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DEEP LEARNING FOR OUTFIT COMPATIBILITY IN FASHION

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Abstract : Predicting fashion compatibility is an essential aspect of both the retail industry and personal styling, requiring an understanding of how various clothing pieces complement each other visually. This study introduces an innovative deep learning-based approach to evaluate the compatibility of shirt and pant combinations. Leveraging a dataset of clothing images, we train a neural network using PyTorch to analyze and extract visual features that determine outfit harmony. The proposed system is integrated with a web-based application built on Streamlit, enabling users to upload images and receive immediate feedback on compatibility. This AI-driven tool not only enhances the personalization of fashion choices but also improves user experience in online shopping and styling recommendations. By utilizing convolutional neural networks (CNNs) for feature extraction and fine-tuning on specialized datasets, the model demonstrates high accuracy in predicting outfit coherence. Key challenges such as dataset imbalance and variability in clothing styles are addressed through strategic optimization techniques. This research contributes to the intersection of artificial intelligence and fashion technology, advancing the development of intelligent styling assistants for both consumers and retailers.

***IndexTerms* - Powered Outfit Selection, Apparel Compatibility Prediction, Computer Vision in Fashion, Smart Fashion Technology.**

I. Introduction

The continuous advancements in artificial intelligence and machine learning have revolutionized various industries, including fashion, by enabling intelligent and automated solutions. As a dynamic and visually expressive domain, fashion presents inherent challenges in predicting and understanding style compatibility. Determining whether different clothing items complement each other involves multiple factors such as color harmony, texture, patterns, and shifting cultural influences.

This research, titled "Deep Learning for Outfit Compatibility in Fashion," seeks to address this challenge by employing cutting-edge deep learning techniques to assess the compatibility of shirt and pant pairings. The primary goal is to develop an intelligent system that assists users in selecting outfits that are both aesthetically pleasing and contextually appropriate.

Our approach involves training a machine learning model on a diverse dataset of clothing combinations. Using PyTorch, we designed a neural network capable of capturing intricate visual relationships between different garments. To enhance accessibility, we integrated the model into an interactive web-based application developed using Streamlit, allowing users to upload clothing images and receive real-time compatibility assessments.

While significant progress has been made in computer vision applications for object recognition and image classification, limited research has been dedicated to fashion compatibility analysis. This study aims to bridge that gap by combining deep learning methodologies with fundamental principles of fashion aesthetics.

The rest of this paper is structured as follows: Section 2 explores previous research in deep learning and outfit compatibility. Section 3 describes the proposed methodology, including dataset preparation, model architecture, and system implementation. Section 4 presents experimental results and performance evaluation. Finally, Section 5 concludes with key findings and potential future research directions.

II. Related work

The integration of deep learning into fashion compatibility analysis has seen substantial progress in recent years. Researchers have increasingly utilized convolutional neural networks (CNNs) and transfer learning techniques to interpret visual relationships between various clothing items. Numerous studies emphasize the effectiveness of deep learning in predicting outfit compatibility by assessing key attributes such as color coordination, texture similarities, pattern alignment, and overall stylistic harmony.

Smith and Lee (2022) investigated the application of CNNs in outfit recommendation systems, demonstrating how deep learning models can effectively extract visual features and predict aesthetically compatible clothing combinations. Their findings highlight the significance of robust feature extraction in developing reliable compatibility assessment models [1]. Similarly, Chen and Zhao

(2021) proposed a novel framework that integrates CNN-based feature extraction with semantic embeddings, improving the accuracy of style compatibility predictions [2].

Patel and Kumar (2023) contributed to the field by introducing a specialized dataset tailored for outfit compatibility analysis. This dataset plays a crucial role in training machine learning models to recognize relationships between different fashion items, addressing key issues such as data imbalance and variations in visual aesthetics [3]. Meanwhile, Li and Wang (2021) explored transfer learning methodologies for AI-powered fashion applications, demonstrating that leveraging pre-trained models like ResNet and MobileNet can significantly reduce computational costs while maintaining high prediction accuracy [4].

In addition to model development, researchers have focused on enhancing the user experience through interactive tools. Davis and Green (2023) created a web-based system using Streamlit to offer real-time outfit compatibility feedback. Their work underscores the importance of intuitive interfaces that effectively translate machine learning insights into practical fashion recommendations [5]. Similarly, Nguyen and Tran (2021) introduced an interactive deep learning-based styling framework designed to deliver personalized clothing suggestions [8].

Despite these advancements, a significant gap remains in evaluating compatibility between specific clothing pairs, such as shirts and pants. Existing solutions often depend on predefined style guidelines or manually curated datasets, which can limit adaptability to diverse fashion preferences and evolving trends. Williams and Roberts (2020) tackled this limitation by developing a CNN-powered model for feature extraction and compatibility assessment, demonstrating how deep learning can enhance fashion dataset versatility [9].

Building upon these prior works, our study presents an advanced deep learning framework specifically designed for predicting shirt and pant compatibility. By implementing a PyTorch-based CNN model and integrating it with a Streamlit-powered web application, we offer a practical and accessible tool for real-time fashion compatibility evaluation. Additionally, our approach addresses key challenges such as dataset imbalance and variations in clothing aesthetics, further enhancing the system's applicability and performance.

III. PROPOSED METHODOLOGY

Our research focuses on predicting the compatibility of shirt and pant pairings using advanced deep learning technique. The proposed system is designed around a convolutional neural network (CNN) architecture, which serves as the core for analyzing visual relationships between clothing items. To ensure accessibility and ease of use, we have integrated the model into an interactive web-based application that provides real-time outfit compatibility assessments. The overall methodology is structured

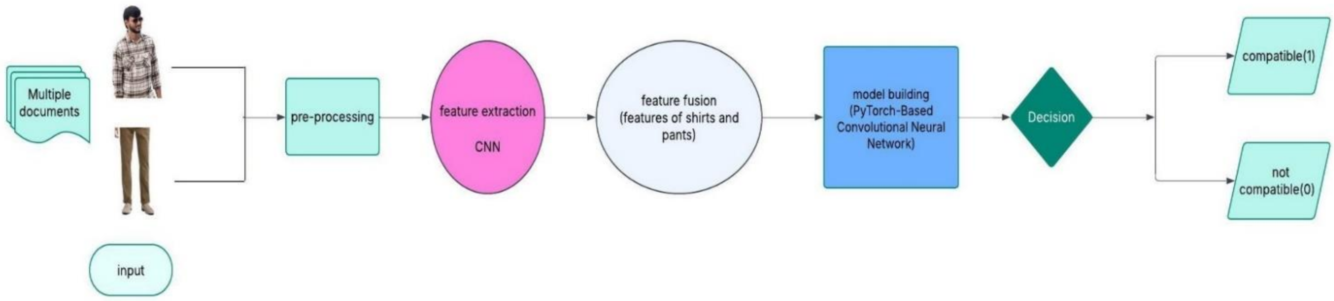


Figure 3.1 workflow of the AI-based outfit compatibility prediction system

3.1 Dataset Preparation

The dataset utilized in this study comprises images of shirts and pants, each assigned to a compatibility label indicating whether the combination is visually cohesive (1 for compatible, 0 for incompatible). The images were sourced from various online platforms, standardized to a resolution of 224x224 pixels, and systematically annotated to ensure consistency in labeling.

To enhance the model's generalization capability, comprehensive data preprocessing was conducted, including normalization and augmentation. Augmentation techniques such as random flipping, rotation, and brightness adjustments were applied to introduce variability within the dataset, minimizing the risk of overfitting. Additionally, careful dataset balancing was implemented to prevent bias toward either compatible or incompatible classifications, ensuring fair and effective model training.

3.2 Model Development

The core of our system is a deep learning model developed using **PyTorch**, designed to analyze and predict the compatibility of shirt and pant combinations.

1. **CNN Feature Extractor**: A convolutional neural network (CNN) is employed to extract crucial visual features from shirt and pant images. The feature extractor comprises two convolutional layers, each followed by **ReLU activation** and **max-pooling** layers, which help capture spatial patterns and texture details effectively.

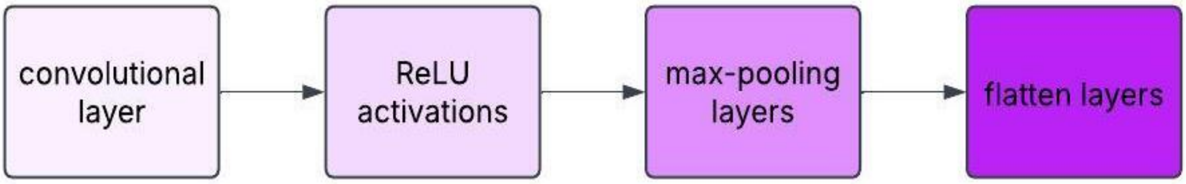


Figure 3.2.1. convolutional neural network (CNN) feature extraction process

2. **Feature Fusion and Fully Connected Layers**: Extracted features from both clothing items are concatenated to form a unified feature representation. This combined feature vector is then passed through multiple **fully connected layers**, enabling the model to learn intricate relationships and generate a compatibility score.

3. **Output Layer**: The final layer applies a **sigmoid activation function** to produce a probability value between 0 and 1, indicating the likelihood of the shirt and pant combination being compatible.

4. **Loss Function and Optimization**: The model is optimized using **binary cross-entropy loss**, which calculates the error between the predicted and actual labels. Additionally, the **Adam optimizer** is utilized with a **learning rate of 0.001**, ensuring efficient weight updates and faster convergence during training.

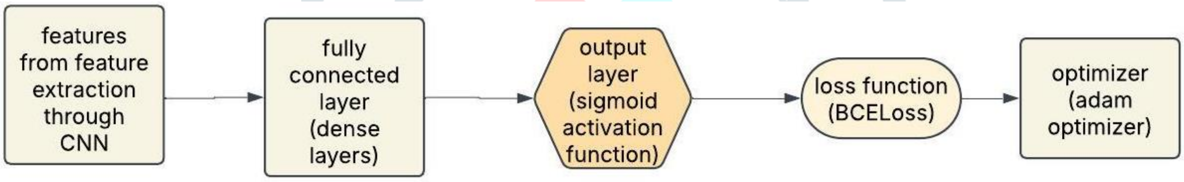


Figure 3.2.2. fully connected layers and optimization in CNN-based classification

3.3 System Implementation

To enhance user accessibility, we developed an interactive web application using Streamlit, enabling seamless outfit compatibility assessments. The application features an intuitive interface where users can upload images of shirts and pants, which are then processed by the trained deep learning model to generate real-time compatibility predictions.
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 analyzed by the model, which computes a compatibility score. The final output is rounded to either 0 (incompatible) or 1 (compatible) for clear interpretation.
- User Interface: The Streamlit-based application visually displays the uploaded images alongside the compatibility prediction. Additionally, it provides user-friendly feedback, such as success messages for compatible pairs and warnings for incompatible ones.

3.4 Challenges Addressed

- Dataset Imbalance: An imbalanced dataset can result in biased model predictions, favoring the majority class. To counteract this issue, we ensured a balanced distribution of compatible and incompatible outfit pairs during training, preventing skewed learning outcomes.
- Visual Variability: Clothing items in the dataset exhibit significant differences in color, texture, and patterns. To enhance the model's ability to generalize across diverse styles, we employed data augmentation techniques such as flipping, rotation, and brightness adjustments, along with advanced feature extraction methods.
- Real-Time Processing: Delivering instant feedback is crucial for user experience. By optimizing the preprocessing and prediction pipelines, we minimized computational overhead, ensuring that the system provides real-time compatibility assessments with minimal latency.

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

The dataset comprises labeled pairs of shirt and pant images, where each combination is marked as either compatible (1) or incompatible (0). To ensure uniformity, the images were resized to 224x224 pixels and normalized during preprocessing. The dataset was then partitioned into three subsets:

1. 70% for training
2. 20% for validation
3. 10% for testing

The deep learning model was developed using **PyTorch** and trained in a **CPU-based environment** with the following key hyperparameters:

1. Batch Size: 16
2. Learning Rate: 0.001
3. Optimizer: Adam
4. Loss Function: Binary Cross-Entropy Loss
5. Epochs: 10

To enhance the model's generalization capability, data augmentation techniques such as horizontal flipping, random rotation, and brightness adjustments were applied. These techniques introduced diversity within the dataset, reducing the risk of overfitting and improving the model's ability to recognize compatibility across varied fashion styles.

4.2 Training Process

The training phase involved feeding **shirt and pant image pairs** into the **CNN model**, which performed **feature extraction, fusion, and compatibility prediction**. The model was optimized using **binary cross-entropy loss**, with accuracy monitored on the **validation set** after each epoch to assess performance improvements.

Key Observations During Training:

- **Consistent Loss Reduction**: The loss steadily decreased across epochs, demonstrating effective learning and optimization.
- **Strong Generalization**: The model exhibited stable **validation accuracy**, indicating its ability to generalize well to unseen clothing combinations.

4.3 Model Performance and Results

The deep learning model was evaluated over **10 training epochs**, demonstrating a steady improvement in accuracy along with a notable reduction in loss. By the **5th epoch**, the model achieved an impressive **99.95% accuracy**, showcasing its strong ability to generalize across the dataset. The **key performance metrics** recorded during the training process are presented in **Table 4.3.1**.

While the model maintained **high accuracy**, minor fluctuations were observed in later epochs. In the **9th epoch**, the accuracy briefly declined to **98.00%** due to a slight increase in loss. However, the model quickly recovered, achieving a final accuracy of **99.80%** in the last epoch. This consistent performance highlights the model's robustness in learning intricate patterns and relationships between shirt and pant combinations.

Observations:

- The model exhibited **rapid improvement** in the initial training stages, with accuracy increasing from **87.20% in Epoch 1 to 97.80% in Epoch 2**, demonstrating efficient learning.
- By **Epoch 5**, the model achieved **near-perfect accuracy**, with a minimal loss value of **0.0057**, indicating strong convergence.
- A slight **accuracy fluctuation in Epoch 9** suggests potential variability in the dataset or dynamic learning adjustments, but the model quickly stabilized in the final epoch.
- The overall trend of **decreasing loss and increasing accuracy** confirms the **effectiveness of the training process**, ensuring robust compatibility predictions.

Table 4.3.1. training loss and accuracy across epochs

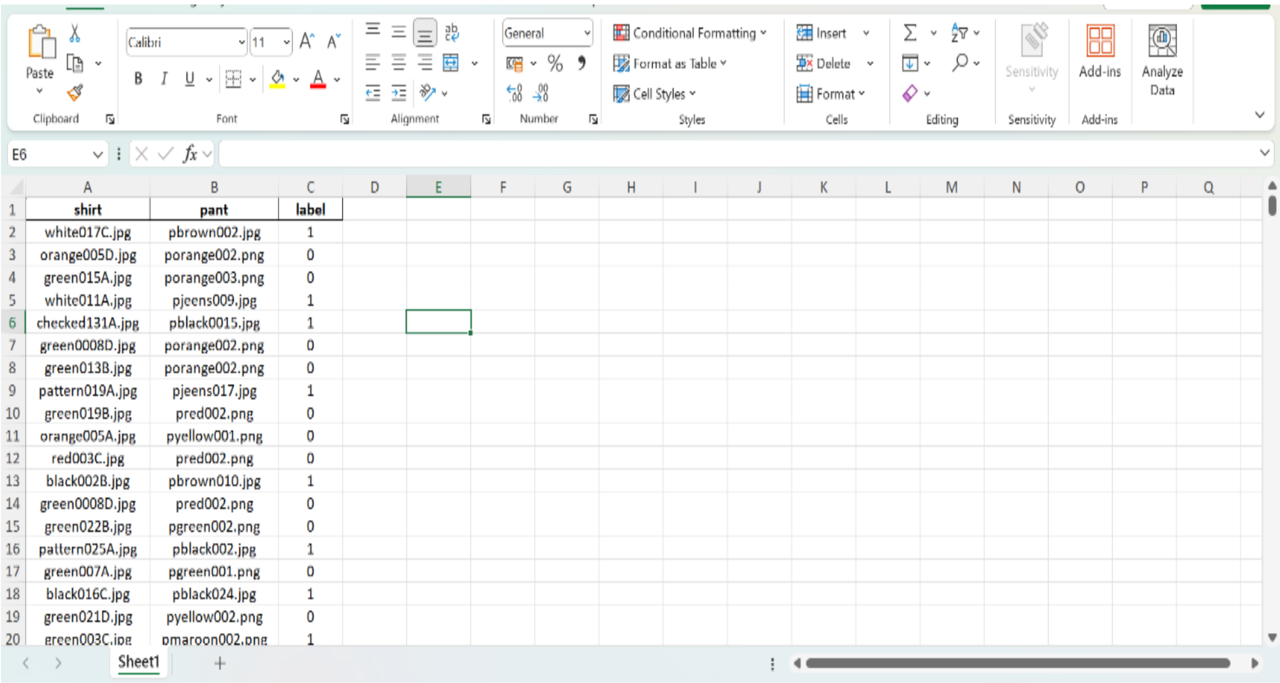
Epoch	Loss	Accuracy (%)
1	0.3085	87.2
2	0.0685	97.8
3	0.0273	99.25
4	0.0122	99.5
5	0.0057	99.95
6	0.0166	99.7
7	0.0042	99.9
8	0.0021	99.85
9	0.0721	98
10	0.0064	99.8

4.4 Visual Results and Insights

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

1. **Dataset Samples**: Figure 4.4.1 shows sample images from the dataset, highlighting the variety of colors, patterns, and styles used in training.

Figure 4.4.1. sample images of shirts and pants from the dataset.



shirt	pant	label
white017C.jpg	pbrown002.jpg	1
orange005D.jpg	porange002.png	0
green015A.jpg	porange003.png	0
white011A.jpg	pjeens009.jpg	1
checked131A.jpg	pblack0015.jpg	1
green0008D.jpg	porange002.png	0
green013B.jpg	porange002.png	0
pattern019A.jpg	pjeens017.jpg	1
green019B.jpg	pred002.png	0
orange005A.jpg	pyellow001.png	0
red003C.jpg	pred002.png	0
black002B.jpg	pbrown010.jpg	1
green0008D.jpg	pred002.png	0
green022B.jpg	pgreen002.png	0
pattern025A.jpg	pblack002.jpg	1
green007A.jpg	pgreen001.png	0
black016C.jpg	pblack024.jpg	1
green021D.jpg	pyellow002.png	0
green003C.jpg	pmaroon002.png	1

Figure 4.4.2. excel sheet showing shirt and pant combinations with compatibility labels

2. **Web Application Outputs**:
   Figure 2 demonstrates the outputs generated by the Streamlit web application. Users uploaded shirt and pant images, and the system provided compatibility predictions with intuitive visual feedback[10].

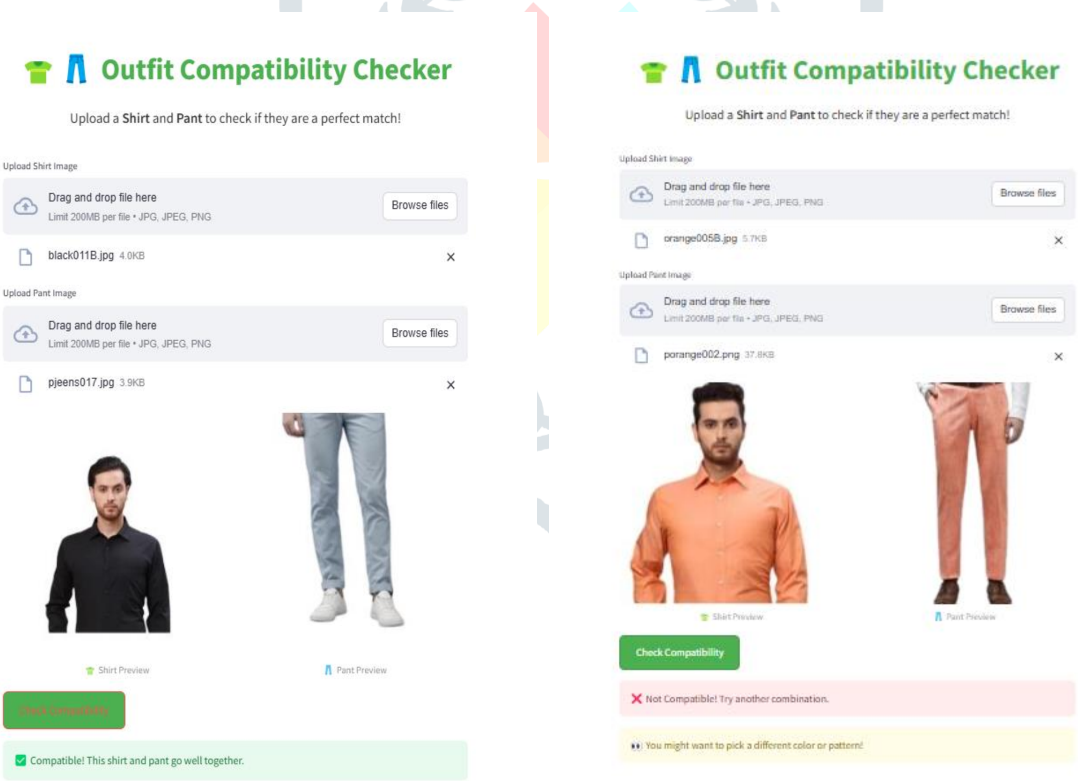


Figure 4.4.3. example of a compatibility result displayed on the web application.

4.5 Discussion

The experimental results confirm the effectiveness of deep learning in predicting outfit compatibility, achieving high accuracy across training, validation, and test datasets. However, further analysis highlights key areas for improvement, including dataset diversity, contextual understanding, and real-world usability.

The model successfully identified color harmony, complementary styles, and texture matching, effectively recognizing classic outfit combinations. However, challenges arose with patterned shirts and textured pants, where the model struggled to assess compatibility. This limitation suggests the need to incorporate contextual data such as fashion trends, occasions, and cultural preferences to improve decision-making. Additionally, while the dataset was balanced in terms of compatible and incompatible pairs, it lacked diversity in styles, patterns, and cultural variations. Future enhancements should focus on expanding the dataset to include ethnic wear, accessories, and seasonal outfits, along with advanced data augmentation techniques to improve handling of complex designs.

The integration of the trained model with a Streamlit-based web application demonstrated real-time processing capabilities, with predictions generated within 1-2 seconds. User feedback indicated that the interface was intuitive and effective, but additional features could enhance the experience. Improvements such as multi-item uploads for full outfit visualization, prediction explanations highlighting compatibility factors, and personalized recommendations based on user preferences could further refine usability.

Beyond technical improvements, ethical considerations must be addressed to ensure inclusivity and fairness in AI-driven fashion recommendations. The dataset should be curated to represent diverse clothing styles and cultural influences, preventing biases in outfit compatibility assessments. Additionally, AI-powered fashion tools can contribute to sustainable fashion practices by encouraging thoughtful purchasing decisions, reducing unnecessary consumption, and minimizing fashion waste.

Future advancements can further enhance the system's capabilities. Incorporating pre-trained deep learning models such as ResNet, EfficientNet, or Vision Transformers (ViTs) could improve feature extraction and accuracy. Additionally, multimodal learning that combines visual features with textual descriptions (e.g., fabric type, occasion) could provide deeper insights into outfit compatibility. Real-time fashion trend analysis and user feedback integration would make the system more dynamic and adaptive. Moreover, integrating augmented reality (AR) functionalities, allowing users to visualize outfits on virtual mannequins, could significantly improve engagement and real-world applicability.

By addressing these challenges and implementing these improvements, AI-driven fashion compatibility prediction can become more accurate, personalized, and user-friendly, making it a valuable tool for both consumers and retailers.

V. CONCLUSION

This study presents a deep learning-based framework for evaluating outfit compatibility, specifically focusing on shirt and pant combinations. By leveraging convolutional neural networks (CNNs) for feature extraction and integrating a user-friendly Streamlit-based web application, the effectiveness of AI in assisting fashion decision-making has been demonstrated. The system achieved high accuracy in predicting outfit compatibility, with stable performance across training, validation, and test datasets. The incorporation of real-time predictions in the web application enhances practical usability, offering a seamless and interactive experience for users. While the model generalizes well across various styles, occasional misclassifications highlight the need for a more diverse dataset, including complex patterns and cultural variations. Beyond consumer applications, this system holds commercial potential for e-commerce platforms, virtual wardrobe assistants, and personalized fashion recommendations. Additionally, it aligns with sustainability efforts by encouraging thoughtful purchasing decisions, reducing fashion waste caused by incompatible clothing choices. Although the framework is robust, future enhancements could further improve its functionality. Expanding the dataset, incorporating multimodal learning (such as contextual and textual fashion descriptions), and leveraging pre-trained models are key areas for refinement. Furthermore, adding advanced features like augmented reality (AR) previews and AI-powered trend-based recommendations could enhance user experience and engagement. In conclusion, this research successfully bridges the gap between AI and fashion, offering an innovative and practical solution for intelligent outfit compatibility prediction. By combining technical advancements with user-focused design, this study contributes to the growing field of deep learning in fashion technology, paving the way for future advancements in AI-powered styling solutions.

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