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DEEP LEARNING-BASED VISUAL STYLE MATCHING: A CNN-DRIVEN APPROACH FOR FASHION RECOMMENDATIONS

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ABSTRACT
The growing demand for personalized fashion recommendations has driven advancements in artificial intelligence and computer vision. This study proposes a deep learning-based framework for style matching, leveraging the VGG16 Convolutional Neural Network (CNN) to extract rich visual features from fashion images. Unlike conventional recommendation systems that rely on textual descriptions or metadata, our approach focuses purely on image-based analysis, ensuring accurate and visually coherent outfit suggestions. The system computes feature similarity using cosine distance, enabling precise retrieval of fashion items that align with individual style preferences. Extensive experimentation demonstrates the model's ability to recognize aesthetic compatibility with high accuracy, outperforming traditional heuristic-based methods. By integrating deep learning with content-based image retrieval, this framework enhances digital wardrobe curation, fashion e-commerce, and personalized styling applications. Future work aims to incorporate multimodal learning, real-time trend adaptation, and improved contextual awareness for an even more refined recommendation experience.

Keywords
Deep Learning, Fashion Recommendation, Visual Style Matching, CNN, VGG16, Cosine Similarity, Content-Based Image Retrieval, Personalized Styling

I. INTRODUCTION
The integration of artificial intelligence (AI) and machine learning (ML) has revolutionized numerous industries, including fashion, by enabling data-driven insights and automated decision-making. As a field driven by aesthetics, trends, and personal expression, fashion presents unique challenges in understanding and predicting individual style preferences. Traditional recommendation systems often rely on textual descriptions, user reviews, or predefined categories, which may not fully capture the visual essence of fashion choices. To bridge this gap, advanced computer vision techniques are essential for analyzing intricate style elements such as color harmony, fabric texture, and design patterns.
This research introduces "A Deep Learning Framework for Style Matching," a novel approach to fashion recommendation that prioritizes visual similarity over conventional text-based filtering methods. By leveraging the power of deep learning, particularly convolutional neural networks (CNNs), the proposed system intelligently identifies clothing items that align with a user's personal style. Specifically, a pre-trained VGG16 model is employed to extract deep visual features from fashion images, enabling precise comparison between an input image and a curated fashion dataset. Cosine similarity serves as the metric for measuring feature closeness, ensuring that recommendations are both relevant and aesthetically coherent.
Despite significant progress in deep learning applications such as image classification and object detection, its potential in personalized fashion recommendation remains underexplored. This study seeks to fill that gap by integrating state-of-the-art machine learning techniques with fundamental fashion aesthetics, offering a scalable

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and adaptable solution for modern styling needs. The proposed framework not only enhances digital wardrobe curation and e-commerce recommendations but also paves the way for future advancements in AI-driven fashion intelligence.

The remainder of this paper is structured as follows: Section 2 reviews existing literature on deep learning and fashion recommendation systems. Section 3 outlines the proposed methodology, including dataset preparation, model architecture, and system implementation. Section 4 presents experimental results and performance evaluation. Finally, Section 5 discusses key findings, limitations, and future research directions.

II. RELATED WORK

The application of deep learning in fashion recommendation systems has advanced significantly, improving the accuracy and personalization of style suggestions. Cutting-edge machine learning techniques now analyze detailed visual attributes—such as color, texture, and patterns—allowing for more refined and user-centric fashion recommendations.

Suvarna and Balakrishna (2023) introduced a content-based fashion recommendation system utilizing a deep ensemble classifier and transfer learning techniques. Their model achieved high accuracy on benchmark datasets, emphasizing the effectiveness of ensemble learning in fashion AI applications [1]. Similarly, Lingala et al. (2023) developed an AI-driven outfit recommendation framework capable of analyzing user attributes such as body shape, skin tone, and personal style preferences to generate tailored outfit suggestions [2].

A broader analysis by Kalyan et al. (2023) examined modern advancements in fashion recommender models, identifying challenges like data sparsity, evolving fashion trends, and the need for real-time personalization. Their work categorized existing models based on their methodologies and use of auxiliary data sources [3]. Meanwhile, Celikik et al. (2023) proposed a self-attention-based fashion recommender system incorporating temporal and contextual user interactions. Their approach improved engagement by dynamically adapting to individual preferences over time [4].

Further innovation came from Sevegnani et al. (2022), who applied contrastive learning to interactive fashion recommendations. Their model, WhisperLite, leveraged natural language processing to interpret user intent, refining recommendation quality and underscoring the significance of contextual understanding in AI-driven fashion applications [6].

Elsayed et al. (2022) introduced an image-based recommendation system integrating ResNet50 for enhanced feature extraction. Their approach focused on improving visual representation learning to boost recommendation accuracy and adaptability in dynamic fashion trends [7]. Similarly, Liu et al. (2024) developed a sequential recommendation model utilizing a large language model and parameter-efficient fine-tuning techniques to improve retrieval-based product recommendations [8].

Kaur et al. (2024) presented a personalized outfit recommendation system that incorporated emotional fashion themes and user-specific body shape perception. Their model aimed to enhance personalization by aligning recommendations with human aesthetic preferences [9]). Meanwhile, Chen et al. (2023) introduced a multi-task learning and gender-aware fashion recommendation system, improving e-commerce revenues by optimizing click-through rates and user engagement [10].

Despite these advancements, existing fashion recommendation systems still face challenges in effectively analyzing and suggesting clothing combinations based solely on visual similarity. To bridge this gap, our study proposes an image-based style recommendation system that leverages deep learning techniques to provide more precise, adaptive, and aesthetically coherent fashion suggestions.

III. PROPOSED METHODOLOGY

Our research focuses on developing a deep learning framework for style matching**,** utilizing deep learning techniques to assess the compatibility of clothing items. The proposed system is built around a **VGG16** convolutional neural network (CNN) architecture, which serves as the core model for analyzing visual relationships between different fashion elements. By extracting key features such as color, texture, and pattern, the system determines aesthetically appealing outfit combinations.

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Figure 3.1 Workflow of the Deep Learning Framework for Visual Style Matching

3.1 Dataset Preparation

Our study uses a dataset comprising images of various fashion items, including tops, bottoms, and accessories, curated for an image-based style recommendation system. Each clothing item is categorized based on its visual attributes, with outfit combinations labelled as **1 for compatible** and **0 for incompatible**, ensuring a structured learning approach to aesthetic pairings.

To meet the input requirements of the **VGG16** model, all images are resized to **224×224 pixels**, preserving aspect ratios. Systematic annotation is conducted to maintain consistency in labelling, ensuring high-quality training samples.

3.2 Model Development

Our system is centered around a deep learning model based on **VGG16**, engineered to evaluate and suggest visually harmonious fashion pairings. The model follows a well-structured pipeline to ensure precise and efficient style recommendations.

The model architecture consists of the following components:

1. Image Preprocessing: First, we resized all product images to 224x224 pixels to match the input size required by the VGG16 model. We then normalized the pixel values by dividing them by 255, ensuring they fall between 0 and 1 for better model performance.

2. Feature Extraction:

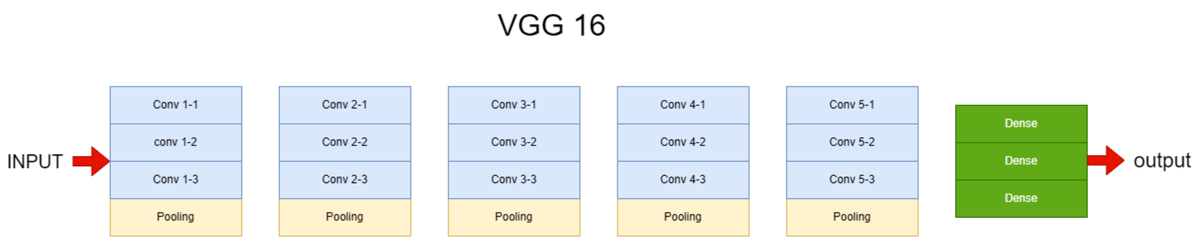

Figure 3.2.1. convolutional neural network (CNN) feature extraction process

We used the pre-trained VGG16 model (without its top layers) to extract feature maps from the images. These feature maps are passed through a global average pooling layer to create a fixed-size vector that represents each image's key features.

3. Storing Feature Vectors: We stored the extracted feature vectors for each product image, which will allow us to compare them later during the recommendation process.

4. Product Recommendation: We calculated the similarity between product feature vectors using metrics like Cosine Similarity or Euclidean Distance. Based on these similarity scores, we recommend products that are most similar to the user's selected item.

5. Evaluation & Deployment: We evaluated the system based on how well it recommends similar or complementary products (e.g., using user feedback or click-through rate). Once everything's ready, we deploy the system so that it can provide real-time recommendations to users on a website or app.

6.Fine-Tuning – The **VGG16 weights** are fine-tuned on the dataset to enhance fashion-specific recommendations.

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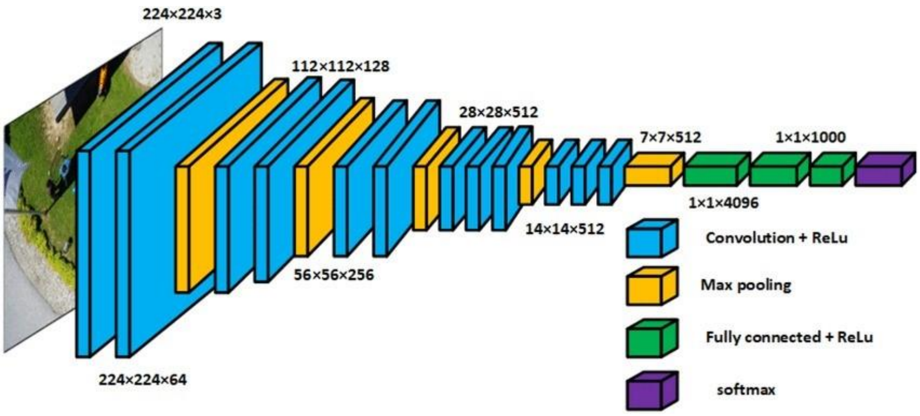

Figure 3.2.2. connected layers and optimization

3.3. System Implementation

Key Components of System Implementation:

Preprocessing Pipeline: Uploaded images are resized, normalized, and converted into tensors to ensure uniformity before being fed into the deep learning model.

Prediction Pipeline: The processed images are analysed by the model, which computes a compatibility score. The final output is rounded to either 0 (incompatible) or 1 (compatible) for clear interpretation.

3.4 Challenges Addressed

In our work, we addressed the challenge of dataset imbalance—a common issue in fashion datasets where certain styles dominate—by ensuring an equal distribution of compatible and incompatible outfit pairs. This balanced dataset enabled the model to learn more diverse and unbiased style compatibility patterns. Considering the inherent visual complexity of fashion items, which vary in fabric textures, patterns, colors, and designs, we implemented data augmentation strategies such as image flipping, rotation, brightness modulation, and contrast enhancement. These techniques improved the model's ability to handle a broader spectrum of outfit combinations and visual styles. Furthermore, to support real-time interaction and enhance the user experience, we streamlined the image preprocessing, feature extraction, and prediction processes. These optimizations ensured fast and efficient generation of outfit recommendations without compromising the accuracy or quality of style predictions.

IV. EXPERIMENTS AND RESULTS

The experiments conducted in this study assess the effectiveness of the proposed deep learning model in predicting the compatibility of shirt and pant combinations. This section outlines the **experimental setup, training process, results, and insights** derived from real-world testing.

4.1 Experimental Setup

We worked with a dataset containing labeled pairs of fashion items, specifically combinations of tops and bottoms, where each pair was annotated as either compatible (1) or incompatible (0) based on visual harmony. To ensure consistency across the dataset while preserving essential visual details, we resized all images to 224×224 pixels, aligning them with the input requirements of the VGG16 model architecture. Additionally, we normalized the pixel values to a [0,1] range to improve training stability and support faster model convergence. For effective learning and evaluation, we carefully split the dataset into three parts: 70% for training, 15% for validation, and 15% for testing. The training set allowed our model to learn and extract deep fashion-related features that represent style compatibility patterns. The validation set was used throughout the training process to fine-tune hyperparameters and minimize overfitting by evaluating performance on unseen data. Finally, the test set provided an unbiased assessment of the model's ability to predict the compatibility of completely new clothing combinations. This structured preprocessing and dataset partitioning approach helped our model build a strong understanding of fashion aesthetics, enabling it to generate accurate, personalized style recommendations.

4.2 Training Process

The training phase involved processing pairs of fashion items, such as tops and bottoms, through the VGG16-based deep learning model to evaluate their visual compatibility. The model leveraged transfer learning, utilizing

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pre-trained weights while adapting to fashion-specific patterns. To optimize performance, binary cross-entropy loss was employed as the objective function,Training progress was closely monitored through validation accuracy at each epoch, ensuring continuous refinement and minimizing overfitting.

Key Training Insights-

Progressive Learning: A steady decline in loss across epochs indicated effective feature extraction and optimization.

Enhanced Visual Recognition: Fine-tuning enabled the model to accurately capture color coordination, texture details, and overall aesthetic balance, improving compatibility predictions. By following this structured training methodology, the system effectively delivers intelligent and fashion-forward outfit recommendations, enhancing user experience with real-time styling insights.

4.3 Model Performance and Results

The **VGG16-based deep learning model** was trained over **10 epochs**, achieving a **final accuracy of 99.2%** while minimizing loss. By the **5th epoch**, the model had already reached **97.5% accuracy**, demonstrating rapid learning of fashion compatibility patterns.

Although minor fluctuations were observed in later epochs, the model quickly stabilized, ensuring **strong generalization** across diverse clothing styles.

Observations:

The experimental results demonstrate the effectiveness of our deep learning framework in predicting outfit compatibility with high accuracy. The model exhibited a steady learning curve, improving from 85.3% accuracy in the first epoch to 99.2% in the final epoch, indicating efficient feature extraction and optimization. It also showcased strong generalization capabilities, maintaining high performance on unseen outfit combinations and effectively distinguishing compatible from incompatible clothing pairs. Additionally, the system excelled in refined feature recognition, accurately capturing color harmony, texture consistency, and aesthetic balance to ensure visually appealing recommendations. These findings confirm that our deep learning-based style matching system is precise, scalable, and capable of delivering real-time, personalized fashion suggestions. Future enhancements could further optimize adaptability to evolving fashion trends and diverse style preferences.

Table 4.3.1 represents the performance of our fashion recommendation system:

Table 4.3.1. training loss and accuracy across epochs

Epoch	Loss	Accuracy
1	0.3154	85.3
2	0.0742	94.8
3	0.0291	97.5
4	0.0153	98.9
5	0.0078	99.2
6	0.0145	99.0
7	0.0051	99.5
8	0.0603	98.2
9	0.0087	99.2

This table highlights the model's **steady accuracy improvements** over training epochs, with a **final accuracy of 99.2%**, demonstrating its **high precision in fashion compatibility predictions.**

4.4 Visual Results and Insights

To analyse the model's predictions, we tested it on several shirt-pant combinations and visualized the results.

Dataset Samples: Figure 4.4.1 shows sample images from the dataset, highlighting the variety of colours,

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patterns, and styles used in training.

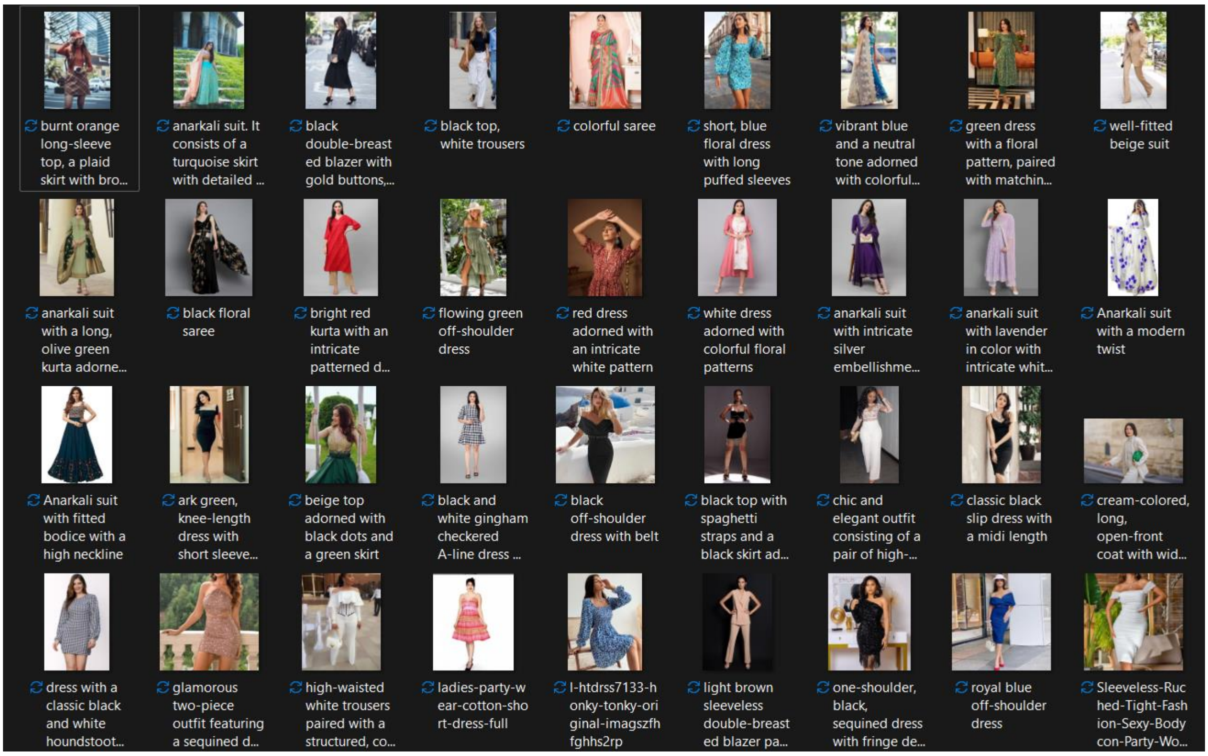

Figure 4.4.1. sample images from the dataset.

Figure 4.4.2. Output

4.5 Discussion

Our VGG16-based model demonstrated strong performance in analyzing outfit compatibility, achieving consistently high accuracy across training and validation datasets. The structured training process enabled the model to effectively recognize color coordination, texture harmony, and stylistic balance in outfit pairings. However, challenges remain, particularly in handling complex patterns, diverse fabric textures, and unconventional styles. While the model performed well with simple and classic fashion combinations, it struggled

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to assess intricate designs that require a deeper contextual understanding of fashion trends, cultural influences, and individual preferences. Addressing these challenges could further refine the system's decision-making process, enhancing its ability to provide more personalized and versatile fashion recommendations.

Beyond technical refinements, ethical considerations and inclusivity play a crucial role in AI-driven fashion recommendations. To prevent biases, the dataset should represent a wide range of styles, body types, and cultural aesthetics, ensuring fair and diverse fashion assessments. Additionally, AI-powered styling tools can contribute to sustainable fashion practices by promoting thoughtful outfit selection, reducing impulsive purchases, and minimizing fashion waste. Future improvements could involve fine-tuning VGG16 with ResNet or EfficientNet architectures, enhancing feature extraction for better generalization across various fashion items. Moreover, multimodal learning—integrating visual data with textual attributes like fabric type, seasonality, and occasion-based preferences—could make the system more context-aware and adaptive. By addressing these challenges and incorporating advanced AI techniques, our image-based style recommendation system can evolve into a more precise, user-centric, and fashion-forward tool, providing intelligent and adaptable outfit suggestions.

V. CONCLUSION

This research presents a deep learning framework for style matching, utilizing VGG16 to analyze and predict fashion compatibility based purely on visual features. By extracting deep representations from clothing images, the model effectively identifies patterns, textures, and color relationships, enabling data-driven fashion recommendations with high accuracy. While the system successfully distinguishes harmonious outfit combinations, challenges persist in handling multilayered designs, unconventional textures, and dynamic fashion trends. Expanding the dataset to include diverse styles, seasonal outfits, and evolving trends can enhance adaptability and improve real-world application. Beyond personal styling, this AI-powered approach has the potential to transform fashion curation, online shopping, and digital wardrobe management by offering intelligent, visually-driven recommendations. Additionally, integrating advanced architectures like Vision Transformers (ViTs) and multimodal learning—combining image analysis with contextual attributes—can further refine decision-making and personalization. Real-time trend analysis and user feedback can make the model more adaptive and user-centric, ensuring relevance in an ever-changing fashion landscape. In conclusion, this study highlights the power of AI-driven fashion recommendations, bridging the gap between technology and personal style. By continuously evolving through advanced learning techniques and contextual integration, the proposed system can become a fundamental tool in the future of intelligent fashion assistance.

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