Innovative Approaches in Predictive Analysis and Personalized Online Shopping Recommendations with AI Powered-Chat

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***Abstract*— Customers are more exposed than ever to the necessary quantity of information about goods and services nowadays. As a result, there is a great deal of variability in consumer demand, making it difficult for retailers to provide the appropriate goods and services in accordance with client preferences. Recommender systems can use consumer evaluations, comments, and shared experiences regarding a product as an efficient way to learn about the preferences of the customer. Users' buying lists, viewer lists, and product purchase counts are regarded as the primary core attributes for doing the analysis of the items watched and purchased in order to recommend products to users. This uses a hybrid recommendation methodology that blends data analytics, collaborative filtering, and machine learning. It is possible to create a framework for forecasting consumer behavior. Users are increasingly using social media in the current situation to get prompt customer assistance; however, the majority of these complaints were unanswered or not addressed at all. A new conversational system has been created to automatically generate responses to user inquiries on social media in order to address this problem.**

Keyword: *AI-Enhanced Personalization; Customer Experiences; intelligence-driven communications; AI-driven Predictive Analytics*

I. Introduction

Artificial intelligence (AI) has revolutionized the way online retailers operate by enabling them to leverage data and predictive analytics to personalize the shopping experience for consumers. Artificial intelligence (AI) algorithms may promote products, customize promotions, and even forecast future trends by examining consumer behavior, preferences, and purchasing patterns. This level of personalization not only enhances the customer experience but also increases conversion rates.

A. Personalized Product Recommendations: The likelihood of a purchase can be increased by using AI algorithms to evaluate consumer data and suggest goods that are likely to be of interest to certain consumers [9].

B. Dynamic Pricing Strategies: AI can maximize revenue and profit margins by dynamically adjusting prices based on variables like consumer behavior, competition, and demand [10].

C. Chatbots and Virtual Assistants: AI can maximize revenue and profit margins by dynamically adjusting prices based on variables like consumer behavior, competition, and demand.

D. The Impact of AI on Conversion Rates

Research has indicated that personalized recommendations powered by AI can significantly boost online businesses' conversion rates[11]. A McKinsey study indicated that personalized recommendations can raise sales by 20%, while a Salesforce report claims that companies who employ AI for product recommendations saw a 26% rise in revenue.

E. The Power of AI-driven Product Recommendations

Product suggestions powered by AI are growing in popularity across all industries and business sizes. The technology that powers these suggestions analyzes vast amounts of data to identify patterns and trends in customer behavior, enabling companies to offer recommendations that are specifically catered to each person's unique needs and preferences[12]. The following are some main advantages of using AI-driven product recommendations:

- A rise in sales
- A Better Experience for Customers:
- Better chances for upselling and cross-selling:
- Effective Marketing Techniques

F. Key Features of AI-powered Recommendation Systems:

- Enhanced Customer Engagement;
- Real-time Data Analysis;
- Customized Product Suggestions;
- Higher Sales and Conversions

The capacity of AI-powered recommendation systems to evaluate data in real-time and offer current product recommendations is another benefit. Recommendation engines driven by AI are transforming the e-commerce sector.

- Dynamic and current product recommendations are produced by real-time data analysis;
- personalized product recommendations can boost sales and consumer engagement.
- Increased income and conversions might result from better customer involvement.

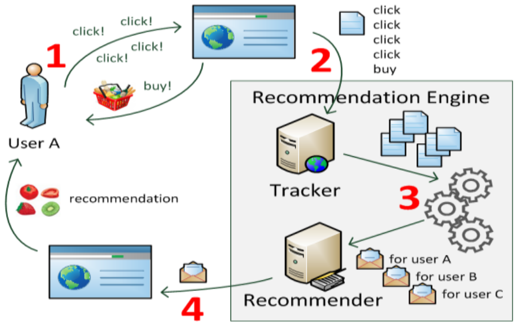

Fig 1. Best Use Cases for AI-Based Recommendation Systems

II. LITERATURE REVIEW

A. Predictive Analysis

Artificial intelligence is rapidly transforming marketing by providing brands and agencies with a powerful new toolkit[13]. While AI may conjure up sci-fi images of robot overlords, the reality is that AI is already here and actively enhancing multiple aspects of marketing. In particular, chatbots, predictive analytics, and other AI technologies are set to become vital components of tomorrow's marketing stack.

B.Chatbots Powered by Conversational AI

According to recent surveys, over 50% of online consumers have used a chatbot when browsing or shopping online. Additionally, chatbots can provide a 24/7 automated experience while lowering customer assistance expenses by up to 30%. With large amounts of conversational data, chatbots continue to improve at understanding and responding to customers just like a human agent would. Brands like Home Depot, Sephora and Microsoft use chatbots via platforms from IBM Watson, Google Dialog flow, and Amazon Lex. While the technology still has room to grow, chatbots are clearly gaining traction and having meaningful interactions with customers daily[14]. As AI capabilities advance, look for chatbots to become a must-have channel for sales and support.

C.Predictive Analytics for Data-Driven Insights

Predictive analytics can help classify customers into segments based on common attributes. It can estimate the likelihood that a customer will churn or conversely, have a high lifetime value. Amazon uses predictive analytics to recommend products based on purchase history and Netflix applies it to suggest new shows based on viewing habits. This type of segmentation and targeting is only possible with an AI-powered system.

C.Automating Personalization

Today's consumers expect personalized experiences. AI has the processing power to deliver dynamic customization at scale. For example, email marketing platforms leverage AI to automatically tailor messaging, subject lines and offers based on individual behaviors. A simple way to use AI for personalization is by integrating a recommendation engine on a brand's website. This automatically suggests relevant products and content for each visitor.

D.Study dealing with Predictive Analysis and Recommendation System

Reference	Title of the Paper	Objectives
Dai, X., & Liu, Q. (2024).	Research on online retail sales shows how artificial intelligence affects consumer buying habits [1].	Highlights the significance of ethical and effective use of AI technology by retailers to gain a competitive edge, improve customer pleasure, and foster long-term prosperity.
Rajkumar, K., Ragupathi, T., & Karthikeyan, S. (2024, March)	Intelligent Chatbot for Hospital Recommendation System[2]	This project's primary goal is to develop an intelligent chatbot that is easy to use for medical advice and assistance.
Gooljar, V., Issa, T., Hardin-Ramanan, S., & Abu-Salih, B. (2024).	A systematic assessment of sentiment-based forecasting models for online transactions in the marketing 5.0 age [3]	The application of artificial intelligence in digital marketing, the transition from traditional to digital marketing, predictive modeling in marketing, and the importance of examining consumer sentiment in reviews.
Paripati, L., Hajari, V. R., Narukulla, N., Prasad, N., Shah, J., & Agarwal, A. (2024)	AI Personalization Algorithms: Predictive Analytics, Recommender Systems, and Other Applications[4]	the disclosure of in-depth interviews conducted with a group of knowledgeable consumers and a comprehensive online poll intended to gather their preferences, viewpoints, and impressions regarding the customized shopping experience
Habil, S., El-Deeb, S., & El-	The best way to predict and target the market is with AI-	examines how these AI-powered solutions may

Bassiouny, N. (2023)	based recommendation systems [5].	produce value for customers and give retailers a competitive edge.
Dongbo, M., Miniaoui, S., Fen, L., Althubiti, S. A., & Alsenani, T. R. (2023)	Sentiment analysis utilizing hybrid machine learning methods is possible with this intelligent chatbot interaction system.[6]	Like a virtual assistant, a chatbot is pre-trained to comprehend user inquiries and provide NLP-based answers.
Thomas, R., & Jeba, J. R. (2024)	A new framework for a sentiment analysis (SA)-based intelligent deep learning-based product recommendation system [7]	A new product recommendation system based on collaborative filtering (CF) and sentiment analysis (SA). The SA was built on top of the LSTM model.
Ahmed, M., Ansari, M. D., Singh, N., Gunjan, V. K., BV, S. K., & Khan, M. (2022)	IoT Smart Devices for a Rating-Based Recommender System Based on Textual Reviews [8]	The authors discussed the benefits of collaborative filtering in the film industry and developed the recommender system using a user-based CF approach..

III IMPACT OF AI ON BUSINESSES

Industry 6.0 is not just about automating factories; it's about integrating cutting-edge technology to alter whole industries, allowing for unprecedented levels of customization, increased productivity, and smarter decision-making Beyond merely automating factories, Industry 6.0 aims to create intelligent, fully integrated production systems that can operate with minimal human intervention. It combines artificial intelligence, quantum computing, large data, cloud computing, energy, cognitive-robot collaboration, and intelligence from human beings[15].

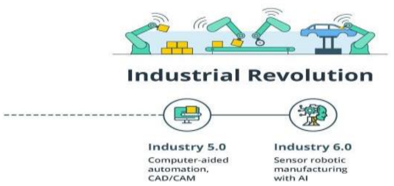

Fig 2. Industry 6.0: Intelligent Manufacturing's Ascent and the Industry's Future

Many research papers on e-commerce products have been written stating their services, their pricing-related recommendations. It is important to understand the consumer behavior and then find the best suited product as per their need. So, an AI helps to identify and suggest similar products and make predictions for the same behavior while at the same time understand the user behavior.

The growth of AI presents businesses platforms with variety of unique benefits and opportunities. It can empower organizations to provide more relevant and better experiences to their customers and build long-term relations with them that were simply not possible before. With the creation of new relationship between man and machine, A.I. could boost labor productivity to much greater extent and doubling the annual economic growth rates by 2035.

1) To generate a repository of Customer data through data analytics. 2) To develop an algorithm to generate purchase recommendations and purchase predictions. 3) To predict Online behavior and targeting customer base by publicizing using predictive analysis/data analytics. 4) To compare the developed virtual assistant in respond to business services.

IV.PROPOSED WORK FOR PREDICTING PURCHASES

A model for forecasting purchases based on a customer's journey from window shopping to completing a transaction is presented in this paper. Figure 3. suggests the proposed model for making purchase predictions. Data visualization component is included after the products are recommended to the users, we need to predict whether or not a user's will purchase a product after viewing it.

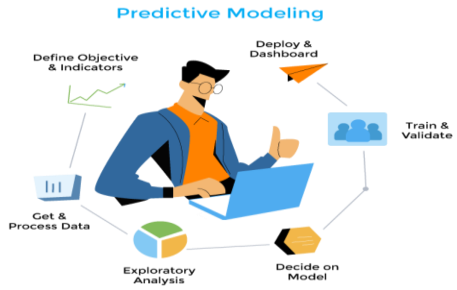

Fig.3.Predictive Modeling

Assume we are statistical consultants who have been engaged by a customer to offer suggestions on how to increase sales of a specific product. In order to indirectly boost sales, we can suggest that our customers adjust their advertising budgets. if we find a correlation between advertising and sales. To put it another way, we want to create a precise model that can forecast sales based on the three media budgets[16].

Say for example : Residential energy consumption Prediction say X = Energy(Joule), Y = Price

$$Y= f(X) \qquad (2)$$

The equations $Y = a + b X$, $Y = a + b X + cX2$, *and* $Y = a + b X + c X^2 + dX^3$ *(3)*

By using Joule, you can predict the Residential energy consumption price , but if you can use other variables like Natural gas Price, Electricity, renewable energy etc., may the prediction become closer to the actual but you will never get exact price. Descriptive analytics is necessary because data scientists must first understand what data to utilize to train machine learning models in order to address the price prediction problem.

X1 = Joule, X2 = Natural Gas X3 = Electricity., etc.,

Y = f (X1,X2,X3,X4….) → if we do so , we may be able to reach closer to Y but the equality still not hold. Therefore no matter what , we will never be exactly predict the price of the residential energy consumption given the inputs and will end up making some error every time we make a prediction.

Two factors, which we shall refer to as the reducible error and the irreducible error, determine how accurate a forecast is for Y. Reducible error irreducible error ˆf will typically not be an exact estimate for f, and this error will be introduced as a result of the inaccuracy. This error is reducible because, by estimating f using the best statistical learning method, we may be able to increase the accuracy of ˆf. Nevertheless, our forecast would still contain some inaccuracy even if it were feasible to create an ideal estimate for f, so that our estimated answer had the form Yˆ = f(X)! This is due to the fact that Y is likewise a function of Error, which is by definition impossible to anticipate from X. The goal is to minimize the reducible error by employing methods for estimating f. Remember that the irreducible error will always give us an upper limit on how accurate our estimate for Y will be. In practice, this bound is nearly always unknown.

A chatbot is a computer program that uses artificial intelligence to simulate human communication. It helps the consumer responding to the questions they have asked. Now a day's many tools and techniques are available for developing chatbots. Detailed Implementation of a chatbot is discussed below

Step 1: Import Libraries & Load the Data

```
#Load the required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
#Plot styling
import seaborn as sns; sns.set()  # for plot styling
%matplotlib inline
plt.rcParams['figure.figsize'] = (16, 9)
plt.style.use('ggplot')
#Read the Excel (.xls) file
dataset=pd.read_excel('C:/Users/Tahir/Desktop/ML_Project1/POS.xls')
#Explore the dataset
dataset.head()#top 5 columns
len(dataset) # of rows
#descriptive statistics of the dataset
dataset.describe().transpose()
print("Data importing")
```

	count	mean	std	min	25%	50%	75%	max
HOUSEHOLD_KEY	10001.0	1.329600e+03	7.441180e+02	7.000000e+00	6.870000e+02	1.366000e+03	2.009000e+03	2.493000e+03
BASKET_ID	10001.0	2.714554e+10	7.973639e+07	2.698485e+10	2.709323e+10	2.716354e+10	2.721309e+10	2.728248e+10
DAY	10001.0	1.433597e+01	6.574946e+00	1.000000e+00	1.000000e+01	1.500000e+01	2.000000e+01	2.500000e+01
PRODUCT_ID	10001.0	1.463294e+06	1.674809e+06	3.316000e+04	9.071280e+05	9.962420e+05	1.083583e+06	9.885390e+06
SALES	10001.0	1.057286e+02	1.666687e+02	0.000000e+00	3.697500e+01	7.665000e+01	1.041250e+02	5.100000e+03
QTY	10001.0	1.304370e+00	8.348353e-01	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	2.000000e+01
STORE_ID	10001.0	2.664174e+03	8.180849e+03	2.700000e+01	3.240000e+02	3.670000e+02	4.100000e+02	3.200400e+04
RETAIL_DISC	10001.0	1.500000e-01	1.793100e-14	1.500000e-01	1.500000e-01	1.500000e-01	1.500000e-01	1.500000e-01
TRANS_TIME	10001.0	1.582079e+03	4.285271e+02	0.000000e+00	1.309000e+03	1.614000e+03	1.917000e+03	2.358000e+03
WEEK_NO	10001.0	2.727527e+00	9.949126e-01	1.000000e+00	2.000000e+00	3.000000e+00	4.000000e+00	4.000000e+00
COUPON_DISC	10001.0	-1.010799e-02	1.939101e-01	-1.600000e+01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
COUPON_MATCH_DISC	10001.0	-1.885813e-03	2.794241e-02	-5.000000e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
PRODUCT_CATEGORY_ID	10001.0	2.136986e+00	8.082282e-01	1.000000e+00	2.000000e+00	2.000000e+00	2.000000e+00	8.000000e+00
PRO_PRICE	10001.0	9.534594e+01	1.400720e+02	0.000000e+00	3.750000e+01	8.900000e+01	8.900000e+01	6.000000e+03

Fig 4. Execution Procedure by importing the Library Files

Step 2: Creating and Preprocessing the Data

To form a model, machine cannot take the raw data. For machine to understand it easily, lot of pre-processing is required. created three different datasets

1.data_sets_final.csv- This dataset is manually created which has following columns: Brand, ProductName, Product_id, source of Information Here, source of Information is: links of ecommerce sites products

2.brand.txt- It has a list of all brands which is available

3. productname.txt : It has a list of products just like brands.

Step 3: Create Training Model

Each input pattern is transformed into numbers to train the model. First, we're going to lemmatize each pattern word and create a list of zeroes of about the same length as that of total number of terms. Only those indexes that include the word in the patterns will be set to value 1. Similarly, by applying 1 to the input class to which the pattern belongs, we set the output. Then we will convert a few examples of brand names and product names in the lookup table along with intents. This is where we insert our lookup table of brand names.

```
[7]: data.rename(columns={"default payment next month": "Label"}, inplace=True)
     lbl = data.Label
     data = pd.concat([lbl, data.drop(columns=['Label'])], axis = 1)
     data.head()
```

[7]:

	Label	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_A
0	1	20000	2	2	1	24	2	2	-1	-1	...	689	0	0	
1	1	120000	2	2	2	26	-1	2	0	0	...	2682	3272	3455	
2	0	90000	2	2	2	34	0	0	0	0	...	13559	14331	14948	1
3	0	50000	2	2	1	37	0	0	0	0	...	49291	28314	28959	2
4	0	50000	1	2	1	57	-1	0	-1	0	...	35835	20940	19146	1

5 rows × 24 columns

Fig.5 Traing Model -Output

Step 4. Train the Model

Training the model comes after the model architecture has been constructed. The model's current state is used to make a prediction during training. The prediction's error is then computed, and the network's weights or parameters are changed to lower the error and enhance the model's prediction. We repeat this process until our model has converged and can no longer learn. Three important criteria must be chosen for this strategy.

Metric: How to evaluate the performance of our model using a metric. We used accuracy as the metric in our experiments.

Loss function: A function that establishes a loss value that the training process then attempts to lower by modifying the network's weights. When it comes to classification problems, the cross-entropy loss is a good option.

Optimizer: A function that determines how to adjust the network weights based on the output of the loss function.

Step 5: Interacting with your chatbot

For the model to chat, a graphical User interface is created for it to interact and is named as GUI chatbot.py. The code I have provided here is a simple chatbot using the Tkinter library in Python. Tkinter is a built-in library that allows for easy creation of graphical user interfaces (GUIs) in Python. First, we import the Tkinter library and the datetime library. The datetime library is used to get the current time, which we will use later in the code. Next, we define a function called “on_submit”, which is called whenever the user submits their input.

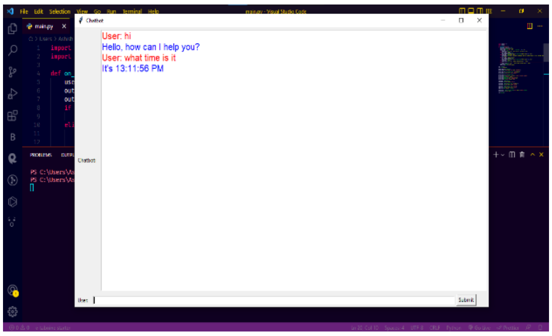

Fig 6.Chatbot Model using Tkinter library

The above code will open a GUI for the chatbot, where users can input their message and receive a response from the chatbot. Feel free to experiment with different responses, and even add new functionality to the chatbot. You can also change the appearance of the GUI by playing around with the Tkinter library.

Step 6. Running the Chatbot

Now we can make a POST request to http://localhost:8080/api/chat, and we should get a response ok.

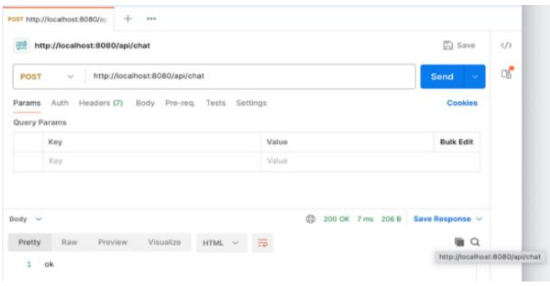

Fig.7.POST Request -Running Environment

Step7.GUI based results

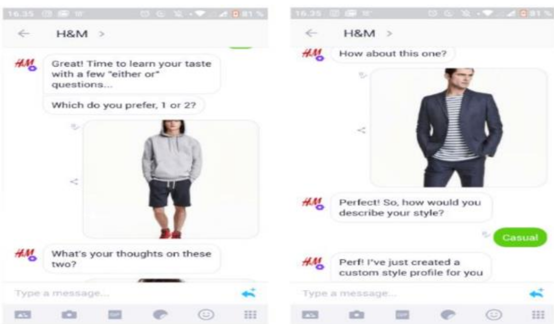

Fig.8.A Framework of GUI based Result

This study examines the model's performance using a variety of parameters. Comparing the outcomes of KNN, LR, and SVM is how effective the suggested study is the following constraints are used in further studies and performance verifications of the proposed models[17].

Recall is calculated by dividing the total number of true positive and false negative values by the total number of positive values that were successfully detected and added together.

$$\text{Recall}=\frac{TP}{TP+FN} \tag{4}$$

Precision is calculated by dividing the total number of successfully identified values by the total number of positive outcomes with false positives.

$$\text{Precision}=\frac{TP}{TP+FP} \tag{5}$$

Recall and precision are used to compute F-Measure.

$$\text{F-Measure}=\frac{2*Recall*Precesion}{Recall+Precision} \tag{6}$$

Accuracy reveals how confidently the model can distinguish between negative and positive classifications

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

False Positive, False Negative, True Positive, and True Negative are represented by the letters TP, TN, FP, and FN, respectively. A Residential energy consumption prediction dataset is used in this study to evaluate the effectiveness of the suggested machine learning classifiers. Accuracy, precision, recall, and f-measure are used to assess how good the proposed models are. The models used data for both training and testing [18].

```python
import pandas as pd
import matplotlib.pyplot as plt

# Define the data in a dictionary
dic = {'KNN': [54.5, 64.0, 58.18, 60.95],
       'SVM': [89.83, 95.92, 92.96, 89.25],
       'LR': [96.33, 97.66, 94.71, 96.15],
       'MODEL': ['Accuracy', 'Precision', 'Recall', 'F-Measure']}

# Create DataFrame
df = pd.DataFrame(dic)

# Set the 'MODEL' column as the index (so we can plot against it)
df.set_index('MODEL', inplace=True)

# Plotting the grouped bar chart
df.plot(kind='bar', figsize=(10, 6), color=['red', 'green', 'blue'])

# Adding titles and labels
plt.title('Comparison of KNN, SVM, and LR for Different Metrics', fontsize=14)
plt.xlabel('Metrics', fontsize=12)
plt.ylabel('Values', fontsize=12)

# Display the plot
plt.xticks(rotation=0)  # Keep the x-axis labels horizontal for readability
plt.show()
```

Fig 9.Evaluating ML Models: KNN, SVM, and LR on Core Metrics

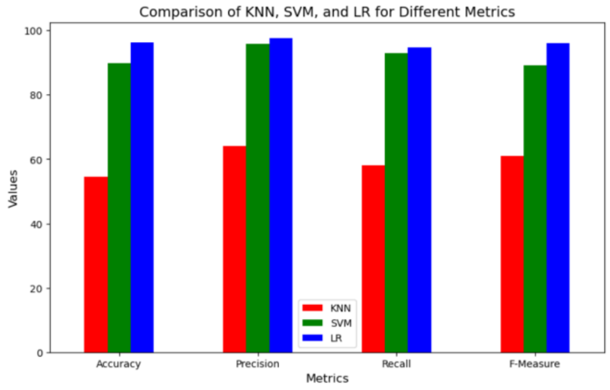

Fig 10.Comparison of KNN, SVM, and LR on Key Evaluation Metrics

An Intel Core i7 PC with a 2.0 GHz processor, 16 GB of RAM, and Windows 10 was used for this investigation. The Keras Python package was used to test and train the algorithms on all datasets. The LR model given above has achieved an impressive accuracy of 96.33% in terms of F-Measure, Accuracy, Recall, and Precision. According to the evaluation results, the LR classifier performs better than the other cutting-edge models for predicting mobile phone prices across all machine learning techniques employed in this work.

V.CONCLUSION & FUTURE SCOPE

The growth of the IT industry has made it possible to comprehend and interpret consumer needs in the most beneficial and effective manner. This paper presents a proposed system that uses data analytics to identify people with similar preferences and make product recommendations. The results of this framework's evaluation on a large dataset for an e-commerce company are encouraging enough to fully integrate the system. Deep neural networks are one type of machine learning technique that has been used to model user behavior and forecast purchases. Here we can ask Chabot about your products which we're looking for. For examples: Body wash, toothpaste, shampoo, face cream, tea bags. It helps to provide the recommendation for the specific products we are looking for. This model has been trained with limited products and brands and can further be extended to train more products. Further analysis can involve real time data testing, and effects on real time data. If model is fine-tuned a bit to make it as a discriminative model, it can further be used to parallel train multiple networks and the output can be fed to a matrix individually.

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