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Article

Development of a system for creating and recommending combination collections in the e-commerce clothing industry

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Abstract: In the clothing sector, matching the right demand with the appropriate user is of great significance. Combination suggestions emerge as an innovative strategy for e-commerce platforms operating in the clothing sector. By providing suitable combination suggestions tailored to the right user, the profit margin of sales increased, and the brand image strengthened. The aim of this study is to develop a recommendation system based on image processing and machine learning that generates combinations from products that may interest users and recommends these combinations to them. 90 million possible combinations have been obtained using a dataset consisting of products detected from images of items sold in the clothing category on Trendyol. These combinations have been trained using the Prod2Vec algorithm to create new pairings. Subsequently, collections have been developed for purchasing looks using image processing methods. In this context, the You Only Look Once (YOLO) model has been selected for clothing classification, while the Convolutional Network Next (ConvNext) model has been employed for calculating image similarity. Models have also been developed for estimating click performance using Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Linear Regression (LR). The prediction performances of the developed models have been evaluated using Coefficient of Determination (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE) metrics. When the developed models have been examined, it has been observed that RF had superior performance. The developed system provided a 5% increase in the time spent on the Trendyol mobile application.

Keywords: creating combination collections; similar product recommendation; machine learning

1. Introduction

In today's world, the e-commerce sector is distinguished as a prominent form of commerce characterized by substantial transaction volumes [1]. In this context, the competitive environment in the sector is extremely intense, making it necessary for companies to take various strategic actions to distinguish themselves. The most critical of these actions is increasing customer satisfaction.

Customer satisfaction is particularly important for e-commerce businesses operating in the clothing sector. By adopting approaches that prioritize customer satisfaction, companies can gain customer loyalty and strengthen their brand reputation. Establishing a strong brand reputation is essential for securing long-term success in a highly competitive market, as it fosters positive communication and encourages repeat purchases. In contemporary strategic sales initiatives, ensuring the supply-demand balance and matching the right demand with the right customer plays a crucial role in enhancing customer satisfaction. In this regard, aligning the right product with the right customer is of great importance [2].

Today's fast-paced consumer landscape, offering a wide range of products in various colors and styles, increases competition in the sector and provides consumers with diverse options. Since each product appeals to different customer profiles, this diversity allows users to experiment with different combinations. Suggesting the right combinations enhances customer satisfaction by providing a personalized experience and plays a vital role in strengthening users' brand loyalty. Furthermore, effective combination suggestions save users time and make their shopping experience more enjoyable by demonstrating how products can be used together. This encourages users to shop more by providing suitable and inspiring style suggestions while also helping brands explore opportunities to enhance customer loyalty and sales rates. Combination collections, on the other hand, attract attention as product groups that bring together compatible clothing and accessories, offering users various style alternatives. These collections facilitate the process for users by allowing them to view and purchase combined pieces in one place. As one of the innovative solutions aimed at increasing product clicks and purchase rates, combination collections provide users with creative style options that personalize and enrich the shopping experience through alternative combination suggestions based on product images. Well-presented combination collections enable users to enjoy a more successful and satisfying shopping experience.

The aim of this study is to develop a recommendation system based on image processing and machine learning that creates combinations from products that may interest users and recommends these combinations to them.

This study is organized as follows: Section 2 includes relevant literature. Methodology is presented in section 3. Details of the system are presented in section 4. Section 5 presents the results of the study. Discussion is presented in section 6. Section 7 concludes the paper.

2. Literature review

Laenen and Moens [3] compared the methods used for clothing recommendation by combining product features obtained from visual and textual data. The differences between traditional combination techniques and attention-based methods were examined, and the importance of polymorphism and detail in fashion product representations was emphasized. It was discovered that visual and textual data provide not only product features but also complementary features, and it was revealed that these data should be integrated effectively. The study demonstrated that attention-based methods outperformed traditional methods. Patil et al. [4] proposed a system that provides product recommendations to both new and existing users by combining collaborative filtering and content-based filtering techniques. As the first step, feature extraction is performed, and recommendations are generated by programming content similarity. New users are provided with recommendations about popular products. The system utilizes the Walmart Product Ratings dataset. Kachbal et al. [5] presented a study of state-of-the-art, fashion-focused recommendation systems. Context awareness and outfit-based recommendations were the two main components of the novel approach to fashion recommendation systems introduced in this research. Personalized fashion discovery was investigated using deep learning algorithms, considering contextual elements such as situation and environment to provide more relevant recommendations. This study is the first to present outfit-based recommendations that include the interaction of entire communities rather than just individual items. Zhou et al. [6] proposed an innovative machine learning method that provides personalized fashion recommendations using the descriptive and aesthetic attributes of clothing items. They also presented a novel approach that reveals hidden relationships between fashion items that are typically purchased in pairs. It was observed that the aesthetic-aware recommendation system provided recommendations with up to 89% accuracy on four real fashion datasets when compared to similar fashion recommendation systems. Erich Robbi et al. [7] proposed a new preference-based approach model for bundle recommendation using the Choquet integral. In this context, preferences for coalitions of environmental attributes were formalized, and product bundles were recommended by considering the synergies between product attributes. Gao et al. [8] reviewed the literature on graph neural network-based recommendation systems. It was noted that there are four dimensions for categorizing existing research in recommendation systems: stage, scenario, goal, and application. Subsequently, challenges in graph construction, placement propagation/aggregation, model optimization, and computational efficiency were systematically analyzed. Ke et al. [9] introduced a new model for bundle recommendation called the Hyperbolic Mutual Learning model for Bundle Recommendation (HyperMBR). In the HyperMBR, the entities (users, items, bundles) of two-view interaction graphs were encoded in hyperbolic space to learn accurate representations. Additionally, a hyperbolic distance-based mutual distillation method was proposed to encourage information transfer between the two views and improve recommendation performance. The results indicated that HyperMBR exhibited strong performance. Artur Pereira et al. [10] discussed AI techniques for personalized recommendation systems in online fashion retail stores. It has been emphasized that customer models are the most crucial component for these systems. Emre Yıldız et al. [11] presented a product recommendation system that combines various data mining techniques to provide the right products at the right time according to customer preferences. The model consisted of three distinct steps: customer segmentation, incorporating the location dimension, and establishing relationship rules for generating product recommendations. The Recency, Frequency, and Monetary (RFM) technique and the K-Means Clustering algorithm were used for customer segmentation. Subsequently, accurate rules were created using the Apriori algorithm, one of the association rule mining methods. Finally, product recommendations were generated using a rule-based heuristic algorithm. The proposed system achieved higher success compared to existing studies when evaluated using error metrics. Jianxin Chang et al. [12] aimed to recommend a bundle of items for users to consume as a whole. In this context, two different graph neural network models were proposed: the Bundle Graph Convolutional Network (BGCN) for pre-generated bundle recommendations and the Bundle Graph Generation Network (BGGN) for personalized bundle creation. In BGCN, user-item interactions, user-bundle interactions, and bundle-item relationships were combined into a heterogeneous graph. In BGGN, bundles were restructured into graphs based on item co-occurrence patterns and user feedback signals. The complex and high-order item-item relationships in the bundle graph were explicitly modeled through graph generation. The results showed that both models achieved successful outcomes. Hiun Kim et al. [13] introduced a Pre-Trained Language Model (PLM) that leverages the textual attributes of web-scale products to create goal-based product collections. They trained a Bidirectional Encoder Representations from Transformers (BERT) model. Additionally, the model's performance was enhanced through search-based negative sampling and category-wise positive pair augmentation. The PLM outperformed the search-based baseline model for intent-based product matching in offline evaluations. Moghtader [14] proposed a recommendation system based on collaborative filtering that uses consumer similarities to infer preferences and suggest product sets for subsequent purchases. The recommendation model was evaluated with transaction data to determine hyperparameters, which were then tested on transactions from the previous month. Additionally, the predicted preferences were analyzed to suggest bundling options and gain empirical insights. Using the cosine similarity metric, the engine achieved an accuracy rate of 38% at the brand level and 7% at the product level. Tunalı and Bayrak [15] developed a product bundle generation engine based on the sales data of a leading fast-food chain. In this study, product basket statistics were extracted, and data patterns were learned using a customized Gaussian Mixture Model based on the targets. Product bundles aligned with the targets were generated using a deep search algorithm that employs mixture models as a prioritization tool. In the proposed model, outputs were generated using weighted targets specific to certain customer groups, overall purchasing preferences, and sales periods. Junheng Hao et al. [16] introduced P-Companion, a deep learning framework for Complementary Product Recommendation modeling, and provided recommendations for products that are often purchased together. In this framework, an encoder-decoder network was employed to predict multiple types of complementary products. A transfer metric learning network was developed to reflect the embedding of the query product into each predicted complementary product type subspace and to further learn the complementary relationships based on distant supervision labels in each subspace. The results indicated that P-Companion is an effective model for providing online recommendations and achieving significant gains in product sales. Liang Chen et al. [17] proposed a neural network solution called the Deep Attentive Multi-Task model (DAM) for recommending a set of products to users. In this model, a factorized attention network was designed to aggregate item embeddings within a bundle, thus obtaining representations of the bundles. Additionally, user-bundle interactions and user-item interactions were jointly modeled in a multi-task manner to enhance user-bundle interactions. The results demonstrated that DAM outperformed existing solutions. Papush [18] presented an innovative model that selects, prices, and recommends a personalized product bundle for online consumers. In the model, relevant products were selected based on consumer preferences, achieving a balance between narrow-minded profit maximization and effective inventory management. In this context, the model was initially framed as a contextual nonlinear multi-armed bandit problem, and an approach algorithm was developed to solve it in real time. Furthermore, robust counterparts were defined under both polynomial and ellipsoidal uncertainty sets. The results indicated that the proposed model significantly outperformed the comparison strategies.

3. Methodology

3.1. Prod2Vec

Prod2Vec is a model designed to understand and identify product similarities in online stores by using products instead of words. Similar to the Word2Vec approach, Prod2Vec represents each product in a vector space and analyzes the co-occurrence probabilities of products [19].

3.2. You Only Look Once

YOLO allows multiple bounding boxes and class probabilities to be estimated simultaneously by a single neural network. It directly improves detection performance by training on entire images. Compared to traditional object recognition methods, this unified model offers several advantages [20].

3.3. Convolutional Network Next

Compared to Vision Transformer and Swin-Transformer models, the ConvNext model exhibits superior performance in several domains, such as object recognition, image segmentation, and classification. Compared to Transformers, this Convolutional Neural Network based model significantly reduces the number of parameters, making training less difficult and accelerating network convergence. The ConvNext model achieves this by increasing the stacking frequency of a single module, using depth-based convolution instead of regular convolution, leveraging the MobileNet Inverse Bottleneck concept, and replacing a significant number of 7 × 7 convolution kernels with 3 × 3 convolution kernels within the modules. To improve convergence speed, the model uses Layer Normalization and the Gaussian Error Linear Unit activation function. The ConvNext network has four versions (T/S/B/L), each with a more complex structure [21].

3.4. Random Forest

Breiman's RF method is a popular ensemble learning technique used in areas such as interaction detection, regression, clustering, and classification. Due to its large diversity and bias, a single Decision Tree (DT) is generally not considered an effective classifier. However, RF often addresses these issues effectively and produces robust models by utilizing ensemble trees. RF generates hundreds of random binary trees to form a forest. Each tree is constructed from a bootstrap sample using a classification and regression tree procedure, with variables randomly selected at each node. The Out-Of-Bag error rate for each tree is calculated using data that is not included in the bootstrap sample. The final class membership and model performance are determined by the majority vote of all trees. Two different types of error rates are calculated: the average loss in accuracy and the average decrease in the Gini coefficient. These metrics are widely used to rank and select variables. The number of variables evaluated at each node and the total number of trees in the forest are two key factors that the user must adjust when running the RF model to reduce out-of-bag error and achieve optimal model performance [22].

3.5. Extreme Gradient Boosting

XGBoost, an efficient gradient tree boosting method that constructs DT sequentially, is renowned for its high efficiency and speed when working with structured datasets, particularly for label categorization. XGBoost combines predictions from multiple DT using the 'bagging' strategy and enhances model performance by reducing sequential errors. These errors are further refined through gradient descent. Additionally, XGBoost improves upon traditional gradient boosting by employing parallel processing techniques to reduce overfitting and address missing data issues [23].

3.6. Linear regression

LR is a statistical method used to model the relationship between a target (dependent) variable (y) and one or more independent (predictor) variables (x). Simple linear regression is employed when there is a single predictor variable, whereas multiple linear regression is used in cases with multiple predictor variables [24].

4. Details of the system

4.1. Creating collections including combination products with machine learning

This study aimed to create a collection utilizing machine learning techniques. In this context, the Prod2Vec approach has been applied, evaluating products as words and the combinations of these products as sentences. Images of clothing products sold on the Trendyol platform have been analyzed to create the dataset [25]. These product sequences have been modeled and used to simulate user interactions. By representing the products in vector space, the trained model has been able to identify the semantic similarities between them. This method resulted in the production of approximately 90 million possible combinations. These combinations have then been trained using the Prod2vec algorithm, providing the creation of new combinations. The best values of the parameters have been determined using grid search. Grid search involves systematically exploring different combinations within specified hyperparameter ranges to maximize model performance. The hyperparameter values of the Prod2vec model are given in **Table 1**.

Table 1. The hyperparameter values of the Prod2vec model.

Hyperparameter	Value
vector_size	150
window	5
Min_count	25

Table 1. (*Continued*).

Hyperparameter	Value
Workers	cores-1
sg	0
cbow_mean	1
hs	0
negative	10
ns_exponent	75
sample	6e-5
alpha	0.025
min_alpha	0.0001

4.2. Creating shop the look collections with image processing methods

In this section of the study, the objective is to present to the user a collection of other products on the platform that are similar to the objects depicted in the product images. In the shop, the look recommendation system, the model developed, and the visual similarity data set have been used. With the help of this data set, combinations of products that will attract the attention of the users are created and suggested to the user. In the image processing section, Deep Neural Network based object detection and image similarity models have been developed.

4.2.1. Object detection for clothing classification

A total of 30,000 images selected from products within Trendyol have been labeled using 9 classes from the category tree. The ground truth classes include bottom wear, top wear, outerwear, one piece, underwear, accessories clothing, baby clothing, shoes, and accessories. The fine-tuned YOLO model has been used for the classification and localization of clothing items present in the input images based on the labeled data. After a single inspection of the input image, the types (classes) and locations (coordinates) of the objects have been determined. The image has then been divided into a grid, and the objects in each cell have been detected, resulting in the creation of suggestion boxes. The classes and locations of these boxes have been predicted by the model trained on labeled data. The most accurate prediction has been obtained by removing unnecessary boxes using the Non-Maximum Suppression technique. In terms of clothing categorization and localization, this method produced fast and effective results.

4.2.2. Image similarity detection

The ConvNext model has been used as the backbone for measuring similarity between two images. The dataset has been created from a total of 1.7 million images obtained from 350,000 different products in the Trendyol catalog. The model has been trained to recognize similarities between clothing products using images of the same product taken from different angles (positive examples) and images of other products (negative examples). The ArcFace loss function has been employed to train the ConvNeXt model. An angular margin has been added to these feature vectors with the ArcFace loss function, thereby enhancing the differentiation between classes. The calculated angles have been optimized using cosine similarity, significantly sharpening the boundaries between the classes. Determining similarity between clothes is given in **Figure 1**.

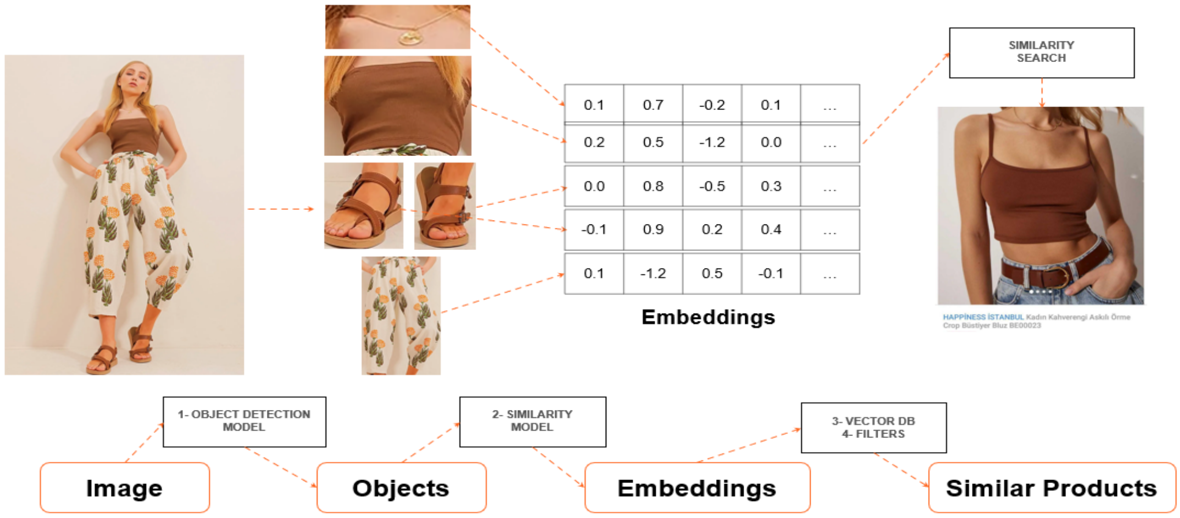

Figure 1. Determining similarity between clothes.

Using the identified similar product images, a test has been conducted on 23,500 products to collect data for analyzing user behavior and category performance. With the help of the collected data, the impact of factors such as user interactions, category relationships, brand similarity, the number of reviews and star ratings, product scores, and search scores has been analyzed. Using the prepared variable pool, the click performance of the recommended products in combinations has been predicted based on their views. This way, the combination products that would attract the highest interest have been identified. The feature importance graph is given in **Figure 2**.

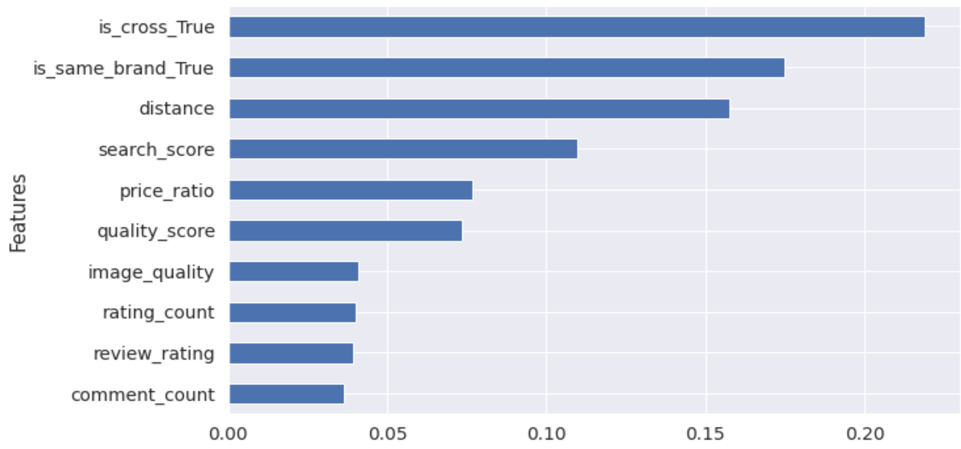

Figure 2. Feature importance graph.

To click performance prediction, both linear and tree-based machine learning models such as RF, XGBoost, and LR have been used. Following the variable selection process, the following information has been incorporated into the model as the final variable set:

- Information on whether the seed and reco pair have been detected through user action data,
- Whether the seed and reco products belong to the same brand,
- The visual similarity score of the reco product,
- The product score obtained from the search algorithm for the reco product.

The reco product set obtained from visual similarity for each seed product is re-ranked by estimating click performance using the variables selected by the trained model.

5. Results

The model has been developed using Prod2Vec to create collections including combination products. The A/B test results, where the collections generated by the model have been recommended first, are presented in **Table 2**. The combination product recommendations page is shown in **Figure 3**.

Table 2. A/B test results where collections created with Prod2Vec are recommended first.

Test parameter	Result
Number of products purchased in the cart	0.32% ± 0.3%
Number of clicks on combination recommendations	3.4% ± 0.61%
Number of combinations viewed	6.17% ± 0.51%
Number of combination products displayed	6.18% ± 0.51%
Number of times combination products have been added to favorites	3.24% ± 1.83%
Number of clicks on combination products	3.23% ± 0.91%

Based on the A/B test results, recommended combinations appear to have positive effects on interactions such as attracting user attention, product clicks, and adding items to favorites.

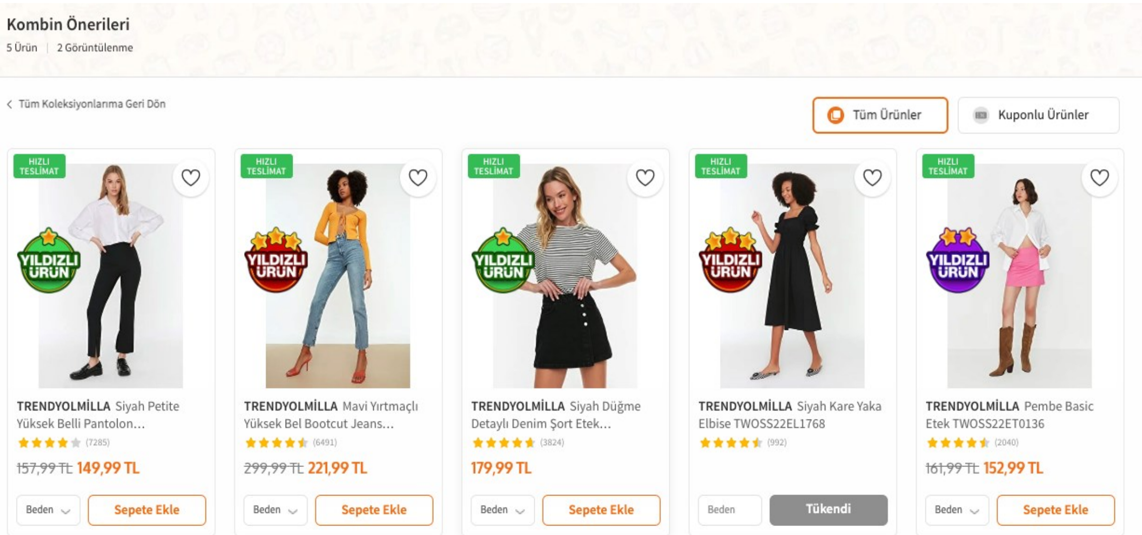

Figure 3. The combination product recommendations page.

With the Shop the Look recommendation system, product combinations likely to capture users' attention are created and recommended to them. **Figure 4** presents the Shop the Look recommendation system shown to users.

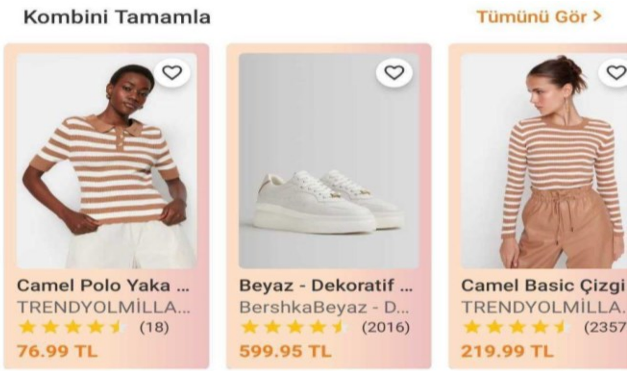

Figure 4. Shop the look recommendation system shown to users.

The prediction models have been developed using RF, XGBoost, and LR to predict the click-through performance of products recommended in combination per view. The most successful results in the developed models have been obtained with RF. The R^2, MSE, and MAE metrics have been utilized to evaluate the performance of the developed models. The error metric values of RF are given in **Table 3**.

Table 3. The error metric values of RF.

Metric	Train	Test
MSE	0.000428	0.000539
R^2	0.379531	0.243584
MAE0	0.012313	0.013080

The click performance of similar products identified using product images has been predicted. Based on these performance predictions, the ranked similar products have been subjected to A/B testing. A/B test results are given in **Table 4**.

Table 4. A/B test results of similar products listed.

	Ab Group	A				B			
	Metric	Numerator	Denominator	Mean	Uplift	Numerator	Denominator	Mean	Uplift
43	shopthelook_att_cart_uq …	2255	4,722,949	0.0005	Ø	5220	4,721,647	0.0011	131.55% ± 8.88%
44	shopthelook_att_fav …	11,271	4,722,949	0.0024	Ø	28,365	4,721,647	0.0060	151.73% ± 5.44%
45	shopthelook_att_fav_per_click …	11,271	135,116	0.0834	Ø	28,365	283,998	0.0999	19.73% ± 3.14%
46	shopthelook_att_fav_per_uq …	11,271	9898	1.1387	Ø	28,365	22,778	1.2453	9.36% ± 1.61%
47	shopthelook_att_fav_uq …	9898	4,722,949	0.0021	Ø	22,778	4,721,647	0.0048	130.19% ± 4.22%
48	shopthelook_att_order …	201	4,722,949	0.0000	Ø	516	4,721,647	0.0001	156.79% ± 33.27%
49	shopthelook_att_order_per_click …	201	135,116	0.0015	Ø	516	283,998	0.0018	22.14% ± 19.7%
50	shopthelook_att_order_per_uq …	201	191	1.0524	Ø	516	487	1.0595	0.68% ± 4.28%

Table 4. (*Continued*).

	Ab Group	A				B			
	Metric	**Numerator**	**Denominator**	**Mean**	**Uplift**	**Numerator**	**Denominator**	**Mean**	**Uplift**
51	shopthelook_att_order_uq …	191	4,722,949	0.0000	Ø	487	4,721,647	0.0001	155.04% ± 32.03%
52	shopthelook_reco_click …	135,116	4,722,949	0.0286	Ø	283,998	4,721,647	0.0601	110.25% ± 2.15%
53	shopthelook_reco_click_per_uq …	135,116	85,444	1.5813	Ø	283,998	151,940	1.8691	18.2% ± 1.04%
54	shopthelook_reco_click_uq …	85,444	4,722,949	0.0181	Ø	151,940	4,721,647	0.0322	77.87% ± 1.24%
55	shopthelook_reco_ctr …	135,116	11,097,544	0.0122	Ø	283,998	18,962,975	0.0150	23.01% ± 1.47%
56	shopthelook_reco_imp …	11,097,544	4,722,949	2.3497	Ø	18,962,975	4,721,647	4.0162	70.92% ± 0.92%
57	shopthelook_reco_imp_per_uq …	11,097,544	857,045	12.948 6	Ø	18,962,975	1,075,426	17.633 0	36.18% ± 0.7%
58	shopthelook_reco_imp_uq …	857,045	4,722,949	0.1815	Ø	1,075,426	4,721,647	0.2278	25.52% ± 0.29%

The results of the test showed that Group B demonstrated higher performance than Group A across nearly all metrics, indicating that Group B is more effective in capturing user interest and encouraging purchasing behavior. Products ranked by predicted click probability are given in **Figure 5**.

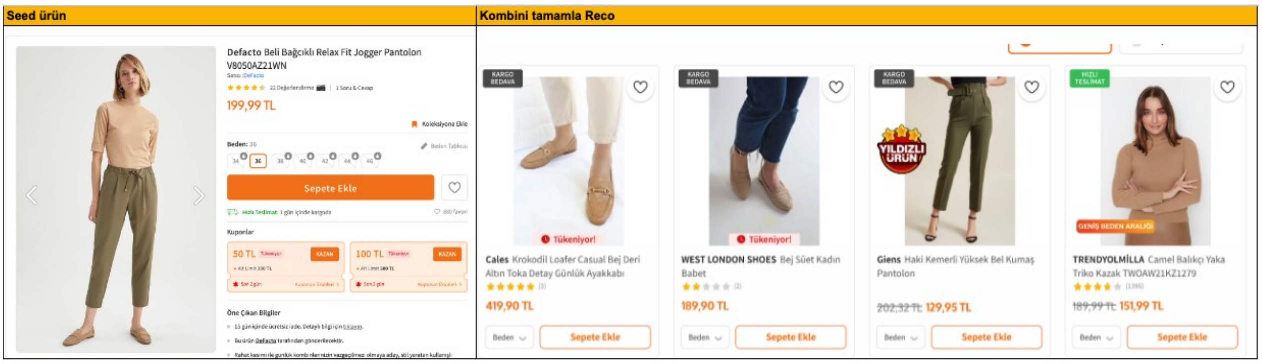

Figure 5. Products ranked by estimated click probability.

6. Discussion

With the developed system,

- The time spent on the Trendyol mobile application has increased by 5%.
- The cross-sell products have been recommended.
- The number of product clicks has increased by 10%.
- The number of products purchased has increased by 3%.
- The daily visit count has increased by 3%.
- Users have been enabled to discover new styles and products.

Users' satisfaction has been increased as they receive personalized recommendations based on their interests and preferred styles. The proposed system demonstrates several notable distinctions from existing approaches in the literature. This study introduces an image processing-based methodology for generating "shop the look" collection recommendations, aimed at enhancing users' purchasing behaviors. The innovation of the system is the use of image processing technologies, which significantly improve the efficiency and accuracy of the recommendation process, thereby enhancing the overall user experience. Click Through Rate (CTR) prediction has been performed using RF, XGBoost, and LR. Based on the prediction results, products have been ranked and presented to users. In this context, the system makes a substantial contribution to the literature by advancing personalized recommendation capabilities and incorporating predictive models. The limitation of this study is that the results have been obtained solely using Trendyol data. This may limit the generalizability of the findings and lead to inferences based only on this specific dataset. Therefore, similar studies conducted with different platforms or data sources would provide an opportunity to evaluate the accuracy and scope of the results within a broader context.

7. Conclusion

The e-commerce sector has experienced significant growth in recent years, driven by widespread internet access and rapid technological advancements. To achieve success, businesses must focus on enhancing customer satisfaction and increasing sales by developing strategies that align with customer needs. In this context, combination collection suggestions emerge as a strategic action that can be undertaken. This study developed a recommendation system based on image processing and machine learning, which generates product combinations that may interest users and suggests these combinations to them. The dataset used comprised products identified from visuals of items sold in the clothing category on Trendyol, resulting in approximately 90 million possible combinations. These combinations have been trained using the Prod2Vec to create new pairings. Subsequently, collections for purchasing appearances have been created employing image processing methods. In this regard, the YOLO model has been chosen for clothing classification, while the ConvNext model has been selected for image similarity calculation. Additionally, models have been developed using RF, XGBoost, and LR to predict click performance. The performances of these models have been evaluated using R^2, MSE, and MAE metrics. The most successful model has been obtained with RF. With the developed system, it has been provided that cross-selling product recommendations. This study introduces a machine learning-based system that generates combination suggestions for users through "shop the look" collections created with image processing techniques from high-purchase-potential products, effectively demonstrating the critical contribution of image processing in this field.

Author contributions: Conceptualization, CU and MFA; methodology, EÇ, MBÖ and SB; software, EÇ, MBÖ and SB; validation, EÇ, MBÖ and SB; formal analysis, EÇ, MBÖ and SB; investigation, EÇ, MBÖ and SB; resources, EÇ, MBÖ and SB; data curation, EÇ, MBÖ and SB; writing—original draft preparation, EÇ, MBÖ, SB, CU and MFA; writing—review and editing, EÇ, MBÖ, SB, CU and MFA; visualization, CU and MFA; supervision, CU and MFA; project administration, CU and MFA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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