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Machine Learning-Based Color Recommendation Engines for Enhanced Customer Personalization

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Abstract

The aim of this research is to explore advanced color recommendation engines to enhance customer personalization based on machine learning. As e-commerce continues to grow, understanding the customer is the most difficult task for the owners. The color match value among garment products is essential in deciding whether products are displayed together, which also affects customer loyalty and purchase intention massively. Moreover, retail owners usually do not take advantage of their historical data to effectively find out what color might better suit their customer. In this research work, three main algorithms of color matching are developed. The effectiveness of the proposed color matching approaches is evaluated via several experiments on real-world datasets.

In the recommendation process, a currently purchased item of a user could match or match better deference with respect to its property colors. Nevertheless, many e-commerce platforms still treat apparel colors as none the like other properties, inappropriately display products independently, which may confuse customers and therefore lose both of sales and brand loyalty. Accurate prediction of mismatch garment colors enhances customer satisfaction and timely profitable product display. A data-driven personalized smart lighting recommender system, employing both supervised and unsupervised learning, is proposed. Two recommendation approaches are developed: color scheme recommendation and routine recommendation. The unsupervised recommendation of routine for lighting is modeled as a cluster problem given a large number of behavioral log data. Moreover, by analyzing users' daily patterns, geographical location, temporal and usage information, the color preference of users is predicted.

Keywords: Personalized color recommendations,Machine learning color engine,AI-driven color personalization,Customer-centric color suggestions,Predictive color preference modeling,Color recommendation system,Adaptive color choice algorithms,User behavior color analysis,Smart color selection ML,Deep learning color preferences,Color personalization technology,Consumer color taste prediction,AI-powered design customization,Intelligent visual merchandising,Data-driven color customization.

1. Introduction

The color of a garment appeals to customers before any other aspect such as design or fabric. The right color choice can directly trigger purchase intentions regardless of the garment's design and fabric quality. Moreover, color recommendation is crucial in enhancing customer personalization, which is an important factor in e-commerce development. The explosive growth of Internet sales in the 21st century has forced retailers to rethink retailing strategies. Rapid changes in fashion trends and colors have triggered an increasing demand for personalized fashion services in online clothing shopping. Hence it is urgent and essential to recommend garments whose color matches the ones that customers are already in possession of, as colors vary widely even in the same fashion style. While a few color recommendation engines do exist, most of them fail to be practically efficient in either accuracy or computation time. Excessive reliance on expert rules often leads to difficulties of transference and personalization, in which prior knowledge of the dataset is essential. A very promising machine learning-based novel approach for color recommendation is proposed. By leveraging large-scale image and textual data and adopting a convolution neural network as the core image processor, fully automatic and precise color recommendation can be achieved. Improved efficiency and accuracy are obtained via the texture-similarity enhanced color clustering algorithm.

Fig 1: Machine Learning Algorithms For Recommendation Engines

1.1. Background and significance The clothing business has continued to develop as a mature market due to its rapid economic growth, yet customers' individualized need increases. Consequently, to satisfy such individualized needs, fashion e-commerce companies globally have been striving persistently to refine appropriate marketing strategies to increase profit and sales. Product Recommendation Systems (PRSs), which are software tools or artificial intelligence (AI), can be applied to filter, analyze, and automatically recommend appropriate items to a user according to modality or content similarity. PRSs can vigorously increase potential profit and sales, decrease the click-through rates and accelerate the pace of human-manned jobs by sifting through datasets too immense for human talent within a few seconds. This paper describes a unique deep learning image recommendation engine to recommend color styles for customers' suggested clothing. Attention mechanism-based deep learning models were designed to recommend apparel color filters (ACFs) while extracting attention masks indicating key areas in clothing images where color filters are needed to adjust. The initial ACFs were trained using absolute color pixel ratios in input clothing images as ground truth ACFs, which would not be applicable for detecting color filters on clothing images with different styles and specifications. Then, quasi-realistic text rendering algorithms were designed to assemble synthetic training datasets with appropriate video game engine styles and scales. Consequently, a better attention mask extraction performance was obtained, eliminating the expensive effort of collecting a large amount of image data with the explicit recommendation ground truth.

Equ 1: Neural Network Scoring Model

$$S_{ij} = f_\theta([U_i, C_j])$$

Where:

- $[U_i, C_j]$ is the concatenated feature vector
- f_θ is a neural network with learnable parameters θ

2. Literature Review

An increasing number of companies and organizations have begun to analyze the massive amounts of diverse data that they have been accumulating over the years in order to improve a variety of aspects of their business. Whereas a smaller sample of data is typically stored in a manageable format by the company itself, scalability issues arise when trying to store and analyze larger and more diverse datasets, such as all the clicks a news website receives every day. To better understand their customers and users, companies leverage data sources in the form of business intelligence (BI) tools – for example, visualization dashboards are used for reporting and understanding metrics – and recommendation engines (REs), which provide product opportunities tailored to specific needs that users might have. Learning about using [APIs] and often underestimated advantages of external data can vastly extend a company's data capabilities. Large cloud providers and many other data sources offer a variety of data publish-subscribe analytics, scrapers, endpoints, and event-based [APIs] with several hundred sales, weather, transportation, and news streams around the globe.

2.1. Historical Context of Color Theory

Motivated by a growing need for personalized and innovative color design tools for a variety of applications, notably in the realm of online retailing, some pioneering studies have been performed to establish an automated color recommendation engine. Computers can be leveraged as highly intelligent color design assistants to generate acceptable color combinations from the color palette in the target image. They can also detect user color patterns, thus prompting users with novel colors for adaptation in order to expand their color assortments or reinforce their existing color patterns. This is done by recommending colors that are concordant with the user's taste or match the template color of the image.

The red-blue color band remains the simplest hue circle. The color orderings of well-known opponent color models tend to follow this red-blue color band, providing consistent topological relationships among colors. It is widely known that color orders, expressed in different spaces in different frameworks, provide alternative geometrical or topological relationships among colors. However, they do not guarantee identical correspondences between color orders. Conformance to sensory or cognitive basis ensures good charting of visual colors to HT color orders. Data-driven or learned topological mappings between RGB and semantic color spaces, or hue spaces with specified color selections, are viable alternatives. Spectral approaches treat spectral intensities and resource coefficients as color variables. Their indirect response to light can be expressed through contrast, reflectance, or CIE spaces.

Numerous online tools and computer programs have been developed for intelligent color management. Ad hoc solutions mostly provide limited access to one or few color relevances. Statistical color settings are made available through tools of preset palettes, trendy colors or color schemes for a variety of applications. Rigorous models or techniques mostly involve either distributed computation or cumbersome color input or output protocols, the latter two hampering traffic efficiency. Moreover, systematic studies or theoretical developments to explore the practical issues of either widespread or scientific consensus of color use have been much sparser in the modern literature, exhaustive tests, exploratory analysis or a priori models to account for or predict visual color orderings. State-of-the-art creative engines mostly render photographic colors or palettes to artistic sense or add lucency effects to flat images.

Fig 2: Color Theory

2.2. Machine Learning in Personalization Recommendations play a crucial role in addressing information overload and making systems intelligent. Business Recommendation Systems have increased popularity among researchers and industries in recent years, compelling e-commerce players to invest heavily in their establishment. Machine Learning is a key technology that implements Business Recommendation Systems and brings tangible business advantages.

Machine Learning based recommendation systems cater to retail businesses, focusing on providing enhanced marketing analytics and targeting. The growth in Internet penetration, coupled with cheap online shopping, large Customer Relations Management databases, and product information, has created opportunities for personalized Marketing-Management Applications. These events have triggered the emergence of Business Recommendation Systems as another step in the evolution of intelligent systems. Business Recommendation Systems wider applications in different domains are also mentioned. In these systems, Business Recommendation Systems can be totally customer-centric or totally content-centric.

The recommendation system matures and becomes part of Business Recommendation Systems by taking more inputs about customers' interests while enhancing personalization. The knowledge domain of Business Recommendation Systems changes from products, actions, and customers to sales transactions, order histories, and usages. Knowledge representation scheme methodology also focuses on short-term and long-term customer interest modeling including the hidden Markov model for purchase history analysis and the Item-to-Item collaborative filtering for related item finding in a specified context. Effective item recommendation has also been generated with it. Thus, hybridized recommendation technologies are tested for improved context-aware recommendation of items.

2.3. Existing Color Recommendation Systems

The key point of recent content-based systems is to extract meaningful features from the content of the items. A cross-domain content-based model calculates the similarity between items in different domains using content features separately for each domain. Besides the general patterns of customers, additional aspects can also have an effect on customer preferences. Understanding the effects of colors in contextual information can further improve the recommendation precision. Different lighting colors influence images displayed on screens in different ways as well. A color recommendation method is proposed which leverages contextual information about the customer and the product to improve recommendation precision. A two-level framework for modeling and learning to rank candidate colors is developed. Contextual features are analyzed to build models for ranking color candidates. Since contextual features are observable attributes of customers and products, a data-driven tuning approach is proposed to select the most effective features and avoid unnecessary manual efforts. As a future direction, the need to explore additional contextual features is mentioned, and potential research problems such as end-to-end learning methods operating on channel values and other surround colors are also pointed out.

Color manipulation is important for modern display devices, which can be used in many applications such as image dithering, colorization, filtering, etc. The colors of an image or picture can be changed to meet certain requirements, which needs efficient solutions. In display devices, the generated images must be transformed accordingly to reach more accurate viewing. Customers who sell digital pictures will also produce invoices in colors consistent with products. For general renderers, the abilities to generate color-consessed images provide more illumination for real-world creations. Colors may be moved into another base or spectrum to meet certain aims as well. These require a diverse range of photo color recommendation analysis and appropriate methodologies. The classification of representative works in the field is presented. Important characteristics of these methods are elaborated, including general output types, requirements for inputs, fields, etc. Related concepts such as base-color selection and available-target-color selection are also discussed.

These methods, applicable to the above-mentioned issues, are categorized into two types: color mapping methods, which move the source colors to target colors in a paired type, and color component that constructs a parameterized domain transformation to change the raster image accordingly. In the acquisition part, manipulations of color abstracts, including color lookup tables and artistic information, deliver a given color style in a simplified or re-synthesized manner. Typical problems are colorization, inpainting, removal or shaping, and assorted-based retrieval. Many consumer-oriented tools are aware of this kind of color manipulation.

3. Methodology

This paper aims to present a system as a preliminary design that attempts to automatically generate color picker recommendations using machine learning methods while retrieving color data based on the state-of-art color data search approach proposed by the previous research. For each product database, a style classification model based on K-means is designed to pre-classify the color search recommendation candidate database in a multi-stage approach based on the styles of different color picker products. A partial random sample color search recommendation result is filtered by the finished pre-classification model and passed as model input data. Various models are evaluated for classification effects, including logistic regression, Light GbM, and a wide and deep learning model. Retrain models explore different color recommendation performance effects based on predictive models proposed in previous research for generating primary color recommendations. Moreover, these outcomes are then filtered again by a linearly weighted multi-process for recommendation changes and selections from the recommendation result. Finally, a brand-new approach that accepts product information and gives style-based color results will be proposed.

Due to their online accessibility, the most recent color palettes can hardly satisfy personal requirements for color composition. Therefore, applications would provide more automated services for users to create their own personal palettes. To handle relatively monotonous repeating tasks, automatic systems need to be established to begin. Style recommendation can narrow down candidates based on the design-specific features of projects and significantly relieve users' burden by conceiving appropriate palettes. Searching preparations require a large collection of color resources but also post-filtering due to their appropriate variations. A generative approach to creating palettes based on a limited number of user-input colors.

The first reference proposed the training of a model for color prediction. A KNN model was trained by logs filtered by the geography location and used to predict colors inside the cluster. Results indicate that grouping users by geography significantly raised prediction accuracy. The second reference proposed a system capable of apparel recommendation based on attributes such as filtering keywords or a style classification model to search candidates based on apparel features directly. The system consists of two components: a training data generator designed to generate diversified training data and an apparel style recommendation model.

Equ 2: Loss Function (Matrix Factorization)

$$\mathcal{L} = \sum_{(i,j)\in\mathcal{K}} (r_{ij} - S_{ij})^2 + \lambda \left(\|U\|^2 + \|C\|^2\right)$$

Where:

- r_{ij} is the observed rating or interaction (e.g. click, like, purchase)
- $\mathcal{K}$ is the set of known user-color interactions
- λ is a regularization parameter to prevent overfitting

3.1. Data Collection Techniques

The growth of internet-based applications has prompted the accumulation of vast amounts of data in various fields, including business, social networks, and healthcare, resulting in the emergence of Big Data. This situation has led to the demand for intelligent data analysis tools and techniques, especially through mining knowledge from large datasets. One critically important issue in developing e-commerce or social networking sites is gaining user trust, which can potentially improve service quality. Recommender systems attempt to identify and recommend the most preferable item to an individual user from a huge amount of data. To do so, recommender systems apply various techniques to predict user interest in items based on related items, users, and the interactions between items and users.

Machine Learning (ML)-based solutions have been of interest in recent years to reduce or avoid the need for human intervention, which is slow, expensive, and error-prone. ML requires the extraction of features, data in ways that allow ML algorithms to find patterns to improve performance. Extensive research has explored ML techniques that use historical data to understand consumer behavior. These efforts focused on common purchase behavior analysis, targeted marketing, and price optimization. Although ML techniques are not widely applied on the sales side of e-commerce, they can significantly improve consumer personalization. One such area is the product color recommendation engine.

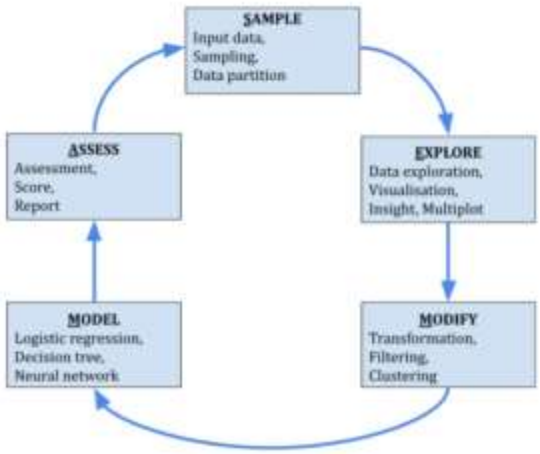

Fig 3: Data Collection for Machine Learning

3.2. Feature Selection for Color Recommendation

Feature selection plays an important role in color recommendation engines. Color information is extracted to construct the Finley-Attached-5k-Deber color name set for a color recommendation engine. In the storage system, two features named Taken and Sent are created. The Taken feature records the color names taken by customers who are used as recommendations and Popularity is the count of the number of each color name through a filter over Dataset. The Sent feature counts the number of recommendations filtered and stored in the color recommendation engine. It should also be noted that a color can be reused over different clients. Therefore, a rudimentary repairing function to remove ClientId from a recommendation can be added for compatibility with Sleeping Spot recommendation function.

A novel multi-color feature selection method is proposed for person re-identification. Multi-color features, consisting of HSV, LAB, RGB and nRnG color features, were extracted and concatenated into a feature vector. D-optimal Partial Least Squares feature selection method was adopted to select an optimal feature subset that could minimize the variance of the regression model. Person re-identification (Re-ID) plays a key role in security management applications. Its goal is to identify a person captured by one or more cameras while using a gallery of known candidates. Pedestrian appearance can be obstructed by clothing and occlusion, and the recognition rate is affected by low video image resolution and light conversion. A common strategy is to combine color and textural features to complement each other. D-Optimal Partial Least Squares is used to select an optimal feature subset that could minimize the variance of the regression model.

A multiple feature selection method with D-optimal partial least squares is proposed for person re-identification. The proposed method considers feature fusion and color feature model and makes full use of feature selection to obtain effective information for a single-shot Re-ID. It has better representation abilities and generalization performances than state-of-the-art methods. Various colors are utilized. However, multi-color or salient color-based methods usually do not take into account smooth color changing and their combination.

3.3. Machine Learning Algorithms Utilized

Machine Learning is a technique in which patterns are discovered by machines from data. The goal of ML is to provide results for a specific task every time it is repeated and to get the same outcome irrespective of the number of observations. Data can be structured, semi-structured, or unstructured, but the commonality among all data types is that they all build a way of anticipating future values through past known scenarios. The dataset utilized in this work, to execute various supervised machine learning (ML) algorithms, is based upon the offline mode of recommendation engine implemented in. In conclusion to recommendations made through the Lighting Recommender system, 10 most suitable color options are provided, out of which one is selected and hard-coded to be applied through the adjacent API. For color prediction recommendation, two supervised machine learning regression algorithms were trained and validated to determine the value of RGB component for the query condition (Unknown Color). namely:

This method utilizes the pre-trained VGG-19 model architecture in the PyTorch framework. The number of output channels of the last Conv layer (512), is greatest among Conv layer Channels, which are reduced in the next layer (FC) to a mere 4096 channel value. This layer is well suited for Feature extraction, and hence, is modified to be fine-tuned here. The ground truth image paths corresponding to 1000 unique color names from the 12 aggregate color families are generated and then made into 128*128 jpg images and resized to 244*244 as PIL images. A dictionary with color name as Key and indexed value from 1000 class Labels is created.

There is no pre-trained CNN model referencing 12 aggregate color families, so it’s constructed based on the proposed structure. It includes 2 Conv Layers (Kernel size = 9, Maxpool size = 5), 3 FC layers with dropouts set to reduce overfitting. Training considering residual images of size 128*128 produced from high Res video frames of lower Res gives an ideal PSNR=35 and is shared alongside. To make predictions on query videos, processing mode is separately implemented to generate frame residuals, and potentially inject noise batches during testing PyTorch-CNN.

4. System Design

To date, most color design applications employ color in specific color spaces, e.g., RGB, Hex, HSL. The use of these representations requires preliminary knowledge of the color or color model from the users, limiting the applicability for the general public. The main goal of this study is to transform colors into attributes for the learning model to automate and simplify color/pants combination personalization. The primary datasets utilized is Pantone textile pattern dataset. Thus, the dataset contains the most fashionable pants. For the two pants’ attributes datasets, they are crawled from Polyvore. The two datasets are for jeans and skirts respectively. Each pants’ attributes dataset contains pants as input, and attributes as label.i.e., color, pattern, style, etc. There are 57 colors classified by Japan color research institute, referred to as JCAR. By analyzing both datasets, colors/pants combination preference experiments are conducted to determine presence/absence of one-pant to another color/pant combination. With color as input, it first clusters clothes, then it recommends pants for the color. The training/validation/testing data is created. The testing data is a pants' data for pants recommendation. For formal exams, the pants are detected in zero-shot setup. To meet flexible customization or semi-personalized recommender demands, ability of its choice of color condition ATED and chromaticity range, CHTED is further examined. In addition, RATED ARRR and CHEDDAR is created to augment text-to-image recommendation candidate and mode descriptor for pants. Text data is utilized for method understanding about the proposed color recommendation tasks, and combined with image input for flexible recommendation of both colors and pants in the same manner. The use of pants' data KDE is proposed, which can help testers customize appearance level in the recommendation scenarios, thus adjusting the experiment focus. Yet, it is noted that pants' color as input is not suitable, which indicates more pants may be needed for good generality. The results show a novel text-color/pants cux recommendation model. The proposed method and datasets motivate additional optional future works including model scope.They deal with a new color scheme and routine recommendation problem and provide technical details of the applied clustering and predictive methods and solutions to the testbed implementation and evaluation challenges, including the representation of the color collection, training data density, and user input. A set of proposed evaluation metrics measures the effectiveness of the recommendation engines, which can be applicable to other lighting coloring or product-related recommender systems.

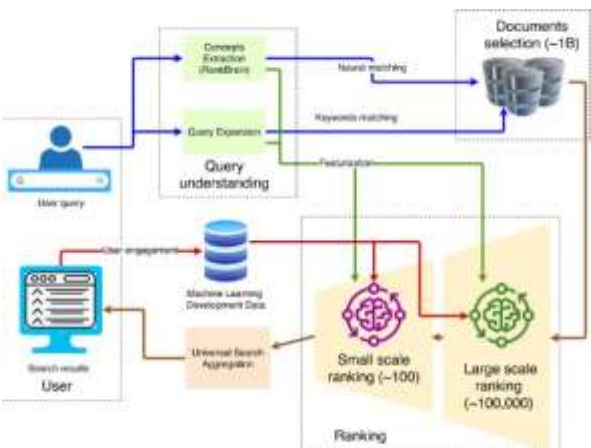

Fig 4: Recommendation System Design

4.1. Architecture of the Recommendation Engine

The personalization of online content is essential to market competitiveness, and recommender systems are widely adopted by online retailers. However, there has been insufficient research on color preference recommendation systems. This research focuses on developing a content-based personalized color recommendation engine to enhance the shopping experience of E-commerce users, employing optimal features and models with diverse settings and metrics to establish better content-based recommender systems.

In building color recommendation engines, diverse modeling approaches and color feature representations are proposed based on the existing generic recommender system design frameworks of elements, representations, models, and evaluations. Several recommendations of settings and techniques regarding diverse learning models, metrics, input representations, and hybrid models are addressed to help E-commerce companies systematically design color recommendation engines of diverse granularities and improve the personal shopping experience on an online clothing platform with easily interpretable recommendations, thus enhancing marketing precision and competitiveness.

Ample research has been conducted on intelligent public lighting systems, including lighting control methods, lighting design, and color recommendation. Recommender systems attempt to identify and recommend the most preferable item to an individual user and predict user interest in items based on related items, users, and the interactions between items and users. Previous studies proposed and implemented a data-driven personalized smart lighting recommender system for a smart electrical grid lighting application by analyzing users' mood, circadian rhythm, and environmental participative data.

4.2. User Interface Design Considerations

Many Web-based recommender systems exist that present recommendations in various ways. There is still very little known about the mechanisms which underlie their effectiveness. In this research we investigate which aspects of a product presentation are important in terms of its recommendee’s purchase willingness. Four different recommendations were presented with modifications to five variables. These factors were analyzed toward purchase decisions and towards a deeper understanding of human–computer behavior in the providing context of a recommendation-driven purchase.

Results confirm the importance of visual aspects in presentation of recommended products. Interactions also differed for recommendations derived with respect to different algorithms. The trade-offs formed by various factors provide some guidance for construction of recommendation interfaces in online stores, also with a view toward adjustment of presentation style to the individual user. Regarding potential applications, a scalability of the approach would suggest a collection of data across purchase events in a number of stores.

The problem of enhancing accuracy of recommendations is a solved one. Methods for improving UI/UX of presenting recommendations are still under-researched. Theory-guided and evidential basis here is considerably lacking. This field could benefit from fast growing eye-tracking and event-tracking technologies, and tools for A/B testing of recommendation interfaces. Recommendations by algorithms producing visible differences could better inform the design of interfaces showing that kind of recommendations.

Specifically at the level of product presentation, the specifics of what influences recommendation success in terms of purchase are largely unknown. The majority of research here in general involves questioning users—it is prone to distortions and not reliable. Better understanding of design not only provides knowledge for building better interfaces but also has implications for algorithmic enhancement on recommendations’ attractiveness, from selecting better candidates to tuning how they should be presented.

4.3. Integration with E-commerce Platforms

Equipping a Recommendation Engine (RE) with Lens Colour Recommendations at a page level as a baseline metric can help gauge user interaction with the Widget, allowing for rapid upscaling of the tool while observing real-life metrics. The scope can also be further increased through integrating the Product-Design side. The RE and Designer Integration also allows for designer training sets to continuously get updated colour diversity while acting as its own RE for other product classes as they naturally arise within the dataset. Lens colour recommendations can also have immediate sales-boosting impact irrespective of catchment products. A basic product-class independent similarity model as the starting point can expand colour recommendations while enabling personalisation through serving user history, with an additional kick from smoothing class anomalies. The Widget itself can be kept small and modular until the interaction is able to grow, drawing different products from pages and through more elaborate explorers to fit with both placement.

The RE works on both training ground truth and page-level metric reduction while sitting scalable to traffic demand on a page basis. The Designer integration and therefore RO implementation can be positioned in the pipeline where the recommended graph would otherwise be taken in, while its symmetric approach can enable product compatibility averaging of an otherwise non-compatible colour matching. Designer task performance allows for training dataset size to exponentially grow alongside improved techniques and catchment product classes. The undertaking originally focuses on the colour as a variant, which is almost orthogonal compared to product class and a deviation that when removed leads to huge databases of skews that though infinitely expand the recommendations tend to fall short on designing, creating, and improvement data need not be on the designer’s side.

5. Implementation

In e-commerce fashion platforms, color recommendation engines based on deep learning techniques can put much more light on users' shopping experiences. Under the precondition of preventing the orientations of garments being from different perspectives, a color prediction model based on Convolutional Neural Network was proposed to recommend major colors of clothing items to users by utilizing the images of garments. Automated color recommendation, a task that can help enhance customer personalization by using data mining mechanisms to generate colors that suit the customer the most, has been gradually applied by many online fashion retailers on their shopping pages. For a target outfit uploaded by a user, those color recommendation systems intelligently recommend augmented or neutralizing colors to the outfit. A system framework is proposed that is designed to choose colors based on transferred style images. With the advancing developments of color recommendation engines, it helps diversify the viewing by matching colors between references and target outfits and classify clothes based on similar color combinations.

To encourage customization to achieve breathtaking styles during the design process, recommender systems for outfits based on a multi-modal deep network were presented. Considering the powerful style representation of the outfit shape predicted by Convolutional Neural Network, another CNN-based outfit shaping model was created to assist in classifying the style for the uploaded outfit shape. To enhance the subjective quality assessment of the recommended outfits, a Multi-task Long Short-Term Memory-based off-the-shelf comment analysis model was trained and leveraged for fine-tuning. An interactive prototype of the mobile recommender system was realized. Even though sometimes showing poor interpretability, the recommendation model is typically trained with a great deal of descriptors tailored to garment design. Such an automatic recommendation engine can effectively assist novice designers in each category. Automatic recommendation systems are developed to help match clothing items together based on various offline data provided by clothing manufacturers and online information obtained from the fashion image database containing detailed semantic labels.

Fig 5: Implement an AI-Based Recommendation System

5.1. Development Environment Setup

To develop a data-driven recommendation engine for providing personalized color choices to be used in smart lighting systems, use Python-based libraries. Use two components as the back-end of the system handling data preprocessing and recommendation methods. Data preprocessing applies data cleaning, content-based filtering, early time and evening time preparation, and hour window division to recommend colors based on user preference and illumination time. Then, the recommendation engine recommends colors using K-nearest neighbor and content-based filtering methods. After selecting the soft recommendation method, user selections are compared with recommended colors, and evaluations are performed based on MSE, MAE, RMSE, and R-square values of included colors in the recommended list. Input historical data should be a pandas DataFrame containing data for at least 30 days with the columns: "time," "hours," "location," "month," "day of the week," "usage," "color" and "brightness." The data on usage should be either "on" or "off" after mapping unnecessary categories by value mapping method. The model does not support various brightness equal to 80% of maximum brightness since it fuzzifies the data by rounding to either a minimum (best lighting) or maximum (the worst lighting) brightness. The time in the input must also be only two sampling points: one for the onset of light usage. The time zone should also be correct since it calculates dusk illumination time and recommends it according to it. Additionally, the hour in "time" column should be either evening or early time based on a 24-hour format.

The recommendation engine includes two recommendation methods: Knn and Content Based Filtering. The default color for "K" in Knn is 1. The result of recommendation is a list of dictionaries with time, month, day of the week, color, and brightness. The "color" field indicates the recommended color in hex format while the brightness field indicates the recommended brightness. All input data should be corrupted at the last minute by a randomizer with a defined randomness value to avoid input error handling. This recommender system successfully helps customers find a color palette on the spatial, light, and color attributes with its KNN and content-based filtering methods.

5.2. Training the Machine Learning Model

To design the recommendation engine based on classical machine learning for the application of perceptual colour recommendation, the first task is to build a machine learning model to predict colour. In this work, a multi-layer feed-forward deep neural network is proposed consisting of three hidden layers, each containing 96 neurons, followed by standard back-propagation (BP) learning. More specifically, a learning rate parameter is chosen to balance maintain accuracy and convergence. The colour prediction models are trained for event colours in two parts. In the first phase, the recommended colours of the 18 classes are presented to evaluate the time taken by them. In the second phase, one colour of each class is evaluated at a time to reveal the neural differences of classes. The input layer consists of 24 variables, which are individual training features. The hidden nodes were selected empirically based on a performance experiment. The output layer comprises 24 nodes predicting 24 colour values. The colour points are defined in the [0, 1] domain. The process of extracting training data is divided into three steps. First, 12 perceptual colour vectors are produced. Next, machine parameters such as lighting, distance, and orientation are randomly generated in ranges and training set codes are randomly ordered to allow input variable possible combinations. Simulated training data are produced using the transfer functions. Finally, the noisy training data are obtained by adding different levels of noise on the true training data to fight against the overfitting problem. Rather than conventional geometric modelling that propagates coordinate values in calculations, the two-channel rule-based 2.5D colour modelling estimates the broadband colour lookup table from three-channel textures [10]. A luminant invariant CIECAM02 colour transfer function is developed to link reflectance and appearance channels for natural scenes. Finally, the RGB-LUV space conversion function unites different colour spaces and colour values together for input and output training standards.

5.3. Testing and Validation Procedures

The primary goal of the evaluation of recommendation engines in this implementation is to measure the impact of a personalized recommendation model on user engagement with the products on the ecommerce platform. The measurement is done with two metrics, Click-Through Ratio (CTR) and Buy-Through Ratio (BTR). CTR is the ratio of clicks on recommended products to the total number of recommended products displayed, while BTR is the ratio of purchases of recommended products to the total number of recommended products displayed. A lift in CTR or BTR following the deployment or implementation of a personalized recommendation model over a non-personalized one indicates that the model is personalized or functioning correctly [8]. In order to better estimate the impact of a recommendation model on the customers of a website, a method is designed in which two sections of users are formed, both having identical recommendation models, and their CTR and BTR metrics are compared. If a comparison between the CTR or BTR of the two sections shows very little difference and high correlation over days, then it may be concluded that the result metrics are not random occurrences and that the customers are impacted by the personalized recommendations. If not, the evaluation metrics do not reflect the recommendations' influence on a customer for that particular website, and therefore, are futile in the analysis of the recommendation engine. The method is based on the concept of A/A Testing in an online experimental setup. This type of experiment divides users into two segments, assigned identical models. The aim is to test if there is truly a lift that can be attributed to using the model and check if it is not just observing a false positive resulting from natural variation. Therefore, all customers are split randomly into two equal sections, each of which is shown product recommendations using the same recommendation model. The data recorded for customers under each section will be marked with the respective flag of the section they fall in, and this method of recording data makes it easier to compute CTR and BTR for the two sections.

Equ 3: User-Color Preference Matrix

$$S_{ij} = U_i \cdot C_j^T = \sum_{k=1}^{d} U_{ik} C_{jk}$$

Let:

- $U \in \mathbb{R}^{m \times d}$ be the matrix of **user embeddings**
- $C \in \mathbb{R}^{n \times d}$ be the matrix of **color embeddings**

6. Conclusion

A novel recommendation engine has been built utilizing machine learning techniques and a dataset containing color palettes derived from multiple fashion e-commerce websites. The recommendation engine determines the probable color to be recommended based on the set of colors present in the user-selected color palette. The dataset is examined for a better understanding of the hidden patterns in the data, assisting in formulating questions of interest. The reinforcement learning-based recommendation engine emulates the human expert system, iteratively perturbing the set of input colors. Based on similarity measures, it provides a list of color suggestions that can assist customers in their decision-making process.

To facilitate understanding of the fashion industry personality segmentation, machine learning iteration is conducted in a combination of topic modeling of product description and user modeling. An interactive recommendation engine aids in understanding how product sympathies can be used as input in an interactive and user-centric mechanism. Network analysis of a clothing industry social media site can predict the fashion tastes and style. Feature representation and user preference learning are approached with graph-based fashion understanding using deep-learning techniques to maintain disentanglement. In essence, the desire for advanced color recognition engines is catered to, broadening the current knowledge of consumer psychology and behavior.

Also, aspects of fashion color recommendation engines that enhance customer personalization in the context of fast fashion-centered e-commerce websites are discussed. The first recommendation engine is based on associations of complementary and classic color palettes. It allows customers to grasp the basic knowledge of colors. It then investigates aspects of interactive stochastic-color palette selection via recurrently perturbing color palettes at the customer interface. The developed system formulates recommendations as multi-selection actions and incorporates semantic similarity measures.

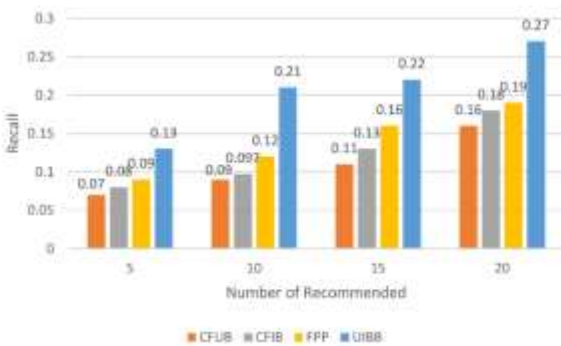

Fig : An E-Commerce Recommendation System

6.1. Emerging Technologies

Ration color recommendation engines have been extensively researched, particularly in the e-commerce domain, to enhance the shopping experience and increase business opportunities. These systems typically generate color recommendations for apparel items automatically or semi-automatically. However, existing engines fail to provide unique color combinations in extreme situations because human domain knowledge is not being applied. Gradient-enhanced color quantization approaches have been studied to address this from a discrete-variable optimization perspective. A clustering-based aesthetic color planning method has been proposed to characterize how well the chosen colors fit with the apparel item and produce harmonious color palettes according to traditional color theory. Both approaches, however, have limitations in terms of efficiency and quality. The former cannot evaluate and generate aesthetically pleasing color combinations, while the latter produces the same palette with the same input.

To overcome these limitations, an innovative hybrid color roll formation engine that combines a generative adversarial network designed specifically for fashion and aesthetics with classical color theory has been developed. Before discovering color combinations, an automatic color quantization method based on a spatial-weighted K-means algorithm is introduced to reduce the color variability of clothing items while maintaining their color distribution. This platform is evaluated in terms of speed and quality for both color palette generation and application to other domains. This engine can enhance the user personalization experience by addressing the overemphasis on graphic design in previous works. Two after-rendering color transfer methods are proposed to remedy the excessive colors in the color roll for markdown purposes. Because color selection is based on the predefined rule and human designers' prior knowledge, this work could provide more intuitive insights into how non-expert users select better colors coupons for apparel products.

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