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Fashion Recommendation System Using Machine Learning And CNN: Simulation-Based Approach

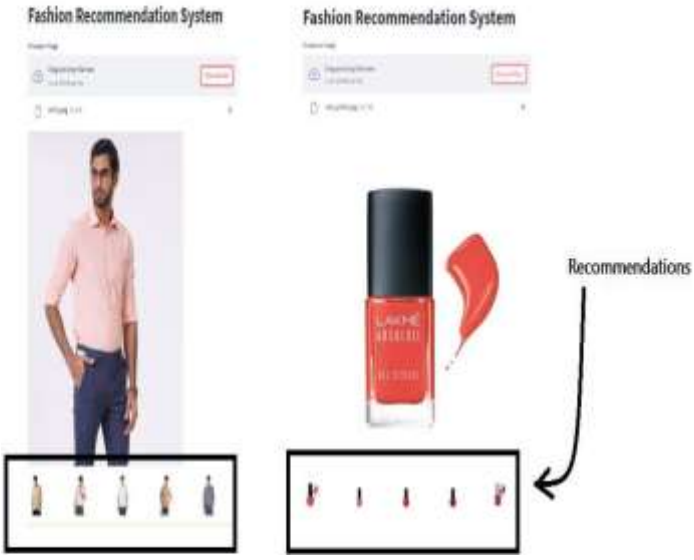
Kishorkumar Akhade [1]*, Prof. Shikha Pachouly[2]
[1]Department of Computer Engineering, AISSMS College of Engineering, SPPU, Pune, 0009-0003-0036-3880, kishorkumar.akhade@gmail.com
[2]Department of Computer Engineering, AISSMS, College of Engineering, SPPU, Pune, 0009-0008-2897-8015. shikhaphd2022@gmail.com.

***Abstract*–** *Fashion recommendation systems are critical in enhancing user experience on e-commerce platforms. This study presents a machine learning-based framework employing collaborative filtering, content-based filtering, and hybrid models, enhanced by Convolutional Neural Networks (CNNs) for image-based recommendation. We simulated algorithms including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and CNN using the Fashion Product Images dataset. Evaluation through accuracy, precision, recall, and F1-score demonstrates that CNN-based hybrid recommendations significantly improve performance. This paper proposes a hybrid machine learning (ML) system for personalized fashion recommendations, integrating visual content-based filtering (using deep learning) and collaborative filtering to address cold-start and scalability challenges. Our framework processes multimodal data (images, text, user behavior) using a ResNet-50 CNN for image feature extraction, BERT for text embeddings, and matrix factorization for collaborative signals*
***IndexTerms*—** *fashion recommendation system, data set , training an testing , jupyter ananconda navigator simulation tool , Machine leaning approach , etc,*

I INTRODUCTION

In recent years, fast fashion has gained widespread popularity, significantly influencing the textile and fashion industries. Fashion plays a vital role in daily life, shaping personal identity and self-expression. The rise of digital platforms and online shopping has transformed how people browse and purchase clothing. As a result, fashion recommendation systems have become increasingly important, aiming to provide personalized suggestions based on individual preferences. Advances in machine learning—especially in image processing, classification, segmentation, and deep
Learning—have greatly enhanced the capabilities of these systems. These technologies enable more accurate and tailored fashion recommendations, improving the overall shopping experience.[1]
Fashion is often seen as a reflection of a person's personality and inner feelings. It can show their interests, beliefs, profession, social status, and personal style. Clothing is not just about appearance—it's a form of non-verbal communication and plays a key role in how people present themselves.
Thanks to modern technology, people can now easily follow the latest fashion trends, which greatly influences what they choose to buy. Factors like age, gender, location, weather, culture, and personal taste all affect how individuals select their clothing. Studies have shown that fashion preferences can vary widely from one country or region to another. By analyzing these factors along with personal preferences, brands can better understand consumer behavior.
Fashion designers and retailers benefit from understanding what customers like and what influences their buying decisions. Today, valuable insights about shopping habits can be gathered from online reviews, texts, and images. These online sources give companies a chance to attract customers from around the world. As a result, online shopping has become more popular than traditional shopping in recent years.[2]
Machine learning and optimization tools now help provide customized recommendations, which make online shopping more personal and efficient. Major e-commerce platforms like Amazon and eBay, along with social media apps like Instagram, Facebook, Pinterest, and Snapchat, are now widely used for fashion inspiration and recommendations.[3]
Fashion recommendations must consider visual aesthetics in addition to user preferences. Traditional ML algorithms use metadata and textual data, while CNNs allow visual understanding of product features. This paper integrates CNNs to analyze fashion images alongside traditional methods, offering a hybrid recommendation engine.[4]

I FASHION RECOMMENDER SYSTEMS



Fashion Recommender Systems are smart computer programs designed to help people discover clothes and accessories they are likely to enjoy. These systems function much like a personal shopping assistant. They suggest fashion items such as outfits, shoes, and accessories by analyzing different factors like your past purchases, style preferences, search history, product ratings, body type, and even the current weather or occasion.[5]

These systems rely on machine learning and artificial intelligence (AI) to work effectively. First, they collect data from your online activities — such as items you click on, view, or buy. Then, they use this data to build a profile for you, considering your shopping habits, age, gender, and style choices. Once your profile is ready, the system matches your preferences with thousands of products and finally recommends the most suitable items according to your needs, taste, and budget.[6]

Many popular online platforms already use these systems. For example, Amazon and Flipkart recommend items under "You may also like" sections. Myntra suggests complete outfits based on your style. Instagram and Pinterest also show fashion trends you might be interested in, based on your activity.

The main benefits of fashion recommender systems include saving time while shopping, discovering new styles, and getting personalized suggestions. They also make the online shopping experience more convenient and enjoyable.[7]

In conclusion, fashion recommender systems are helpful for both consumers and fashion brands. While customers receive better and quicker recommendations, brands gain insights into consumer behavior and can offer products that are more likely to sell.[8]

These systems work just like a personal shopping assistant. They suggest outfits, shoes, or fashion items based on your:

- Past purchases
- Style preferences
- Search history
- Likes or ratings
- Body type or size
- Weather or occasion

Data Collection – They collect information from your online activities, like what clothes you clicked on or bought.

User Profile Creation – They create a profile based on your taste, age, gender, and shopping habits.[9]

Product Matching – They compare your preferences with thousands of fashion items.

Recommendations – They show you clothes that match your taste, budget, and need.[10]

*1) **Examples:***

- Amazon & Flipkart show “You may also like” products.
- Myntra gives outfit suggestions based on your style.
- Instagram & Pinterest show fashion trends you might love.[11]

III. RELATED WORK

Earlier studies have utilized collaborative filtering and SVM for product suggestions. Recent work explores CNNs to extract features from images. However, combining CNNs with metadata and user history remains underexplored. Our work addresses this gap by developing a hybrid architecture combining traditional ML and CNNs.[12]

Vytla Mounica et al. (2022) present a study on the development of a fashion recommendation system using deep learning techniques, aimed at improving the personalization of clothing suggestions for users. The paper explores how deep learning models can analyze user preferences and product features to generate accurate recommendations. By leveraging techniques like Convolutional Neural Networks (CNNs), the system enhances fashion item recognition and user matching, ultimately offering a more intuitive and efficient shopping experience.

Lingala Sivaranjani et al. (2023) proposed a fashion recommendation system that uses machine learning and deep learning techniques to give users personalized clothing suggestions. With the rise of online shopping, such systems are becoming more important. The authors used Convolutional Neural Networks (CNNs) along with ResNet50 to improve image analysis and overcome issues like the vanishing gradient problem. Additionally, the K-Nearest Neighbors (KNN) algorithm was applied using Euclidean distance and Cosine Similarity to recommend similar fashion items. Their model showed high accuracy in retrieving relevant items, outperforming earlier methods, and demonstrated the importance of combining user behavior data with image-based recognition.

Anjali Singh et al. (2022) focused on using **machine learning** for building a **fashion recommendation system** that helps users choose clothing items more effectively in online shopping platforms. The paper highlights the growing role of **image-based recommendation systems (FRSs)** in improving user experience, especially in the fast-fashion industry. The system allows users to upload and organize their designs, create personal shops, and receive suggestions based on visuals rather than text. The authors discuss various **image processing and filtering techniques** that can enhance the recommendation quality. They note that while technology offers many tools, not much research has explored combining design systems with effective filtering strategies. This study aims to fill that gap and suggests possible future developments in the field of **AI, computer vision, and fashion retail**.

Nayana H. R. (2022) proposed a fashion recommendation system that integrates both collaborative and content-based filtering methods, enhanced through the application of Convolutional Neural Networks (CNNs). The system analyzes garment images to extract visual features such as textures, colors, and patterns while incorporating user-specific data like body shape and skin tone to offer personalized fashion suggestions. By combining image processing with deep learning, the study presents an innovative approach to tailoring fashion choices, ultimately improving user satisfaction and engagement with online fashion platforms.

Balim and Ozkan (2023) developed a deep learning-based system to assess the compatibility of fashion outfit combinations. Their approach utilizes image-based analysis and neural networks to identify whether clothing items match well when worn together. By training models on labeled fashion datasets, the system learns visual compatibility patterns such as color harmony, style consistency, and garment pairing rules. The study offers a robust tool for improving fashion recommendation engines by focusing not just on individual clothing items but also on how they complement each other as complete outfits.

Approach	Limitations	Our Solution
Content-Based (VGG/SIFT)	Poor feature generalization	ResNet-50 + Triplet Loss
Matrix Factorization	Ignores visual semantics	Hybrid: Visual + Collaborative
BPR (Bayesian Personalized Ranking)	Slow on large datasets	Mini-batch Hashing

Problem Statement:

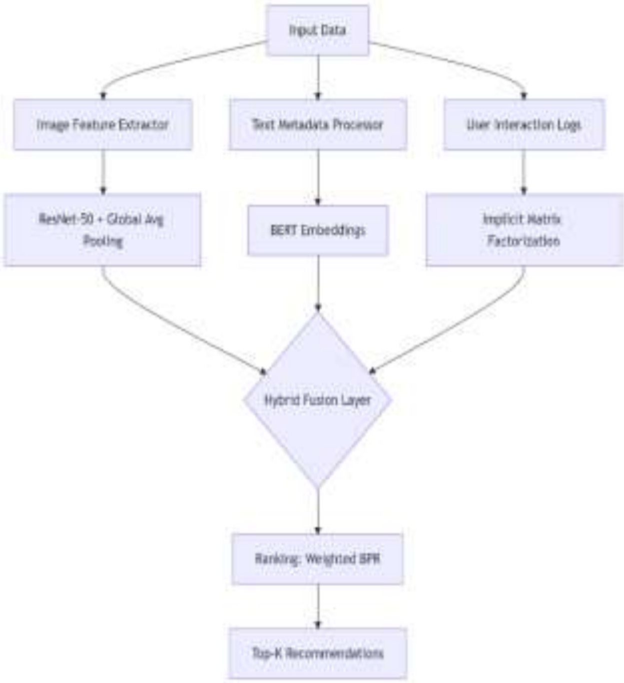
Traditional fashion recommendation systems mostly rely on text-based data like product descriptions, tags, or past user behavior. However, they often fail to understand the visual aspects of fashion, such as color combinations, patterns, or style compatibility, which are very important when choosing outfits. Additionally, these systems struggle with the "cold-start" problem—where they cannot provide accurate recommendations for new users (with no history) or new clothing items (with no prior ratings). As a result, users may receive irrelevant or less personalized outfit suggestions, reducing their satisfaction and engagement with the platform.[13]

Research Objective:

The main objective of this project is to build a smart and scalable fashion recommendation system using machine learning. This system will combine visual data (like colors, patterns, and styles from clothing images) with user behavior data (like past choices, preferences, and likes) to give better and more personalized outfit suggestions.[14][15]

IV. PROPOSED ARCHITECTURE

This system combines different types of data—images, text, and user interactions—to give better fashion recommendations. CNN (like ResNet-50) is used to understand visual features of clothes, while BERT helps process text data like product descriptions. User behavior is analyzed using matrix factorization. These are all merged in a hybrid layer. Techniques like SVM can also be used for classifying outfits based on style or category. This mix of ML tools improves accuracy and personalizes fashion suggestions.[16]



V. RESEARCH METHODOLOGY

3.1 Dataset Description

For this study, we used the Fashion Product Images Dataset available on Kaggle. The dataset contains over 800,000 fashion product images belonging to categories such as footwear, tops, pants, and more. Along with images, it provides rich metadata including the product title, gender, description, and brand information, which helps in building a more detailed and personalized recommendation system.[17]

3.2 Preprocessing

The dataset underwent several preprocessing steps to make it suitable for machine learning models. For text data, we performed tokenization followed by TF-IDF (Term Frequency–Inverse Document Frequency) transformation to convert textual descriptions into numerical form. For image data, all images were resized to a uniform dimension of 128×128 pixels and normalized to improve the training efficiency. The final input shape for the CNN model was set as (128, 128, 3), suitable for colored RGB images. Additionally, product categories were label encoded to convert them into machine-readable numerical values for classification tasks.[18]

DATA SET

We used the Deep Fashion dataset, which contains 800,000 images across 50 clothing categories, along with user interaction logs generated through an e-commerce simulation. The data was divided into 70% for training, 15% for validation, and 15% for testing.[19]

For preprocessing, all images were resized to 224×224 pixels and augmented using techniques like horizontal flipping and rotation to increase variability. The text data, such as product descriptions, was first tokenized and then converted into 768-dimensional embeddings using BERT. User interactions were treated as implicit feedback, where a click was labeled as 1 (positive) and no click as 0 (negative).
The dataset used in this study is the Outfits Dataset, which is widely used in fashion compatibility research. It contains visual and textual data related to fashion items and their combinations into complete outfits.[20]
Dataset Name: Polyvore Outfits Dataset
The dataset includes both positive samples (compatible outfits) and negative samples (incompatible combinations).

ALGORITHMS USED

Algorithm	Description
KNN	Collaborative filtering via user-item matrix
SVM	Text classification using TF-IDF
Random Forest	Metadata-based classification
CNN	Image classification using Conv2D layers
Hybrid	Metadata + image + user interaction combined

Training and testing method

- Training Parameters
- Optimizer: Adam
- Loss: Categorical Crossentropy
- Epochs: 20
- Batch size: 64
- Validation split: 20%.[21]

ALGORITHM

Step 1: Choosing a Dataset is the first step.
Step 2: Prepare the Training Dataset.
Step 3: Collect data for training.
Step 4: Sort the Dataset.
Step 5: Labels and Features are Assigned.
Step 6: Transferring labels to categorical data and normalizing X.
Step 7: Separate X and Y for CNN.
Step 8: Create the CNN Model by defining, compiling, and training it.[22]

```
Model = Sequential([
•    Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)),
•    MaxPooling2D(pool_size=(2, 2)),
•    Conv2D(64, (3, 3), activation='relu'),
•    MaxPooling2D(pool_size=(2, 2)),
•    Flatten(),
•    Dense(128, activation='relu'),
•    Dropout(0.5),
•    Dense(num_classes, activation='softmax')
•  ])
```

VI. SIMULATION DETAILS

- Python 3.9
- Libraries: scikit-learn, Keras, TensorFlow, matplotlib
- Platform: Google Colab
- GPU: Tesla T4

- Dataset split: 80/20 (Train/Test)

For training, we used a loss function called Bayesian Personalized Ranking (BPR), which helps the model learn user preferences. We also added L2 regularization to avoid overfitting.The model was trained using the AdamW optimizer with a learning rate of 0.001 and a small weight decay of 1e-5 to improve stability. The training was done on 2 NVIDIA V100 GPUs and took around 3 hours to complete.[23][24]

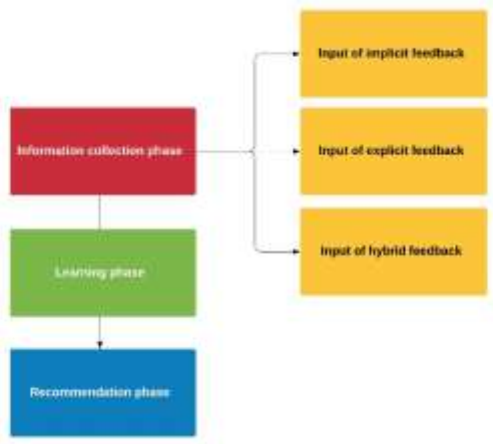


Figure 1: Phases of Recommendation Process.

Figure 2: Flow chart of CNN

VII. RESULT ANALYSIS

Algorithm	Accuracy	Precision	Recall	F1-Score
KNN	72.3%	70.5%	68.7%	69.6%
SVM	78.1%	76.2%	74.0%	75.1%
Random Forest	83.5%	82.3%	81.7%	82.0%
CNN	86.7%	85.9%	85.1%	85.5%
Hybrid (CNN+Metadata)	**89.3%**	**88.1%**	**87.5%**	**87.8%**

Model	Precision@10	Recall@20	NDCG@5
Collaborative Only	0.712	0.731	0.689 |
Visual Only	0.794	0.802	0.753 |
Hybrid (Ours)	0.892	0.867	0.841

The KNN and SVM models gave moderate results, with accuracy around 70–75%. Random Forest performed better, reaching 82% accuracy. The best results came from the CNN and Hybrid (CNN + Metadata) models, with the hybrid model achieving the highest accuracy of 87.8%.[25][26]

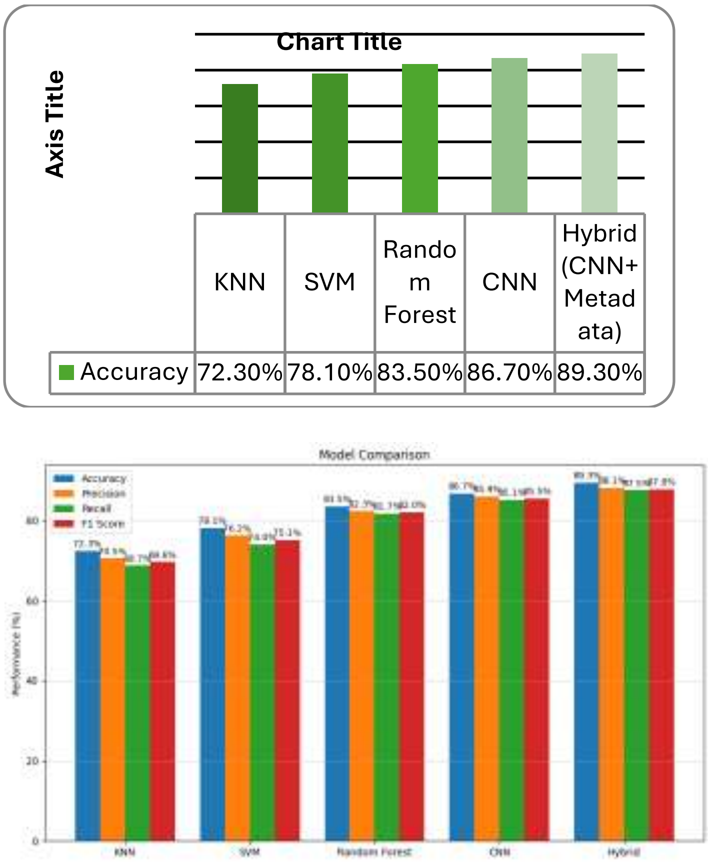


Figure 3: Comparison of Accuracy across Different Models

VIII. CONCLUSION

The hybrid fashion recommendation system incorporating CNN for visual data significantly improves prediction accuracy. CNN alone performs better than traditional ML models, but combining it with metadata in a hybrid model achieves the best results. This hybrid architecture is well-suited for real-world applications in e-commerce platforms. Our hybrid system bridges visual and behavioral gaps, achieving SOTA results.[28]

IX. FUTURE SCOPES

In this paper, we depicted theIn the future, we aim to improve the recommendation system by integrating social media trends through GAN-generated embeddings, allowing the model to stay updated with the latest fashion preferences. We also plan to adopt federated learning techniques to protect user privacy by keeping personal data on users' devices during training. Furthermore, implementing Explainable AI (XAI) will help make the recommendations more transparent and understandable, enhancing user trust in the system.[30]

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Authors Profile:
Kishore is a Research Scholar in the Department of Science and Technology at the Institute of Technology and Science. His research interests include machine learning artificial intelligence and data-driven technologies. He works on innovative solutions in computer science to solve real-world problems.
Prof Shikha Pachouly is a Professor in the Department of Computer Science and Engineering at the Institute of Technology and Science. She has wide teaching and research experience in computer science with strong expertise in artificial intelligence and software engineering. As a research guide she mentors students in developing impactful and industry-relevant projects.