Report

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Report on,

Image-Based Service Recommendation System: A JPEG-Coefficient RFs Approach

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Abstract:
Online shopping platforms are quickly expanding worldwide, relying heavily on search engines for product discovery through keyword matching. However, customer demand for more interactive and efficient searching methods has led to the proposal of an image-based approach. This innovative idea allows users to input or select an image, which will then generate similar products for them to browse. The recommendation system consists of two phases: classifying products using Machine Learning in Phase 1, and retrieving similar products in Phase 2. By utilizing Random Forests for classification and image features for extraction, the system achieves a 75% accuracy rate in Phase 1, which improves to 84% when integrated with Deep Learning. Phase 2 further demonstrates the system's effectiveness, achieving a 98% accuracy rate in recommending products to users.

Introduction:
Online retail websites are experiencing rapid growth and popularity, with a significant percentage of consumers using online services to make purchases. However, the increasing number of products available online has posed a challenge for users in selecting the desired items. To address this issue, recommendation systems have become essential for enhancing user experience and increasing sales for retailers. Traditional E-commerce search engines often rely on text-based searching, which can lead to inaccurate recommendations. As a result, the use of machine learning algorithms such as Neural Networks, Decision Trees, and Deep Learning has gained traction in improving the recommendation system by incorporating visual search based on images of products.
In this paper, the authors propose a novel approach to enhance the online shopping experience by implementing image-based searching techniques. The recommendation system consists of two main phases: classifying products based on image characteristics in Phase 1, and retrieving similar products based on image features in Phase 2. The proposed approach utilizes Random Forests as a meta-classifier for product classification and extracts image features using JPEG coefficients. The evaluation of the model shows promising results, with an accuracy of 75% in Phase 1 and 98% in Phase 2.

The implementation of the recommendation system allows users to submit or select an image of a product, which then retrieves similar products for their consideration. The proposed approach is based on learning features from user-generated images to recommend products effectively. The paper also includes discussions on related work, ML models, JPEG features, and a comparative analysis of the image-based recommendation approach. Overall, the study highlights the potential of image-based recommendation systems in improving the online shopping experience and enhancing customer satisfaction.

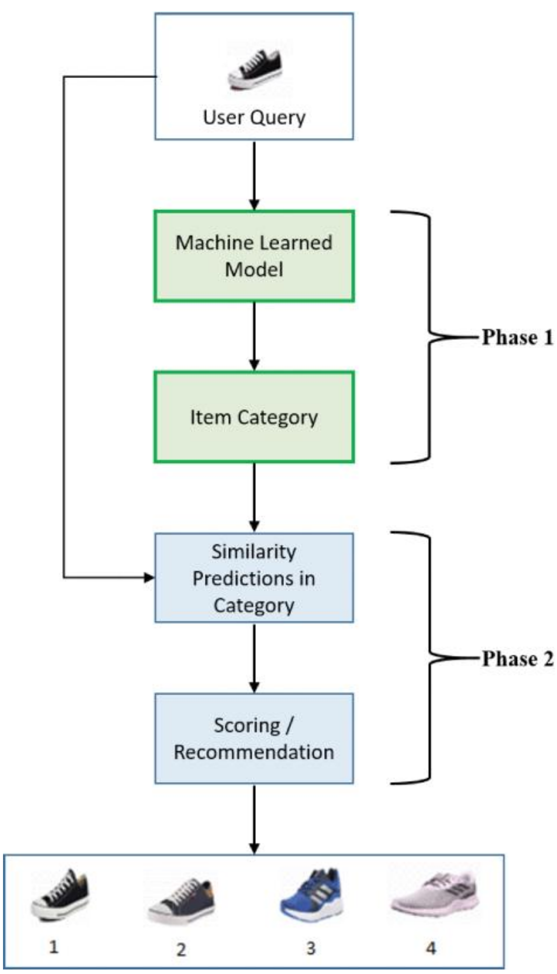
Literature Review:

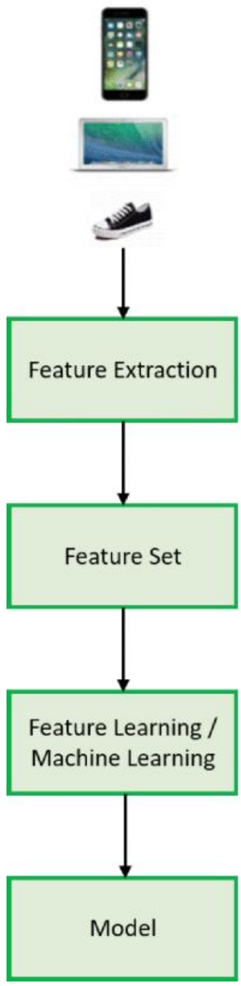
The authors in [1] propose a novel approach for One-Class collaborative filtering based on users' fashion-aware personalized ranking and high-level visual features extracted by CNN. In [2], the approach models human sense of relationships between objects for image-based recommendations. In [4], the authors aim to recommend images using various techniques including TPR, CNNC, GMM, MCL, and TAR. [5] applies Alex-Net DL to model one thousand image categories, while [6] classifies images into relevant classes using CNN. Image similarity is investigated in [7] and [8] based on category similarity. Machine learning helps classify images into categories for retrieval. NN is used in [9] to calculate similarities within categories. [12] focuses on learning similarity for multi-products in a single image, while [13] concentrates on image similarity and semantics. [14] proposes new similarity metrics for event descriptions, [15] suggests a semantic image browser. [23] addresses long queries with a contextual-based image recommendation system, [24] uses Geo-tagged images for travel recommendations, and [25] recommends landmarks for road-based travel. [26] discusses content-based image recommendations, while [27] suggests personality-based recommendations based on traits in images.

Proposed Model:

The recommendation system is based on the user submitting or selecting an image of a product, and similar products or images are recommended to the user. The system consists of two phases: category learning and recommendation. In the category learning phase, the system models and learns the class or category of the product based on image characteristics. The recommendation phase retrieves similar products from the corresponding category based on the category learned in Phase 1.

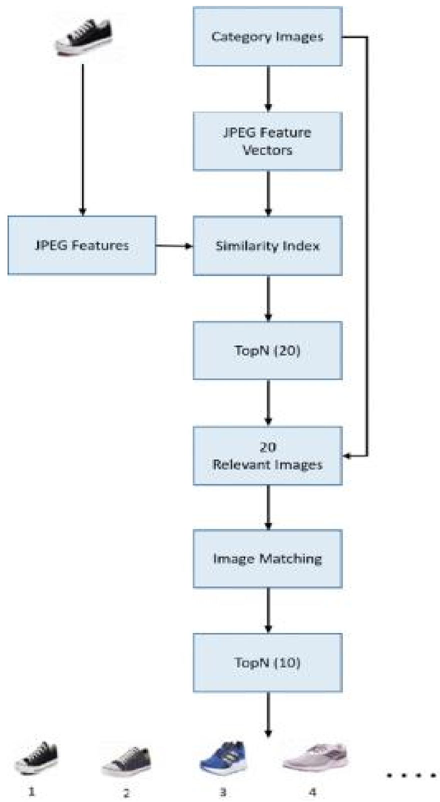
The system uses machine learning and deep learning techniques for feature extraction and classification. The RF classifier is used for learning the class of products and extracting image features, with JPEG coefficients being used as features. The RF classifier learns the distribution of features for different categories of objects, and the final model is used to predict the category of the query image.





In Phase 2, image-based recommendations are made by retrieving similar products in the same category as the query image. The system calculates the similarity between the feature vector of the query image and the feature vectors of the category images using the Euclidean distance. The top 20 similar images are selected as possible recommendations. To enhance the matching process, the system also uses the Structural Similarity Index (SSIM) for image-based similarity matching, including color histograms in the process.

Overall, the recommendation system is based on learning features from user-based images to recommend similar products. The system uses a combination of machine learning and deep learning techniques to classify products and make recommendations based on image similarities. The system aims to improve recommendation accuracy by including image-based similarity matching, considering both item matching and color matching of items for a robust recommendation process.



Experimental Evaluation:

This section discusses the dataset used, the performance evaluation of the Phase 1 and Phase 2 of the recommendation system, and the related parameters and factors analyzed. The dataset consists of 3.5 million Amazon product images across 20 categories, with 100 images randomly selected per class. The dataset is based on JPEG coefficients as feature vectors due to their efficiency, effectiveness in compressing images, and high performance compared to other feature extraction methods.

For Phase 1 performance analysis, a Random Forest (RF) meta-classifier is used for its generalization capabilities. The 10-folds cross-validation approach is employed to train and test the model, with Precision, Recall, and F-measure used for evaluation. The RF approach is compared with other machine learning models such as Logistic Regression, Naïve Bayes, SVM, and Deep Learning. The results show that the RF approach outperforms the other models, with the integration of RF with Deep Learning further improving performance.

In Phase 2 evaluation, the Autocorrelogram vector-based Euclidian distance is used due to the subjective nature of recommendation and lack of baseline for comparison. Autocorrelograms are chosen for their performance in image retrieval and ability to capture spatial correlations. Comparative evaluation is done using K-Nearest Neighbor (KNN) and Search-based approaches. The results show that subjective similarity scores for the "Struct-Hist" approach, KNN, and Search-based retrieval are very similar, indicating that humans focus more on global image features rather than detailed differences. Overall, the proposed recommendation system shows promising results in both Phase 1 and Phase 2 evaluations, with the RF approach and Autocorrelogram-based retrieval performing well and highlighting the importance of feature selection and model integration in enhancing recommendation system performance.

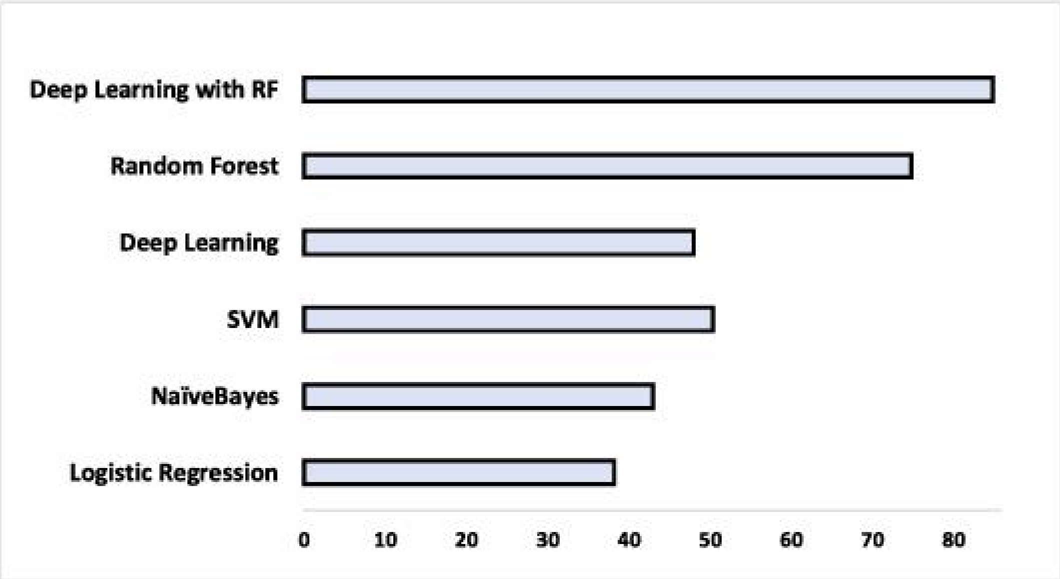


fig : Performance evaluation of Phase 1 based on Precision. The X-axis shows the % Precision values

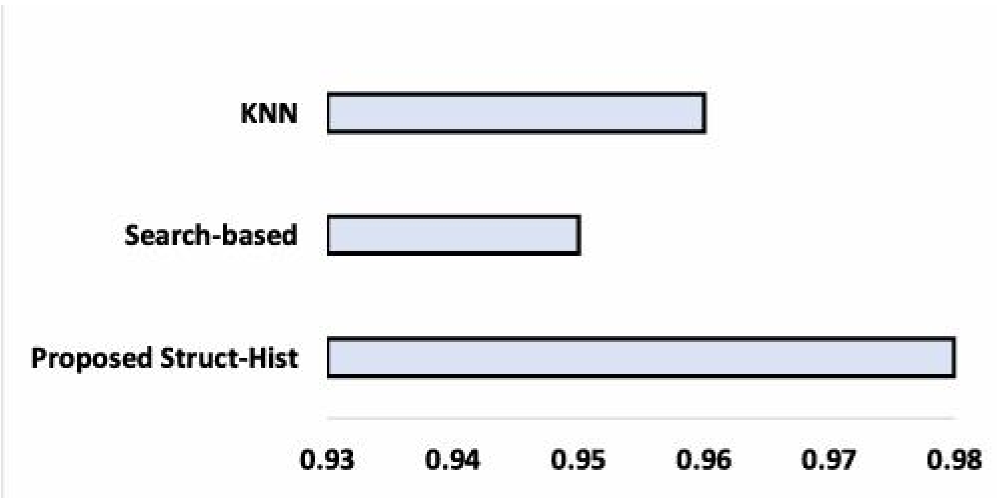


fig : Evaluation of the recommendation phase Phase 2

Struct-Hist step of the proposed approach by the Euclidian similarity.

Time Complexity:

Parameters	Avg. Time (Seconds)
Time for calculating and learning the JPEG features by RF	35
Time to find the category of the query image by the JPEG and RF	0.03
Time for calculating and learning the Deep features by RF	1000
Time to find the category of the query image by the Deep features and RF	0.3
Time to find the top 20 related items from the dataset	1
Time to retrieve the 10 related items out of 20 already retrieved	0.003

Table 1 displays the average time taken by different modules in seconds using a Core i7 with a Titan Nvidia GPU. The time for calculating and learning JPEG features by RF is 35 seconds, while finding the category of a query image using JPEG and RF takes 0.03 seconds. Deep feature calculation and learning by RF takes 1000 seconds, with a querying time of 0.3 seconds. In Phase 2, finding the top 20 related items takes 1 second, and retrieving 10 out of 20 associated items takes 0.003 seconds.

Conclusion:

The article presents a two-phase image-based product recommendation system. In Phase 1, the system learns the product class using RF classifier and JPEG image features, achieving 75% accuracy. Phase 2 involves retrieving similar products using a combination of Euclidean distance and Struct-Hist approach, yielding accurate recommendations. The system outperforms other methods and can be applied to computer vision problems. Future plans include integrating non-image data, and using RNN architecture for recommendations. The study contributes to recommendation systems and demonstrates the effectiveness of the proposed algorithm.