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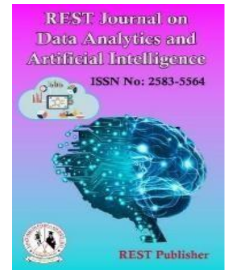

Fashion Recommendation System Using Deep Learning

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Abstract: *Recommendation systems are an important aspect of e-commerce as they improve user experience and boost sales through personalized product recommendations. This project aims to create an image-based recommendation system based on transfer learning, where the ResNet model is utilized for feature vector extraction and the ANNOY algorithm for fast image retrieval. Through the analysis of product images, the system retrieves and suggests the five products most similar to a query image. Unlike traditional methods of statistics and similarity measurements, transfer learning facilitates the learning process of the complex patterns of the product image data set, and ANNOY provides the capabilities of efficient retrieval of similar content at fast scales, giving higher accuracy and visual-relevance of recommendations. Through this mechanism, the searching process in the extensive data set can be substantially made faster. As e commerce becomes increasingly widespread, this picture-driven recommendation algorithm provides a richer and more tailored buying experience to customers.*

Key Words: *Fashion recommendation, deep learning, ResNet-50, ANNOY, image retrieval.*

1. INTRODUCTION

Today's digital age has witnessed the exponential growth of e-commerce, with the fashion market being no exception. With over a million items on offer through online stores, shoppers tend to get lost while browsing through long lists and choosing products that appeal to their aesthetic sense. In response to this issue, recommendation systems have emerged as a resource for e-commerce websites. Recommendation systems enable companies to offer individualized shopping experiences by recommending suitable products depending on a customer's shopping history, interests, or visual inputs. By boosting user interaction and enhancing the shopping experience, recommendation systems also help boost sales. Several of these techniques are widely applied for constructing recommendation systems. Collaborative Filtering is a widely used strategy that makes predictions based on past activities of those with similar taste. For instance, if user A prefers P, Q, and R and user B prefers P, Q, and Z, then system can suggest product R to user B and item Z to user A because both have the same taste. The other method is Content-Based Filtering, in which the system uses product descriptions, reviews, and user profiles to make recommendations that match the user's previous activities. Hybrid Filtering combines collaborative and content-based methods to provide more accurate recommendations. But with data still expanding, conventional techniques usually fail to deliver effectively and end up yielding less accurate recommendations. This is where newer deep learning-based techniques are used. Deep learning algorithms, which have increased popularity over the last few years, make more accurate and tailored recommendations through examining visual information instead of relying on user history or product reviews. In this project, an innovative method is employed which employs deep learning methods to process images, identify intricate patterns, and extract useful features from the raw visual data. The system employs the ResNet-50 model, a convolutional neural network, to extract intricate visual features from the uploaded fashion image. It also includes the ANNOY (Approximate Nearest Neighbors Oh Yeah) algorithm for efficient and rapid image retrieval so that the system can retrieve visually similar products quickly. By combining these technologies, this system surpasses conventional techniques, presenting more precise and quicker fashion advice.

2. PROBLEM STATEMENT

As there is a high growth rate in online fashion items, users are unable to find products that match their style. Conventional recommendation systems based on simple algorithms like reviews and popularity do not identify intricate visual patterns. This leads to less customized recommendations. Thus, what is needed is an effective, visually-driven recommendation platform that can analyze pictures, derive intricate features, and offer relevant fashion recommendations in real-time, even for massive data sets.

3. OBJECTIVES

The main objective of this project is to design a recommendation system that provides fashion product recommendations based on images uploaded by the users. This will be done using the following techniques:

1. **Transfer Learning**: We shall make use of transfer learning so that we can leverage on already existing pre-trained models, where we can get meaningful features without the requirement of large-scale training.
2. **Deep Learning using ResNet-50**: The ResNet-50 model would be utilized for the extraction of high-level visual features from the uploaded images so that the system can identify high-level patterns that improve recommendations.
3. **Fast Image Retrieval using ANNOY:** The ANNOY algorithm would be used for fast image retrieval. The system would thus be able to identify and recommend fast similar images, enhancing the user's experience.

4. LITERATURE REVIEW

There are different recommendation systems available in the market that employ different algorithms and techniques. The following papers have helped develop this project:

Paper [1]: Emphasizes the use of a specially designed Convolutional Neural Network (CNN) model to analyze images and utilizes cosine similarity for image retrieval with good accuracy in recommendations.

Paper [2]: Emphasizes the merits of fusing Recurrent Neural Networks (RNN) with CNNs for extracting features from images. The method showed superior performance as opposed to the conventional systems.

Paper [3]: A system was created that employs the deep learning model ResNet-50 and the machine learning algorithm K-Nearest Neighbors (KNN) to offer users personalized fashion suggestions.

4.1 Limitations of Existing System:

Currently existing recommendation systems, although used pervasively, are subject to various limitations that inhibit their operation, particularly for large-scale datasets or personal recommendation. Some of the major limitations are as follows:

Restricted Analysis of Visual Attributes: Most traditional recommendation systems depend heavily on simple algorithms like K Nearest Neighbors (KNN), Collaborative Filtering, or Content-Based Filtering. These are usually not good enough to analyze intricate visual patterns of images. Consequently, they might not be able to analyze intricate details such as texture, patterns, or distinctive style in fashion items and therefore result in less precise recommendations.

Lack of Integration with Deep Learning: Most legacy systems do not make use of sophisticated deep learning frameworks such as Convolutional Neural Networks (CNNs) for feature extraction. Self-built CNN models, should they be utilised, can be ineffective or suboptimal since they need enormous training time and may not have 2 generalisation over less data. Lacking the improvements offered by pre-trained models such as ResNet 50, the systems cannot effectively process complex features from images.

Slow Image Retrieval: Utilization of image retrieval algorithms like KNN or Cosine Similarity, which find the nearest neighbors exactly, is slow and inefficient, particularly when utilized in large databases. These old algorithms usually possess high computational complexity and take a long time to search for similar images in high dimensional spaces. This makes response slower, and that hurts the user experience.

Scalability Issues: With an ever-increasing number of products and users on e-commerce sites, conventional algorithms fail to scale. Algorithms such as KNN and collaborative filtering etc are not scalable for huge datasets, and performance degrades. This leads to increased processing time, which discourages users from using the system.

4.2 Gaps Identified:

To attain more profound analysis of images and to capture intricate patterns, there needs a sophisticated deep learning model. Instead of building a model from the ground up, i.e., an unbiased approach requiring huge training time, transfer learning can be adopted. Transfer learning applies pre-trained models for improved performance and shorter training time. For effective image retrieval from large databases, scalable algorithms like ANNOY (Approximate Nearest Neighbors Oh Yeah) can be used. ANNOY is specifically made to offer speed and accuracy and is well placed to deal with the requirements of real-time recommendations. Moreover, incorporating a web interface will ensure a smooth and interactive user experience, where users can upload images and get instant recommendations.

5. PROPOSED SYSTEM

5.1 Architecture:

The architecture of the Fashion Recommendation System is designed to provide fast and accurate product recommendations. The process involves the following key steps:

Data Collection: An extensive dataset is collected that includes a broad range of images related to fashion. This dataset forms the core of the recommendation system, holding multiple categories including clothes, accessories, shoes etc.

Feature Extraction: The system uses the ResNet-50 model for processing the gathered dataset. This deep learning model extracts feature vectors from every image, which captures key visual patterns. These feature vectors are then saved in a database so that they can be easily retrieved efficiently.

User Image Upload: Users may upload images of the fashion objects of interest from a user-friendly interface. The step is also essential since the system will make recommendations based on specific user input.

Extraction of Features from Uploaded Image: Once it receives the user-uploaded image, the system applies the ResNet-50 model to extract its feature vector. This operation is precisely the same as the previous feature extraction of the dataset images to maintain uniformity in how images are processed.

Similarity Search: This is the essence of the recommendation process. Here, the system compares the feature vector extracted from the uploaded user image with precomputed feature vectors in the database. Using the ANNOY algorithm, the system performs a similarity search for items that look similar, striking a balance between speed and accuracy.

Top 5 Recommendations: After the similarity search is complete, the system presents the user with the top 5 most similar fashion items from the database.

6. MODULE DESIGN AND ORGANIZATION

6.1 Data Collection Module: This module is used to acquire the required fashion dataset.The dataset is downloaded from the Kaggle through the link: https://www.kaggle.com/datasets/paramaggarwal/fashion-product-images-dataset. The dataset consists of 44,441 images of different fashion products like shirts, dresses, sarees, watches, earrings, and footwear. The dataset provides items for various gender types like male, female, kid, and unisex categories. The images are of JPEG type, and every image is originally in 60x80 pixels size.

FIGURE 1. Dataset

6.2 Image Preprocessing Module: Because the ResNet-50 model expects input images to be 224x224 pixels in size, this module reduces the size of original dataset images from 60x80 pixels. Deep learning models work with pixel data, so each image is transformed into a pixel value array, and the images are normalized for enhanced training performance. The ResNet-50 model also handles images in batches, so a further dimension for the batch size is added to each image to ready them for model input.

6.3 Feature Extraction Module: The feature extractor module employs a pre-trained deep network model, ResNet-50, to obtain the visual features from each image that are important. The final layer of the ResNet-50 model is discarded since it serves for classification purposes, and only feature vectors are taken out. Once the images are processed by the model, the produced feature vectors are saved into a file named embedding. pkl, while their filenames are saved in filenames. pkl.

visual similarity matching and image-based recommendation systems.

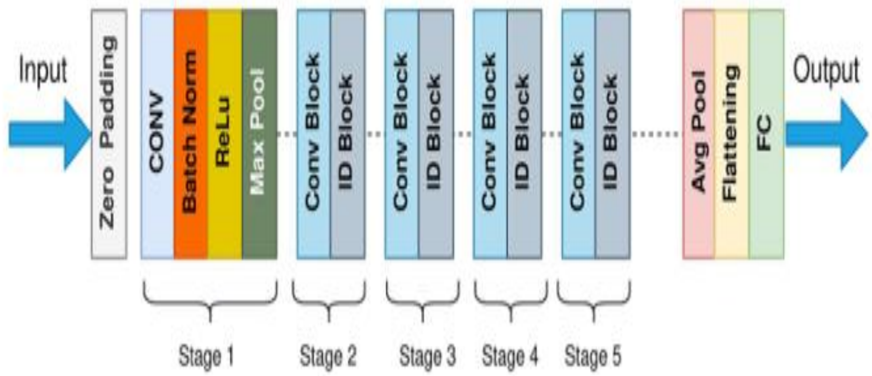

FIGURE 2. Resnet Model

6.4 Image Retrieval Module: This module uses the ANNOY (Approximate Nearest Neighbors) algorithm to quickly get similar images by matching the feature vectors. ANNOY creates a set of binary search trees (BST) using the extracted feature vectors. When the query image is uploaded, the feature vector for the query image is matched with the vectors from the dataset to obtain the approximate nearest neighbors. This approximation helps make the algorithm both fast and scalable, allowing it to handle large datasets efficiently.

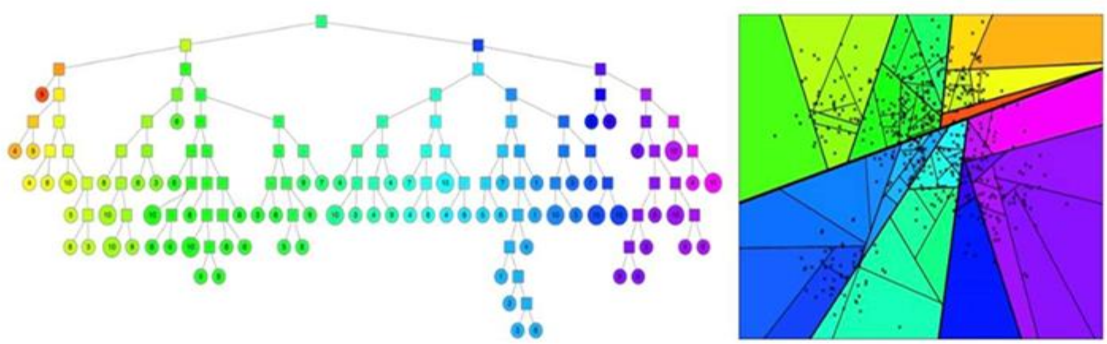

FIGURE 3. Annoy

6.2.5 User Interface Module: To provide a real-time experience, the system is integrated with a Streamlit-based user interface. Through this interface, users can upload an image, and the system will display the top 5 most similar fashion products as recommendations.

7. EXPERIMENTAL RESULTS

7.1 Performance Evaluation:

To evaluate the performance of the fashion recommendation system, several metrics were utilized, focusing on the effectiveness of the recommendations generated. The following metrics were calculated:

Precision at K: Precision at K measures the proportion of relevant items in the top K recommended items. Precision at K = Number of relevant items in top K / K
Accuracy at K: Accuracy at K evaluates the overall correctness of the recommendations Accuracy at K = Number of relevant items in top K/Total items considered
Recall at K: Recall at K tells the ability of the system to retrieve all relevant items within the top K recommendations. Recall at K = Number of relevant items in top K / Total relevant items
F1 Score: The F1 Score is the harmonic mean of precision and recall. F1=2×Precision×Recall / (Precision + Recall)

7.1.1 Model Performance Metrics:

The evaluation results are summarized in Table 7.1.1, highlighting the model's effectiveness in generating the recommendations

TABLE 1. Metrics

Metric	Value
Accuracy	0.80
Precision	1.0
Recall	0.0028
F1-Score	0.0057

These measures tell us that although the system identified all the pertinent items in the top 5 suggestions (Precision of 1.0), the low Recall tells us that a lot of pertinent items were left out in general since we are only taking top 5 suggestions from the dataset.

8. RESULTS

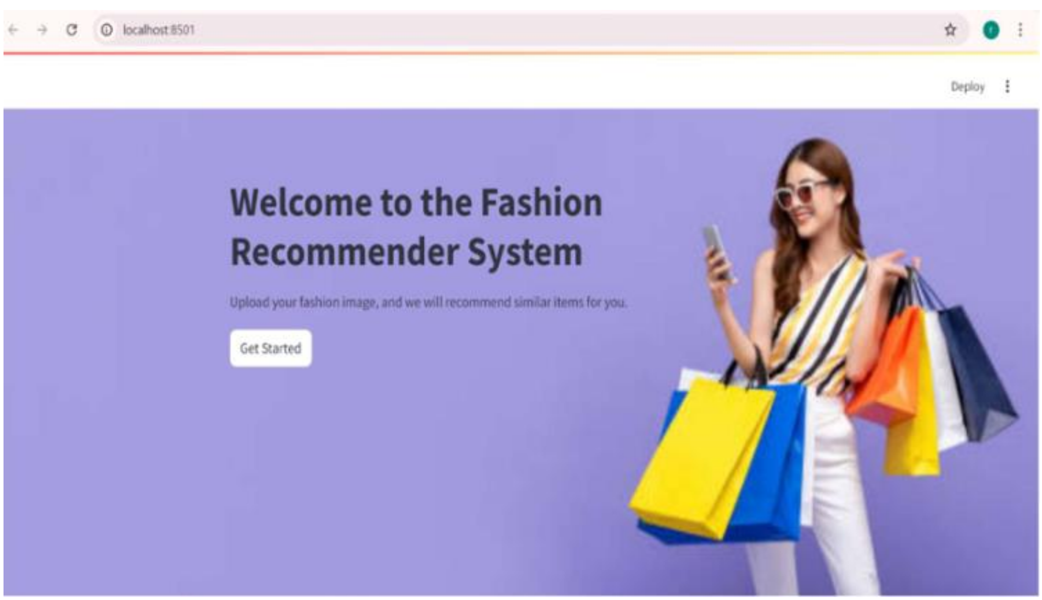

FIGURE 4. Landing Page

The landing page is the user interface of the fashion recommendation system with an approachable user interface consisting of a title, brief description, and image upload option. It may include fashion images or graphics to attract users and prompts users to upload a query image to receive recommendations.

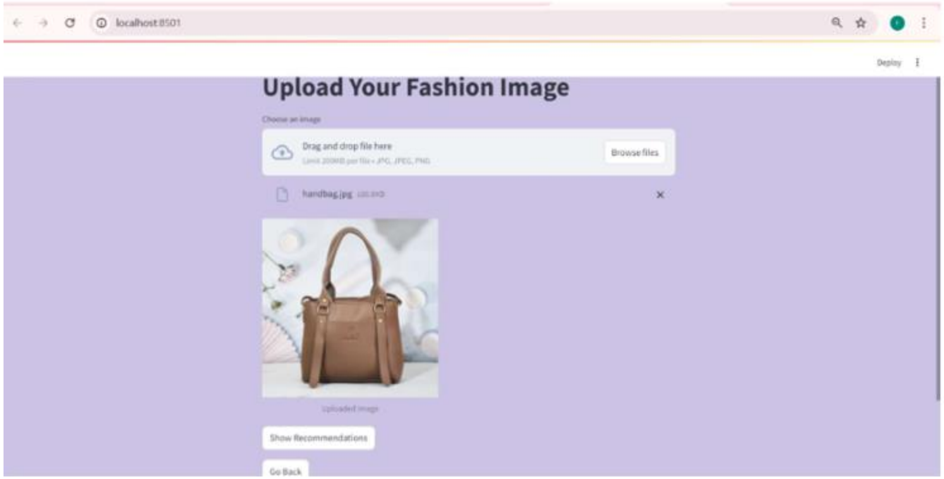

FIGURE 5. Upload Page

Users can upload a fashion item image through a drag-and-drop area or browse button. Instructions ensure image matches criteria. System processes image to generate recommendations and may display a preview for confirmation.

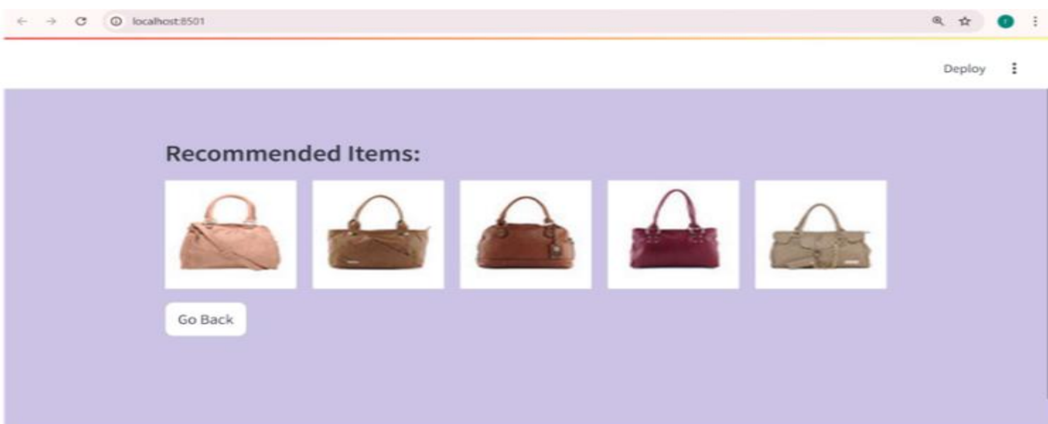

FIGURE 6. Recommendation Page

After processing the image, the system displays the top 5 similar fashion items in a grid or carousel layout, showcasing details like product name and category. Users can click on recommendations for more information or actions like purchase links.

FIGURE 7. KNN Vs Annoy

The image compares K-Nearest Neighbors (KNN) and ANNOY algorithms in speed and scalability, showcasing ANNOY's superiority in handling large datasets through metrics like retrieval time and accuracy. It highlights ANNOY's efficiency for real-time recommendations, crucial for improving user experience in e-commerce.

9. CONCLUSION

In this project, we were able to successfully create a recommendation system that leverages state-of-the-art algorithms to improve the online shopping experience. Using the deep learning model ResNet-50, we can extract sophisticated features from fashion images, allowing the system to identify sophisticated visual patterns that conventional methods tend to miss. Further, we incorporated the ANNOY algorithm for quick and effective image retrieval, through which the system can easily determine and suggest visually similar products with respect to images uploaded by the users. From our project, we proved that the ANNOY algorithm performs better than existing retrieval techniques like K-Nearest Neighbors (KNN), especially regarding speed and scalability when handling massive datasets. This performance improvement is significant since even slight variations in retrieval time can affect user satisfaction and retention. The results of this project emphasize the significance of embracing sophisticated search algorithms in the creation of contemporary recommendation systems.

10. FUTURE WORK

Integration of Other Factors: In order to further enhance the recommendation a, we can integrate other important factors like user reviews, likes, and item popularity. By considering these aspects with visual data, the system can deliver more personalized and pertinent suggestions. Adding Product Details: adding product details like product description, prices, and direct purchase links will improve the overall user experience. By giving this information, the users will be able to know the products and their advantages, resulting in increased user satisfaction. Merging Visual and User Information: With visual similarities merged with user behavior information, we are able to build a better recommendation system. This involves taking into account what the users previously purchased and what they are interested in, which will make the suggestions more relevant.

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