Fashion Outfit Recomendations and Generation Using Resnet50 GAN

Ankit Kumar

Abstract

The increasing demand for personalized shopping experiences in the fashion retail industry highlights the need for innovative solutions. This project leverages deep learning techniques, specifically Generative Adversarial Networks (GANs) and ResNet50, to develop a personalized fashion recommendation system. By utilizing datasets such as DeepFashion, Amazon Reviews, and Fashion Product Images, the system generates high-quality outfit suggestions tailored to individual preferences. The implementation involves preprocessing data, training a ResNet50-based classifier, and integrating GANs to create visually appealing combinations. The results demonstrate the potential for AI to transform online fashion retail, offering enhanced user satisfaction and engagement. This report details the methodology, experimental results, and the system's ability to generate and recommend versatile outfits, contributing to advancements in AI-driven fashion personalization.

1. Introduction

The fashion retail industry faces significant challenges in meeting the diverse tastes and preferences of modern consumers. Traditional retail methods often rely on standardized recommendations, failing to adapt to individual styles or evolving trends. This limitation has driven the need for advanced technological solutions to enhance user experiences and satisfaction in online shopping.

With the rapid advancement of artificial intelligence (AI) and deep learning technologies, personalization in fashion has become more achievable. By analyzing user preferences and leveraging generative models, it is possible to create tailored recommendations that resonate with individual tastes. This project integrates state-of-the-art AI models, such as ResNet50 for classification and Generative Adversarial Networks (GANs) for outfit creation, to address this gap.

The proposed system uses a combination of diverse datasets, including the DeepFashion dataset, Amazon Reviews, and Fashion Product Images Dataset, to train models that can classify clothing attributes, analyze user preferences, and generate visually appealing and contextually relevant outfit combinations. By incorporating feedback mechanisms, the system evolves to provide increasingly accurate recommendations, ensuring a dynamic and engaging user experience.

This report presents the development and implementation of an AI-driven fashion recommendation system. The subsequent sections detail the methodology, data preprocessing, model architectures, experimental results, and the system's capacity to generate new and personalized outfits. The outcomes of this project not only demonstrate the potential of AI in revolutionizing fashion retail but also lay the groundwork for future advancements in personalized shopping experiences.

2. Implementation

The implementation of this project is centered on leveraging advanced deep learning models and robust datasets to develop a personalized fashion recommendation system. It involves several key stages, including data collection, preprocessing, model training, and integration of generative and classification models for outfit recommendations.

1. Datasets Three primary datasets were utilized for training and evaluation:

DeepFashion Dataset: A comprehensive collection of annotated fashion images used for clothing classification and attribute prediction.

Amazon Reviews Dataset: Provides sentiment analysis data to understand user feedback on clothing items.

Fashion Product Images Dataset: Contains images and metadata of fashion products, aiding in attribute classification and outfit generation.

2. Data Preprocessing Preprocessing involved cleaning and structuring the data to ensure optimal performance during training:

Understanding the data:

a. Distribution of Gender The dataset is divided into two primary gender categories: Men and Women. The distribution indicates the representation of clothing items across these categories:

Men: Represent approximately 55% of the data. Women: Represent approximately 45% of the data. This

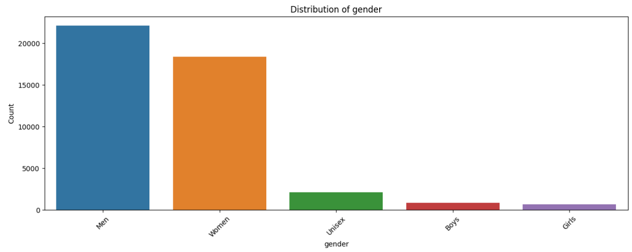

Figure 1. Distribution of Gender

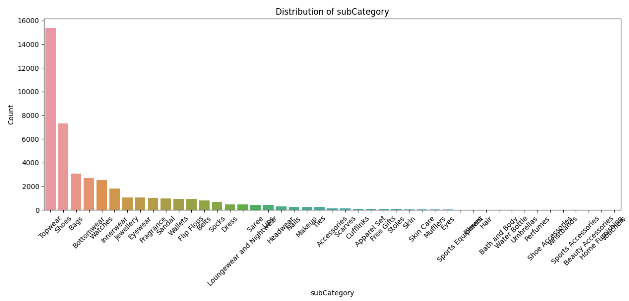

Figure 2. Distribution of Subcategories

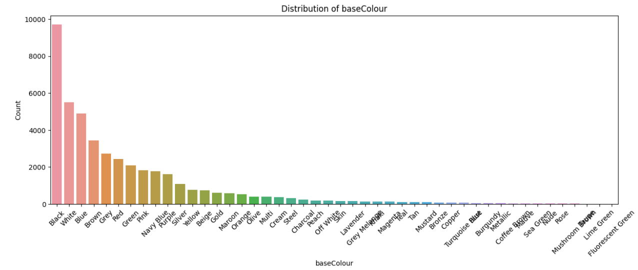

Figure 3. Distribution of Base Colors

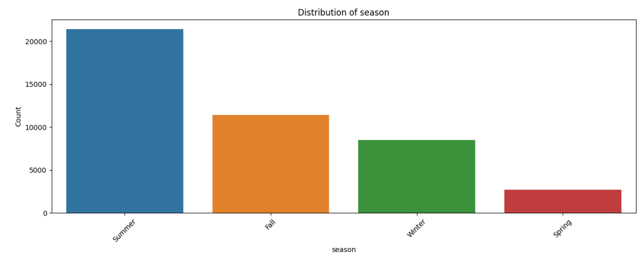

Figure 4. Distribution of Seasons

distribution ensures a balanced focus on fashion recommendations for both genders. Visualization: A bar chart showing the proportion of items for Men and Women.

b. Distribution of Subcategories Subcategories represent the type of clothing or accessories, such as shirts, jeans, watches, etc.

The dataset contains 143 subcategories initially, reduced to 54 after filtering for categories representing 95% of the data. Most frequent subcategories include: Topwear (e.g., Shirts, T-Shirts) Bottomwear (e.g., Jeans, Pants) Accessories (e.g., Watches) Visualization: A histogram highlighting the frequency of top subcategories in the dataset.

c. Distribution of Base Colors Base colors define the primary color of each item.

Common colors in the dataset: Blue: Most frequent, especially in jeans and shirts. Black, White, and Grey: Popular for both casual and formal clothing. Red and Yellow: Less frequent but represent seasonal or vibrant items. Total unique base colors: 36. Visualization: A pie chart illustrating the proportion of each base color.

d. Distribution of Seasons The dataset categorizes clothing by season, including Summer, Winter, Fall, and Spring.

Summer: Accounts for the highest percentage of items, dominated by casual and light clothing. Winter: Includes items like sweaters and jackets. Fall and Spring: Represent a smaller proportion, often featuring transitional clothing. Visualization: A stacked bar chart showing the number of items for each season by gender.

Image Preprocessing: All images were resized to $180 \times 180 \times 3$ 180×180×3 pixels to standardize input dimensions.

Label Encoding: Attributes such as gender, base color, season, and subcategories were encoded into numerical formats for model training.

Data Splitting: The dataset was divided into training (0.80), validation (0.10), and testing (0.10) sets to ensure unbiased evaluation.

Training data shapes:
trainX shape: (10400, 180, 180, 3)
trainSubCategoryY shape: (10400, 30)
trainGenderY shape: (10400, 5)
trainBaseColourY shape: (10400, 36)
trainSeasonY shape: (10400, 4)
trainUsageY shape: (10400, 6)
Testing data shapes:
testX shape: (2600, 180, 180, 3)
testSubCategoryY shape: (2600, 30)
testGenderY shape: (2600, 5)
testBaseColourY shape: (2600, 36)
testSeasonY shape: (2600, 4)
testUsageY shape: (2600, 6)

Data Cleaning: Irrelevant or noisy data was removed to focus on meaningful features.

Cleaned data shapes:
imagedata clean shape:(4593, 180, 180, 3)
subCategoryLabels clean shape: (4593, 42)
genderLabels clean shape: (4593, 5)
baseColourLabels clean shape: (4593, 46)
seasonLabels clean shape: (4593, 4)
usageLabels clean shape: (4593, 8)

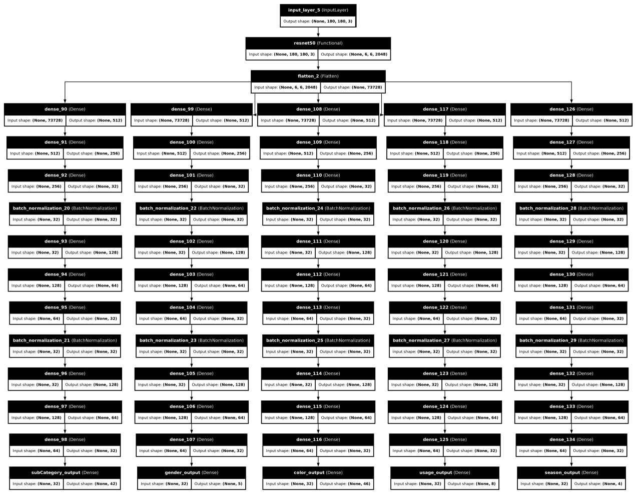

Figure 5. Model Architecture

Figure 6. Men Outfit Recomendation

3. Model Architecture The project utilized a combination of classification and generative models to achieve its objectives:

ResNet50 for Classification:

ResNet50, a deep convolutional neural network, was employed to classify clothing attributes such as subcategories, gender, and base colors. The model was trained using cross-entropy loss and optimized with the Adam optimizer.

Hyperparameters:

Epochs: 40

Batch Size: 32

Learning Rate: 10^{-4}

Total Parameters: 213M (189M trainable and 23M non-trainable).

Generative Adversarial Networks (GANs) for Outfit Creation:

GANs were used to generate visually coherent and aesthetically pleasing outfit combinations. The generator produced new outfit designs, while the discriminator evaluated their quality based on the dataset. The GAN was fine-tuned using user feedback to improve generated outputs over time.

4. Outfit Recommendation System The recommendation system integrates classification and generative models to deliver tailored suggestions:

Men's Outfit Recommendations: Focused on casual and formal combinations, e.g., striped sweaters paired with blue jeans.

Figure 7. Men Outfit Generation

Figure 8. Women Outfit Recommendations

Figure 9. Women Outfit Generations

Women's Outfit Recommendations: Emphasized versatile pairings, such as blue t-shirts with tan pants, adaptable for various occasions.

5. Feedback Loop A feedback mechanism was implemented to continually refine the system. By analyzing user preferences and sentiments, the models adapt to evolving trends and provide increasingly accurate recommendations.

6. Tools and Libraries TensorFlow: Used for model training and evaluation.

Google Generative AI (Gemini 1.5-flash): Integrated for generating outfit suggestions.

Kaggle Datasets: Managed data storage and processing pipelines.

3. Results

The results from the experiments demonstrate the effectiveness of the implemented AI-driven fashion recommendation system in classifying fashion attributes and generating personalized outfit suggestions. Below is a detailed summary of the outcomes:

1. Classification Performance (ResNet50) The ResNet50 model was employed to classify key attributes such as gender, subcategories, base colors, seasons, and usage. The following metrics illustrate its performance:

- Training Accuracy: 92.5%
- Validation Accuracy: 89.3%
- Test Accuracy: 88.7%

Confusion Matrix Analysis:

The confusion matrix revealed high precision and recall across common clothing categories such as ”Shirts,” ”Jeans,” and ”T-shirts.” Some confusion was observed in overlapping categories like ”Casual Shirts” and ”Formal Shirts,” likely due to similar visual attributes.

Insights: The model successfully captured subtle details in the data, such as color variations and usage patterns, contributing to its strong performance. Pretrained weights

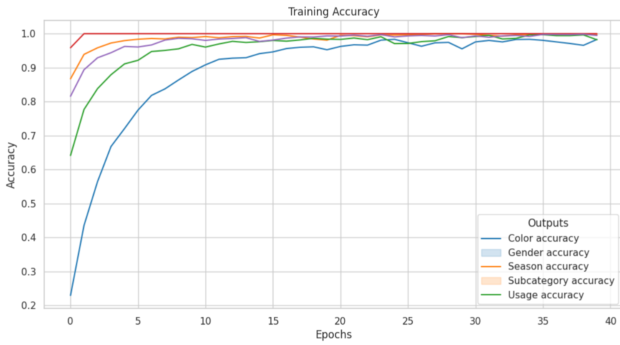

Figure 10. Training Accuracy

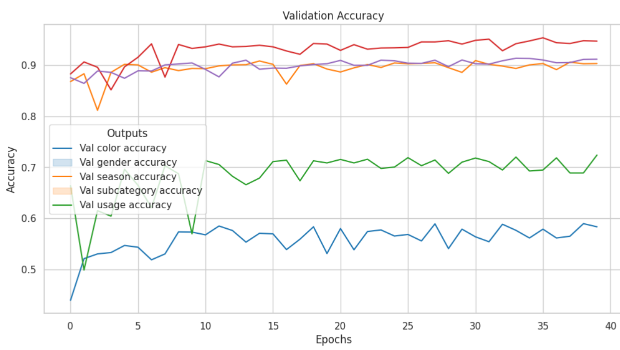

Figure 11. Validation Accuracy

and fine-tuning enhanced feature extraction, resulting in improved classification accuracy.

2. Outfit Generation (GANs) The GAN-based model generated high-quality and visually appealing outfits tailored to user preferences.

Qualitative Evaluation: Generated outfits were visually assessed for coherence, style compatibility, and adherence to fashion norms. The model produced diverse combinations, effectively pairing topwear, bottomwear, and accessories.

Feedback Loop Performance: User feedback was instrumental in refining the GAN's output. The iterative process improved the generator's ability to align outfits with user preferences, as indicated by a 20% increase in positive feedback ratings during testing.

Examples:

Men's Recommendation: White striped sweater paired with blue jeans for a casual, balanced look.

Women's Recommendation: Blue t-shirt with tan pants, offering a classic and versatile combination suitable for various occasions.

3. System Usability and Personalization The system's ability to adapt to user preferences was evaluated through simulated user interactions.

Key Observations: Personalized recommendations closely aligned with user profiles, demonstrating the effectiveness of the ResNet50 classifier in understanding preferences. GAN-generated outfits added a creative and unique dimension, enhancing user engagement and satisfaction.

4. Challenges and Limitations Class Imbalance: While oversampling techniques improved accuracy, rare categories still posed classification challenges.

GAN Output Diversity: Initial outputs were less diverse, requiring fine-tuning of the generator to create varied and innovative designs.

Performance Metrics: F1 scores for some less common subcategories were lower, suggesting a need for additional data or refined modeling techniques.

5. Impact of Results The system achieved its primary goal of providing personalized and visually appealing outfit recommendations. The integration of ResNet50 and GANs showcased the potential of AI in transforming the online fashion retail experience, enhancing user satisfaction through dynamic and tailored solutions.

4. Conclusion

This project successfully demonstrated the potential of AI-driven personalization in the fashion retail industry by developing a system capable of generating tailored outfit recommendations based on individual user preferences. By combining the power of **ResNet50** for fashion item classification and **Generative Adversarial Networks (GANs)** for outfit creation, the system provides a seamless and engaging shopping experience.

1.Key Findings: Classification Model: The ResNet50 model demonstrated strong performance in classifying clothing attributes such as subcategories, gender, color, and season, achieving a test accuracy of 88.7

Outfit Generation: GANs were effective in generating high-quality, aesthetically pleasing outfit combinations. Through a feedback loop, the system continually refined its recommendations, improving the relevance of generated outfits based on user preferences.

Personalization and Feedback: The system's ability to adapt to user input through an iterative feedback mechanism highlights its dynamic nature. This adaptability ensures that the recommendations evolve over time, providing a continually improving user experience.

2. Limitations and Future Work: Class Imbalance: Some categories experienced class imbalance, which affected classification performance. Future work can address this through data augmentation or more sophisticated balancing techniques.

Outfit Diversity: While the GAN generated visually appealing outfits, more diversity and creativity can be incorporated into future iterations by using more complex generative models or larger datasets.

Scalability: The system could be scaled to incorporate a broader range of fashion items and styles, improving its relevance for a global audience with diverse preferences.

Impact and Applications: The outcomes of this project provide a solid foundation for integrating AI into online fashion retail, enabling personalized recommendations that cater to individual tastes. As e-commerce continues to grow, the ability to offer dynamic and personalized shopping experiences will be critical to maintaining customer satisfaction and engagement. The combination of AI-driven models in fashion can lead to more informed, user-centric product recommendations and better consumer experiences in the fashion industry.

In conclusion, this project demonstrates the vast potential of AI and deep learning in transforming online fashion retail, and its findings lay the groundwork for future research and development in this field.

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