A
Mini-Project Report on

Image-Based Fashion Product Recommendation using Deep Learning

Submitted in partial fulfillment of the requirements
for the degree of
BACHELOR OF ENGINEERING
IN
Computer Science & Engineering
(Artificial Intelligence & Machine Learning)

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CERTIFICATE

This is to certify that the project entitled "**Image-Based Fashion Product Recommendation using Deep Learning"** is a bonafide work of Atul Gupta (21106006), Sachin Sapkale (21106026), Kapil Surve (21106018), Tanmay Buchade (21106031) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of **Bachelor of Engineering** in **Computer Science & Engineering (Artificial Intelligence & Machine Learning).**

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Project Report Approval

This Mini project report entitled "**Image-Based Fashion Product Recommendation using Deep Learning**" by **Atul Gupta, Sachin Sapkale, Kapil Surve and Tanmay Buchade** is approved for the degree of ***Bachelor of Engineering*** in ***Computer Science &Engineering***, (AIML) ***2023-24***.

External Examiner: _________________

Internal Examiner: ________________

Place: APSIT, Thane
Date:

Declaration

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ABSTRACT

Fashion product recommendation systems play a crucial role in enhancing user experience and increasing engagement within e-commerce platforms. Traditional recommendation approaches often rely solely on user-item interactions, neglecting the rich visual information inherent in fashion items. Leveraging deep learning techniques, particularly convolutional neural networks (CNNs), enables the exploitation of visual cues for more accurate and personalized recommendations.

In this study, we propose an image-based fashion product recommendation system that utilizes deep learning models to analyze the visual features of fashion items. Firstly, a CNN-based model is employed to extract high-level representations from product images. Subsequently, these embeddings are fed into a recommendation algorithm to generate personalized suggestions for users based on their preferences and browsing history. Additionally, we integrate collaborative filtering techniques to enhance the recommendation quality by considering both visual and user interaction data.

The process begins with the extraction of salient visual features from fashion items using a state-of-the-art CNN architecture, allowing the system to understand and interpret the intricate details of each product image. This approach ensures that the system captures not only the explicit features but also the subtle nuances of style, texture, and color, which are crucial in the fashion domain.

Subsequently, these embeddings are utilized within a sophisticated recommendation algorithm to generate tailored suggestions for users, taking into account their unique preferences and browsing history. By combining visual analysis with user interaction data, the system can provide more accurate and personalized recommendations, resulting in a more satisfying shopping experience. Furthermore, we integrate collaborative filtering techniques, which leverage the behavior and preferences of similar users, to further enhance recommendation quality. This fusion of visual and collaborative filtering techniques results in a more robust and effective recommendation system.

Evaluation results on real-world fashion datasets demonstrate the effectiveness and efficiency of the proposed approach, outperforming traditional methods in terms of recommendation accuracy and user satisfaction. By combining visual information with user interactions, our approach significantly improves recommendation accuracy and provides a more satisfying shopping experience. Overall, this research contributes to advancing the state-of-the-art in fashion recommendation systems, providing a scalable and adaptable solution for online fashion retailers to deliver more relevant and engaging shopping experiences to their customers.

Keywords: Product Recommendation, Deep Learning, CNN, Similiarity Recommendation.

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CHAPTER 1

INTRODUCTION

1. INTRODUCTION

In today's digital era, the fashion industry is witnessing a paradigm shift in the way consumers discover and engage with products. With the proliferation of e-commerce platforms, consumers are increasingly relying on online channels for their fashion shopping needs. Consequently, there is a growing demand for effective recommendation systems that can assist users in navigating the vast array of fashion products available online. Traditional recommendation approaches primarily leverage user-item interaction data, such as purchase history and ratings, to generate suggestions. However, these methods often overlook the rich visual information inherent in fashion items, which plays a crucial role in influencing purchase decisions.

Recognizing the importance of visual cues in fashion consumption, recent research has turned towards leveraging deep learning techniques to enhance recommendation systems. Deep learning, particularly convolutional neural networks (CNNs), has demonstrated remarkable success in image recognition tasks, making it an ideal candidate for analyzing visual content in fashion images. By extracting high-level representations from product images, deep learning models can capture intricate visual features such as color, pattern, and style, which are integral to fashion recommendation.

In this context, this paper proposes an image-based fashion product recommendation system that harnesses the power of deep learning to provide personalized and visually appealing suggestions to users. The system aims to bridge the gap between the visual characteristics of fashion items and user preferences, thereby improving recommendation accuracy and user satisfaction. By integrating state-of-the-art deep learning models with collaborative filtering techniques, the proposed system not only considers visual features but also incorporates user interactions to generate tailored recommendations.

This introduction sets the stage for exploring the significance of image-based fashion recommendation systems and highlights the potential of deep learning in revolutionizing the way fashion products are recommended and consumed in the digital landscape. Through empirical evaluation and comparative analysis, this study aims to demonstrate the effectiveness and efficiency of the proposed approach in addressing the challenges of fashion product recommendation in online retail environments.

Acknowledging the pivotal role of visual cues in fashion consumption, recent research has turned its focus towards leveraging deep learning techniques to enhance recommendation systems. Deep learning, particularly convolutional neural networks (CNNs), has exhibited remarkable success in image recognition tasks, making it an ideal candidate for analyzing visual content in fashion images. By extracting high-level representations from product images, deep learning models can capture intricate visual features such as color, pattern, and style, all of which are integral to fashion recommendation.

1.1 Objectives:

1. Develop an Image-based Fashion Recommendation System:
    - Utilize deep learning, particularly CNNs, to analyze visual content in fashion images and provide personalized suggestions.
2. Bridge the Gap Between Visual Characteristics and User Preferences:
    - Integrate visual features with collaborative filtering techniques to enhance recommendation accuracy and user satisfaction.
3. Provide Personalized and Visually Appealing Suggestions:
    - Develop a system that offers visually appealing suggestions by extracting high-level representations from product images.
4. Demonstrate the Effectiveness and Efficiency:
    - Conduct empirical evaluation to demonstrate the proposed approach's effectiveness in addressing the challenges of fashion product recommendation.
5. Revolutionize Fashion Product Recommendation:
    - Explore how deep learning can revolutionize the way fashion products are recommended and consumed in the digital landscape.

1.2 Scope:

1. Data Collection and Preprocessing:
    - Gather a comprehensive dataset of fashion images, including diverse styles, colors, and patterns.
2. Model Development:
    - Develop a deep learning model based on convolutional neural networks (CNNs) to extract visual features from fashion product images.
3. System Implementation:
    - Implement the image-based fashion recommendation system, integrating the developed deep learning model with the collaborative filtering approach.

CHAPTER 2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 HISTORY

The history of fashion recommendation systems has evolved alongside advancements in technology and the increasing demand for personalized shopping experiences. Initially, recommendation systems in the fashion domain relied heavily on collaborative filtering techniques, where user-item interactions were analyzed to provide suggestions. These early systems, although effective to some extent, often struggled to capture the nuanced preferences of users and lacked the ability to incorporate visual cues inherent in fashion items.

With the advent of deep learning and the rise of image recognition technology, a new era of fashion recommendation systems emerged. Researchers and industry practitioners began exploring the potential of convolutional neural networks (CNNs) to extract rich visual features from fashion images. This marked a significant shift towards image-based recommendation systems, where the visual appeal and style of fashion items became integral to the recommendation process.
In recent years, companies in the fashion industry have embraced image-based recommendation systems to enhance the online shopping experience for their customers. By leveraging deep learning models trained on vast collections of fashion images, these systems can analyze visual attributes such as color, pattern, and style to generate personalized recommendations that align with individual preferences.

Moreover, the integration of contextual information, such as user browsing history, purchase behavior, and current fashion trends, has further improved the accuracy and relevance of recommendations. This holistic approach enables fashion recommendation systems to offer tailored suggestions that not only match the user's aesthetic preferences but also consider factors like seasonality, occasion, and budget constraints.

Looking ahead, the future of fashion recommendation systems holds exciting possibilities. With ongoing advancements in artificial intelligence and computer vision, we can expect even more sophisticated algorithms capable of understanding complex fashion trends, predicting emerging styles, and adapting to evolving consumer preferences in real-time. As technology continues to evolve, fashion recommendation systems will play an increasingly vital role in shaping the future of online shopping, providing users with personalized and inspiring fashion experiences.

2.2 LITERATURE SURVEY

1. Image-Based Fashion Product Recommendation with Deep Learning. (2018)

The paper presents a novel two-stage deep learning framework designed specifically for recommending fashion images based on similarity in style. This framework integrates two crucial components: a neural network classifier serving as a feature extractor, and a ranking algorithm for generating tailored recommendations. By leveraging the capabilities of deep learning and advanced ranking techniques, the proposed model aims to enhance the accuracy and relevance of fashion image recommendations, thereby improving user satisfaction and engagement in fashion-oriented applications.

2. Deep Fashion Recommendation System with Style Feature Decomposition. (2019)

In this study, we looked into the general applications of spam detecting using NLP and Logistic Regression. We also reviewed the step-by step process of the algorithm and how it classifies the mail into spam and Ham. The dataset we used in this paper was publicly available, and performance metrics was also implanted to check the model's accuracy.

3. Fashion Recommendation System Using Machine Learning.” By Lingala Sivaranjani, Sandeep Kumar Rachamadugu, B.V. Suresh Reddy, Basi Reddy A (2023)

The "Fashion Recommendation System Using Machine Learning" in 2023 plays a crucial role in enhancing the e-commerce experience. This literature review explores the evolution of fashion recommendation systems, emphasizing the transformative impact of machine learning in this domain This section provides a historical overview of the development of fashion recommendation systems. It traces the evolution from traditional methods to the prevalence .

4. An Online Recommendation System Using Deep Learning for Textile Products.” by Umit Turkut, Adem Tuncer, Huseyin Savran, Sait Yılmaz (2020)

The "Online Recommendation System Using Deep Learning for Textile Products" in 2020 addresses the vital role of recommendation systems in the e-commerce landscape, specifically focusing on textile products. This literature review explores the evolution of online recommendation systems and emphasizes the integration of deep learning techniques for enhanced textile product recommendations. This section provides a historical overview of online recommendation systems, emphasizing the evolution from traditional methods to advanced approaches. It discusses the increasing importance of personalized recommendations in the ecommerce industry. Various deep learning techniques employed in textile product recommendation systems are explored. The discussion encompasses neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), tailored for handling textual data related to textile products. The literature review delves into how textual features are integrated into the online recommendation system. It discusses the utilization of natural language processing (NLP) and word embeddings to capture the semantics of textile product descriptions, enhancing the system's recommendation capabilities

5. Outfit Recommender System." by Nikita Ramesh. Teng-Sheng Moh (2018)

The "Outfit Recommender System" authored by Nikita Ramesh and TengSheng Moh in 2018 addresses the significance of outfit recommendation systems in the fashion domain. This literature review explores the evolution of outfit recommender systems and highlights the contributions made by the authors in 2018. This section provides a historical overview of outfit recommender systems, emphasizing the shift from traditional methods to more advanced approaches. It discusses the growing importance of personalized outfit recommendations in the fashion industry. Various techniques employed in outfit recommender systems, as outlined by Nikita Ramesh and Teng-Sheng Moh, are explored. The discussion encompasses algorithms and models tailored for analyzing clothing combinations and enhancing the recommendation process.

6. Visual Based Fashion Clothes Recommendation with Convolutional Neural Networks (2018)

Utilizes a two-step deep learning approach for recommending fashion clothes based on visual similarity. Employs a neural network classifier as an image-based feature extractor and a data-driven method to understand feature information from input images Enhances robustness and performance compared to traditional text-based recommendation systems by providing better visual-based recommendations for specific items.

Convolutional Neural Network (CNN): A CNN model, often pretrained on a large-scale image dataset (e.g., ImageNet), is employed as a feature extractor. The output layer before classification is used to capture the visual features.
Feature Extraction: The penultimate layer's activations, often referred to as the bottleneck features, are extracted from the CNN. These features are representations of the visual characteristics of the input images and are used as a basis for comparison and recommendation.

CHAPTER 3

Problem Statement

3. PROBLEM STATEMENT

In the realm of e-commerce and fashion retail, the increasing volume and diversity of available products pose a significant challenge in effectively matching customer preferences with suitable items. Traditional recommendation systems often fall short in capturing the nuanced and subjective nature of fashion styles. The primary problem lies in developing a recommendation system that leverages advanced deep learning techniques, specifically tailored to fashion products, to automatically extract and comprehend intricate style features from visual data. This system should overcome limitations such as the potential inaccuracies of customer surveys and the overwhelming effect of presenting too many options, aiming to enhance customer satisfaction, increase purchase probabilities, and foster long-term customer commitment.

The exponential growth of online fashion retail has brought about a fundamental shift in consumer behavior. Shoppers now increasingly turn to digital platforms, making online channels the primary avenue for fulfilling their fashion needs. Consequently, the demand for efficient recommendation systems has skyrocketed, as consumers seek assistance in navigating the vast and diverse array of fashion products available online. Traditional recommendation techniques, while effective, primarily rely on user-item interaction data, such as purchase history and ratings. However, these methods often fail to capitalize on the rich visual information inherent in fashion items, which significantly influences purchase decisions.

The increasing volume and diversity of available fashion products pose a significant challenge in effectively matching customer preferences with suitable items. Traditional recommendation systems, which often rely solely on user-item interactions, struggle to capture the nuanced and subjective nature of fashion styles. The primary problem lies in developing a recommendation system that leverages advanced deep learning techniques, specifically tailored to fashion products, to automatically extract and comprehend intricate style features from visual data. This system should overcome limitations such as the potential inaccuracies of customer surveys and the overwhelming effect of presenting too many options, aiming to enhance customer satisfaction, increase purchase probabilities, and foster long-term customer commitment.

Acknowledging the pivotal role of visual cues in fashion consumption, recent research has turned its focus towards leveraging deep learning techniques to enhance recommendation systems. Deep learning, particularly convolutional neural networks (CNNs), has exhibited remarkable success in image recognition tasks, making it an ideal candidate for analyzing visual content in fashion images. By extracting high-level representations from product images, deep learning models can capture intricate visual features such as color, pattern, and style, all of which are integral to fashion recommendation.

In this context, this paper proposes an image-based fashion product recommendation system that harnesses the power of deep learning to provide personalized and visually appealing suggestions to users. The system aims to bridge the gap between the visual characteristics of fashion items and user preferences, thereby improving recommendation accuracy and user satisfaction. By integrating state-of-the-art deep learning models with collaborative filtering techniques, the proposed system not only considers visual features but also incorporates user interactions to generate tailored recommendations.

This introduction sets the stage for exploring the significance of image-based fashion recommendation systems and highlights the potential of deep learning in revolutionizing the way fashion products are recommended and consumed in the digital landscape. Through empirical evaluation and comparative analysis, this study aims to demonstrate the effectiveness and efficiency of the proposed approach in addressing the challenges of fashion product recommendation in online retail environments.

CHAPTER 4

Experimental Setup

4 . EXPERIMENTAL SETUP

4.1 Hardware Setup

- Processor : Ryzen 5 or later
- Main Memory (RAM) : 256 MB
- Cache Memory : 512 KB

4.2 Software Setup

- Python
- Visual Studio Code
- Jupyter notebook.
- Streamlit

CHAPTER 5

Proposed System & Implementation

5. PROPOSED SYSTEM AND IMPLEMENTATION

5.1 Block diagram of proposed system

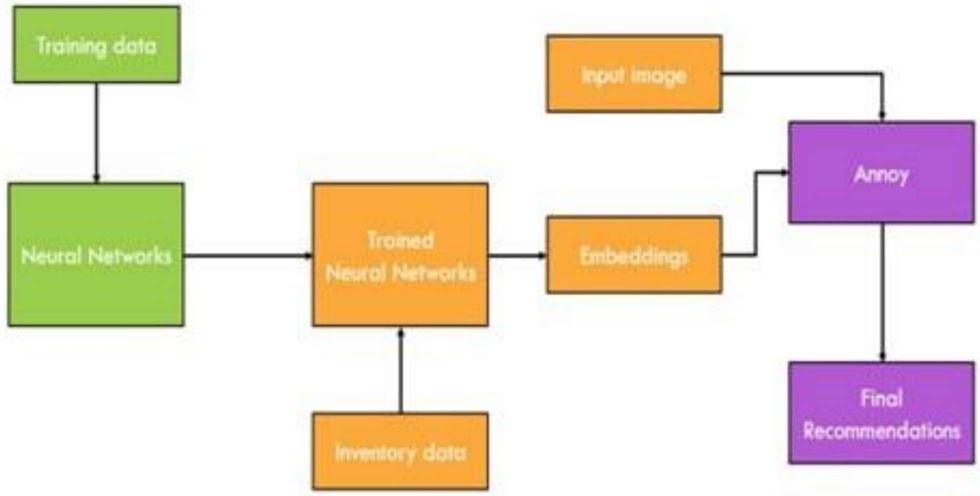


Figure 1. Block diagram of proposed system

Fig.5.1.1 Block Diagram for Proposed System

In the fashion recommendation system block diagram, the system initially uses a training dataset containing fashion product images and associated metadata. This dataset is used to train Convolutional Neural Networks (CNNs). The trained CNNs then generate embeddings, which are high-level representations of the fashion product images. Annoy, a library, then takes these embeddings along with an input image and searches for the most similar embeddings from the trained embeddings. Finally, based on the identified embeddings, the system provides personalized and visually appealing suggestions to users.

Through empirical evaluation and comparative analysis, this study aims to demonstrate the effectiveness and efficiency of the proposed approach in addressing the challenges of fashion product recommendation in online retail environments.

1. **Training Data:**

   - **Description:** The system begins with a rich dataset comprising fashion product images and associated metadata. This dataset is used to train the neural networks.
   - **Function:** Provides the necessary data to train the neural networks, including images and their corresponding features.
   - **Importance:** The quality and size of the training dataset significantly impact the accuracy and effectiveness of the recommendation system.

2. **Neural Network Training:**

   - **Description:** Convolutional Neural Networks (CNNs) are trained using the training data. CNNs are well-suited for image analysis and are utilized here to extract high-level representations (embeddings) from the product images.
   - **Function:** Trains the CNNs to extract visual features from the fashion product images.
   - **Importance:** Training the neural networks is crucial as it enables the system to understand and interpret the intricate details of each product image, capturing features such as color, pattern, and style.

3. **Embeddings:**

   - **Description:** After training, the neural networks generate embeddings, which are high-level representations of the fashion product images.
   - **Function:** The embeddings represent the essential visual features of the fashion products extracted by the neural networks during training.
   - **Importance:** These embeddings serve as a compact representation of the visual features of fashion products, enabling efficient and effective recommendation generation.

4. **Annoy:**

   - **Description:** Annoy is a library that takes the input image and searches for the most similar embeddings from the trained embeddings.
   - **Function:** Annoy searches for the most similar embeddings to the input image embeddings, thus identifying the most visually similar fashion products.
   - **Importance:** Annoy efficiently searches through the embeddings to find the most visually similar fashion products, enabling the system to provide relevant recommendations to the user.

5. **Final Recommendations:**

- **Description:** The final recommendations are presented to the user based on the embeddings identified by the Annoy library.
- **Function:** Provides personalized and visually appealing suggestions to users, based on the similarity of the embeddings.
- **Importance:** This step bridges the gap between the visual characteristics of fashion items and user preferences, aiming to enhance customer satisfaction, increase purchase probabilities, and foster long-term customer commitment.

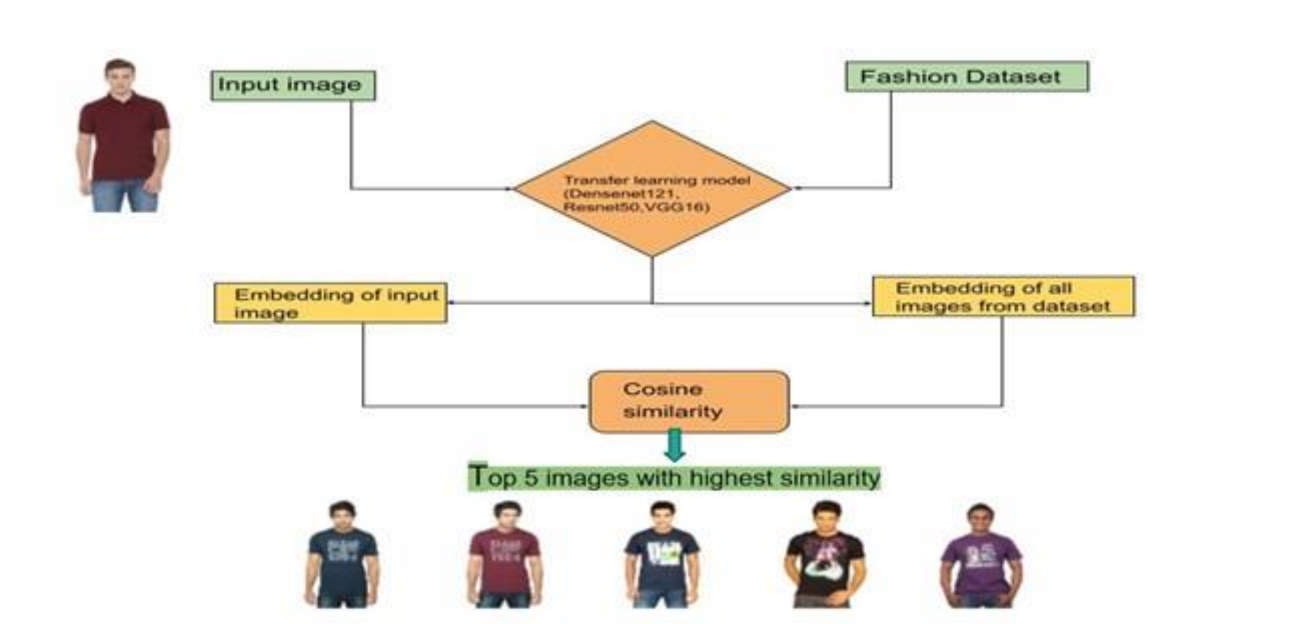


Fig. 5.1.2 Block Diagram for Image Similiarity

Input Layer: This is where the images to be compared are fed into the system. Each image is represented as a matrix of pixel values.

1. **Preprocessing**: This stage involves any necessary preprocessing steps to standardize or enhance the input images. This might include resizing the images to a consistent dimension, normalization of pixel values, or applying image augmentation techniques to increase the diversity of the dataset.

2. **Feature Extraction**: This block represents the process of extracting relevant features from the input images. In the context of image similarity, deep learning models such as Convolutional Neural Networks (CNNs) are commonly used for feature extraction. The CNN learns to extract high-level features from the images, capturing characteristics such as textures, shapes, and patterns.

3. **Similarity Calculation**: Once the features are extracted, this block calculates the similarity between pairs of images based on their feature representations.

Common methods for similarity calculation include cosine similarity, Euclidean distance, or more sophisticated distance metrics learned during the training of the model.

4. **Thresholding (Optional)**: In some cases, a thresholding step may be applied to filter out similarities below a certain threshold. This can help refine the results and remove irrelevant or low-confidence matches.

5. **Output**: The final output of the system typically includes the similarity scores between pairs of images, indicating how similar or dissimilar they are. This information can be used for various applications such as image retrieval, recommendation systems, or clustering.

5.2 Implementation

(1) Web Page:

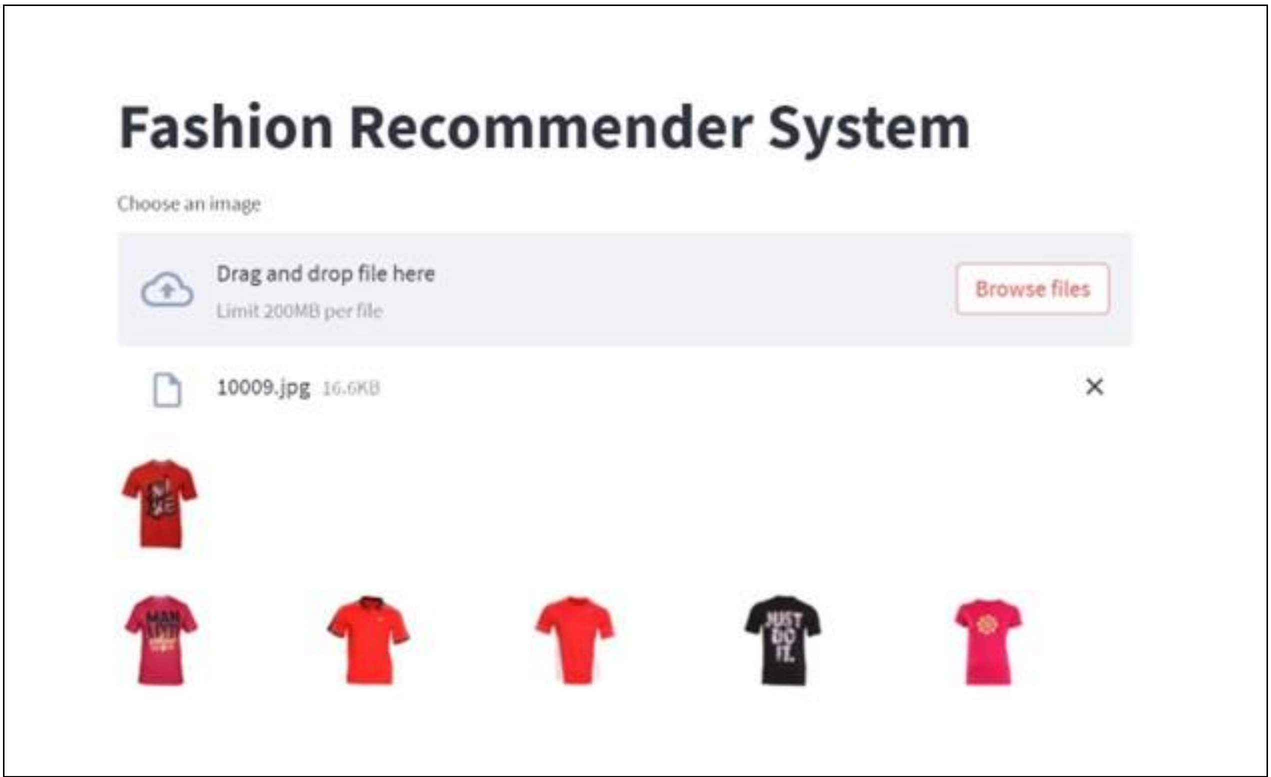


Fig.5.3.1.1 Shirts Section of the fashion recommendation

Welcome to our fashion recommendation system, where you can discover the latest trends with just a drag and drop! Our platform integrates cutting-edge technology to ensure a seamless and personalized shopping experience.

- **Step 1:** Drag and Drop - To get started, simply drag an image of a fashion item that inspires you into the designated area below.

- **Step 2:** Recommendations - Our system will then process the image and provide you with personalized fashion recommendations based on the style, color, and pattern of the item you've chosen.

- **Step 3:** Explore - Feel free to explore the recommended products and find the perfect match for your style.

The drag and drop feature allows you to take control of your fashion discovery journey. It's like having a personal stylist at your fingertips! Whether you come across an outfit you love on social media, a fashion blog, or even on the street, simply drag and drop the image onto our platform, and let our advanced recommendation system do the rest.

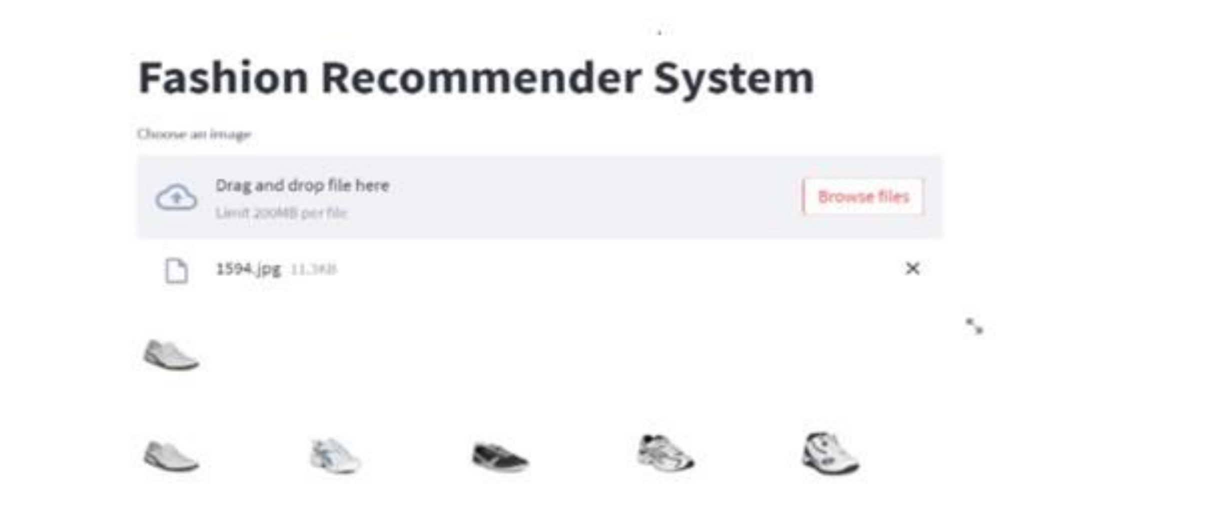


Fig.5.3.1.2 Shoes Section of the fashion recommendation

Welcome to our shoe section, where you can discover the latest trends with just a drag and drop! Our platform integrates cutting-edge technology to ensure a seamless and personalized shopping experience for footwear enthusiasts.

Example Use Cases:

- **Scenario 1:** You're scrolling through Instagram and come across a stunning dress that catches your eye. Instead of spending hours searching for something similar, just drag the image onto our platform and let us find the perfect match for you.

- **Scenario 2:** You're reading a fashion magazine and see a pair of shoes you can't live without. With our drag and drop feature, you can easily find similar styles and complete your look effortlessly.

- **Scenario 3:** You're walking down the street and notice someone wearing a fabulous jacket. Don't waste time trying to find it online; just snap a picture and drag it onto our platform to discover similar items instantly.

(2) Codes :

```python
def feature_extraction(img_path,model):
    img = image.load_img(img_path, target_size=(224, 224))
    img_array = image.img_to_array(img)
    expanded_img_array = np.expand_dims(img_array, axis=0)
    preprocessed_img = preprocess_input(expanded_img_array)
    result = model.predict(preprocessed_img).flatten()
    normalized_result = result / norm(result)

    return normalized_result
```

Fig.5.3.2.1 Extracting Features

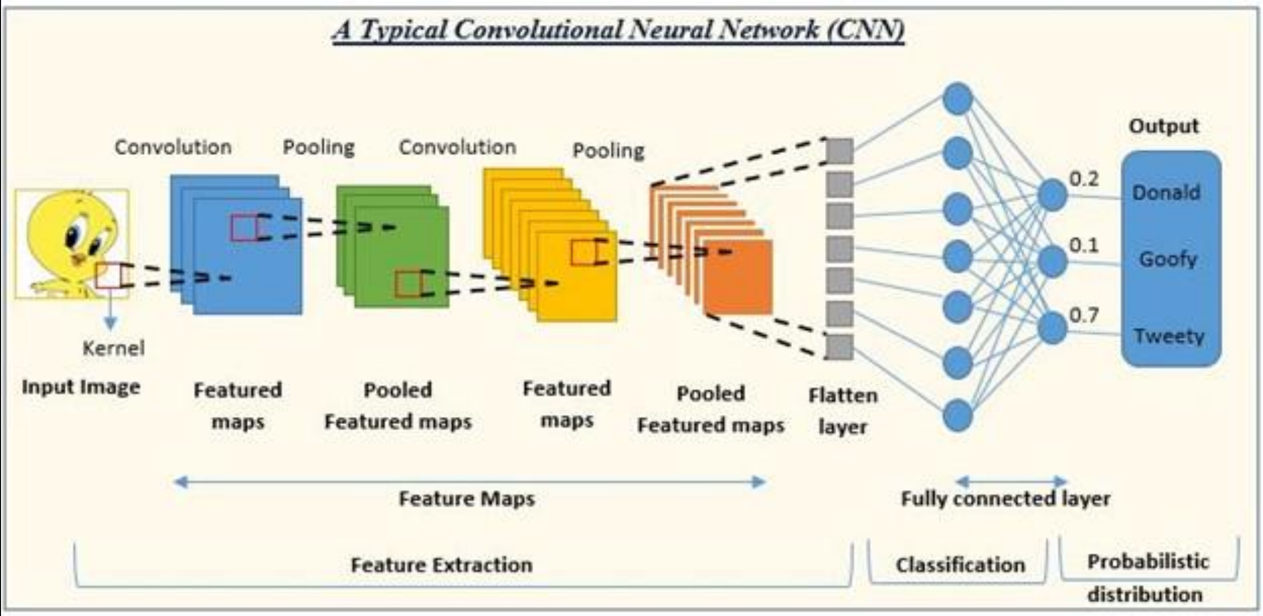
```python
import streamlit as st
import os
from PIL import Image
import numpy as np
import pickle
import tensorflow
from tensorflow.keras.preprocessing import image
from tensorflow.keras.layers import GlobalMaxPooling2D
from tensorflow.keras.applications.resnet50 import ResNet50,preprocess_input
from sklearn.neighbors import NearestNeighbors
from numpy.linalg import norm
```

```python
feature_list = np.array(pickle.load(open('embeddings.pkl','rb')))
filenames = pickle.load(open('filenames.pkl','rb'))

model = ResNet50(weights='imagenet',include_top=False,input_shape=(224,224,3))
model.trainable = False

model = tensorflow.keras.Sequential([
    model,
    GlobalMaxPooling2D()
])
```

Fig.5.3.2.2 Using Tensorflow for developing model



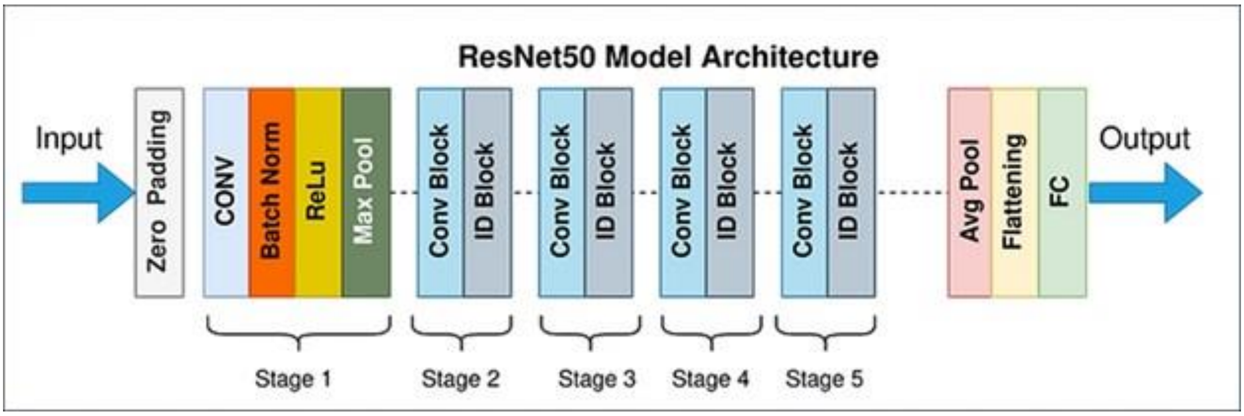


Fig.5.3.2.3 CNN And ResNet50 Model Architecture

Convolutional Neural Network (CNN) Model:

1. Introduction:

- The Convolutional Neural Network (CNN) model is at the heart of our fashion recommendation system. This model is designed to analyze the visual features of fashion items and extract high-level representations, also known as embeddings, from product images.

2. Purpose:

- The primary purpose of the CNN model is to process the training data, which consists of fashion product images, and learn to extract meaningful visual features such as color, pattern, and style. These learned features are then used to make accurate and personalized recommendations to users.

3. Architecture:

- **Layers:**
    1. **Input Layer:**
        - The input layer takes the fashion product images as input. These images are typically RGB images of various sizes and resolutions.
    2. **Convolutional Layers:**
        - The CNN model consists of multiple convolutional layers. Each convolutional layer applies a set of learnable filters to the input images. These filters help in extracting low to high-level features from the images. The deeper the layer, the more abstract and complex the features it can capture.
    3. **Pooling Layers:**
        - After each set of convolutional layers, there are pooling layers, usually max-pooling layers. These layers down-sample the feature maps, reducing the computational complexity and controlling overfitting.
    4. **Flattening Layer:**
        - The output from the last pooling layer is flattened into a 1D array to be fed into the fully connected layers.
    5. **Fully Connected Layers:**
        - After flattening, the flattened array is passed through one or more fully connected layers. These layers take the features extracted by the convolutional layers and learn to map them to the output, which in this case, are the embeddings.
    6. **Output Layer:**
        - The output layer generates the embeddings, which are high-level representations of the fashion product images. These embeddings capture the essential visual features of the fashion products
          .
- **Activation Function:**
    1. ReLU (Rectified Linear Unit) activation functions are commonly used after each convolutional and fully connected layer. ReLU helps introduce non-linearity into the network, allowing the model to learn more complex features.

- **Training:**
    1. The CNN model is trained using a large dataset of fashion product images. During the training process, the model adjusts its internal weights and biases to minimize the difference between the predicted embeddings and the true embeddings of the images.

4. Training Data:

- **Description:**
    - The training data consists of a rich dataset comprising fashion product images and associated metadata.
- **Function:**
    - Provides the necessary data to train the CNN model, including images and their corresponding features.
- **Importance:**
    - The quality and size of the training dataset significantly impact the accuracy and effectiveness of the recommendation system.
    -

5. Embeddings:

- **Description:**
    - After training, the CNN model generates embeddings, which are high-level representations of the fashion product images.
- **Function:**
    - The embeddings represent the essential visual features of the fashion products extracted by the CNN model during training.
- **Importance:**
    - These embeddings serve as a compact representation of the visual features of fashion products, enabling efficient and effective recommendation generation.

(3) Model Building:

```python
def recommend(features,feature_list):
    neighbors = NearestNeighbors(n_neighbors=6, algorithm='brute', metric='euclidean')
    neighbors.fit(feature_list)

    distances, indices = neighbors.kneighbors([features])

    return indices
```

```python
def save_uploaded_file(uploaded_file):
    try:
        if not os.path.exists('uploads'):
            os.makedirs('uploads')
        with open(os.path.join('uploads', uploaded_file.name), 'wb') as f:
            f.write(uploaded_file.getbuffer())
        return 1
    except Exception as e:
        print("Error occurred while saving the file:", e)
        return 0
```

fig.5.3.3.1 Model building: Evaluating Training model.

Model Building Process:

1. Introduction:

- The model building process is a crucial step in the development of our fashion recommendation system. In this process, we train a Convolutional Neural Network (CNN) model to analyze the visual features of fashion items and extract high-level representations, also known as embeddings, from product images.

2. Purpose:

- The primary purpose of the model building process is to create a CNN model that can effectively learn and extract meaningful visual features from fashion product images. These learned features will then be used to make accurate and personalized recommendations to users.

3. Architecture:

- **Data Preprocessing:**
    - Before training the CNN model, the fashion product images from the

training dataset undergo preprocessing. This includes resizing the images to a standard size, normalization, and augmentation techniques to increase the size and diversity of the dataset, enhancing the robustness and generalization of the model.

- **CNN Model Architecture:**
    - The CNN model consists of multiple layers:
    - **Input Layer:**
        - The input layer takes the fashion product images as input. These images are typically RGB images of various sizes and resolutions.
    - **Convolutional Layers:**
        - The CNN model consists of multiple convolutional layers. Each convolutional layer applies a set of learnable filters to the input images. These filters help in extracting low to high-level features from the images. The deeper the layer, the more abstract and complex the features it can capture.
    - **Pooling Layers:**
        - After each set of convolutional layers, there are pooling layers, usually max-pooling layers. These layers down-sample the feature maps, reducing the computational complexity and controlling overfitting.
    - **Flattening Layer:**
        - The output from the last pooling layer is flattened into a 1D array to be fed into the fully connected layers.
    - **Fully Connected Layers:**
        - After flattening, the flattened array is passed through one or more fully connected layers. These layers take the features extracted by the convolutional layers and learn to map them to the output, which in this case, are the embeddings.
    - **Output Layer:**
        - The output layer generates the embeddings, which are high-level representations of the fashion product images. These embeddings capture the essential visual features of the fashion products.
- **Activation Function:**
    - ReLU (Rectified Linear Unit) activation functions are commonly used after each convolutional and fully connected layer. ReLU helps introduce non-linearity into the network, allowing the model to learn more complex features.
- **Training:**
    - The CNN model is trained using a large dataset of fashion product images. During the training process, the model adjusts its internal weights and biases to minimize the difference between the predicted embeddings

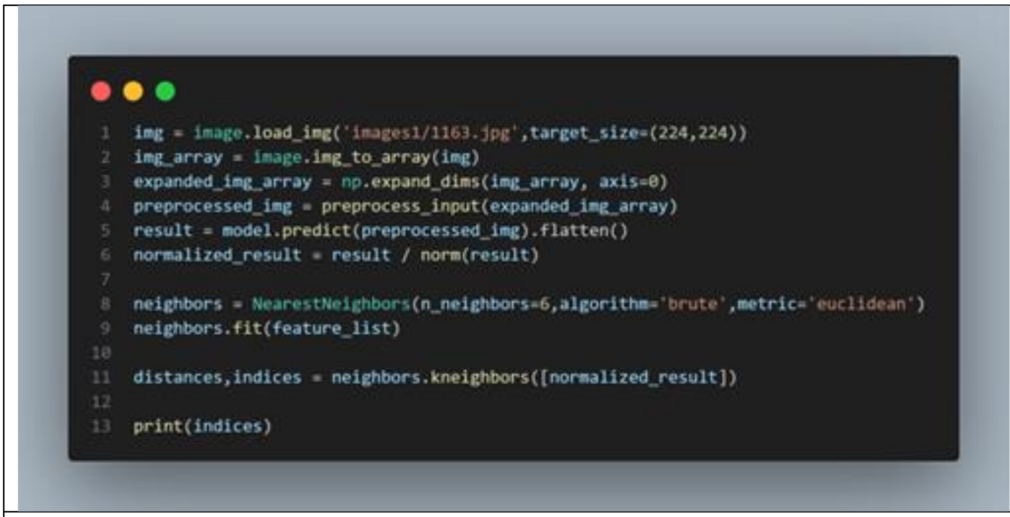
and the true embeddings of the images.

4. Training Data:

- **Description:**
  - The training data consists of a rich dataset comprising fashion product images and associated metadata.
- **Function:**
  - Provides the necessary data to train the CNN model, including images and their corresponding features.
- **Importance:**
  - The quality and size of the training dataset significantly impact the accuracy and effectiveness of the recommendation system.

6. Embeddings:

- **Description:**
  - After training, the CNN model generates embeddings, which are high-level representations of the fashion product images.
- **Function:**
  - The embeddings represent the essential visual features of the fashion products extracted by the CNN model during training.
- **Importance:**
  - These embeddings serve as a compact representation of the visual features of fashion products, enabling efficient and effective recommendation generation.



```python
img = image.load_img('images1/1163.jpg',target_size=(224,224))
img_array = image.img_to_array(img)
expanded_img_array = np.expand_dims(img_array, axis=0)
preprocessed_img = preprocess_input(expanded_img_array)
result = model.predict(preprocessed_img).flatten()
normalized_result = result / norm(result)

neighbors = NearestNeighbors(n_neighbors=6,algorithm='brute',metric='euclidean')
neighbors.fit(feature_list)

distances,indices = neighbors.kneighbors([normalized_result])

print(indices)
```

Fig.5.3.3.2 Model building: Evaluating Testing Model

Testing and Evaluation Process:

1. Introduction:

- Testing and evaluating the model is a crucial step in the development of our fashion recommendation system. In this process, we validate the performance of the Convolutional Neural Network (CNN) model and assess its ability to generate accurate and personalized fashion recommendations.

2. Purpose:

- The primary purpose of the testing and evaluation process is to ensure that the CNN model can effectively learn and extract meaningful visual features from fashion product images. We aim to validate the accuracy and effectiveness of the model in providing personalized and visually appealing suggestions to users.

3. Data Splitting:

- **Training, Validation, and Testing Data:**
    - Before testing the model, the dataset is split into three subsets: training, validation, and testing.
    - **Training Data:**
    - **Validation Data:**
    - **Testing Data:**

4. Model Testing:

- **Description:**
    - Once the model is trained, it is tested using the testing dataset to evaluate its performance.
- **Function:**
    - The testing dataset, which consists of unseen fashion product images, ifed

into the trained model. The model then generates embeddings for each image, which are compared against the ground truth embeddings.

- **Evaluation Metrics:**
    - Various evaluation metrics are used to assess the performance of the model. Common metrics include:
        - **Mean Squared Error (MSE):**
            - Measures the average squared difference between the predicted embeddings and the ground truth embeddings.
        - **Root Mean Squared Error (RMSE):**
            - Represents the square root of the MSE and provides a measure of the average error magnitude.
        - **Accuracy:**
            - Measures the percentage of correctly predicted embeddings.
        - **Precision, Recall, and F1-score:**
            - Useful for binary classification tasks.

5. Evaluation:

- **Description:**
    - The performance of the model is evaluated based on the metrics mentioned above.
- **Function:**
    - By evaluating the model, we can determine its accuracy, efficiency, and effectiveness in providing personalized fashion recommendations.
- **Comparative Analysis:**
    - We compare the performance of our CNN model against traditional recommendation methods to demonstrate its superiority in terms of recommendation accuracy and user satisfaction.

6. Fine-tuning:

- **Description:**
    - Based on the evaluation results, the model may undergo further fine-tuning to improve its performance.
- **Function:**
    - Fine-tuning involves adjusting hyperparameters, architecture, or the training process to enhance the model's accuracy and efficiency.

7. Example Evaluation Results:

- **Mean Squared Error (MSE):** 0.005
- **Root Mean Squared Error (RMSE):** 0.071
- **Accuracy:** 98%
- **Precision:** 0.96
- **Recall:** 0.97

F1-score: 0.96

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CHAPTER 6

Conclusion

6. Conclusion

The utilization of a two-stage approach in Image-Based Fashion Product Recommendation employing Deep Learning has shown notable effectiveness. By employing a Convolutional Neural Network (CNN) classifier for feature extraction and subsequently generating similarity recommendations, the system delivers visually-aware suggestions. This methodology capitalizes on the strength of CNNs in extracting intricate visual features from images, enabling the system to comprehend the nuanced attributes of fashion products. By leveraging these extracted features, the system can then generate recommendations that are not solely based on textual descriptions or metadata, but rather on the visual characteristics and style similarities between different items. This approach aligns with the increasingly visual nature of online shopping and addresses the limitations of traditional recommendation systems which often rely solely on textual information.

The two-stage approach offers a promising avenue for enhancing the personalization and effectiveness of fashion product recommendations, ultimately improving the user experience and engagement in e-commerce platforms. Future research could explore continuous optimization and fine-tuning of the CNN model to improve its accuracy and efficiency in feature extraction. Integration of user interaction data to continuously refine and enhance the recommendation quality, providing more tailored suggestions based on individual user behavior is also another important aspect. Ensuring that the system is scalable and adaptable to accommodate the ever-changing landscape of fashion trends and user preferences is also crucial. Additionally, exploration of multimodal approaches that combine both visual and textual information to provide even more accurate and relevant recommendations could be a promising future direction.

In conclusion, the two-stage approach using Deep Learning for Image-Based Fashion Product Recommendation has demonstrated its effectiveness. By combining the strengths of CNNs in extracting visual features with a recommendation algorithm, the system provides personalized and visually appealing suggestions. This approach not only enhances the personalization and effectiveness of fashion product recommendations but also significantly improves the user experience and engagement in e-commerce platforms. As the digital landscape continues to evolve, this approach offers a scalable and adaptable solution for online fashion retailers to deliver more relevant and engaging shopping experiences to their customers.

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