

## Facial Recognition Based Product Recommendation System Using Past Purchases

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**Abstract**—This study proposes a Facial Recognition-Based Product Recommendation System that enriches e-commerce through the use of facial characteristics and purchase history. With a new K-Nearest Neighbors (KNN) algorithm, the system examines user emotions and buying patterns to make real-time personalized recommendations. Through the combination of computer vision and deep learning, it does away with manual input, providing a hassle-free and interactive shopping experience. The system constantly learns from user tastes, providing dynamic and emotionally intelligent recommendations. This technology represents a major leap forward in personalized retail, opening the door to AI-powered shopping that maximizes customer interaction and satisfaction, ultimately defining the future of user-focused e-commerce with smart, adaptive, and emotion-sensing technology.

**Keywords**—KNN, collaborative filtering. OpenCV

### INTRODUCTION

The era of the digital age has opened the door to a revolutionary time of e-commerce, where decision-making based on data and targeted user experiences take center stage. With consumers gravitating towards online shopping for its convenience and ease of access, the need for precise and customized product recommendations cannot be emphasized more. Conventional recommendation systems that tend to work on collaborative filtering or content-based filtering have hugely enhanced the online shopping experience. But they tend to lack in response to the emotional aspect of user preferences, which is responsible for decision-making regarding purchases. This study proposes a novel method to overcome this shortcoming in the form of a Facial Recognition-Based Product Recommendation System. Utilizing the latest technologies like facial recognition and the K-Nearest Neighbors (KNN) algorithm, this system plans to bridge the gap between users' emotions and their purchasing history, hence redefining online shopping for everyone.

E-commerce sites habitually collect large amounts of information regarding users' behavior and choice. Although this information plays a big role in creating product recommendations, it fails to record the subtleties of user emotions and sentiments while shopping. Emotions are of great influence over buying decisions and, most of the time, users find it difficult to articulate such emotions via manual input. Thus, the necessity of a recommendation system that is able to identify and respond to user emotions is clearly seen. The suggested system makes use of facial recognition technology in order to harvest useful emotional intelligence from users' facial expressions, which act as a proxy for their emotions when shopping. By applying the KNN algorithm to correlate these emotional expressions with their past purchase history, the system generates personalized recommendations that align with the users' emotional state in real-time. This not only enhances the user experience but also contributes to increased user engagement and satisfaction. This research holds significant implications for the e-commerce landscape. The combination of facial recognition and KNN introduces an emotionally intelligent recommendation system that is extremely user-centric. As we move towards a future where user satisfaction and personalization are the top priorities in the retail sector, this Facial Recognition-Based Product Recommendation System has the potential to revolutionize the online shopping experience, giving us a glimpse of the future of retail where every purchase is emotionally resonant and actually personalized.

## II.LITERATURE OVERVIEW

The literature on facial recognition-based product recommendation systems has significantly advanced with the integration of artificial intelligence and machine learning techniques. Several studies have explored different methodologies to improve recommendation accuracy by incorporating facial recognition for user authentication, analyzing past purchase behaviour, and leveraging collaborative filtering to enhance personalization. These systems aim to provide tailored product suggestions by identifying users through facial recognition and utilizing their purchase history to predict future preferences.

Ghulam Mustafa et al. (2024) introduced Onto Commerce, an e-commerce recommendation system that combines ontology and sequential pattern mining. Ontology offers a structured representation of product attributes, while sequential pattern mining identifies user behavior trends to enhance recommendation accuracy. The hybrid approach improves personalization but could be data-intensive.

Shulin Xu et al. (2023) proposed a cloud service recommendation system using a hierarchical knowledge graph. Organizing knowledge into layers increases accuracy in identifying cloud computing products with user requirements. Knowledge-based systems assist in making difficult decisions but need structured domain knowledge.

Muhammad Ibrahim et al. (2023) suggested a hybrid neural collaborative filtering model for making precise recommendations. Neural networks expand conventional collaborative filtering by learning profound user-item relations, enhancing the accuracy of the recommendations. However, this does require significant computational resources.

Yanju Zhang et al. (2020) enhanced collaborative filtering by adding intuitionistic fuzzy reasoning to deal with missing values. The approach provides more reliable suggestions by resolving the uncertainty of users' preferences.

S. Reddy et al. (2019) suggested a content-based movie recommender system based on genre correlation. In this method, movie features, e.g., genre, are used to recommend films to users based on their previous choices. Content-based filtering performs well in cases where adequate metadata are present but might be hampered by the "cold start" issue for new users.

T. Xueli Wang et al. (2024) used machine learning methods to enhance product design user experience. Based on user comments and likes, the system adjusts design decisions to maximize customer satisfaction. Machine learning in user experience design works well but needs updated data

**Table 1: Comparison Table**

Year	Author(s)	Proposed Work	Proposed Algorithm
2021	S. R. Chavare, C. J. Awati, S. K. Shirgave	Smart recommender system using deep learning	Deep Learning
2023	H. Chen, C. Fu, C. Hu	Secure recommendation system with federated matrix factorization	Federated Matrix Factorization
2024	M. Vinutha, R. B. Dayananda, A. Kamath	Personalized skincare product recommendation	Content-Based Machine Learning
2024	J. Alanya-Beltran	Learning recommendation system in e-learning	Collaborative Filtering & ML
2024	J. Panduro-Ramirez	Sentiment analysis in product recommendations	Machine Learning
2023	M. D. Bhagat, P. N. Chatur	Product recommendation with deep learning & collaborative filtering	Deep Learning & Collaborative Filtering
2023	R. Chauhan, K. N. Vaghela, et al.	Movie recommendation system	Content-Based Machine Learning
2024	M. S. Rahman, T. D. Sarkar, et al.	Smart recommendation in e-commerce	Element-by-Element Collaborative Filtering
2021	M. Tahir, R. N. Enam, S. M. Nabeel Mustafa	E-commerce platform with ML-based recommendation	Machine Learning
2022	V. Malik, R. Mittal, S. V. Singh	E-commerce product recommendation using NLP & ML	NLP & Machine Learning

### III. METHODOLOGIES AND APPROACHES

To develop a Facial Recognition Based product Recommendation System, a structured method is needed.

This method combines facial recognition, machine learning, and recommendation algorithms to provide personalized product recommendations

## 1.Data Collection and Preprocessing

The system captures live facial information from a webcam or smartphone's camera,as well as user purchase history and demographic data.Image preprocessing methods like normalization and noise elimination provide quality data for analysis.

## 2.Facial Recognition

The Local Binary Pattern Histogram (LBPH) algorithm is employed in facial recognition.It efficiently extracts facial features,providing accurate and efficient user authentication prior to making recommendations.It works effectively under different light conditions.

## 3.Machine Learning-Based Recommendation System

The recommendation engine combines various machine learning methods K-nearest neighbours(KNN) determines similar users with comparable shopping habits .Collaborative filtering recommends products based on user similarity and buying habits.Hybrid approaches blend collaborative filtering with content-based recommendations for increased accuracy.

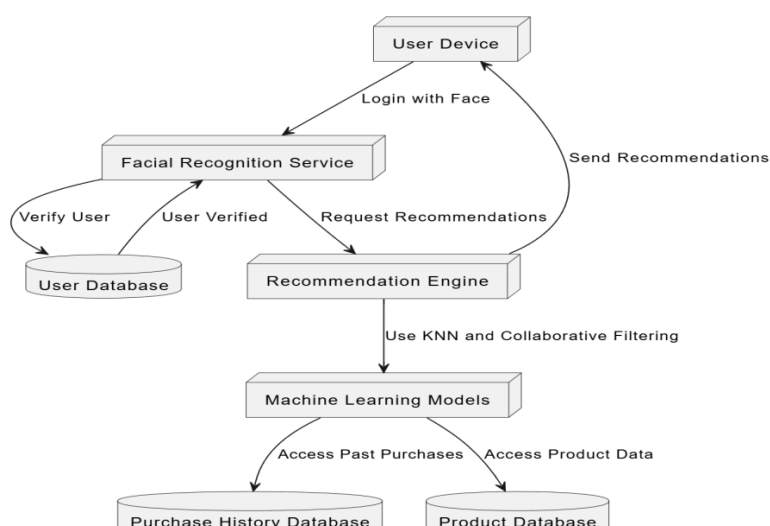
## 4.System Integration And Deployment

The frame work is developed using Flask or Django for backend and React for Angular for frontend.It uses cloud services such as AWS,Google Cloud,or Azure for scalability.User preferences and purchase history are stored using MongoDB or PostgreSQL.

## 5.Evaluation And Performance Optimization

Performance is measured in terms of precision, recall, and f1-score to determine emotion labelling accuracy. Mean Average Precision and Click through rate (CTR) are used to determine recommendation effectiveness. A/B testing ensures that the system is improved upon based on user behaviour to promote ongoing improvement.

This Facial Recognition-Based Product Recommendation System offers an adaptive, personalized, and user-oriented shopping experience, making e-commerce sites more efficient and enjoyable.



**Fig1: Architecture diagram for proposed system**

## IV.IMPLEMENTATION

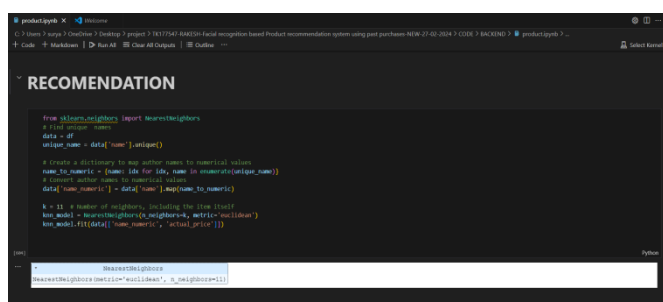
Collaborative filtering is a well-known recommendation system method that forecasts a user's preference based on the past behavior of similar users. It is based on the principle that users with similar past preferences will have similar future preferences. One of the most common algorithms for collaborative filtering is k-Nearest Neighbors (KNN).

In this implementation, we first create a data set for user-product interactions. The data is organized in the form of a User-Item Matrix where one row for each user and one column for each product are found, and the values represent frequency of purchases. We use the KNN algorithm with cosine similarity to find the most similar users. After similar users are determined, the system suggests products they have interacted with but the target user hasn't yet bought.

The KNN algorithm operates by calculating the similarity of users from their purchase history. It finds the k most similar users for a user and suggests products that the similar users have interacted with. This method assists in creating personalized recommendations without explicit product features.

Even though KNN-based collaborative filtering is effective, it could be subjected to challenges like the cold-start problem where new items or users do not have enough interaction data and data sparsity where users have only interacted with a few of the existing products. Nevertheless, through the selection of hyper parameters like the number of neighbors (k) and the application of effective similarity measures, the recommendation system can be fine-tuned for improved performance.

This deployment offers a straightforward yet efficient recommendation strategy, which can be extended with sophisticated methods such as matrix factorization or deep learning-based recommendation systems for dealing with large datasets.



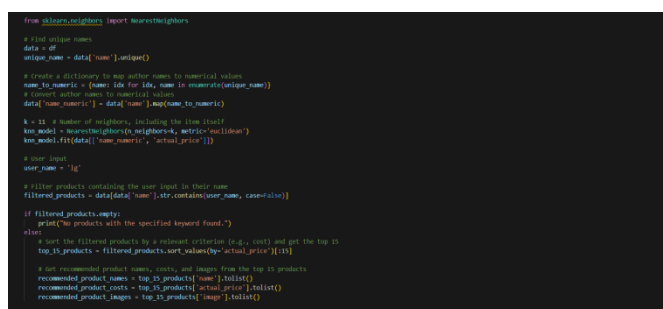
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from sklearn.neighbors import NearestNeighbors
# Find unique users
data = df
unique_user = data['user'].unique()

# Create a dictionary to map user names to numerical values
user_to_numeric = {user: idx for idx, user in enumerate(unique_user)}
# Convert user names to numerical values
data['user_numeric'] = data['user'].map(user_to_numeric)

# k is a number of neighbors, including the item itself
knn_model = NearestNeighbors(n_neighbors=k, metric='euclidean')
knn_model.fit(data[['user_numeric', 'actual_price']])

```



```

# user input
user_name = 'lg'

# Filter products containing the user (not in their name)
filtered_products = data[data['user'] != user_name, :]

if filtered_products.empty:
    print("No products with the specified keyword found.")
else:
    # Sort the filtered products by a relevant criterion (e.g., cost) and get the top 10
    top_10_products = filtered_products.sort_values(by='actual_price')[1:11]

    # Get recommended product names, costs, and images from the top 10 products
    recommended_product_names = top_10_products['name'].tolist()
    recommended_product_costs = top_10_products['actual_price'].tolist()
    recommended_product_images = top_10_products['image'].tolist()

```

**Fig2:Implementation Of Knn For Recommendation**

## V. FINDINGS AND TRENDS

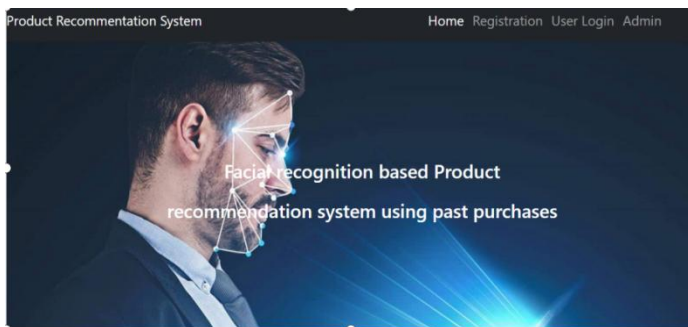
Facial recognition-based recommendation systems are increasing personalization by incorporating emotion detection, multi-modal data and real-time processing using cloud AI and edge computing. Privacy and security must still be the priority, with the need for robust encryption and adherence to regulations such as GDPR. Beyond this, AR and VR integration are revolutionizing online shopping into immersive experiences.

Trending topics such as AI-powered emotion recognition through deep learning, growing application of voice and gesture recognition, and 5G-facilitated real-time recommendation are part of the new landscape. Ethical AI and transparency are becoming increasingly relevant, promoting fairness in recommendations. Meta verse and virtual shopping are transforming e-commerce and opening the door to smarter, more interactive, and emotionally empathetic retailing.

## VI. CHALLENGES AND GAPS

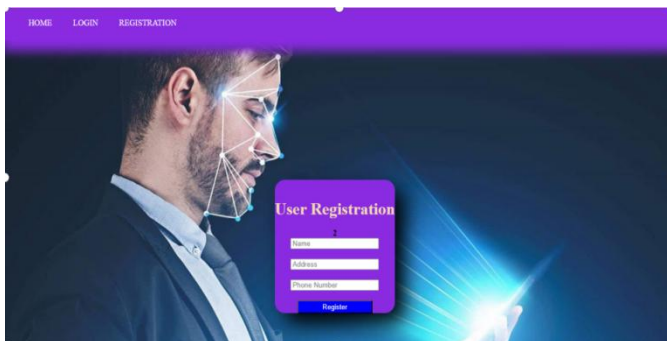
One of the primary challenges is the cold-start issue, wherein new products and users have inadequate interaction data to enable accurate recommendations. Sparsity in data is another challenge since the majority of users only engage with a minority of the existing products, hence fewer collaborative observations. The selection of  $k$  also has an influence on accuracy—too low provides too personalized yet inaccurate recommendations, whereas too high averages out user preferences. Scalability problems come into play when dealing with large datasets since computing pairwise similarities is computationally intensive. Moreover, popularity bias gives more importance to popular items purchased often, leaving niche or newly introduced items behind. To cover these loopholes, combining hybrid models, implicit feedback, and real-time updates can improve accuracy, personalization, and scalability.

## VII. RESULTS



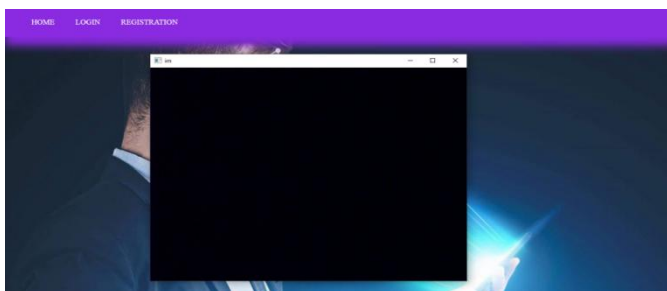
**Fig3: Index page**

When user want to access PRS he has do user registration during this step our system will use facial reorganization to capture user facial features which will stored our database.



**Fig4: User Registration Page**

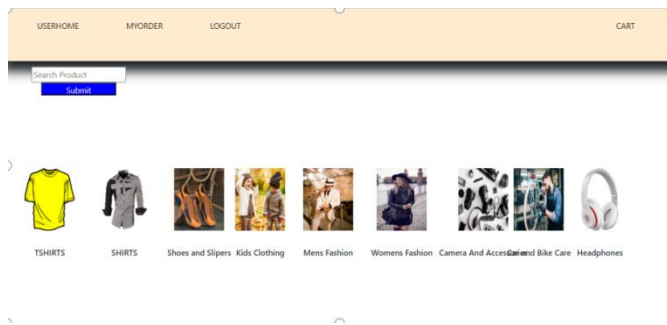
The image represents the registration page where the user can do the registration. The user should give details like name, address, phone number after the user given details the system can scan the user images and stores the images in the data base.



**Fig5: Facial login**



Here the log in can be done using face scanning it recognizes the face if the user is registered or not. If the user is registered, the user will get logged in; the user can see the home page like in the below picture.



**Fig6: User Home Page**

## VIII.CONCLUSION

The Facial Recognition-Based Product Recommendation System combines facial recognition technology with machine learning algorithms, namely K-Nearest Neighbors (K-NN) and collaborative filtering, to deliver an extremely personalized shopping experience. Based on user emotions, historical purchases, and interests, the system suggests relevant products, promoting user engagement and ease of use in digital shopping.

Core modules are user registration, face login, input of products, recommendation results, and tracking of result history. Collaborative filtering makes predictions on user preference from similar user activity, whereas K-NN determines the desired recommendations through proximity-based analysis. Inasmuch as the method is effective, it still faces shortcomings such as data sparsity, the cold-start problem, and privacy.

Future developments may include multi-modal data analysis, such as voice and gesture recognition, to enhance accuracy. Moreover, the inclusion of augmented and virtual reality can make the shopping experience more immersive. Enhancing security and scalability will be critical for mass adoption. This system is a significant breakthrough in e-commerce, making shopping more dynamic, intuitive, and user-focused.

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