MADHAV INSTITUTE OF TECHNOLOGY & SCIENCE GWALIOR

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NAAC Accredited with A++ Grade

Project Report

on

Fashion Recommendation and Customization System

Submitted By:

Eshita Nagariya (0901AM211023)

Shreya Gupta (0901AM211057)

Faculty Mentor:

Dr. Anshika Srivastava

Assistant Professor

CENTRE FOR ARTIFICIAL INTELLIGENCE

MADHAV INSTITUTE OF TECHNOLOGY & SCIENCE

GWALIOR - 474005 (MP) est. 1957

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CERTIFICATE

This is certified that **Eshita Nagariya** (0901AM211023) and **Shreya Gupta** (0901AM211057) has submitted the project report titled **Fashion Recommendation and Customization System** under the mentorship of **Dr. Anshika Srivastava**, in partial fulfilment of the requirement for the award of degree of Bachelor of Technology in **Artificial Intelligence and Machine Learning** from Madhav Institute of Technology and Science, Gwalior.

Anshika 23/11/2023

Dr. Anshika Srivastava
Faculty Mentor
Assistant Professor
Centre for Artificial Intelligence

22/11/23

Dr. R. R. Singh
Coordinator
Centre for Artificial Intelligence

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DECLARATION

I hereby declare that the work being presented in this project report, for the partial fulfilment of requirement for the award of the degree of Bachelor of Technology in **Artificial Intelligence and Machine Learning** at Madhav Institute of Technology & Science, Gwalior is an authenticated and original record of my work under the mentorship of **Dr. Anshika Srivastava, Assistant Professor**, Centre for Artificial Intelligence

I declare that I have not submitted the matter embodied in this report for the award of any degree or diploma anywhere else.

Eshita
Eshita Nagariya
0901AM211023
AIML Third Year
Centre for Artificial Intelligence

Shreya
Shreya Gupta
0901AM211057
AIML Third Year
Centre for Artificial Intelligence

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Eshita

Eshita Nagariya
0901AM211023
AIML Third Year
Centre for Artificial Intelligence

Shreya Gupta
0901AM211057
AIMLThird Year
Centre for Artificial Intelligence

ABSTRACT

The fashion industry is experiencing a digital revolution where the combination of artificial intelligence and deep learning is playing a key role in improving personalized experiences. In this work, we present a fashion recommendation system with a k-nearest neighbour (KNN) algorithm that leverages the power of the deep convolutional neural network (CNN) RESNET50 to identify similar items. Extract high-level features from fashion images using the RESNET50 model to capture complex patterns and patterns. KNN was then used to determine nearest neighbour based on unique embedding obtained from the RESNET50 model.

A method that combines deep learning with traditional KNN allows the system to provide better and more diverse recommendations. The RESNET50 model helps uncover rich representations that capture global and local characteristics of fashion objects. KNN is based on the neighbour discovery technique to improve the recommendation by considering the relationship and similarity between vectors. This collaboration improves the ability to understand the intricacies of fashion, providing more accurate and personalized recommendations for users.

The integration of RESNET50 and KNN increases the level of fashion recognition, providing a powerful and effective way to capture invisible features and improve neighbour detection.

Keyword : Fashion Recommendation System , RESNET50 ,Convolutional Neural Network (CNN) ,K-Nearest Neighbours (KNN) , Deep Learning , Feature Extraction , Fashion Dataset , Personalized Recommendations , Image Recognition , Neighbour Detection , Machine Learning ,Image-based Recommendation

सार

फैशन इंडस्ट्री एक डिजिटल क्रांति का सामना कर रही है, जहाँ कृत्रिम बुद्धिमत्ता और डीप लर्निंग का संयोजन व्यक्तिगत अनुभवों को सुधारने में महत्वपूर्ण भूमिका निभा रहे हैं। इस कार्य में, हम एक फैशन रिकमेंडेशन सिस्टम प्रस्तुत करते है जिसमें KNN एल्गोरिदम का उपयोग किया गया है जो कनवोल्यूशनल न्यूरल नेटवर्क (CNN) RESNET50 का उपयोग करता है ताकि समान आइटम्स की पहचान की जा सके। RESNET50 मॉडल का उपयोग करके फैशन छवियों से उच्च-स्तरीय विशेषताएँ निकाली जाती हैं ताकि जटिल पैटर्न्स और रूपरेखाएँ पकड़ी जा सकें। फिर KNN का उपयोग RESNET50 मॉडल से प्राप्त अद्वितीय एम्बेडिंग्स के आधार पर करता है ताकि निकटतम पड़ोसी का निर्धारण किया जा सके।

इसमें डीप लर्निंग को पारंपरिक KNN के साथ मिलाने का एक तरीका है जिससे सिस्टम बेहतर और विविध रिकमेंडेशन प्रदान कर सकता है। RESNET50 मॉडल मदद करता है जो फैशन वस्त्र वस्तुओं की वैशिष्ट्यिकता को समझने के लिए समृद्धि से भरा प्रतिष्ठान उत्पन्न करने में। KNN एम्बेडिंग्स के बीच संबंध और समानता को ध्यान में रखकर सिफारिश को सुधारने के लिए पड़ोसी खोज तकनीक पर आधारित है। यह सहयोग फैशन की जटिलताओं को समझने की क्षमता को बढ़ाता है, उपयोगकर्ताओं के लिए और सटीक और व्यक्तिगत सिफारिशें प्रदान करता है। RESNET50 और KNN के सम्मिलन से फैशन पहचान का स्तर बढ़ता है, अदृश्य विशेषताओं को पकड़ने और पड़ोसी पहचान को सुधारने के लिए एक शक्तिशाली और प्रभावी तरीका प्रदान करता है।

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Chapter 1: INTRODUCTION

In the rapidly evolving landscape of e-commerce, personalized recommendation systems play a pivotal role in enhancing user experience. This project focuses on the development of a Fashion Recommendation System that leverages state-of-the-art technologies, specifically ResNet-50 for feature extraction and k-Nearest Neighbors (KNN) for neighbour detection. By utilizing deep learning for feature extraction, the system aims to capture intricate visual patterns within fashion items. [1]We add a function using streamlit to visualize their customize product before buying them.

1.1 Objectives :

1.1.1 Image Feature Extraction:

- Utilize ResNet-50, a deep convolutional neural network (CNN), for image feature extraction.
- Leverage the pre-trained ResNet-50 model to capture high-level features from fashion images.

1.1.2 Semantic Embeddings:

- Transform the extracted features into semantic embeddings that represent the unique characteristics of fashion items.

1.1.3 Hybrid Recommendation System:

- Combine collaborative filtering (KNN-based) and content-based filtering (ResNet-50-based) approaches to build a hybrid recommendation system.
- Enhance the system's accuracy by leveraging both user-item interactions and item features.

1.1.4 Personalization :

- To visualize their customize product before buying them.

1.2 Project Features:

1.2.1 Feature Extraction with ResNet-50:

1.2.1.1. Deep Convolutional Neural Network (CNN):

- ResNet-50, a state-of-the-art deep learning architecture, will be employed for its ability to capture intricate hierarchical features in images.
- The system will use the pre-trained ResNet-50 model, benefiting from the knowledge it has gained through extensive training on large-scale image datasets.

1.2.1.2 High-Level Feature Representation:

- ResNet-50 will extract high-level features that represent complex patterns, textures, and shapes present in fashion images.
- The feature extraction process enables the model to discern unique visual characteristics of different fashion items, enhancing its ability to understand the subtleties of user preferences.

1.2.1.3 Transfer Learning:

- Leveraging transfer learning, the pre-trained ResNet-50 model avoids the need for training from scratch, making the system computationally efficient.
- The model is fine-tuned on a fashion-specific dataset to adapt its learned features to the nuances of the fashion domain.

1.2.2 Neighbour Detection using KNN:

1.2.2.1 Similarity Measure:

- KNN is employed for its simplicity and effectiveness in identifying visually similar items.
- The Euclidean distance or cosine similarity measure is often used to quantify the similarity between the feature vectors of fashion items.

1.2.2.2 Personalized Recommendations:

- KNN considers the preferences of "neighbours" (users with similar tastes) to provide personalized recommendations based on visual similarities.
- The system dynamically adjusts to changing user preferences by updating the KNN model with real-time user interactions.

1.3 Feasibility:

The feasibility analysis for incorporating pre-trained ResNet-50 models and KNN in a fashion recommendation system focuses on technical, operational, and economic aspects. The availability of pre-trained ResNet-50 models facilitates rapid development, but considerations for compatibility and periodic updates are crucial. KNN's operational efficiency in real-time recommendations is contingent on dataset size and optimization efforts. Seamless integration with existing systems and user-friendly feedback mechanisms enhance operational feasibility. While leveraging pre-trained models minimizes training costs, initial setup costs, and the potential for prolonged return on investment need consideration. Risk analysis, scalability planning, and adaptability to evolving trends contribute to project viability. Balancing these factors ensures the successful deployment of a fashion recommendation system, optimizing user satisfaction, and supporting long-term economic sustainability.

1.4 System Requirements:

1.4.1 Hardware:

Adequate computational resources capable of running deep learning models.

1.4.2 Software:

TensorFlow and Keras

ResNet-50

PIL (Pillow)

NUMPY

Scikit-learn (sklearn)

OpenCV (cv2)

Pickle

Chapter 2: Literature Review :

2.1 Fashion Recommendation Systems:

Fashion recommendation systems are vital in e-commerce, using sophisticated algorithms to elevate user experience. Adomavicius and Tuzhilin (2005) offer a foundational survey on recommender systems, detailing collaborative and content-based filtering methods. These systems analyze user behavior and preferences, suggesting fashion items based on similarities with others' choices or content attributes. This enhances customer engagement and satisfaction, contributing to the success of online fashion platforms..

2.2 Feature Extraction Methods:

Feature extraction is a process in which relevant information or distinctive features are identified and extracted from raw data to reduce dimensionality and capture the most important aspects of the data.

Feature extraction in domains like deep learning sees notable success with models like ResNet-50. He et al. (2016) introduce ResNet-50, highlighting its prowess in capturing intricate visual patterns and hierarchical features. This deep learning architecture utilizes residual learning, facilitating the training of exceptionally deep networks. The success of ResNet-50 showcases the significance of advanced feature extraction methods in tasks such as image recognition, demonstrating their ability to enhance model performance by extracting and representing essential information from complex data.

2.3 Neighbor Detection Techniques:

Neighbor detection is crucial in recommendation systems, commonly employing the k-Nearest Neighbors (KNN) algorithm. Cover and Hart (1967) introduced the classic KNN algorithm, emphasizing its simplicity and effectiveness in identifying similar items. KNN relies on proximity metrics to find items with comparable features, making it a robust technique for collaborative filtering. Despite its simplicity, KNN remains relevant in various domains for its ability to efficiently identify neighbors in a dataset, providing valuable insights for personalized recommendations.

2.4 Fashion Recommendation with Deep Learning:

Fashion recommendation systems employing deep learning utilize advanced neural networks to offer highly accurate and personalized suggestions. These systems process vast datasets, extracting intricate features from fashion images through Convolutional Neural Networks

(CNNs) and employing Natural Language Processing (NLP) for textual data such as product descriptions. Hybrid models integrate both visual and textual information, often using parallel branches for image and text analysis. Siamese networks distinguish similarities and differences among fashion items, enabling the system to recommend stylistically aligned products. User profiling involves creating embeddings of user preferences based on interactions, with sequential models capturing evolving preferences over time.

Training involves large-scale datasets for generalization, and transfer learning employs pre-trained models fine-tuned for fashion recommendation. The continuous refinement of suggestions relies on user feedback, integrating explicit (likes, dislikes) and implicit (user behavior) feedback. Evaluation methods, including A/B testing, ensure the system's effectiveness, fostering iterative improvements. Ultimately, these deep learning-powered systems enhance the fashion e-commerce experience, providing visually appealing and personalized recommendations to users based on their unique style preferences.

Chapter 3: Preliminary Design :

3.1 Architecture of ResNet-50:

ResNet-50 stands for 50-layer Residual Network. (2016). It is known for its success in image classification and is part of the ResNet family, which solves the problem of training deep neural networks. The main innovation of ResNet-50 is the introduction of residuals that allow the network to learn residual functions rather than directly affecting the outputs. [3]

ResNet-50 architecture consists of convolutional operations, batch normalization and nonlinear activation. It also includes personal identification and high-speed connections so that the network is built over one or more layers. ResNet-50's deep representation learning capabilities make it suitable for specialized applications in many domains, including fashion.[3,6]

3.2 Effectiveness of feature extraction in fashion:

ResNet-50 The effectiveness of feature extraction in fashion comes from its ability to capture the complexity of visual patterns and representation in images. Fashion products often contain complex materials, colors and patterns, which are important for understanding consumer preferences. ResNet-50's deep architecture enables it to learn hierarchical features, from low-level details such as texture to high-level information such as pattern and shape.[3,7]

ResNet-50's content rendering ability is particularly impressive in the field of fashion, where beauty and style are important. The remaining connections in the architecture allow the network to focus on learning the remaining features, improving its ability to represent content effectively. Therefore, the features extracted by ResNet-50 can capture the unique characteristics of fashion items, which is suitable for applications such as fashion recognition.[3,6,7]

3.3 Process of Extracting Features from Fashion Images:

K-nearest neighbour (KNN) algorithm is a simple and easy method used in pattern detection. Good for identifying similar objects based on vectors. In the context of feature extraction using ResNet-50, each fashion item is represented as a feature vector in a multidimensional space. KNN mainly uses Euclidean distance to evaluate the similarity between vectors and select the nearest neighbour of the target.[9][10]

KNN can identify the function with similar effects by calculating the distance between feature vectors in the extracted feature space. The algorithm facilitates personalized recommendations by providing the largest sample or group of people closest to the product.[4] This approach improves the accuracy of recommendations by using ResNet-50's ability to capture complex visual patterns. The simplicity and efficiency of KNN make it a suitable choice for detecting neighbours in a given environment.

Chapter 4: Methodology:

4.1 Data Collection:

Each product is identified by an ID like 42431. You will find a map to all the products in styles.csv. From here, you can fetch the image for this product from images/42431.jpg and the complete metadata from styles/42431.json.

To get started easily, we also have exposed some of the key product categories and it's display name in styles.csv.

4.2 Importing Libraries:

```
import tensorflow

import numpy as np

from numpy.linalg import norm

from tensorflow import keras

from keras.preprocessing import image

from keras.layers import GlobalMaxPooling2D

from keras.applications.resnet50 import ResNet50, preprocess_input

import os

from tqdm import tqdm

import pickle
```

4.3 Feature Extraction with ResNet-50:

4.3.1 Getting File names:

```
filenames = []
for file in os.listdir('Imagess'):
    filenames.append(os.path.join('Imagess', file))
```

Output :

```
['Imagess\\10054.jpg', 'Imagess\\10649.jpg', 'Imagess\\10671.jpg',
```

Fig 4.1 Name of image files

4.3.2 ResNet – 50:

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

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

The provided code initializes a ResNet50 model pretrained on the ImageNet dataset. The `include_top=False` argument excludes the densely connected layers at the top of the network, allowing the model to be customized for a specific task. The input shape is set to (224, 224, 3). The `trainable=False` freezes the weights of the pretrained layers to prevent further training. The Sequential model is then extended by adding the pretrained ResNet50 model followed by a GlobalMaxPooling2D layer, which reduces spatial dimensions, capturing essential features for downstream tasks like classification or feature extraction. This architecture is often used for transfer learning.

4.3.3 Model Summary :

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 global_max_pooling2d (Glob  (None, 2048)              0
 alMaxPooling2D)

=================================================================
Total params: 23587712 (89.98 MB)
Trainable params: 0 (0.00 Byte)
Non-trainable params: 23587712 (89.98 MB)
_________________________________________________________________
```

Fig 4.2 Model Summary

4.3.4 Feature Extraction:

```
def extract_features(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
feature_list = []

for file in tqdm(filenames):
    feature_list.append(extract_features(file, model))
print(feature_list )
```

```
[array([0.        , 0.13786623, 0.02861855, ..., 0.        , 0.02109945,
       0.0254743 ], dtype=float32), array([0.01678325, 0.07988843, 0.01536004, .
       0.07193094], dtype=float32), array([0.        , 0.01889432, 0.01939535, .
       0.03598769], dtype=float32), array([0.        , 0.1426816 , 0.0115129 , .
       0.03496324], dtype=float32), array([0.        , 0.03735101, 0.03000848, .
       0.04117039], dtype=float32), array([0.        , 0.0565765 , 0.00359287, .
       0.02440979], dtype=float32), array([0.00107657, 0.12545267, 0.00774988, .
       0.0681839 ], dtype=float32), array([0.        , 0.06920397, 0.00619468, .
       0.05023292], dtype=float32), array([0.        , 0.1438349 , 0.0065473 , .
```

Fig 4.3 Feature List

4.3.5 Dumping of features list:

```
pickle.dump(feature_list, open('embeddings.pkl', 'wb'))
pickle.dump(filenames, open('filenames.pkl', 'wb'))
```

4.4 Input for Model:

```
def save_uploaded_file(uploaded_file):
try:
        with open(os.path.join('Uploads', uploaded_file.name),'wb') as f:
        f.write(uploaded_file.getbuffer())
        return 1
except:
        return 0
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 4.4 User file uploader

4.5 Recommendation using KNN:

```
def recommend(features, feature_list):

neighbors = NearestNeighbors(n_neighbors=5, algorithm='brute', metric='euclidean')

neighbors.fit(feature_list)

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

return indices
```

4.6 Website using Streamlit:

```
st.title("Fashion Recommendation System")
uploaded_file = st.file_uploader("Choose an image")
if uploaded_file is not None:
    if save_uploaded_file(uploaded_file):
        display_image = Image.open(uploaded_file)
        st.image(display_image)
        features = feature_extraction(os.path.join("Uploads", uploaded_file.name), model)
        st.text(features)
        indices = recommend(features, feature_list)

        col1,col2,col3,col4,col5 = st.columns(5)
        with col1:
            st.image(filenames[indices[0][0]])
        with col2:
```

```
        st.image(filenames[indices[0][1]])
    with col3:
        st.image(filenames[indices[0][2]])
    with col4:
        st.image(filenames[indices[0][3]])
    with col5:
        st.image(filenames[indices[0][4]])
```

4.7 Customization Using Streamlit:

```
if st.button("Customize"):
    # The link will open a new tab/window with the specified URL
    st.markdown("[Customize your own design!](http://localhost:8501)")
import streamlit as st
from PIL import Image

def combine_images(background, overlay):
    # Resize the overlay image to a smaller size (adjust as needed)
    overlay = overlay.resize((100,150))
    # Calculate the position to center the overlay on the background
    x_position = (background.width - overlay.width) // 2
    y_position = (background.height - overlay.height) // 3
    # Create a copy of the background image
    combined_image = background.copy()
    # Paste the overlay on top of the background with the mask
    combined_image.paste(overlay, (x_position, y_position))
    return combined_image

st.markdown("<h1 style='color: pink; background-color: brown; text-align: center; font-size:40px; font-family: 'Helvetica', sans-serif;'>UPLOAD YOUR IMAGE TO CUSTOMIZE THIS T-SHIRT</h1>", unsafe_allow_html=True)
# Predefined image (replace with your own image path)
predefined_image_path = "Imagess/Isolated_black_t-shirt_front_prev_ui.png"
predefined_image = Image.open(predefined_image_path)

# Display the predefined image
st.image(predefined_image, caption="Predefined Image", use_column_width=True)
```

```python
uploaded_logo = st.file_uploader("Choose your image", type=["png", "jpg", "jpeg"])
if uploaded_logo is not None:
    st.success("Image successfully uploaded!")

    # Display the uploaded logo on top of the predefined image
    combined_image = combine_images(predefined_image, Image.open(uploaded_logo))
    st.image(combined_image, caption="Combined Image", use_column_width=True)
```

Chapter 5: Final Analysis and Design:

5.1 Results

5.1.1. Recommendations:

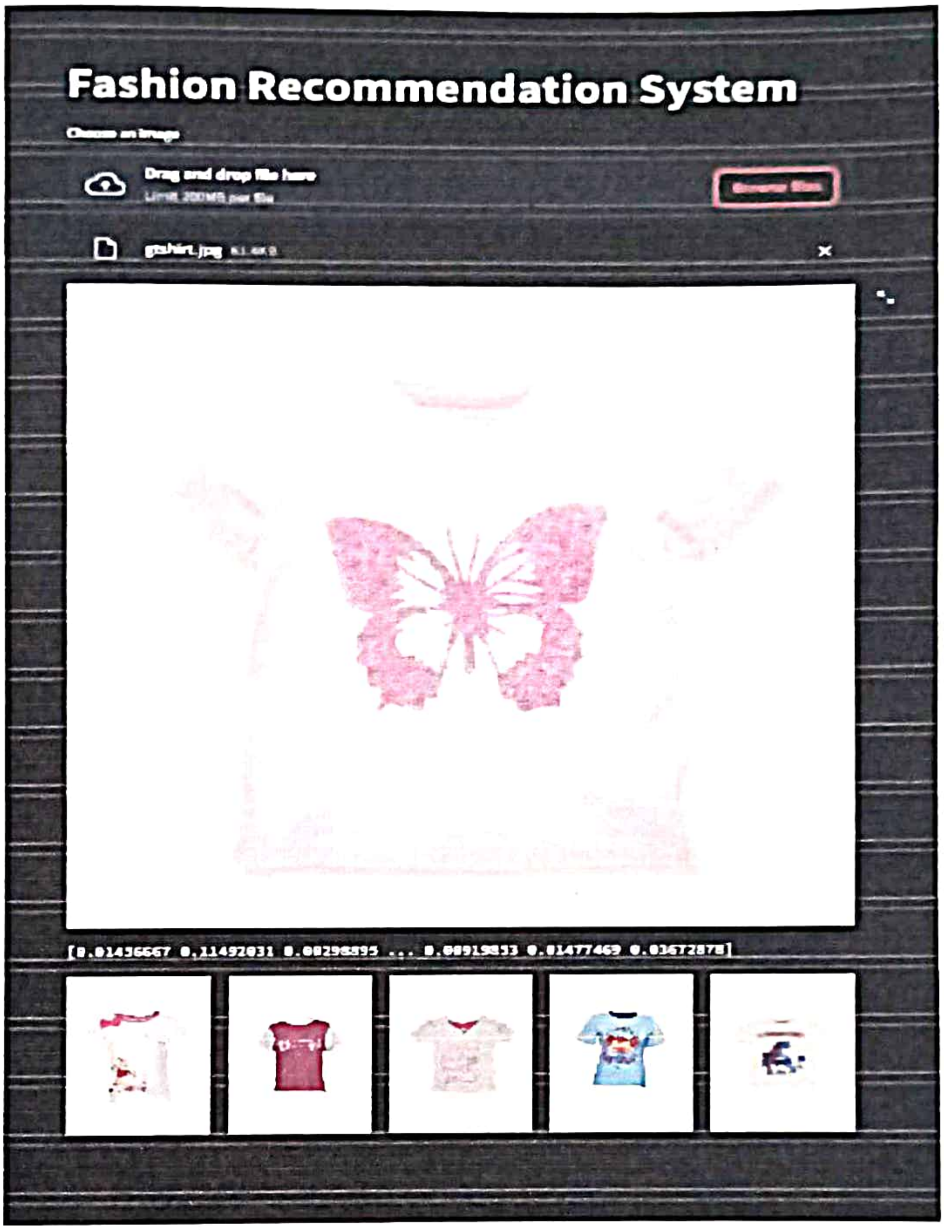

Fig 5.1 Recommendation for t-shirt

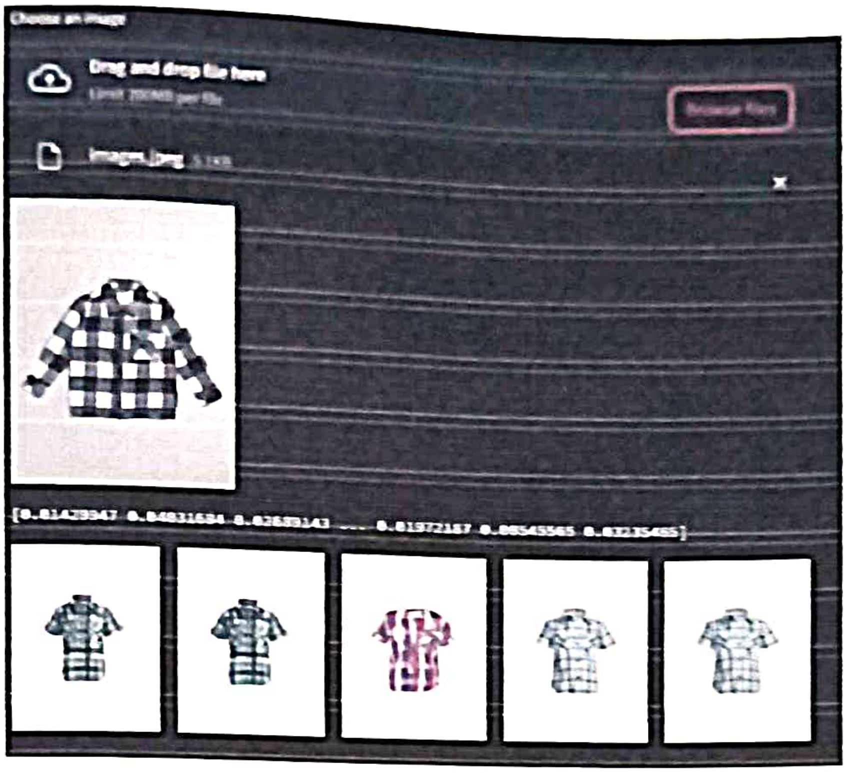

Fig 5.2 Recommendation for shirt

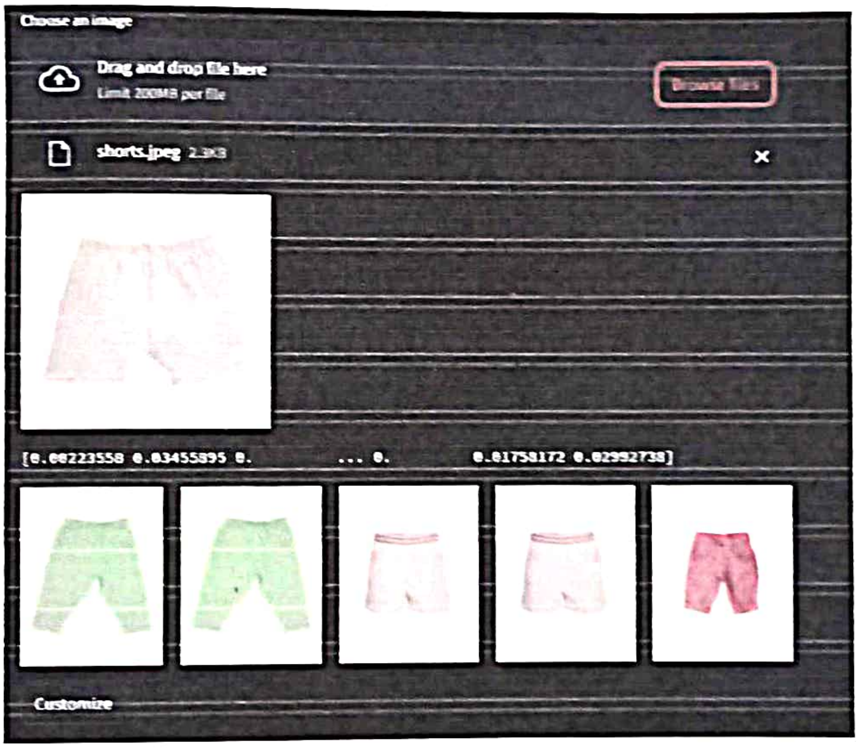

Fig 5.3 Recommendation for shorts

5.1.2 Customization:

Fig 5.4 Preview before customization

Fig 5.5 Customization 1

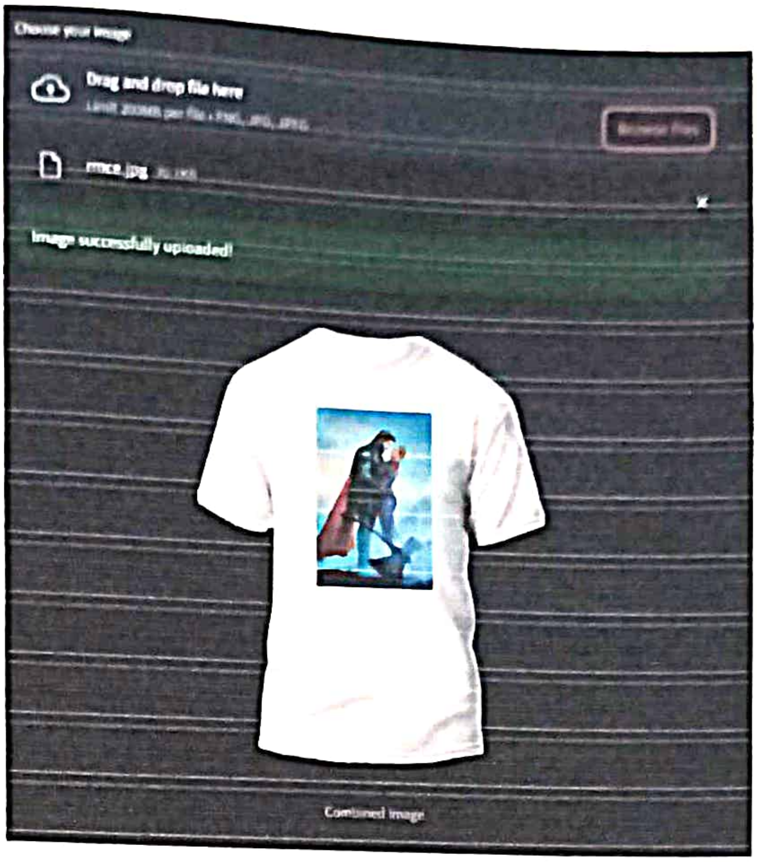

Fig 5.6 Customization 2

5.2 Application :

The Fashion Recommendation System enhances e-commerce platforms by delivering a personalized and visually engaging shopping experience. Widely applied in fashion retail websites, it boosts user engagement and loyalty by suggesting tailored product choices. This system significantly elevates conversion rates, transforming online shopping into an immersive and satisfying journey for users.

5.3 Problems Faced :

Implementing the Fashion Recommendation System posed challenges, notably in managing computational resources for real-time recommendations and coping with extended model training times. Addressing these hurdles necessitated a focused effort on optimizing code efficiency. Techniques such as parallel processing, model compression, and leveraging specialized hardware were employed to streamline computational resource usage. Additionally, algorithmic optimizations and caching mechanisms were introduced to enhance real-time recommendation responsiveness. This strategic approach not only mitigated the impact of resource-intensive operations but also contributed to a more scalable and robust system. The refined code efficiency ultimately improved the system's overall performance, ensuring a seamless and responsive experience for users while minimizing computational overhead during both real-time recommendations and model training.

5.4 Limitations :

Although the system exhibits enhanced accuracy, it is not without limitations. Its effectiveness is contingent upon the quality and diversity of the training dataset, posing challenges in scenarios where data may be limited or unrepresentative. Persistent issues like cold start problems, where recommendations are challenging for new or rarely seen items, persist. Handling sparse data remains a challenge, impacting the system's ability to provide accurate suggestions in data-scarce situations. Addressing these limitations requires ongoing research efforts, exploring innovative approaches to enhance recommendation algorithms. Continuous improvements in dataset quality, addressing cold start issues, and devising strategies to handle sparse data will contribute to the system's adaptability, ensuring more robust and reliable fashion recommendations in diverse and evolving scenarios

Chapter 6: Conclusion and Future Scope:

6.1 Conclusion:

Product recommendations engines are the best way to deliver customers with an improved user experience.Through machine learning, manual curation, and specific algorithms, a product recommendations engine can help bring customers the relevant products they want or need. It allows marketers to provide customers with relevant product recommendations in real time. As a part of an e-commerce personalization strategy, product recommendations dynamically populate products onto websites, apps, call centers, oremails, enhancing the customer experience. Using specialized algorithms, product recommendation engines are now able to support even the largest of product catalogs. The engine is able to intelligently select which algorithms and filters to apply in any given situation, for any given individual shopper. This means that the marketers can maximize conversions and average order value.

6.2 Future Scope:

The evolution of fashion recommendation systems is driven by advancements in artificial intelligence and data analytics. The theoretical underpinnings involve the continued development of algorithms that can efficiently process and analyze vast amounts of user data. Concepts from machine learning, including supervised and unsupervised learning, reinforcement learning, and neural networks, play a crucial role in improving recommendation accuracy.

The future of these systems also aligns with the principles of user-centered design, emphasizing a seamless and personalized user experience. As technology progresses, there will be an increased emphasis on transparency and interpretability of recommendation algorithms, addressing concerns related to privacy and algorithmic bias.

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