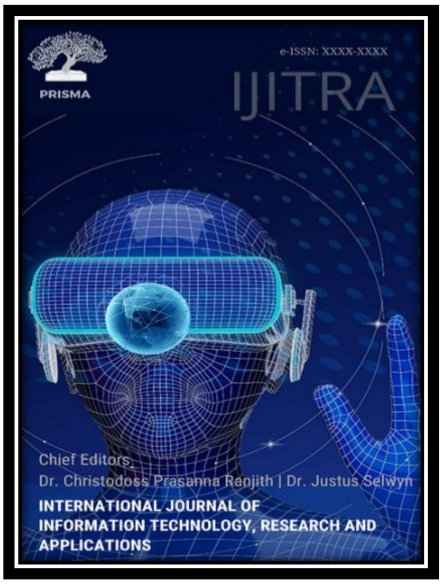


International Journal of Information Technology, Research and Applications (IJITRA)

P. Bavithra Matharasi, Sariya Fathima, (2024). Fashion Fusion: Exploring Apparel Recommendation Systems across companies using Machine Learning Approach, 3(2), 16-26.

ISSN: 2583 5343

DOI: 10.59461/ijitra.v3i2.98

The online version of this article can be found at:
https://www.ijitra.com/index.php/ijitra/issue/archive

Published by:
PRISMA Publications

International Journal of Information Technology, Research and Applications (IJITRA) is a journal that publishes articles which contribute new theoretical results in all the areas of Computer Science, Communication Network and Information Technology. Research paper and articles on Big Data, Machine Learning, IOT, Blockchain, Network Security, Optical Integrated Circuits, and Artificial Intelligence are in prime position.

PRISMA
PUBLICATIONS
https://www.prismapublications.com/

Fashion Fusion: Exploring Apparel Recommendation Systems across companies using Machine Learning Approach

P. Bavithra Matharasi[1], Sariya Fathima[2]
[1, 2]Department of Computer Science,
Mount Carmel College, Autonomous, Bengaluru, Karnataka, India, 560052

Article Info

Article history:

Received March 31, 2024
Accepted May 26, 2024
Published June 17, 2024

Keywords:

Fashion Recommendation Systen
K-Nearest Neighbor
Machine Learning
Random Forest Regressor
Term Frequency-Inverse Document Frequency

ABSTRACT

Recommendation technology is an advanced technology which gives users an improved service to get more information about a product. Fashion recommendation system is same as having a personal stylist who can recommend products based on user's preference. It uses data from users shopping history to recommend the trending outfits for making shopping easier. This paper aims to analyse a model for fashion recommendation system using K-Nearest Neighbor (KNN). Analysis of the services provided to the consumer like category, gender, and brand across companies should be relevant which helps in improving consumer overall shopping experience. Using Content-based Filtering the products are filtered based on user's preference and out of all recommended products the one with highest rating product is predicted using Random Forest Regressor. The comparison between algorithms is made to take best of all, to enhance the performances.

Corresponding Author:

P. Bavithra Matharasi
Department of Computer Science,
Mount Carmel College, Autonomous,
Bengaluru, India
E-mail: P.BAVITHRA.MATHARASI@mccblr.edu.in

1. INTRODUCTION

An online apparel store fashion recommendation system works similarly to fashion expert, making suggestion for costume based on past history or purchased, making users shopping experience satisfying and guiding the user in finding the outfits which is best suited for them.

In order to increase sales, it is important to target on user service. Fashion Recommendation System suggest in e-commerce, retail, blogging, and social media by giving some styling tips.

Using content-based filtering, collaborative filtering, machine learning, challenges including integration, scalability, privacy, bias, and personalization are addressed. This paper gives solutions based on user preferences using content-based filtering and machine learning methods like Random Forest regression, K-Nearest Neighbor (KNN) giving you a personalized online shopping experience similar to having offline shopping.
To predict K-Nearest Neighbor labels, this study uses methods for filtering, predicting, and evaluating related data points. It offers recommended products, makes it easier to locate products based on user preferences across companies, and recommends more research on the use of graphical user interfaces to enhance shopping experiences.

A. 1.1. Organization of paper

The paper is structured as follows: Section 1 Introduction of Research work Section 2 Literature review of related work. In Section 3 proposed K-Nearest Neighbor (KNN) technique is described in detail. Section 4 presents the experimental results. Finally, Section 5 provides the paper's conclusion.

2. LITERATURE REVIEW

Using a deep learning model an improved recommendation system is was developed by Seema Wazarkar et al [1] for consumers with different body shapes and types. It helps users to select clothing items based on their body shape. Proposed system is evaluated with respect to multiple deep learning models as well as traditional machine learning approaches. Xception model performed by achieving 94% accuracy and a loss of 0.02%.

Cairong Yan et al. [2] provide differentiated fashion recommendation using knowledge graph and data augmentation. The experimental results show that by using a data algorithm to improve data quality, the factorisation machine model produces higher recommendation accuracy, the constructed knowledge graph can alleviate the cold star problem for recommendation, and the differentiatedrecommendation strategy achieves better recommendations for active and inactive user.

The work presented has been developed in the context of the Feedback project founded by Regione Toscana, and it has been conducted on real retail company Tessilform, Patrizia Pepe mark. The recommendation system has been validated in store, as well as online. Pierfrancesco Bellini et al[3] have evaluated a recommendation system for fashion retail shops based on a multi clustering approach of items and users' profiles in online and on physical stores.

Using CNN method Fashion recommendation system has been evaluated by Anjan M. et al[4] which will recommend clothing images supported the style sort of the provided clothing images. This paper focus on the images of upper body as well as the lower body clothing and with human model in the images. The authors come up with an idea to build a content-based recommendation system using ResNet-50 convolution neural network.

Paul Ruh [5] has done study on Optimizing Product Recommendations for a Try-Before You-Buy Fashion E- Commerce Site and aims to optimize the current product recommendations of a Belgium start-up called Curve Catch that sells women's lingerie articles online and relies on a try-before-you-buy concept. Data sparsity was addressed by labeling each unique product per customer and minority classes were synthetically oversampled. However, results also underlined well-known limitations of recommendation systems. Both models struggled especially when identifying products a customer is likely to buy, while it was rather easy to identify products a customer is not likely to buy.

Choi et al [6] developed a personalized fashion recommendation system that utilizes implicit data from social networks. The system captures user preferences and behavior through data mining and uses this information to provide customized fashion recommendations. The authors tested the system with real users and found that it improved user satisfaction and purchase intention.

Using Machine Learning Technology fashion picture analysis is helpful for a variety of fashion-related applications, including fashion retrieval and fashion recommendations was evaluated by Nongmeikapam Thoiba Singh [7]. The effectiveness of the fashion forecasting analyzer website should continue to increase in the years to come as a result of the increased research spurred by this advancement in fashion forecasting.

Aketi Thanuja et al [8] have evaluated Fashion Recommendation system using deep learning. This method increases the likelihood of a user discovering his or her preferred apparel items. FRSs (fashion recommendation systems) recently piqued the interest of fast fashion merchants since they provide a more personalise customer experience for clients. Due to technological advancements, this field of AI technology seems to have a great deal of potential in image enhancement, interpretation, categorization, and segmentation.

It recommends products based on both the product attributes and user ratings. A good example of such hybrid recommender is the music recommender system developed by Li et al[9], which suggests music in terms of user ratings and audio features.

The authors G Mohammed Abdulla et al[10] present a robust personalized size recommendation system which predicts the most appropriate size for users based on their order history and product data. Both users and products in a size and fit space using skip-gram based Word2Vec model and employ GBM classifier to predict the fit likelihood. The result analyse the performance of system through extensive offline and online testing, compare technique.

A primary research study was conducted on Indian college students aged between 18 and 24 tears using fashion clothing involvement skilldeveloped by O'Cass[11] to understand the importance of fashion clothing in their lives. The scale had constructs related to consumption involvement, products involvement, advertising involvement, and purchase decision involvement. Research findings show a high correlation of consumption involvement with the other three involvement dimensions. The result show that Indian youth has an involvement with branded fashion wear.

Shetkar et al [12] introduce the concept of the mid brain connective proposing a model that focuses on optimising the connections and integration between the mind, brain and body. This approach aims to empower

individuals for more effective decision making ultimately contributing to their overall well-being.
The goal of this work is to research, investigate and rank the nonconforming variables in garments acquired from e-commerce sites. Data was gathered by Vineer Kaushik et al[13] through visits and interactions with college students as well as standardized online questionnaires. Nonconforming elements such as visual variation, functional inconvenience, cloth, attribute variation, haptic variation, aesthetic difference and fit variation were discovered based on the results of exploratory investigation.

3. METHODOLOGY

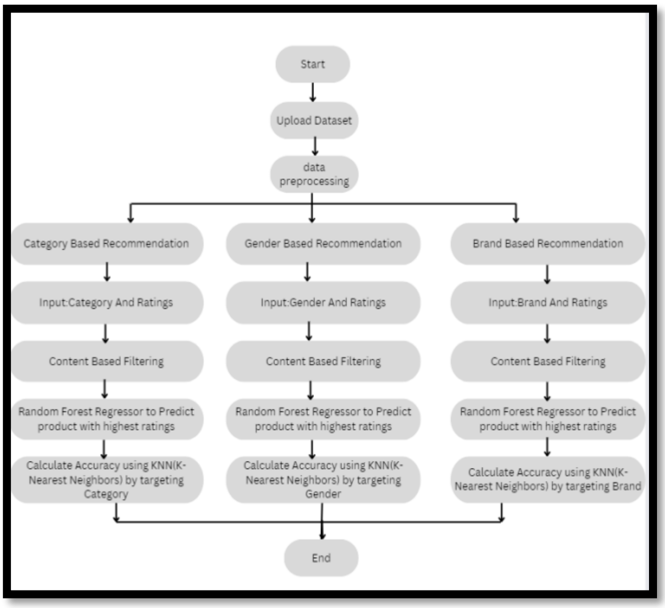


Figure 1: Flow of the proposed research

Teaching computers to learn from data and make predictions or judgments without explicit programming is known as machine learning. The aim of Machine Learning is to learn from trained data and predict for new data. This paper recommends products based on user's preferences. Therefore, the machine learning is required to predict the recommendation products. The dataset is taken from Kaggle. The analysis of user preference can compare based on prices, ratings and discounts across various companies. So that user can get to know which company is giving more discount on same product and the consumer can make best online shopping experience. Here are few steps where we use Machine Learning code for implementation:
Step 1: Data Collection
The process of collecting data from various sources and organise into information and compiling to make decisions. The dataset contains 527602 rows and 10 columns.
The fields of datasets are URL, Name_of_company, Product_id, BrandName, DiscountPrice (in Rs), OriginalPrice (in Rs), Number of ratings, Ratings. Here the explanation of fields is given below:
URL: It contains the product URL, which makes user to get more detail about product.
Example: Link of products
Name_of_company: Companies which are there in dataset.
Example: Myntra
Product_id: Unique id of product.
Example: 102255
BrandName: The brand name is given for the users looking for particular brand can find it easier.
Example: Roadster
Category: The category available for user to make their shopping easier.
Example: Western
category_by_Gender: Based on gender it is easier to classify products.
Example: Men
DiscountPrice (in Rs): The discount provided on product is given in Indian currency.
Example: 850

OriginalPrice (in Rs): The price before discount is also given in Indian currency to make user make advantage out of discount.
Example: 1200
Number of ratings: The total number of ratings is assigned to show user number of people reviews on products.
Example: 405
Ratings: User looking for high ratings product will be satisfied from ratings provided.
Example: 5.0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 527602 entries, 0 to 527601
Data columns (total 10 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   URL                   527602 non-null  object
 1   Name_of_company       527602 non-null  object
 2   Product_id            527602 non-null  int64
 3   BrandName             527588 non-null  object
 4   Category              527591 non-null  object
 5   category_by_Gender    527602 non-null  object
 6   DiscountPrice (in Rs)  527586 non-null  float64
 7   OriginalPrice (in Rs)  527586 non-null  float64
 8   Number of ratings     527562 non-null  float64
 9   Ratings               527602 non-null  float64
dtypes: float64(4), int64(1), object(5)
memory usage: 40.3+ MB
None
```

Figure 2: Dataset with datatypes

Step 2: Data Preprocessing

The process of transforming raw data into an information by cleaning the data having missing values and null values to guarantee the accuracy and completeness of the dataset.
It is very important to have a clean and transformation data. To clean data by dropping uncompleted values, replacing numerical values by using substitution zeros.
In this dataset 'BrandName' and 'Category' fields are essential fields to recommend products to user, Since the null values where predicted, so we drop the rows to make enhancement in results performance. Similarly, there was some more missing values "DiscountPrice (in Rs)," "OriginalPrice (in Rs)," and "Number of ratings", therefore by using substitution method with we substitute zeros in missing values places. Later, it is cross check to guarantee the data is prepared for further modelling.

```
URL                      0
Name_of_company          0
Product_id               0
BrandName                0
Category                 0
category_by_Gender       0
DiscountPrice (in Rs)    0
OriginalPrice (in Rs)    0
Number of ratings        0
Ratings                  0
dtype: int64
```

Figure 3: Clean dataset

Step 3: Feature Engineering

To improve the performance of machine learning models, data must be created by changing preexisting datasets. This process entails turning raw data into knowledge that may be utilized to improve outcome performance.
TF-IDF Vectorization (Term Frequency-Inverse Document Frequency) is a method of text feature extraction that creates a matrix of TF-IDF features from documents. In this matrix, a Name_of_company is represented by each row, and a unique word from each column. The value in each cell indicates the word's relative relevance is accompanying Name_of_company.

Step 4: Model Selection

Random Forest Regressor is in a group of decision-makers in which each give an opinion on information. Then, average of all those opinions is taken to make a final decision.

Random Forest Regressor helps in product evaluations based on Name_of_company. This tool resembles an intelligent calculator that builds on past performance. It performs well on prediction. It is trained with a method that converts Name_of_company into numerical values so that it easily evaluates. Once trained, it can display user preference ratings of products. Consider the following equation:

Content-Based Filtering

Here content-based filtering used to filter user preference products and recommend related products to user.

$$\mathrm{Score}(i,u) = \sum_{j \in I_u} \mathrm{Sim}(i,j) \times \mathrm{Rating}(u,j) \tag{1}$$

Score(i , u): Predicted score of items i for user u.
i: item for which score is evaluated.
u: recommendations made for users.
Iu: list of items the user interacted.
Sim(i , j): similarities between items in i and j.
Rating(u , j): the user preference u for item j.

Random Forest Regressor equation

Here Random Forest Regressor is used to predict best outfit among all recommended products based on ratings.

$$\hat{Y}_i = \frac{1}{T} \sum_{t=1}^{T} \mathrm{Tree}_t(x_i) \tag{2}$$

Where, $\hat{Y}_i$ represents predicted value for i-th sample
T represents number of trees in the forest
Treei (xi) represents predicted t-th tree for i-th sample

K-Nearest Neighbor

Using KNN it is easy to train and test data. Based on the accuracy it is easier to know the result performance.

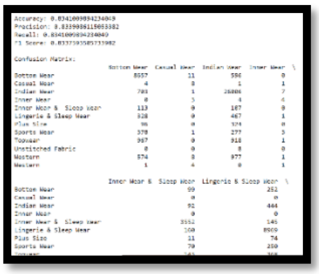
Euclidean Distance formula

$$d(P,Q) = \sqrt{\sum_{i=1}^{n} (P_i - Q_i)^2} \tag{3}$$

Where, P and Q are the elements of dataset with two features x and y.
Pi and Qi are the values of the i-th characteristic of the data points P and Q
The squared differences between Pi, Qi and P, Q is calculated by adding all features, and the square root is taken to give the total distance.

Step 5: Evaluation

The model is achieved by selecting the K-Nearest Neighbors (KNN) classifier. It is best suited for the current classification challenge. KNN is chosen, because of it has ability to classify products into many categories according to their features. The classifier is set to take five closest neighbors when generating predictions with parameter n_neighbors is 5, which is a frequently default value used. This decision demonstrates the classifiers to find patterns in the data and producing precise predictions in response, which gives appropriate model. Cross Validation is done just to prevent overfitting of data.



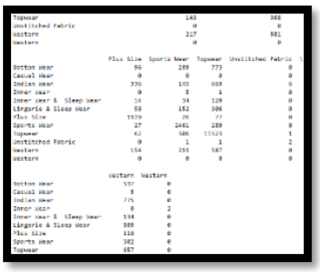


Figure 5: Confusion matrix for category recommendation

In the figure 5 we see the data is well trained and has not overfitted. This confusion matrix represents the performance of various classified apparel categories model. Each column predicted category, while each row predicted actual category. The numbers in the matrix express the quantity of products that are categorized into each set of actual and predicted categories.

```
Accuracy: 0.9168846430873043
Precision: 0.9168291169228616
Recall: 0.9168846430873043
F1 Score: 0.916855610623563

Confusion Matrix:
         Men  Women
Men    33463   4445
Women   4325  63283
Confusion Matrix:
[[33463  4445]
 [ 4325 63283]]
```

Figure 6: Confusion matrix for gender recommendation

In Figure 6, the classification model is used. The rows correspond to the actual classes (men and women), and the columns correspond to the predicted classes. A confusion matrix displays the counts of correct and incorrect predictions.

```
Accuracy: 0.7737878615565412
Precision: 0.769024272216239
Recall: 0.7737878615565412
F1 Score: 0.7665024852183164
Confusion Matrix:
[[ 48   0   0 ...   0   0   0]
 [  0  10   0 ...   0   0   0]
 [  0   0 109 ...   0   0   0]
 ...
 [  0   0   0 ...   0   0   0]
 [  0   0   0 ...   0  45   0]
 [  0   0   0 ...   0   0   1]]
```

Figure 7: Confusion matrix for brand recommendation

In figure 7, the result gives the count of current and incorrect prediction for each class in a classification model. This is done for brand-based recommendation.

```
Enter the category you are interested in: Western
Enter the minimum rating you desire (0-5): 5
Filtered Products:
       Name_of_company                                        URL  \
10            FlipKart  https://www.flipkart.com/puma-graphic-print-wo...
23              Meesho  https://www.meesho.com/pretty-fashionista-men-...
89817           Myntra  https://www.myntra.com/dresses/style-quotient/...
90167           Myntra  https://www.myntra.com/jeans/calvin-klein-jean...
95421           Myntra  https://www.myntra.com/tshirts/mast--harbour/m...
108234          Myntra  https://www.myntra.com/tshirts/jockey/jockey-w...
111575          Myntra  https://www.myntra.com/jackets/kazo/kazo-women...
115523          Myntra  https://www.myntra.com/jumpsuit/urbanic/urbani...
115830          Myntra  https://www.myntra.com/tshirts/mango/mango-wom...
116130          Myntra  https://www.myntra.com/leggings/twin-birds/twi...

        Product_id           BrandName  Ratings
10          102268                PUMA      5.0
23           78904          RanchRidge      5.0
89817     11305048      Style Quotient      5.0
90167     14780296  Calvin Klein Jeans      5.0
95421     15287878      Mast & Harbour      5.0
108234    11862708              Jockey      5.0
111575    10776382                Kazo      5.0
115523    15852218             URBANIC      5.0
115830    16125100               MANGO      5.0
116130    14222944          TWIN BIRDS      5.0
Product with the Highest Predicted Rating:
Product ID: 102268, URL: https://www.flipkart.com/puma-graphic-print-women-round-neck-blue-t-shirt/p/itm8bb50830773a0?pid=TSHGBDTZAF4KXNDZ&lid=LSTTSHG
```

Figure 8: Recommending products based on Category

Figure 8 represents the operation of category-based recommendations depending on user preference. It asks the users preferred category and the minimum ratings. The user preference category is filtered using content-based filtering, and a selection of products is recommended based on Random Forest Regressor, which predict the products with the highest ratings.

```
Enter the Gender you are interested in: Women
Enter the minimum rating you desire (0-5): 5
Filtered Products:
   Name_of_company                                               URL  \
9         FlipKart  https://www.flipkart.com/jahal-fashion-embroid...
10        FlipKart  https://www.flipkart.com/puma-graphic-print-wo...
11        FlipKart  https://www.flipkart.com/zingat-fashion-embroi...
12        FlipKart  https://www.flipkart.com/craze-n-world-self-de...
13        FlipKart  https://www.flipkart.com/shree-impex-embroider...
14        FlipKart  https://www.flipkart.com/katariya-collection-e...
15        FlipKart  https://www.flipkart.com/zinariya-fab-embroide...
16        FlipKart  https://www.flipkart.com/mert-india-embellishe...
17        FlipKart  https://www.flipkart.com/nplash-fashion-embroi...
18        FlipKart  https://www.flipkart.com/kedar-fab-embroidered...

    Product_id          BrandName    Category category_by_Gender  Ratings
9       102545      jahal fashion  Indian Wear             Women      5.0
10      102268               PUMA      Western             Women      5.0
11      102546      ZINGat FaSHION Indian Wear             Women      5.0
12      102547      CRAZE N WORLD  Indian Wear             Women      5.0
13      102548        Shree Impex  Indian Wear             Women      5.0
14      102549 katariya collection Indian Wear             Women      5.0
15      102550       Zinariya Fab  Indian Wear             Women      5.0
16      102551         Mert India  Indian Wear             Women      5.0
17      102552      NPLASH FASHION Indian Wear             Women      5.0
18      102553          Kedar Fab  Indian Wear             Women      5.0
Product with the Highest Predicted Rating:
Product ID: 102545, URL: https://www.flipkart.com/jahal-fashion-embroidered-semi-stitched-lehenga-choli/p/itm4649c09a50d6d?pid=LCHGCFZUTZ83RDYK&lid=LS
```

Figure 9: Recommending products based on Gender

Figure 9 demonstrates gender-based recommendation. First it takes the users preferred gender and the minimum rating. Then based on user preference it is filtered using content-based filtering, recommended products are displayed. Based on Random Forest Regressor's products with the highest ratings among them is predicted.

```
Enter the Brand Name you are interested in: Roadster
Enter the minimum rating you desire (0-5): 5
Filtered Products:
       Name_of_company                                               URL  \
47            FlipKart  https://www.flipkart.com/roadster-regular-wome...
124842          Myntra  https://www.myntra.com/sweatshirts/roadster/ro...
131547          Myntra  https://www.myntra.com/tops/roadster/roadster-...
136189          Myntra  https://www.myntra.com/tops/roadster/roadster-...
136249          Myntra  https://www.myntra.com/tops/roadster/the-roads...
136712          Myntra  https://www.myntra.com/shorts/roadster/roadste...
140016          Myntra  https://www.myntra.com/shirts/roadster/roadste...
140133          Myntra  https://www.myntra.com/shirts/roadster/roadste...
143243          Myntra  https://www.myntra.com/tshirts/roadster/roadst...
143271          Myntra  https://www.myntra.com/tops/roadster/the-roads...

        Product_id BrandName     Category category_by_Gender  Ratings
47          102255  Roadster  Bottom Wear              Women      5.0
124842    15158648  Roadster      Western              Women      5.0
131547    16961234  Roadster      Western              Women      5.0
136189    14928180  Roadster      Western              Women      5.0
136249    13399278  Roadster      Western              Women      5.0
136712    13756832  Roadster      Western              Women      5.0
140016    15221438  Roadster      Topwear                Men      5.0
140133    14878012  Roadster      Topwear                Men      5.0
143243    15191972  Roadster      Western              Women      5.0
143271    13399338  Roadster      Western              Women      5.0
Product with the Highest Predicted Rating:
Product ID: 102255, URL: https://www.flipkart.com/roadster-regular-women-black-jeans/p/itmfgbpruggqy3ph?pid=JEAFGBZ5QZYNHZSJ&lid=LSTJEAFGBZ5QZYNHZSJY0
```

Figure 10: Recommending products based on Brand

Figure 10 illustrates how it works on brand-based recommendation. It first explores users preferred brand and minimum ratings, then it filters the user preference brand by using content-based filtering and it suggests a few products. Using Random Forest Regressor the highest rated product is found.

Step 6: Result

Classifier is well trained using the features in which list of variables are assign. X is assign in features, and Y has the targeted variable. The trained data is divided into two parts: a training part has 80% of the data and a 20% in a testing part. While making predictions, n_neighbors = 5 include the five closest neighbors. classifier.fit is applied to the classifier to train data.The tested data is predicted using classifier.predict then accuracy is computed.

Using K-Nearest Neighbors (KNN) 83% Category is reported.

```
features = ['Product_id', 'DiscountPrice (in Rs)', 'OriginalPrice (in Rs)', 'Number of ratings', 'Ratings']
X = data[features]
y = data['Category']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

Accuracy: 0.8341009894234049
```

Figure 11: Accuracy got by Targeting Category

Using K-Nearest Neighbours (KNN) 91% Gender is reported.

```
features = ['Product_id', 'DiscountPrice (in Rs)', 'OriginalPrice (in Rs)', 'Number of ratings', 'Ratings']
X = data[features]
y = data['category_by_Gender']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

Accuracy: 0.9168846430873043
```

Figure 12: Accuracy got by Targeting Gender

Using K-Nearest Neighbours (KNN) 77% Brand were reported.

```
features = ['Product_id', 'DiscountPrice (in Rs)', 'OriginalPrice (in Rs)', 'Number of ratings', 'Ratings']
X = data[features]
y = data['BrandName']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

Accuracy: 0.7737878615565412
```

Figure 13: Accuracy got by Targeting Brand

4. RESULTS AND DISCUSSION

The result is determined by experimenting different algorithms, using clothing categories, gender, and specific brands, for fashion recommendation system accuracy percentages show how well it can match your preferences: 83% for categories, 91% for gender, and 77% for specific brands. Comparation between Accuracy of Category, Gender, Brand Name.
This paper compares different algorithm to choose best out of all.

Random Forest Classifier (4)

$\hat{y}(x) = \mathrm{argmax}_k \sum_{i=1}^{n} \mathrm{I}(T_i(x) = k)$

Where,

There are 'n' trees in the forest.
There are 'K' classes in total.
'T_i' represents the ith tree's forecast for input 'x'.

Decision Tree Classifier (5)

$h(x) = \sum_{m=1}^{M} c_m \cdot I(x \in R_m)$

Where,

'M' represents the total number of leaf nodes.
The class label linked to the mth leaf node is 'c_m'.
The region denoted by "R_m" is the mth leaf node.
When x falls within Rm, the indicator function 'I' returns 1, and when it doesn't, it returns 0.

Light Gradient Boosting Machine (6)

$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$

Where,
y_i is the predicted value for ith observation.
K is total number of trees in ensemble.
fk(x_i) prediction of kth tree for ith observation

Algorithm	Category Accuracy	Gender Accuracy	Brand Accuracy
RandomForest Classifier	79%	88%	46%
Decision Tree Classifier	78%	87%	72%
K-Nearest Neighbor	83%	91%	77%
LightGradientBoosting Machine	59%	76%	59%

Figure 4: Comparison between algorithm

When comparing algorithms for model, it is important to look into accurate factors, knowing the need of computer power, and whether they work with huge data. Also see if it can handle unusual data, if it is easy to understand, and if they work well with new data. Additionally, consider how complex the models they create are, whether they support making your features better, and if they handle imbalanced or missing data. By considering these factors and testing different algorithms, this paper finds what works best for making models.

Recommende Based	Method	Accuracy	Precision	F1score	Recall
Category	K-Nearest Neighbors	0.834%	0.8339%	0.8337%	0.834%
Gender	K-Nearest Neighbors	0.9168%	0.91682%	0.91685%	0.9168%
Brand	K-Nearest Neighbors	0.773%	0.7690%	0.76650%	0.773%

Figure 14: The accuracy on different recommendations

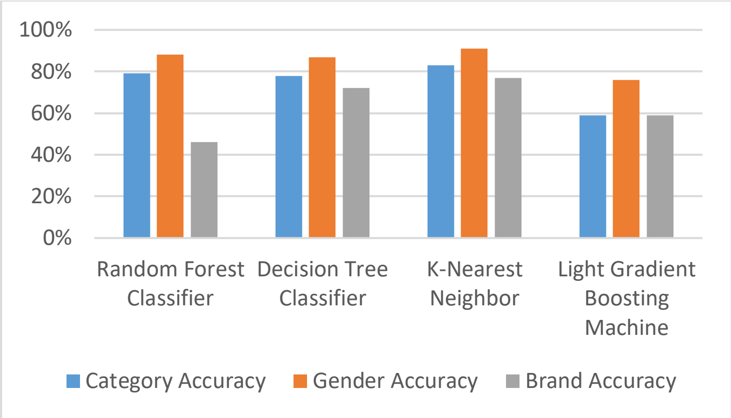


Figure 15: The Comparison between Results

An online fashion recommendation algorithm takes gender, category, and brand into account. By using Random Forest Regressor, K-Nearest Neighbors and Content-based filtering, the system enhances brand loyalty, online buying, and the overall shopping experience with a high accuracy rate. This technique makes it easier to find clothing, interesting products, and new brands. By producing recommendations for clothing and products based on gender, brand, and category preferences, a fashion recommendation system filters and enhances online shopping, increasing brand loyalty and improving the overall shopping experience. In the future, the program might be improved by adding a graphical user interface (GUI) for developing mobile applications, giving consumers a more user-friendly and accessible way to anticipate brands based on product details.

REFERENCES

[1] Seema Wazarkar et al, "advanced fashion recommendation system for different body types using deep learning models", July 2022.

[2] Cairong Yan et al, "Differentiated fashion recommendation using knowledge graph and data augmentation", July 2019.

[3] Pierfrancesco Bellini et al, "Multi clustering recommendation system for fashion retail", January 2022.

[4] Anjan M et al, "fashion recommendation system using CNN. International Journal of advanced research, ideas and innovations in technology", 2020.

[5] Paul Ruh, "optimising product recommendations for a try before-you-buy fashion e-commerce site", 2023.

[6] Sanghun Choi et al, "personalised recommendations system based on products specifications values", October 2006.

[7] Nongmeikapam Thoiba Singh et al, "fashion forecasting using machine learning techniques", February 2023.

[8] Aketi Thanuja et al, "Fashion Recommendation System using Deep Learning", April 2022, Journal of Emerging Technologies and Innovative Research.

[9] Prof. Meera Sawalkar et al, "Fashions Recommendation System", May 2023, Journal of Emerging Technologies and Innovative Research (JETIR).

[10] Li et al, "A hybrid clothes recommend a system based on use the ratings and product features", 2014.

[11] G Mohammed Abdulla et al, "Shop your Right Size: A System for Recommending Sizes for Fashion products", May 2019.
[12] Shetkar et al, "predictors of fashion clothing involvement among Indian youth", Oct 2010.
[13] Vineet Kaushik et al, "Non-conformance in apparels: exploring online fashion retail in India", May 2019.

BIOGRAPHIES OF AUTHORS

	**P.Bavithra Matharasi:** Bavithra Matharasi is an accomplished author and Associate Professor in the Department of Computer Science at Mount Carmel College, located in Bengaluru, India. With a passion for interdisciplinary research, Bavithra has made significant contributions to various fields within computer science. Her research endeavors have not only contributed to the academic community but have also addressed real world challenges, fostering innovation and technological advancement. She can be contacted at email:Bavithra.Matharasi@mccblr.edu.in
	**Sariya Fathima** Received Bachelor of Science in Computer Science from St. Anne's First Grade College for Women (Bangalore University), located in Bengaluru, India. Sariya is pursuing her Master of Science in Computer Science with Data Science (Autonomous), located in Bengaluru, India. She can be contacted at email: M22CS05@mccblr.edu.in