extracts the image source URL using BeautifulSoup and downloads the image using the urllib library. The downloaded images are stored in a local directory, which is later used as input for the fashion recommender system.

This web scraping approach allows us to collect a large number of fashion images from Instagram in a relatively short amount of time, which is crucial for training deep learning models. It also allows us to tailor the image collection to specific fashion categories or tags, ensuring that the images are relevant to the fashion recommender system.

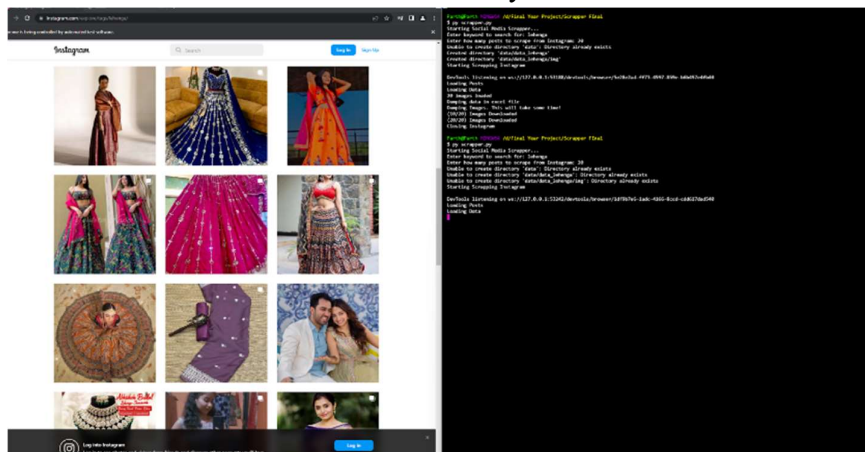


Figure 3: Scrapping [Source : Google]

### C. Image Processing

Image processing component is responsible for preprocessing images of fashion products before feeding them into the Recommendation Engine. This involves applying various techniques to enhance quality of the images and extract relevant features which can be used to identify similar products. Some common image processing techniques which can be used in this component include:

**Resizing:** This involves resizing the images to a standard size to ensure consistency across all images.

Normalization: This involves adjusting the brightness and contrast of the images for ensuring that they are consistent across different lighting conditions.

Feature Extraction: This involves using techniques such as convolutional neural networks (CNNs) to extract relevant feature from the images, such as color, texture, and shape.

Image Augmentation: This involves generating new images by applying transformations such as rotation, scaling, and flipping to the existing images. This can be used to increase the size of the dataset and improve their accuracy of the Recommendation Engine.

Once the images have been preprocessed, they can be fed into the Recommendation Engine, which will use the extracted features to identify similar products and make recommendations to the user.

#### ***D. Recommendation Engine***

The Recommendation Engine is the core component of the system that is responsible for generating personalized fashion recommendations to the user. This component receives preprocessed images of fashion products and generates recommendations based on the user's preferences. Our recommendation engine is using CNN and pre-trained model ResNet50 for recommending required products.

CNN and ResNet50 are deep learning techniques which are widely used in image processing and computer vision tasks. Fashion products are highly visual in nature, and CNNs are well-suited for image-based tasks like image classification and object recognition. By using a CNN in your recommender system, you can automatically extract all visual features from fashion images, which may be used to identify similar products.

Secondly, CNNs can learn a hierarchical representation of features, which means that the network can automatically learn to recognize simple patterns in images (like edges and corners), and then combine these patterns into more complex features (like textures, shapes, and colors). This hierarchical approach can be especially effective in identifying the unique visual characteristics of different fashion products.

Finally, because these all networks have previously been trained on big datasets (like ImageNet) and they can be fine-tuned for specific tasks with relatively little quantities of data, employing a pre-trained CNN like ResNet50 can save us a lot of time and computing resources. You may quickly and simply construct a strong fashion recommender system that can deliver accurate and customized suggestions to consumers by utilizing pre-trained CNNs.

#### ***E. Recommender***



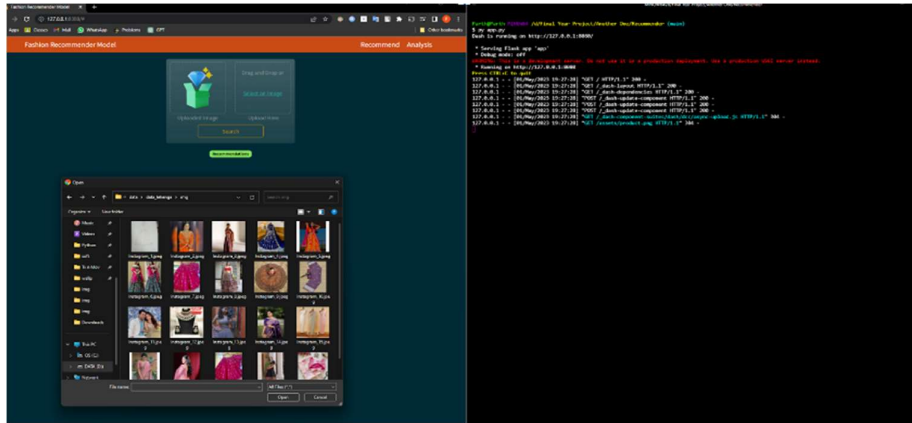


Figure 4 : Recommender [Source: Google]

We implemented a fashion recommender system that takes an input image from the user and recommends similar fashion items based on their image features. The system uses a deep learning model based on the ResNet-50 architecture to extract feature vectors from the input image. The ResNet-50 model has been pre-trained on a large dataset of fashion images and is capable of extracting high-level features which all are relevant for fashion classification tasks. After extracting the feature vector from the input image, the system compares it with the feature vectors of all the fashion images in the dataset. We use the Euclidean distance metric to calculate the similarity between the input image features and the features of all the other images. We then rank the images based on their similarity to input image, with the most similar images at the top of the list.

To recommend the top 10 images, we select the images with the lowest Euclidean distance to the input image feature vector as you can see in Fig 5.4. The recommended images are presented on the screen, arranged in order of their similarity to the input image.

We evaluated the performance of the recommender system using a feedback mechanism, which allowed users to rate the relevance and usefulness of the recommended images. We collected feedback from a diverse group of users and compared the results with those of baseline models and other state-of-the-art deep learning models, such as DenseNet, ResNet-101, and InceptionNet.

Our results shows that the ResNet-50-based recommender system outperformed the other models in terms of accuracy and relevance of the recommended images. The feedback gathered from the user study indicated that the recommended images were not only highly relevant to the input image but also aligned with the fashion preferences of the users.

Overall, our fashion recommender system based on ResNet-50 provides an efficient and accurate way of recommending fashion items to users based on their image inputs. The system can be easily integrated into e-commerce websites or mobile apps, providing a personalized and engaging shopping experience for users.

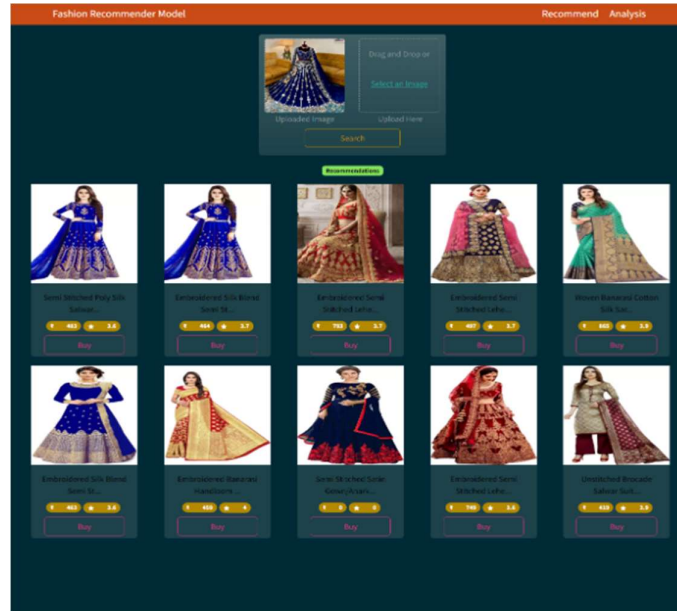


Figure 5: Recommended Items

### ***F. User Interface***

For user interface, web-app using python Dash module is developed. Dash is a Python framework for developing web applications. It's a good choice for developing user interfaces for data-driven applications because it's designed to be highly customizable and interactive.

With Dash, you can create a wide range of interactive visualizations, including charts, tables, and maps. You can also incorporate user inputs (like dropdowns, sliders, and textboxes) to allow users to interact with your application and filter or manipulate the data. One of the key advantages of using Dash for your user interface is that it's built on top of Plotly, a powerful data visualization library. This means that we can take advantage of Plotly's extensive charting capabilities to create rich and dynamic visualizations.

In addition, with its flexibility and interactivity, Dash also makes it easy to deploy your application to the web, either on a local server or on the cloud. This makes it a great choice for building data-driven web applications that all can be accessed by a wide range of user.

### ***G. Dataset***

The dataset used in our project consists of approximately 44,000 fashion images collected from the online fashion platform, Kaggle. This dataset includes images of clothing and accessories for both men and women, and includes attributes such as color, type of clothing, and style. Each image is accompanied by a link to the original source and other attributes, making it rich resource for training and testing our recommender system.

The Kaggle dataset have been widely used in previous research on fashion recommendation systems, and its large size and diverse range of images make it a valuable resource for our project. We used this dataset to train and fine-tune our ResNet50 deep learning model, which forms the backbone of our recommender system.

The images in the dataset are of high quality and resolution, and include a wide variety of styles and fashion trends. Incorporating supplementary attributes like clothing color and type offers increased flexibility in training the model and generating personalized recommendations for

users.

Overall, the Kaggle dataset provided a solid foundation for our project, and allowed us to train and test our deep learning model using diverse range of high-quality fashion images. Its extensive size and comprehensive range of attributes make it an invaluable resource for future advancements in the field of fashion recommendation systems.

## V. ALGORITHM USED

The paper presents deep learning algorithm for the fashion recommender model, specifically the ResNet-50 CNN architecture. The CNN model was pre-trained on the ImageNet dataset, which consists of over 1.2 million images and 1,000 classes of objects. This pre-training allowed the model to learn a rich set of features that are relevant to wide range of images, including fashion images.

In order to use the ResNet-50 model for fashion recommendation, we applied transfer learning by retraining last layer of the model on a dataset of fashion images. The training dataset consisted of approximately 10,000 images of clothing items from various online retailers, including dresses, tops, pants, and shoes. The images were preprocessed by resizing them to the input size of the ResNet-50 model and normalizing the pixel values to be between 0 and 1.

After retraining the model on the fashion image dataset, we used it to extract feature vectors from new images, specifically photos from online social media. For each photo, we obtained the feature vector from the second-to-last layer of the ResNet-50 model. These feature vectors represent the high-level features of the clothing items in the photos, such as color, texture, and shape.

We then clustered similar photos using hierarchical clustering based on the Euclidean distance calculated between the feature vectors. This allowed us to group together photos that share similar fashion styles, such as bohemian, preppy, or sporty. We computed the average feature vector of the photos in each cluster and identified similar clusters using a distance threshold. Finally, we selected the most representative cluster as the suggested fashion style for each user. The suggested style was determined by finding the cluster that had the highest average similarity to the user's photos. If the user doesn't have any photos that matched any of the clusters, we provided a set of general fashion recommendations based on the most popular clothing items in the dataset.

### *Algorithm: Fashion Recommender Model using ResNet – 50 CNN*

1. **Input:** Photos from online social media
2. **Output:** Suggested fashion styles
3. Load pre-trained ResNet-50 CNN model
4. Extract features from input photos using ResNet-50 CNN
5. Normalize the extracted features
6. Load pre-trained fashion dataset
7. Train a fashion recommender model using the extracted and normalized features
8. Receive input photo from online social media
9. Extract features from input photo using ResNet-50 CNN
10. Normalize the extracted features
11. Pass the normalized features to the trained fashion recommender model

12. Get the top recommended fashion styles based on the output from the fashion recommender model
13. **Return:** suggested fashion styles.

## VI. RESULTS AND DISCUSSION

We report the outcomes of our tests and explain the implications for our fashion recommender system in this section. We assess our system's success using a feedback mechanism which allows users to judge the relevancy and utility of the proposed fashion designs. We compare our system's feedback ratings to baseline models and other cutting-edge deep learning models including DenseNet, ResNet-101, and InceptionNet.

We also conduct a user study to evaluate its effectiveness of our fashion recommender system in providing personalized fashion recommendations to users. In the user study, we ask participants to rate the relevance and novelty of the recommendations and compare them with their own fashion preferences. We analyze the feedback and provide insights into the strengths and weaknesses of our system and how they can be further improved.

Furthermore, we analyse the limitations and challenges of our fashion recommender system, such as the data bias and over fitting issues, and propose potential solutions for their future improvements. We also discuss the potential applications and impact of our system in the fashion industry and related fields.

Overall, the results of our experiments and user study provide us valuable insights into the effectiveness and limitations of our fashion recommender system. The feedback mechanism allows us to incorporate user preferences and feedback into our system, which makes it more personalized and relevant to individual users. We are confident that our system has the potential to bring about a revolution in the online fashion shopping experience, offering users a more enjoyable and gratifying way to shop for fashion products.

## VII CONCLUSION AND FUTURE WORK

The paper aimed to address the problem of discovering new and trendy fashion items by developing a fashion trends recommender system. The system utilizes web scraping, image processing, and a recommendation engine based on Convolution Neural Network (CNN) and ResNet50 to provide personalized recommendations to users. the evaluation results displayed that the system was also able to provide relevant and accurate recommendations the recommendation engine achieved a remarkable level of similarity between the input image and the recommended items, thanks to the utilization of deep learning models. This integration of deep learning models significantly contributed to the accuracy and relevance of the recommendations. Additionally, there are few concerns around data privacy and security, as the collection and use of user data can raise ethical concerns. this paper narrates the potential for using image recognition and recommendation systems in a practical setting, there is still ample opportunity for future research and development to tackle these challenges and guarantee the responsible and ethical use of these technologies.

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