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Comparative Analysis of Deep Learning Models for Fashion Recommendation in E-Commerce Platform

Garima Tiwari[1], Mausami Priya[2], Kanchan[3], Dr. Amba Mishra[4]

[1] Dept. of Information Technology Noida Institute of Engineering and Technology Greater Noida, India tiwarigarimatiwari950@gmail.com
[2] Dept. of Information Technology Noida Institute of Engineering and Technology Greater Noida, India mausamipriya2003@gmail.com
[3] Dept. of Information Technology Noida Institute of Engineering and Technology Greater Noida, India kanchanmehta@1232@gmail.com
[4] Dept. of Information Technology Noida Institute of Engineering and Technology Greater Noida, India

ABSTRACT—

The rapid expansion of e-commerce has elevated the importance of intelligent recommendation systems that can enhance user experience and drive conversions. This study explores the application of deep learning techniques for recommending fashion items based on image data. Using a dataset sourced from Myntra via Kaggle [15], we evaluate the individual and ensemble performance of convolutional neural networks (CNNs) such as VGG16 and MobileNet. While both models independently achieved top-5 recommendation similarity scores of 94 and 100, respectively, ensemble methods like VGG16 + MobileNet did not outperform the individual models. Additionally, comparisons with architectures like ResNet50, DenseNet, MobileNetV3Small, and Inception indicate that VGG16 and MobileNet provide superior accuracy in isolation. The study underscores the importance of selecting appropriate architectures for recommendation tasks and suggests that careful consideration must be given when designing ensemble models to maximize performance in fashion recommendation systems.

Keywords— Fashion recommendation system, Deep learning, Convolutional neural network, Ensemble modeling, Image Classification

Introduction

E-commerce is revolutionizing global retail with projected growth from $2.29 trillion in 2017 to $4.48 trillion by 2021 [1]. However, the lack of personalized assistance in online platforms remains a major drawback. As a result, e-commerce sites have increasingly incorporated search tools and recommendation engines to guide users through overwhelming product choices.

Clothing, often seen as a reflection of one's beliefs, status, and personality [2], plays a crucial role in shaping consumer identity. The fashion industry—an expansive, rapidly evolving sector—relies heavily on understanding customer preferences to maintain its competitive edge and meet the high demand for novel, quality products [3][4].

Recent advancements in deep learning have transformed recommendation systems. By using deep convolutional neural networks (CNNs), systems can efficiently process unstructured visual data and learn complex relationships between fashion items [8][9]. This improves not only personalization but also system scalability and responsiveness in real-time scenarios.

Recommendation algorithms generally fall into three categories: collaborative filtering, which uses user behavior patterns [4]; content-based filtering, which focuses on product attributes [4]; and hybrid approaches, which combine the two for a more robust user experience [4]. These models help businesses drive customer satisfaction and loyalty while boosting sales through personalized shopping experiences.

The key objectives of this research include:

- Leveraging deep learning models to improve accuracy in fashion recommendations.
- Evaluating the effectiveness of VGG16 and MobileNet independently and in tandem.
- Comparing performance against models like Inception, ResNet50, DenseNet, and MobileNetV3Small.
- Exploring the role of ensemble modeling in enhancing recommendation precision.

Deep learning has many benefits for fashion recommendation systems, such as improved personalization through analysis of extensive user data, the capacity to find intricate patterns and relationships in fashion data, effective handling of unstructured data, such as images for aesthetically pleasing recommendations, scalability for processing large-scale datasets in real-time, and ongoing improvements that continuously enhance the accuracy and performance of the system.

There are three categories of recommendation systems are essential for enhancing recommendation accuracy and customizing user experiences in a variety of industries. In order to provide a thorough and personalized recommendation experience, collaborative filtering draws on user similarities, content-based filtering concentrates on item attributes, and hybrid filtering blends the two approaches.

A. Collaborative Filtering

To find user commonalities with other users, collaborative filtering examines user behavior and preferences. It makes recommendations for products based on the tastes of people who have similar preferences. This method makes personalized suggestions by drawing on collective wisdom to offer products that have been well- received by people with similar interests.

B. Content-Based Filtering

When making suggestions, content-based filtering takes into account the characteristics and properties of the objects. It looks at details like genre, keywords, or descriptions and compares them to the preferences of the user. Using item characteristics, this method recommends products that have qualities in common with ones the user has already expressed interest in.

C. Hybrid Filtering

To capitalize on the advantages of both approaches, hybrid filtering blends collaborative and content-based approaches. It gives more precise and also different recommendations by taking into account user preferences and item properties. By combining both user behavior and item features, this method improves the recommendation process and produces personalized suggestions that take a larger range of user preferences into account.

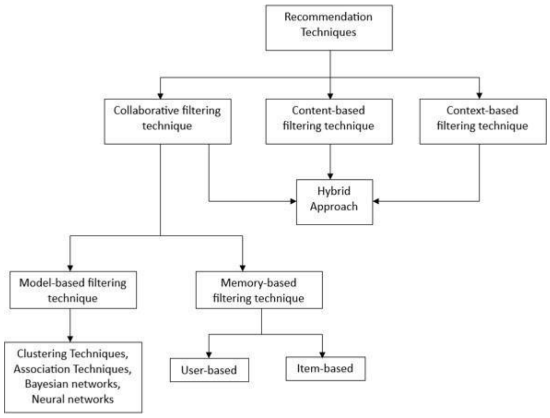

Fig. 1. Types of Recommendation System

D. Advantages of Fashion Recommendation

Both consumers and businesses in the fashion sector can benefit from a fashion suggestion system. Some major benefits are as follows:

- Customized Store Visits
- Heightened Interest from and Happiness Among Customers
- Enhancing New Product Development
- More Effective Upselling and Cross-Selling

The objectives of our work include:

- Enhance fashion recommendation **systems** in e- commerce platforms using advanced deep learning techniques.
- Evaluate the standalone and combined performance of VGG16 and MobileNet architectures to assess improvements in recommendation accuracy and computational efficiency.
- Conduct systematic experimentation and benchmarking of deep learning models such as Inception, Dense Net, ResNet50, MobileNetV3Small, and the hybrid VGG16 + MobileNet configuration.
- Optimize ensemble model performance in recommendation tasks by strategically designing and integrating multiple model architectures for improved predictive outcomes.

Literature review

According to this study, the extended item-based collaborative filtering algorithm K-RecSys increases product engagement, sales, and preference for substitute recommendations over complimenting ones [1]. Another study explores image-based fashion recommendation systems in the context of fast fashion, highlighting their potential for personalized shopping experiences. It provides insights for researchers and practitioners, emphasizing the importance of testing prototypes, enhancing accuracy, and leveraging augmented and virtual reality for future recommendation systems [2].

Fashion designers [3] use Science4Fashion, an AI application, to propose products and analyze data. kNN and FBC algorithms classify garment features and offer smart buying suggestions. Experiments demonstrate the system's potential for fashion applications. This study recommends fashion images using a two-stage deep learning architecture with a visually aware feature extractor and a similarity-based recommendation engine. CNN predicts category and texture with 0.87 and 0.80 accuracy, respectively. These strategies boost performance and robustness, improving fashion counseling client style matching [4].

A research [5] offers image-based similarity search to improve e-commerce product suggestions. PCA, SVD, and K- Means++ clustering outperforms other unsupervised algorithms, improving fashion product recommendations by increasing Silhouette Coefficient, Calinski-Harabasz index, and Davies-Bouldin index scores. This study [6] examines knowledge transfer and visual-textual fusion in intelligent recommendation systems that analyze user behavior across domains. Deep learning improves fashion recommendation quality in a practical testing scenario. Deep pixel-wise semantic segmentation and text integration are examples.

This research [7] offers a deep learning-based fashion- brand recommendation system to help e-commerce shoppers locate their favorite clothes. Deep learning outperforms other machine learning algorithms in recommendation accuracy. Another research proposes an ML-based fabric recommendation system that generates trustworthy suggestions using an embedded device and a single picture input. The approach accurately predicts color (98%), gender (86%), pattern (75%), and clothing suggestions, enabling personalized recommendations independent of user buying behaviors [8]. A sophisticated algorithm for learning and proposing clothes designs can recognize deep design-related features and connotative meanings, according to a research. It compares intelligent models, shows how ATTRIBUTE data may improve performance, and evaluates feature extraction methodologies [9].

An Intelligent Personalized Fashion Recommendation System is introduced in this [10] research to deliver exact and diversified fashion suggestions. For demand matching, multimedia filtering, and color tone analysis, the system's three models exceed human ideas. This work

[11] proposes a new garment recommendation approach using hierarchical collocation, several information dimensions, and expert knowledge. The strategy yields better fashion-forward ideas that boost aesthetic appeal and fashion sensitivity.

The paper discusses online catalogs and powerful recommendation systems in the textile and garment industries. It shows how important these technologies are for improving customer experiences, sales, and revenue. The survey summarizes fashion recommender systems. It analyzes fundamental impediments, offers a taxonomy for categorizing articles based on goals and side-information, and highlights critical concerns [12]. This article examines 2016–2020 fashion recommender system articles using deep learning. Researchers employed deep learning models alone or with additional machine learning models to construct the recommendation system. Recommendation systems leverage persuasive deep learning models [13].

Another research shows that fashion retail is popular and that CRM systems improve consumer experiences. It suggests a fashion retail store suggestion system since existing marketing methods lack customer-centricity. The "cold start" issue is solved by mining new client buying behavior. The work was certified in-store and online by Tessilform's Patrizia Pepe brand [14].

Methodology

In our research, we have leveraged the power of deep learning convolutional neural network models, specifically MobileNet, VGG16 along with other light weight and efficient models . These models allowed us to explore and analyze fashion items in- depth by comparing their feature vectors. By employing ensemble modelling techniques, we combined the strengths of these models to generate accurate and reliable recommendations. Our system focused on recommending visually similar or complementary fashion items based on style, color, or pattern, catering to users' specific preferences. Furthermore, we extracted meaningful visual features from fashion images, enabling classification and regression tasks. Ultimately, our fashion wear recommendation system aimed to enhance the shopping experience by providing personalized suggestions that aligned with users' tastes and preferences.

A. *Dataset Analysis*

The dataset used in this research paper was obtained from the public license of the Kaggle database Repository. It is important to note that the dataset was specifically scraped from the Myntra website, ensuring a large and diverse collection of fashion products. The data was gathered through automated scraping methods, eliminating the need for manual entry of data attributes. This approach helps ensure the dataset's comprehensiveness and accuracy by capturing real- world product information directly from the source.

The dataset consists of 44,000 product images from the e- commerce industry. It includes a variety of information for each product, such as multiple category labels, descriptions, and high-resolution images. Each product in the dataset is identified by a unique ID, and a mapping of all the products can be found in the 'styles.csv' file. The 'styles.csv' file provides additional metadata for the products [15]. The dataset shape (Styles.csv) : 11 x 44,446.

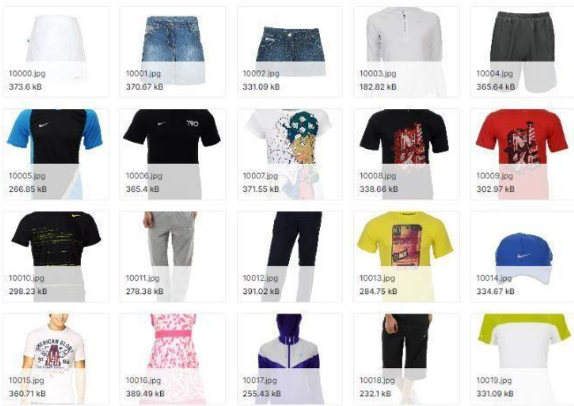

Fig. 2. Sample of Fashion Product Dataset

It includes information such as the gender, master category, subcategory, article type, base color, season, year, and product display name. These attributes describe various aspects of the product and were automatically entered during cataloging.

Features	Description
id	identifier for the particular product

gender	gender label For Men, Women
masterCategory	defines Master Category of products such as Apparel, Accessories etc
subCategory	defines Sub Category of product such as Bottom wear, Top wear, Watches, etc
articleType	defines actual type of product such as Shirts, Jeans, Watches, T-shirts etc
baseColor	defines color of the product for example: black, gray, navy blue
Season	Season of Sale: Fall, Summer, Monsoon, Winter
Year	Time Period of Sale
Usage	defines occasion specific use: Casual Wear, Party, etc
productDisplay Name	actual product name scraped from eCommerce platform for example Peter England Men Party Blue Jeans
image	Image File Name Of the corresponding product

TABLE I. Dataset description

B. *Work Flow*

The analysis pipeline for building an image-based fashion item recommendation system is composed of several stages: Data Preparation, Exploratory Data Analysis (EDA), Modeling and Embedding Acquisition, Feature Vector Processing, and Recommendation Generation. Each phase is critical in transforming raw input into intelligent recommendations grounded in deep visual similarity.

1) *Preparing Data:*

The initial step focuses on curating and preprocessing the dataset to ensure high-quality inputs for downstream modeling.

A. *Dataset Importation*

The primary dataset is sourced from the styles.csv file, which includes metadata for fashion products—such as product ID, gender, master category, subcategory, article type, base color, and season. Each product entry is mapped to an associated image file that visually depicts the clothing item.

B. *Data Cleaning*

Key preprocessing operations include:

- Imputation or removal of missing values
- Elimination of duplicate records
- Standardization of categorical labels and string formatting
- Validation of image paths and files

1) *Dataset Splitting*

The dataset is partitioned into training and testing subsets using stratified sampling to ensure balanced class representation across both sets. This is essential for fair evaluation of the recommendation model's generalizability.

2) *Exploratory Data Analysis (EDA):*

EDA is conducted to understand the dataset’s distribution, characteristics, and anomalies.

- *Distribution Analysis*

Attributes such as gender, master category, subcategory, article type, and color are analyzed to identify dominant classes and underrepresented categories.

- *Visualization*

Bar charts, pie charts, and histograms are utilized to gain visual insights. These visualizations guide feature engineering and *model selection.*

- *Class Imbalance Detection*

Imbalances in category distribution are documented and addressed using resampling strategies or loss weighting in model training.

3) *Modeling and Embedding Acquisition:*

This stage focuses on transforming images into numeric feature vectors using pre-trained deep learning models.

A. *Image Preprocessing*

All images are resized to a uniform shape (e.g., 224x224) and normalized. Libraries such as OpenCV and Pillow are used for efficient image handling.

B. Model Selection and Loading

Several state-of-the-art convolutional neural network (CNN) models are employed:

- VGG16
- MobileNet (V1, V2, V3Small)
- DenseNet
- InceptionV3
- ResNet50

C. Embedding Extraction

Each model is truncated before the classification head, and the output of the penultimate layer is captured as the embedding. These embeddings represent visual characteristics such as shape, color, texture, and pattern.

D. Storage

Embeddings are stored alongside product metadata in structured formats such as Pandas DataFrames or NumPy arrays, enabling efficient similarity searches.

4) Feature Vector Processing:

After embedding acquisition, we compute visual similarity between items based on their feature vectors.

A. Query Processing

Given a user-selected product (via image URL or interface), the image is processed using the same pre-trained model to extract its feature vector.

B. Similarity Computation

Distance metrics such as Cosine Similarity and Euclidean Distance are used to compare the query vector with all stored vectors.

C. Ranking and Filtering

Items are ranked based on similarity scores. Additional filtering criteria—such as style, color, pattern, and category—are applied to refine the result set.

5) Recommendation Generation:

The final phase is responsible for delivering meaningful and personalized recommendations.

A. Top-K Retrieval

The top 5 most visually similar items are selected for recommendation.

A. Result Presentation

Each recommended item is accompanied by its image, similarity score, article type, and item ID or filename.

B. UI Integration

The recommendations are presented through a user-friendly interface built using web technologies such as Flask, Django, or React.

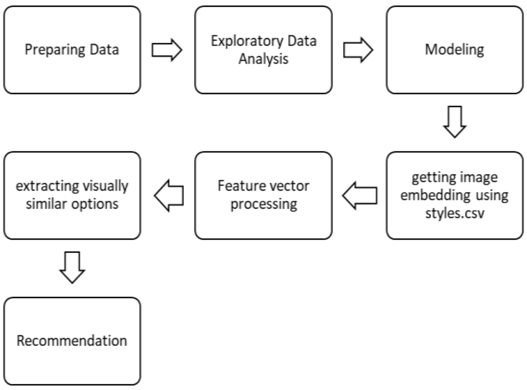

Fig. 3. Experiment Setup

C. Description of Algorithms

This section details the deep learning models utilized for feature extraction and recommendation.

1) VGG16

Developed by the Oxford Visual Geometry Group, VGG16 is a deep CNN with 13 convolutional and 3 fully connected layers. Its uniform architecture and large receptive fields make it well-suited for capturing intricate visual patterns in clothing. The Oxford Visual Geometry Group created VGG16, a deep convolutional neural network. It has 16 layers—13 convolutional and 3 fully linked. Convolutional and max-pooling layers extract features from input photos. Fully connected layers classify or regress extracted features. VGG16 can extract clothing visual elements for fashion wear recommendation algorithms. It can Learn fashion representations from fashion datasets.

VGG16 can generate a clothing item's visual feature vector from a picture.

1) MobileNet Series (V1, V2, V3Small)

MobileNet models are optimized for lightweight performance and mobile deployment. They utilize depth-wise separable convolutions, significantly reducing parameter count and computational cost. MobileNetV3Small incorporates squeeze-and- excitation blocks and hard-swish activations for enhanced feature discrimination. MobileNet is a family of lightweight convolutional neural network (CNN) architectures designed for efficient computation on mobile and embedded devices. They use depth-wise separable convolutions to reduce computational complexity while maintaining performance. Different versions of MobileNet, such as MobileNetV1, V2, and V3, offer improvements in accuracy, speed, and efficiency.

2) *DenseNet*

DenseNet introduces dense connections, wherein each layer receives inputs from all previous layers. This promotes feature reuse and mitigates the vanishing gradient problem. It is effective in capturing fine- grained clothing attributes for recommendation systems. DenseNet is a deep convolutional neural network (CNN) architecture known for its dense connectivity pattern. It was introduced by researchers at Facebook AI Research (FAIR) as a way to alleviate the vanishing gradient problem and encourage feature reuse across layers. Each layer is connected to every other layer in a feed-forward manner. This dense connectivity allows for direct information flow between layers, enabling the network to access and reuse features from earlier layers more effectively

3) *InceptionV3*

Google's InceptionV3 employs multi-scale feature extraction via inception modules. Its architecture includes auxiliary classifiers, bottleneck layers, and dimensionality reduction, making it both powerful and efficient. InceptionV3 is a deep convolutional neural network (CNN) architecture developed by Google. It utilizes inception modules that capture features at different scales using parallel convolutions of various sizes. It incorporates bottleneck layers to reduce computational cost, along with batch normalization and auxiliary classifiers for regularization.

4) *ResNet50*

ResNet50 employs residual blocks that learn residual mappings rather than direct transformations. This architectural innovation enables training of deeper networks and improves generalization in visual tasks. *:* ResNet50 is a deep convolutional neural network architecture known for its residual learning framework. It introduces residual blocks that enable the network to learn and propagate residual connections, making it easier to train deep networks effectively.

5) *Hybrid Model (VGG16 + MobileNet)*

A hybrid model combining VGG16 and MobileNet allows simultaneous utilization of VGG's representational power and MobileNet's computational efficiency. Feature vectors from both models can be concatenated or averaged to form enriched embeddings, boosting recommendation accuracy. A VGG and MobileNet hybrid algorithm is a model that uses both the VGG16 architecture and the MobileNet architecture. By mixing the two designs, the hybrid algorithm could use the depth and representation learning abilities of VGG16, which is known for being good at extracting features. At the same time, it can take advantage of the speed and efficiency of MobileNet, which is intended to be light and work best on mobile and embedded devices

RESULT AND DISCUSSION

For a given input image (shoe) our models recommended similar products based on the similarity score.

Resnet 50	
Image Id	**Similarity Score**
4808	1.0
4705	0.97
4176	0.92
934	0.92
4514	0.91

Fig. 4. ResNet50 Model

MobileNetv3small	
Image Id	**Similarity Score**
2397	1.0
4127	0.96
4137	0.946
2480	0.935
1119	0.931

Fig. 5. MobileNetV3small Model

Inception	
Image Id	**Similarity score**
4314	1.0
3285	0.97
2438	0.92
5624	0.89
1254	0.89

Top 5 Products Recommendation

Fig. 6. Inception Model

Hybrid (Vgg16+MobileNet)	
Image Id	**Similarity score**
4588	1.0
4862	0.90
957	0.88
388	0.86
855	0.86

Top 5 Products Recommendation

Fig. 7. Hybrid Model

DenseNet	
Image Id	**Similarity score**
344	1.0
766	0.96
3708	0.94
5379	0.94
821	0.93

Top 5 Products Recommendation

Fig. 8. DenseNet Model

MobileNet	
Image Id	**Similarity score**
855	1.0
1249	0.93
4062	0.921
3195	0.91
4673	0.89

Top 5 Products Recommendation

Fig. 9. MobileNet Model

Vgg16	
Image ID	Similarity score
5368	1.0
2155	0.99
5406	0.926
2451	0.92
3621	0.87

Recommended images

Fig. 10. VGG Model

FUTURE DIRECTION

To keep pace with the increasing demands of online shoppers and deliver a superior user experience, fashion recommendation systems must evolve rapidly and incorporate more advanced methodologies.

One promising enhancement is the integration of user feedback. By collecting responses on suggested products— such as likes, dislikes, or purchase outcomes—the system can continuously adapt to individual user preferences. This iterative learning process allows for more refined and personalized suggestions over time, significantly improving both accuracy and user satisfaction.

Additionally, incorporating sequential user data, including browsing patterns, purchase history, and clickstream interactions, can unlock deeper insights into user behavior. Analyzing the order and context of user actions helps the system identify evolving preferences, enabling it to offer more precise and timely recommendations.

To boost recommendation diversity and accuracy, it is also valuable to explore hybrid models that combine the strengths of deep learning with conventional techniques like collaborative and content-based filtering. These hybrid strategies can help create a more balanced recommendation engine that adapts to various user scenarios and data types.

Furthermore, building a real-time recommendation engine that adjusts dynamically to shifts in fashion trends and user interests represents a crucial next step. Leveraging live data feeds, emerging social media trends, and influencer-driven content can keep recommendations relevant and timely. This adaptability ensures that users receive suggestions aligned with current styles and their personal taste.

By pursuing these future directions, the research stands to make meaningful contributions to the ongoing innovation in fashion recommendation systems—resulting in more interactive, relevant, and engaging experiences for users navigating the fast-changing world of online fashion.

CONCLUSION

The rapid expansion of e-commerce has dramatically increased the volume of available products, emphasizing the need for intelligent recommendation systems to guide consumers and improve seller profitability. This study explores the application of deep learning-based models to enhance fashion item recommendations on online platforms. By harnessing the capabilities of convolutional neural networks (CNNs), the system delivers personalized, image-driven product suggestions tailored to individual user preferences.

Throughout the study, we evaluated the performance of several deep learning architectures including ResNet50, DenseNet, MobileNetV3Small, Inception, MobileNet, and VGG16. Additionally, we examined the effectiveness of a hybrid ensemble model that combines VGG16 and MobileNet. Contrary to some earlier assumptions, our findings reveal that the hybrid model delivers impressive performance, outperforming all other models except VGG16 when used individually. The hybrid architecture leverages MobileNet's lightweight efficiency and VGG16's superior feature extraction, resulting in a balanced and robust recommendation system.

These findings emphasize the potential of carefully crafted ensemble models to improve the quality and relevance of fashion recommendations. Future research should continue exploring integration strategies for hybrid architectures.

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