
Thank You
Result and Analysis
Exploratory Data Aanalysis
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Introduction
Model Construction
Dataset Description
Future Research
Methodology

Fashion Product Recommendation System

Sushma Bulusu
Nischita Biradar
Akshita Nimmala

Introduction

Fashion recommendation systems transform the shopping experience by tailoring suggestions to individual preferences, ultimately enhancing user satisfaction and revolutionizing the way people engage with fashion.

Problem Statement

Motivation

Application

Problem Statement

In the digital fashion industry, the challenge lies in optimizing user experience and facilitating efficient product discovery. Users often face difficulty in navigating vast selections and finding visually appealing items akin to their preferences.



Introduction

Fashion recommendation systems transform the shopping experience by tailoring suggestions to individual preferences, ultimately enhancing user satisfaction and revolutionizing the way people engage with fashion.

Problem Statement

Motivation

Application

Motivation

The goal is to boost user engagement, simplify browsing, and cater to diverse fashion tastes, ensuring efficient navigation and tailored recommendations.

Introduction

Fashion recommendation systems transform the shopping experience by tailoring suggestions to individual preferences, ultimately enhancing user satisfaction and revolutionizing the way people engage with fashion.

Problem Statement

Motivation

Application

Application

- Classification organizes products, while visual similarity finds related items.
- Mimics in-store browsing, simplifying search for visually similar products.

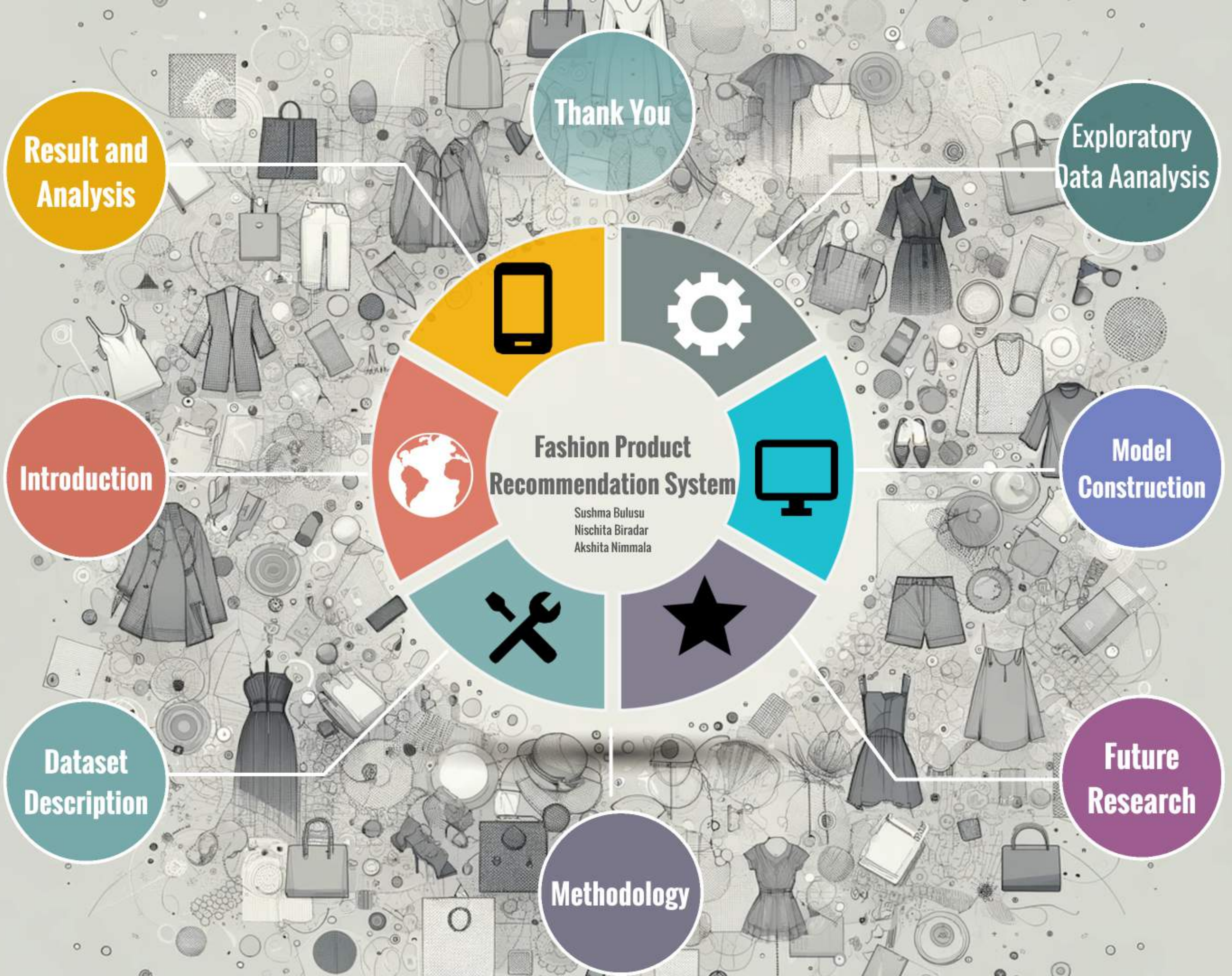
Introduction

Fashion recommendation systems transform the shopping experience by tailoring suggestions to individual preferences, ultimately enhancing user satisfaction and revolutionizing the way people engage with fashion.

Problem Statement

Motivation

Application


Thank You
Result and Analysis
Exploratory Data Aanalysis
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Introduction
Model Construction
Dataset Description
Future Research
Methodology

Methodology

This study employed a dual-component machine learning approach in the fashion domain, amalgamating image classification and visual similarity recommendations using the ResNet50 neural network architecture. The methodology harnessed GPU computational power to manage the demanding tasks of training and inference.

Step 1:

Step2:

Step 3:

Step 4:

Step 1: Setting up Computational Environment and Data Preprocessing

Step 1: Setting up Computational Environment and Data Preprocessing

- Established a computational environment and loaded essential libraries for image manipulation and deep learning.
- Conducted data preprocessing to eliminate erroneous entries, ensuring dataset quality.

Step 1: Setting up Computational Environment and Data Preprocessing

Methodology

This study employed a dual-component machine learning approach in the fashion domain, amalgamating image classification and visual similarity recommendations using the ResNet50 neural network architecture. The methodology harnessed GPU computational power to manage the demanding tasks of training and inference.

Step 1:

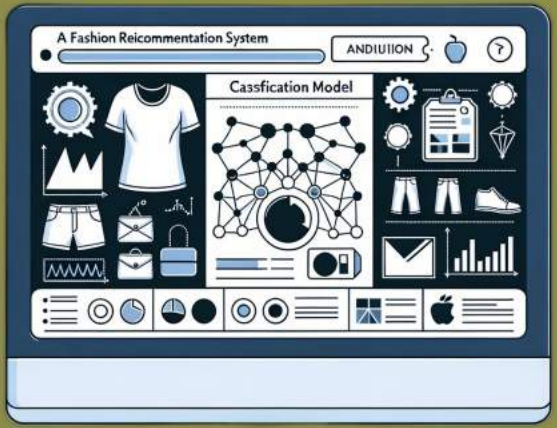
Step2:

Step 3:

Step 4:

Step 2: Analysing the Data

- Explored and analyzed dataset for insights on gender, categories, and subcategories.
- Visualized sales trends, product distribution, and usage patterns for strategic



Step 4:

Methodology

This study employed a dual-component machine learning approach in the fashion domain, amalgamating image classification and visual similarity recommendations using the ResNet50 neural network architecture. The methodology harnessed GPU computational power to manage the demanding tasks of training and inference.

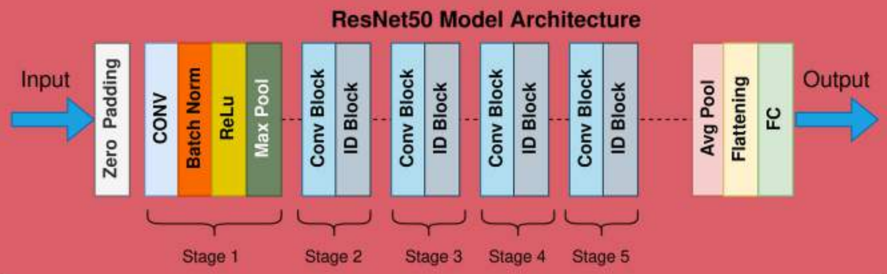
Step 1:

Step2:

Step 3:

Step 3: Transfer Learning ResNet50 Model for Classification:

- Leveraged the pre-trained ResNet50 model and fine-tuned it to the specific fashion classification task.
- Retrained the model on the fashion dataset, enabling it to differentiate between various article types based on visual features.



Methodology

This study employed a dual-component machine learning approach in the fashion domain, amalgamating image classification and visual similarity recommendations using the ResNet50 neural network architecture. The methodology harnessed GPU computational power to manage the demanding tasks of training and inference.

Step 1:

Step2:

Step 3:

Step 4:

Step 4: Development of Visual Similarity Recommendation Engine:

- Employed GPU-accelerated computing to transform images into high-dimensional embeddings.
- Utilized these embeddings to identify visually similar items, calculating distance metrics in the embedding space to measure similarity.

Methodology

This study employed a dual-component machine learning approach in the fashion domain, amalgamating image classification and visual similarity recommendations using the ResNet50 neural network architecture. The methodology harnessed GPU computational power to manage the demanding tasks of training and inference.

Step 1:

Step2:

Step 3:

Step 4:


Thank You
Result and Analysis
Exploratory Data Aanalysis
Introduction
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Model Construction
Dataset Description
Future Research
Methodology

Dataset Description

Sourced from Kaggle, this dataset focuses on the fashion e-commerce industry, comprising various attributes of products available for sale.The folder named 'fashion-dataset' encompasses the following crucial components:

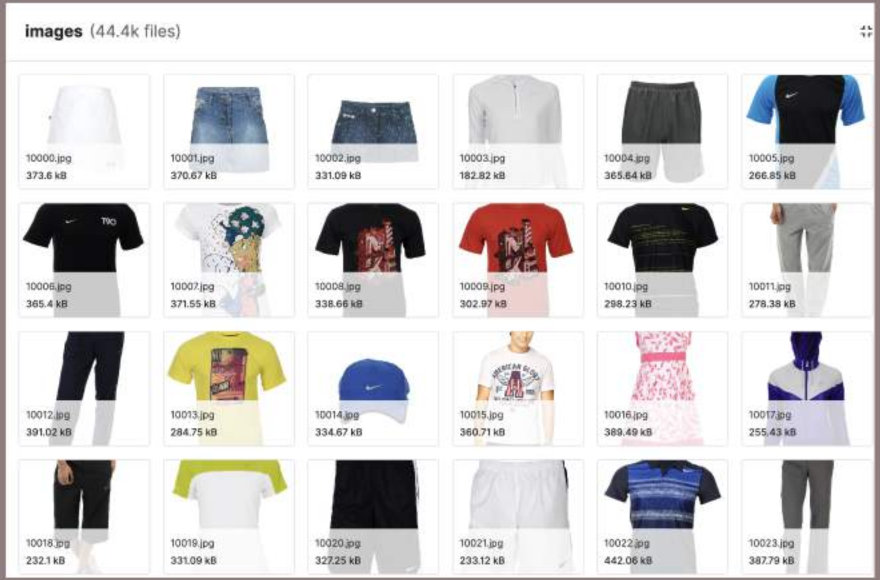
- 'images'
- 'styles'
- 'images.csv'
- 'styles.csv'

'images' dataset

'styles.csv' dataset

Images Dataset

- Collection of image files depicting fashion products within the dataset.
- Provides visual representation linked to structured fashion metadata for analysis , classification and recommendation tasks.



Dataset Description

Sourced from Kaggle, this dataset focuses on the fashion e-commerce industry, comprising various attributes of products available for sale.The folder named 'fashion-dataset' encompasses the following crucial components:

- 'images'
- 'styles'
- 'images.csv'
- 'styles.csv'

'images' dataset

'styles.csv' dataset

styles.csv dataset

- Structured Metadata: Contains detailed information about fashion products in a tabular format.
- Key Attributes: Includes columns like 'id', 'gender', 'category', 'color', 'season', aiding in segmentation and analysis.

id	gender	masterCategory	subCategory	articleType	baseColour	season	year	usage
The product ID assigned in the product catalog.	Clothing targeted to which gender.	Primary category.	Secondary Category.	Type of clothing	Descriptive color name.	Which fashion season is this targeted to.	Which fashion year is this from.	How is the to be used
1163 60.0k	Men 50% Women 42% Other (3649) 8%	Apparel 48% Accessories 25% Other (11757) 26%	Topwear 35% Shoes 17% Other (21697) 49%	Tshirts 16% Shirts 7% Other (34159) 77%	Black 22% White 12% Other (29174) 66%	Summer 48% Fall 26% Other (11525) 26%	2007 2019	Casual Sports Other (600
15970	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011	Casual
39386	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012	Casual
59263	Women	Accessories	Watches	Watches	Silver	Winter	2016	Casual
21379	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011	Casual
53759	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012	Casual
1855	Men	Apparel	Topwear	Tshirts	Grey	Summer	2011	Casual
30805	Men	Apparel	Topwear	Shirts	Green	Summer	2012	Ethnic

'color', 'season', aiding in segmentation and analysis.

id	gender	masterCategory	subCategory	articleType	baseColour	season	year	usage
The product ID assigned in the product catalog.	Clothing targeted to which gender.	Primary category.	Secondary Category.	Type of clothing	Descriptive color name.	Which fashion season is this targeted to.	Which fashion year is this from.	How is the to be used.
1163 60.0k	Men 50% Women 42% Other (3649) 8%	Apparel 48% Accessories 25% Other (11757) 26%	Topwear 35% Shoes 17% Other (21697) 49%	Tshirts 16% Shirts 7% Other (34159) 77%	Black 22% White 12% Other (29174) 66%	Summer 48% Fall 26% Other (11525) 26%	2007 2019	Casual Sports Other (600
15970	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011	Casual
39386	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012	Casual
59263	Women	Accessories	Watches	Watches	Silver	Winter	2016	Casual
21379	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011	Casual
53759	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012	Casual
1855	Men	Apparel	Topwear	Tshirts	Grey	Summer	2011	Casual
30805	Men	Apparel	Topwear	Shirts	Green	Summer	2012	Ethnic

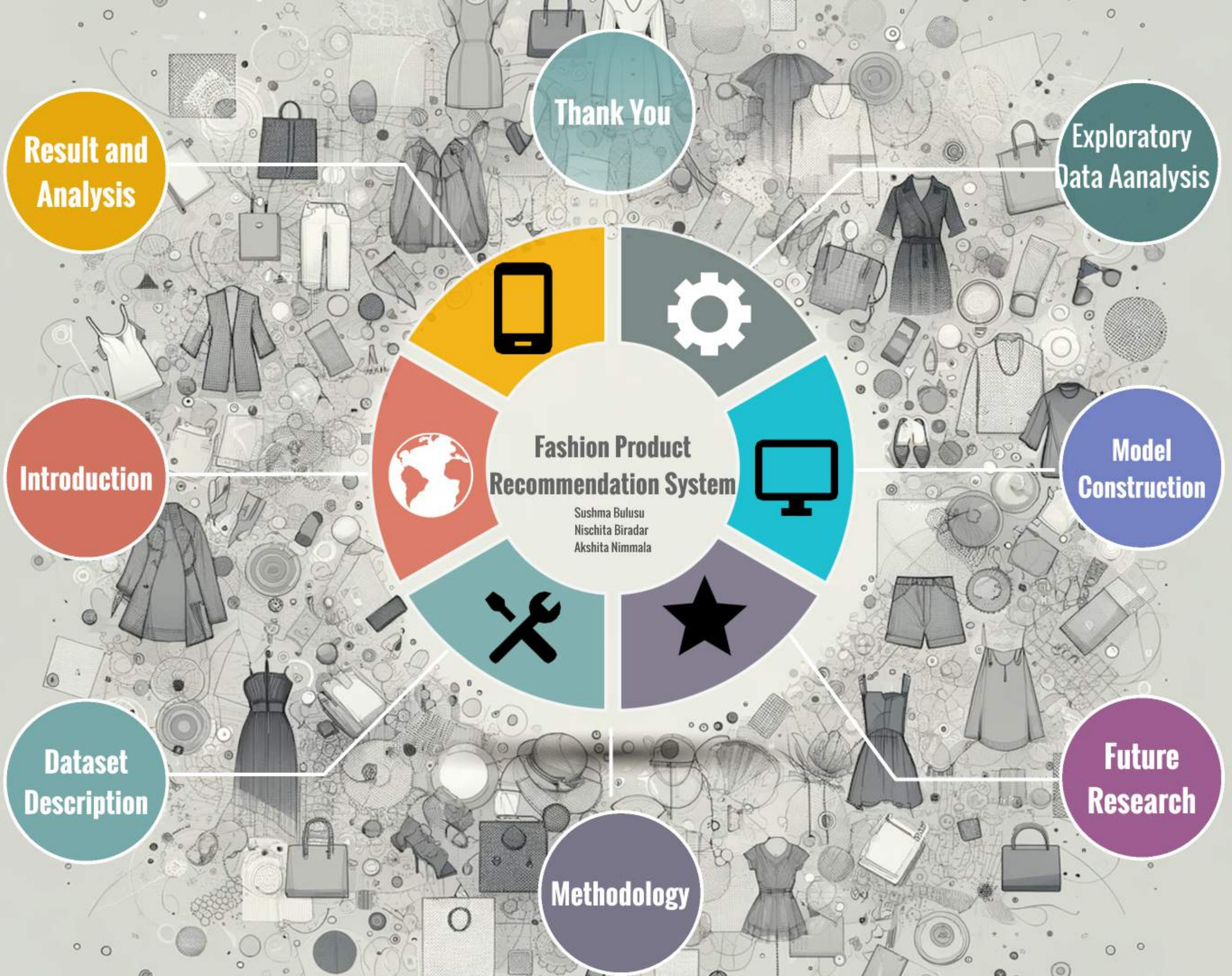
Dataset Description

Sourced from Kaggle, this dataset focuses on the fashion e-commerce industry, comprising various attributes of products available for sale.The folder named 'fashion-dataset' encompasses the following crucial components:

- 'images'
- 'styles'
- 'images.csv'
- 'styles.csv'

'images' dataset

'styles.csv' dataset



Thank You
Result and Analysis
Exploratory Data Aanalysis
Introduction
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Model Construction
Dataset Description
Future Research
Methodology

Exploratory Data Analysis

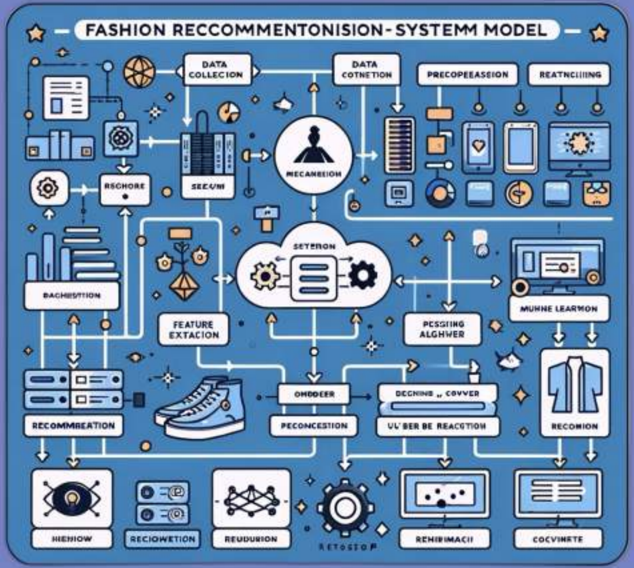
- Analyzed sales trends across genders, categories, subcategories, and article types.Identified best-selling categories and subcategories.
- Identified top-performing categories and subcategories in terms of sales.
- Developed an interactive dashboard using Python's Streamlit library to present visualizations and insights derived from the sales data.

Link to dashboard: https://fashionappuctrecommendationsystem-twfnnegaj8ekdaarypzpsn.streamlit.app/


Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Thank You
Exploratory Data Aanalysis
Model Construction
Future Research
Methodology
Dataset Description
Introduction
Result and Analysis

Model Construction

- Employed deep learning methodologies as the foundation for the fashion product recommendation system
- Utilized transfer learning for fashion image feature extraction, effective product categorization.



Classification using Transfer Learning

Recommendation using visual similarity search

Data Preprocessing, Augmentation and Normalization

Integrated CSV and JPG files to form a unified dataframe for streamlined data analysis.

Mitigated class imbalances by selecting Article Types with a minimum of 275 images, diminishing potential biases.

```
Class with the most images: Tshirts, Count: 7067
Class with the least images: Hair Accessory, Count: 1
```

```
Number of classes with more than 275 images: 35
Classes and their image counts:
Tshirts                 7067
Shirts                  3217
Casual Shoes            2845
Watches                 2542
Sports Shoes            2036
Kurtas                  1844
Tops                    1762
Handbags                1759
Heels                   1323
Sunglasses              1073
Wallets                  936
Flip Flops               914
Sandals                  897
```

Employed transformation functions such as Resize, CenterCrop, Horizontal flip, ToTensor, Normalize to standardize and ensure uniformity within the dataset.

```
'train': transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
]),
'val': transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
```

Transfer Learning using Resnet50

1. Employed Transfer Learning: Adapted ResNet50's last layer to our dataset for resource-efficient modeling.

2. ResNet50 Overview: Utilized a pre-trained deep convolutional neural network with 50 layers trained on the extensive ImageNet database.

3. Implemented Fine Tuning: Tailored dataset, adjusted parameters, and fine-tuned the final layer to fit our merchandise categories.

4. Optimized Model Architecture: Altered ResNet50's last layer from its original 1000-class output to the number of categories in our dataset.

Fine Tuning

1

Model Adaptation & Optimization:
Adjusted ResNet50's final layer and utilized SGD with momentum for optimization

2

Learning Rate Management:
Implemented a scheduler for gradual learning rate reduction, facilitating faster learning initially, followed by precise adjustments for convergence.

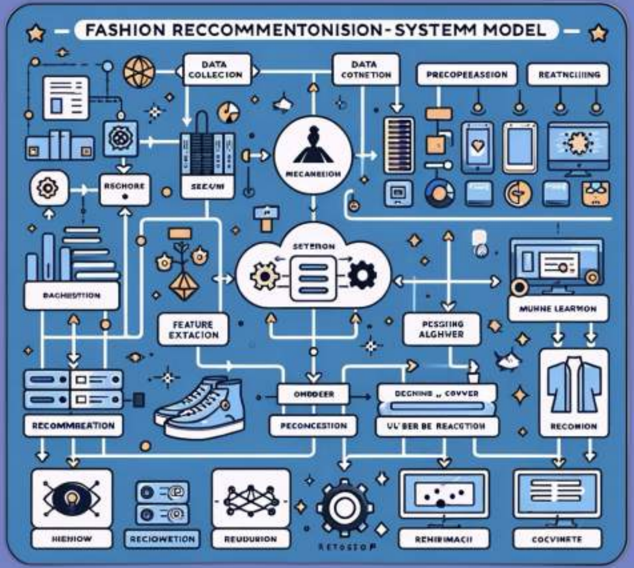
```
model_ft = models.resnet50(pretrained=True)
num_ftrs = model_ft.fc.in_features

#Change the number of outputs in the last layer to the number of different item types
model_ft.fc = nn.Linear(num_ftrs, len(class_names))

model_ft = model_ft.to(device)

#Measuring Model Performance
criterion = nn.CrossEntropyLoss()

# Observe that all parameters are being optimized
optimizer_ft = optim.SGD(model_ft.parameters(), lr=0.001, momentum=0.9)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)
```

Before fine tuning:

After fine tuning:

Model Construction

- Employed deep learning methodologies as the foundation for the fashion product recommendation system
- Utilized transfer learning for fashion image feature extraction, effective product categorization.



Classification using Transfer Learning

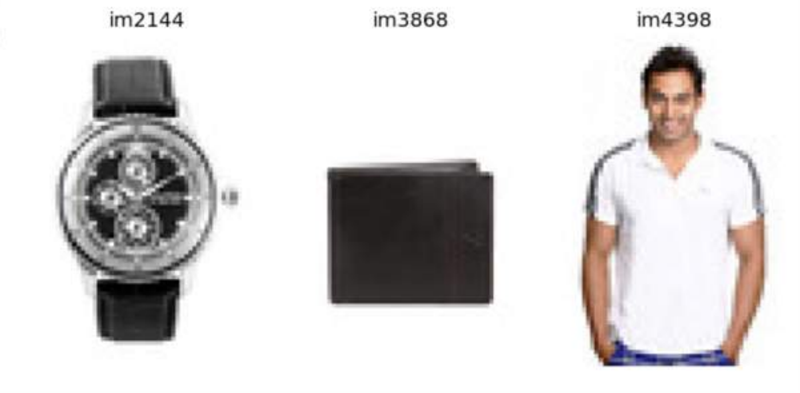
Recommendation using visual similarity search

Data Preprocessing

```python
def check_image_exists(image_filename):
    """
    Checks if the desired filename exists within the filenames found in the given directory.
    Returns True if the filename exists, False otherwise.
    """
    global images
    if image_filename in images:
        return image_filename
    else:
        return np.nan

df['image'] = df["id"].apply(lambda image: check_image_exists(str(image) + ".jpg"))
df = df.reset_index(drop=True)
df.head()
```

	id	gender	masterCategory	subCategory	articleType	baseColour	season	year	usage	productDisplayName	image
0	15970	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011	Casual	Turtle Check Men Navy Blue Shirt	15970.jpg
1	39386	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012	Casual	Peter England Men Party Blue Jeans	39386.jpg
2	59263	Women	Accessories	Watches	Watches	Silver	Winter	2016	Casual	Titan Women Silver Watch	59263.jpg
3	21379	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011	Casual	Manchester United Men Solid Black Track Pants	21379.jpg
4	53759	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012	Casual	Puma Men Grey T-shirt	53759.jpg

```python
# generation of a dictionary of (title, images)
figures = {'im'+str(i): import_img(row.image) for i, row in df.sample(6).iterrows()}
# plot of the images in a figure, with 2 rows and 3 columns
plot_figures(figures,2,3)
```



Recommendation Using Visual Similarity Search

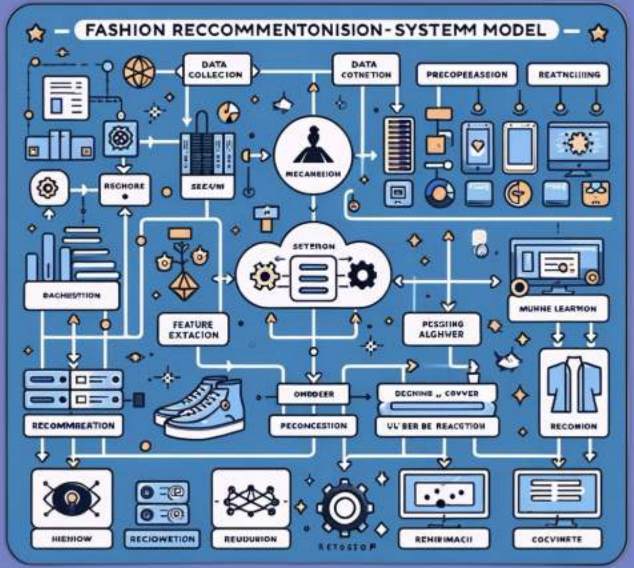
- Feature Extraction using ResNet Model
- Feature Vector Creation
- Forward Pass and Feature Vector Extraction

Vector Extraction

```
def vector_extraction(resnetmodel, image_id):

    # Using concept of exception handling to ignore missing images
    try:
        # 1. Load the image with Pillow library
        img = Image.open(image_location(image_id)).convert('RGB')

        # 2. Create a PyTorch Variable with the transformed image
        t_img = Variable(standardize(convert_tensor(s_data(img))).unsqueeze(0))

        # 3. Create a vector of zeros that will hold our feature vector
        # The 'avgpool' layer has an output size of 512
        embeddings = torch.zeros(512)

        # 4. Define a function that will copy the output of a layer
        def copy_data(m, i, o):
            embeddings.copy_(o.data.reshape(o.data.size(1)))

        # 5. Attach that function to our selected layer
        hlayer = layer.register_forward_hook(copy_data)

        # 6. Run the model on our transformed image
        resnetmodel(t_img)

        # 7. Detach our copy function from the layer
        hlayer.remove()
        emb = embeddings

        # 8. Return the feature vector
        return embeddings
```

Model Construction

- Employed deep learning methodologies as the foundation for the fashion product recommendation system
- Utilized transfer learning for fashion image feature extraction, effective product categorization.



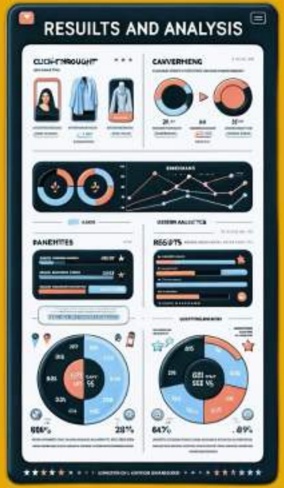
Classification using Transfer Learning

Recommendation using visual similarity search


Fashion Product
Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Thank You
Exploratory
Data Aanalysis
Model
Construction
Future
Research
Methodology
Dataset
Description
Introduction
Result and
Analysis

Results and Analysis

- Enhanced model accuracy and demonstrated its effectiveness in fashion classification tasks.
- The recommendation system demonstrated efficiency in suggesting visually similar items.

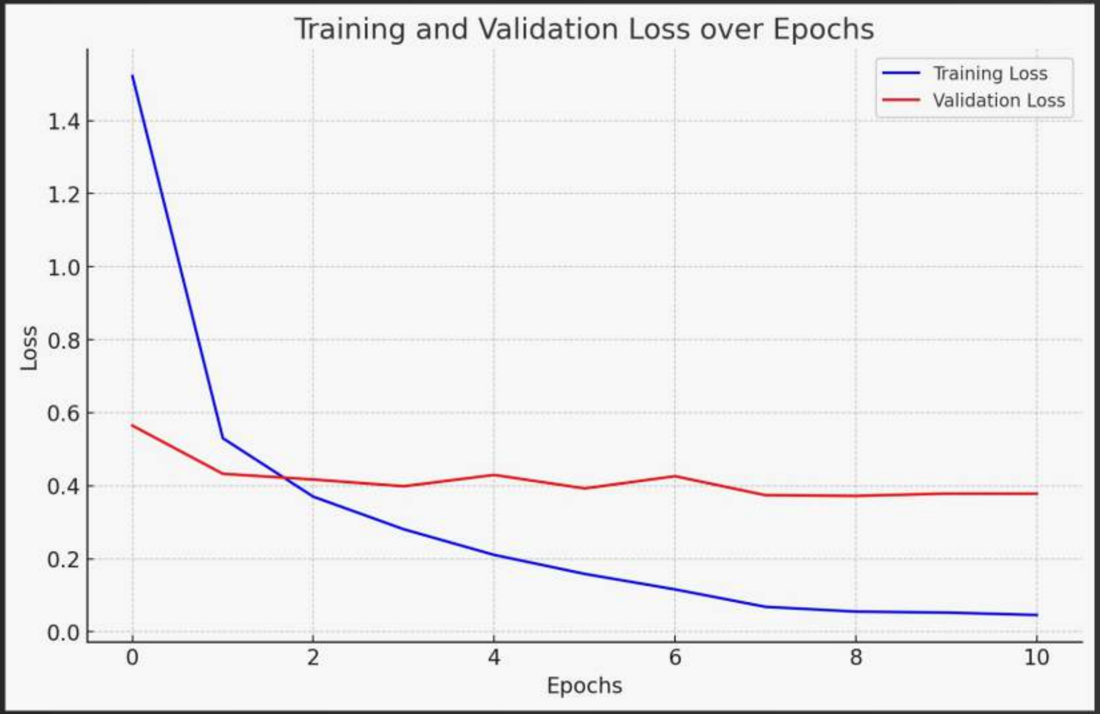


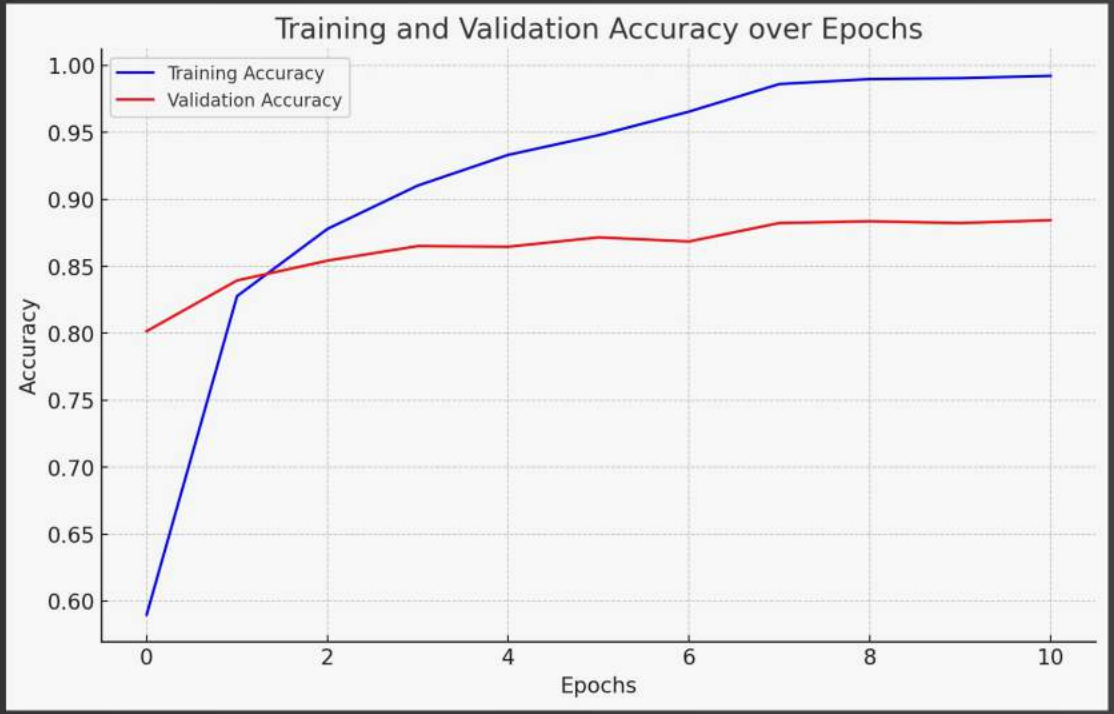
Model Performence Metrics

Classification Results

Recommendation Results

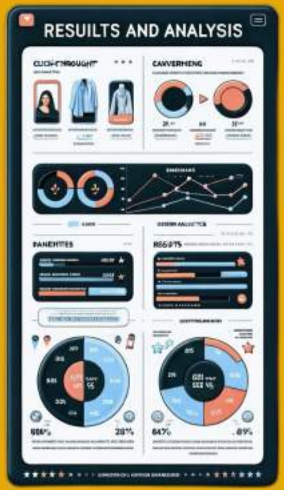
Model Performance Metrics





Results and Analysis

- Enhanced model accuracy and demonstrated its effectiveness in fashion classification tasks.
- The recommendation system demonstrated efficiency in suggesting visually similar items.

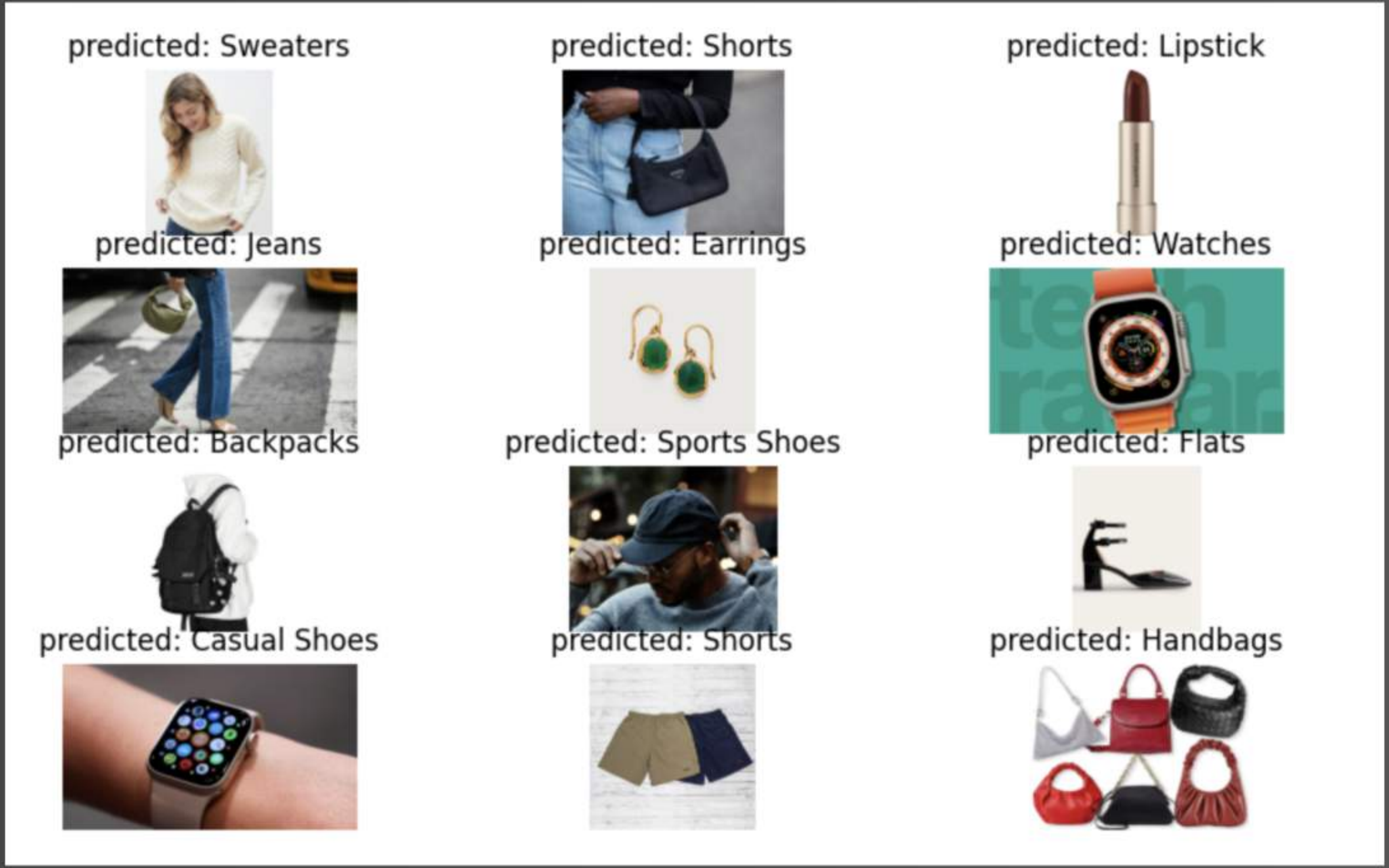


Model Performence Metrics

Classification Results

Recommendation Results

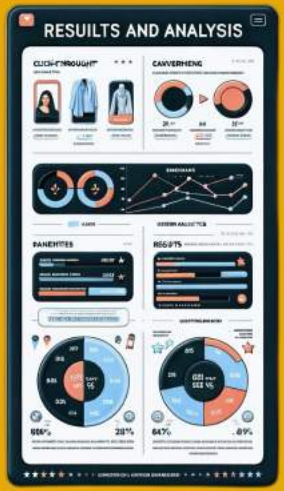
Classification Results



The model has predicted various categories of fashion related items such as as sweaters,jeans,shorts,lipstick etc.

Results and Analysis

- Enhanced model accuracy and demonstrated its effectiveness in fashion classification tasks.
- The recommendation system demonstrated efficiency in suggesting visually similar items.



Model Performence Metrics

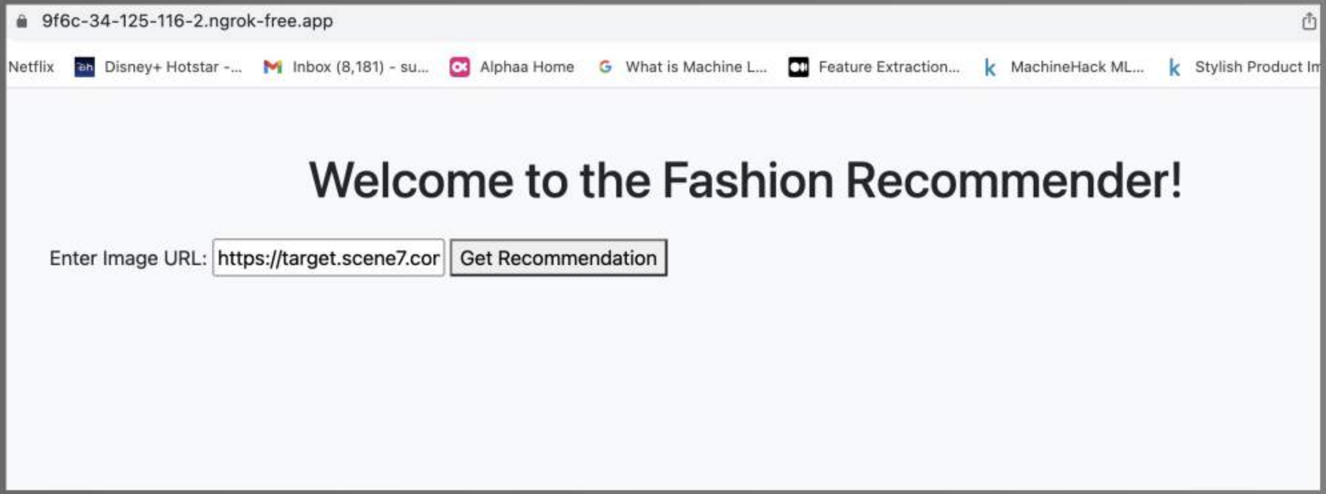
Classification Results

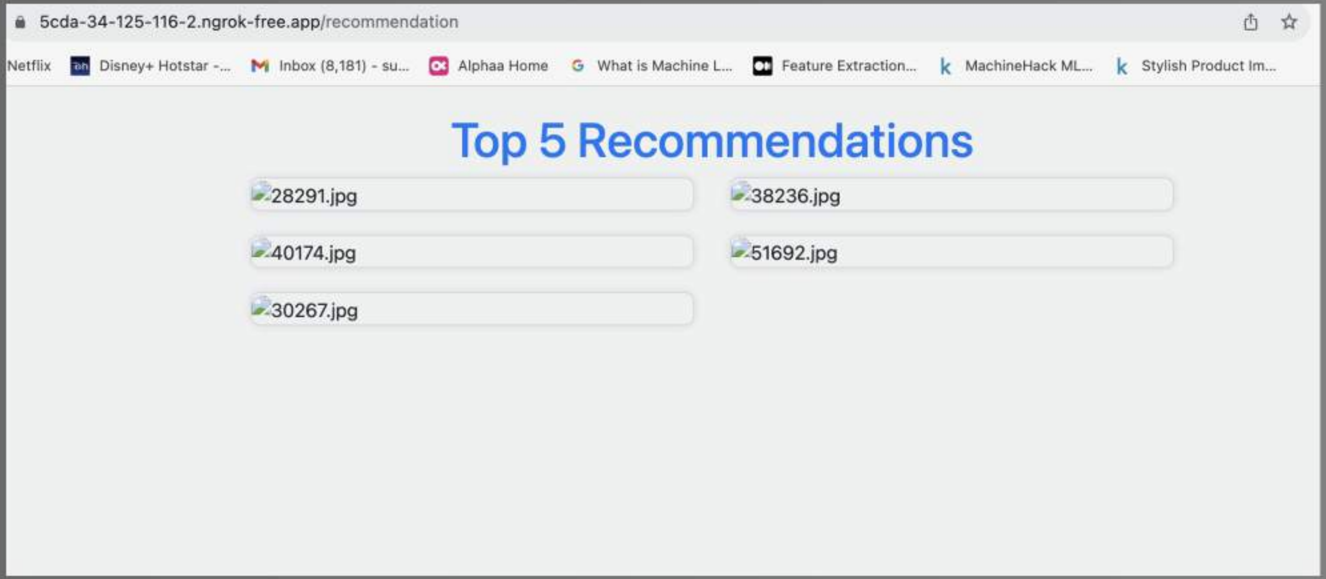
Recommendation Results

Top 5 Recommendation Results

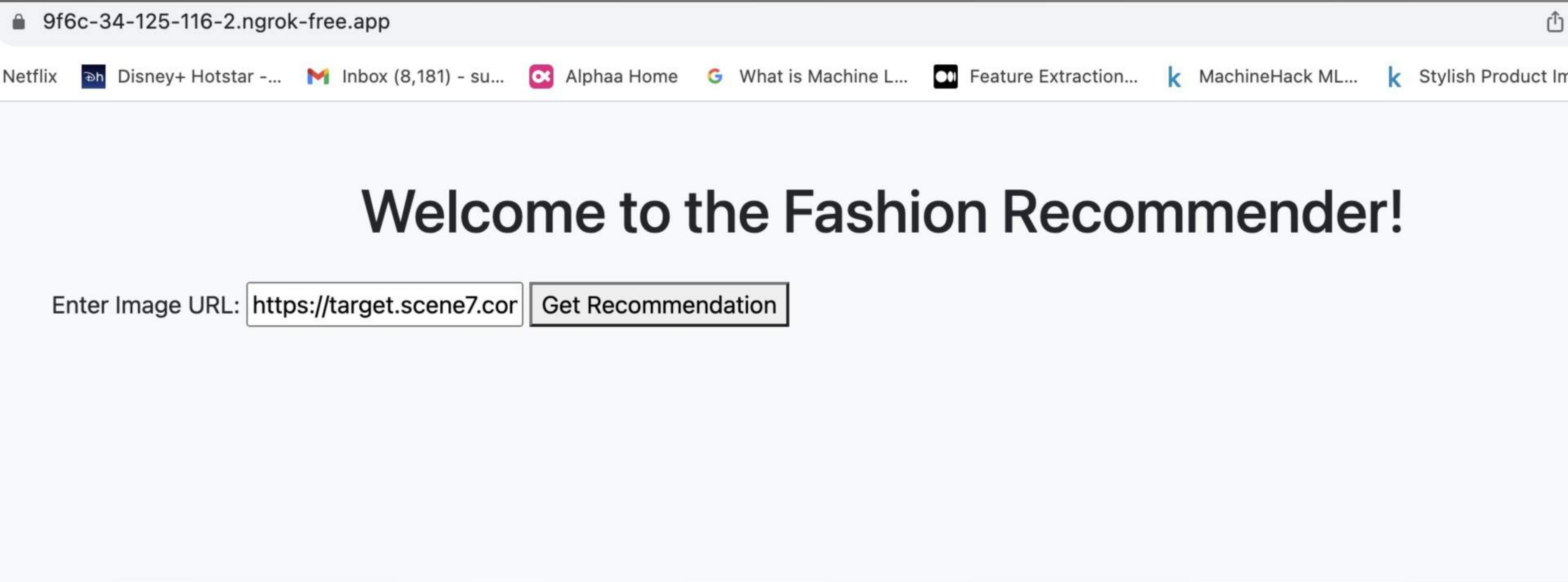
The recommendation system successfully identifies and presents the top 5 visually similar items to a user-input fashion item.

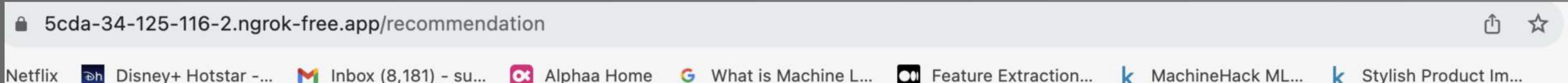
Our Attempt at UI Development





Our Attempt at UI Development





5cda-34-125-116-2.ngrok-free.app/recommendation

Netflix | Disney+ Hotstar -... | Inbox (8,181) - su... | Alphaa Home | What is Machine L... | Feature Extraction... | MachineHack ML... | Stylish Product Im...

Top 5 Recommendations

28291.jpg

38236.jpg

40174.jpg

51692.jpg

30267.jpg

Results and Analysis

- Enhanced model accuracy and demonstrated its effectiveness in fashion classification tasks.
- The recommendation system demonstrated efficiency in suggesting visually similar items.

Model Performence Metrics

Classification Results

Recommendation Results

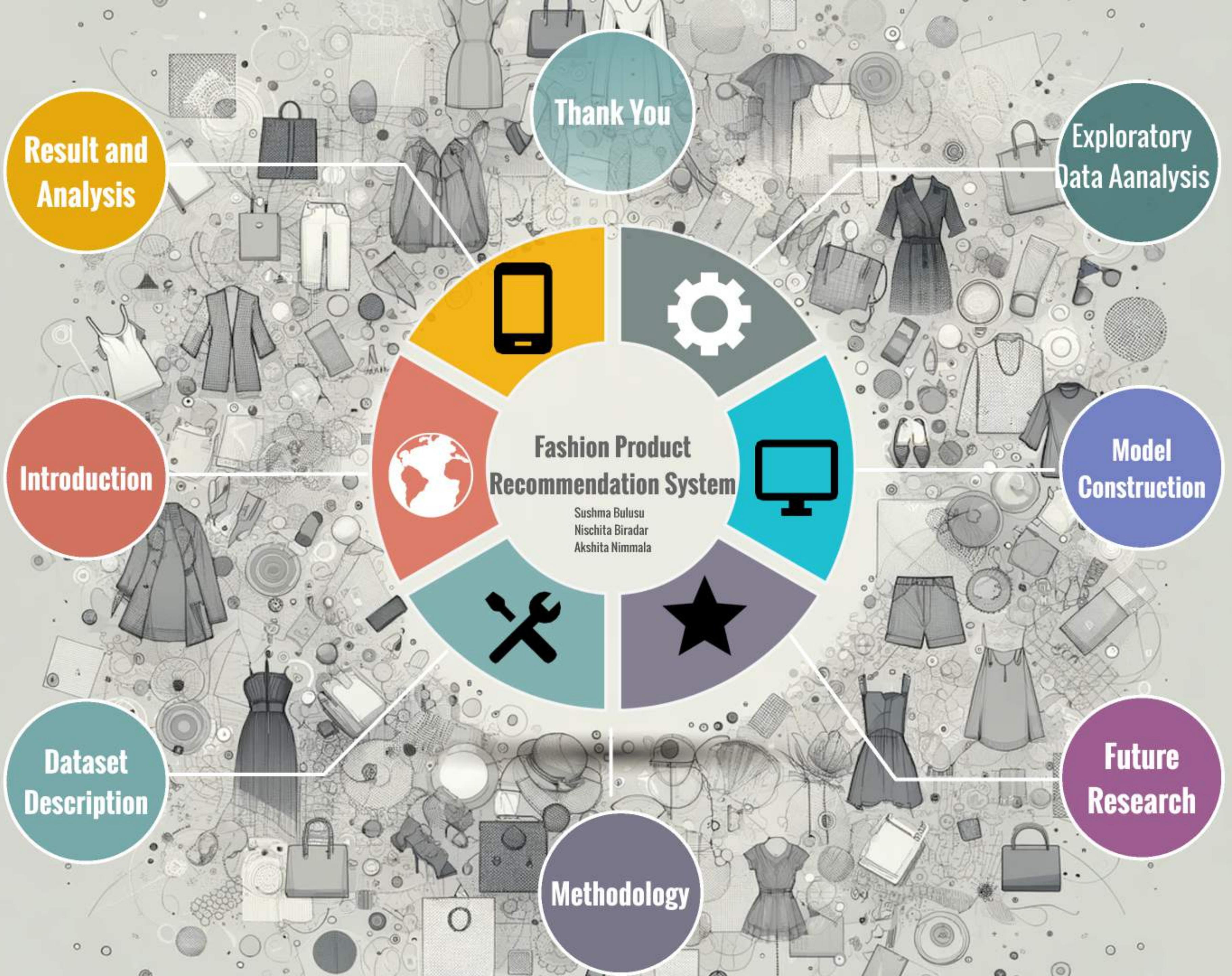

Thank You
Result and Analysis
Exploratory Data Aanalysis
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Introduction
Model Construction
Dataset Description
Future Research
Methodology

Future Research

- Integrating user interaction data for improved personalization.
- Exploring multi-modal recommendations for a holistic approach.
- Incorporating contextual cues for more relevant suggestions.
- Enhancing deep learning for fine-grained item analysis.
- Applying reinforcement learning for adaptive recommendations.
- Addressing fairness and bias issues in recommendations.


Thank You
Result and Analysis
Exploratory Data Aanalysis
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Introduction
Model Construction
Dataset Description
Future Research
Methodology

Thank You !


Thank You
Result and Analysis
Exploratory Data Aanalysis
Fashion Product Recommendation System
Sushma Bulusu
Nischita Biradar
Akshita Nimmala
Introduction
Model Construction
Dataset Description
Future Research
Methodology