Retailer Recommendation Using Facial Recognition

Submitted in partial fulfillment of the requirements of the degree of

Bachelor of Engineering

By

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Project Report Synopsis Approval for Bachelor of Engineering

This project report entitled "***Retailer Recommendation Using Facial Recognition***" by "***Dhawale Saurabh Bhupesh***, ***Gode Sameer Ashokrao, Hande Devendra Girish***" is approved for the degree of **Bachelor of computer Engineering.**

Date: ___________

Prof. Kanchan Doke Guide	Prof. Kanchan Doke Project Co-Ordinator
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Declaration

I declare that this written submission entitled “**Retailer Recommendation Using Facial Recognition”** represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Place:

ABSTRACT

The goal of this project is to provide user with a very personalized selection of shops to buy from by using face recognition. Crucially, face recognition technology enables offline stores to do what their online counterparts have been doing for years – identify shoppers, link them to past purchases and generate personalized product recommendations based on the data.

When a retailer knows its customers, it can serve them more effectively. Facial recognition has the potential to give traditional stores a wider view, showing who’s buying what and when. Access to this data allows shops to identify problems and grasp opportunities, providing superior customer service that will keep shoppers happy and engaged.

Facial recognition will consider certain aspects of a customer such as gender, emotion and age to recommend shops which will best provide what the customer may want.

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Chapter – One

INTRODUCTION

The world is moving towards online shopping due to the benefits it provides to the customers. Big ecommerce sites like Amazon, Flipkart etc. provide tailored recommendations to their customers based on their previous behavior. These aid the customers during their shopping and provide satisfactory shopping experience. These recommendations are given by recommender systems employed by the sites. As these systems evolve and become more complex, more accurate predictions and recommendations are given to the users. If this continues, retail business might wane in the future.

Hence, a system which uses user's facial characteristics to provide personalized recommendations to the customers can help provide business advantage to the retail stores.

Understanding your customer has become an essential aspect for retailer. Knowing your customer gives you an edge in marketing strategy.

Main objectives are:

- To provide the customer a personalized experience.
- To provide a better marketing strategy for offline retailers.

1.1 Problem definition and objective

Our system aims to solve the problem of nonexistence of proper recommendation system for offline retailers. The system aims to bridge the gap between the offline retailers and online retailers in terms of personalization and search engine recommendations. This will help the customers to have a much better personalized buying experience at offline brand outlets and they will consider them as a real alternative to the online retailers.

The Phoenix Market City Mall currently has an implemented system which directs their customers to a particular floor for a specific brand. Interaction from customer's side is required on the touch screen for the system to function. Other offline retailers are not even capable of providing this basic interaction to their customers, this is where the online retailers gain an upper hand on the offline retailers with their search engines, recommendations and personalization coupled with discounts.

Our model aims to suggest customers with recommendations by using facial recognition, the model will consider the age, gender, emotion and old buying pattern of the user to provide recommendation. Thus, our objective of providing a personalized experience to customer on the basis of his personal identity and search-based recommendations will surely boost the revenues of offline retailers. Our Model aims to better the accuracy of facial recognition.

Chapter - Two

LITERATURE SURVEY & EXISTING SYSTEM

2.1 Existing Systems

The Phoenix Market City Mall currently has an implemented system which directs their customers to a particular floor for a specific brand. Interaction from customer's side is required on the touch screen for the system to function. Other offline retailers are not even capable of providing this basic interaction to their customers, this is where the online retailers gain an upper hand on the offline retailers with their search engines, recommendations and personalization coupled with discounts.

This offline retail system, however, does not understand or make a personalized experience for the customer. Thus, the online retail market is blooming in the past decade.

We have 3 survey papers related to our project they are –

1. Age Group Estimation and Gender Recognition Using Face Features [1]
    - This technique uses support vector machine and gives an accuracy of around 82% while classifying images and estimating age and gender. But accuracy is low as compared to Deep Learning models.
2. An Image Mining System for Gender Classification & Age Prediction Based on Facial Features [2]
    - This Technique uses AdaBoost to give an accuracy of 88%, but Adaboost is sensitive to outliers, which is not good for our goal.
3. Partial Face Recognition: Alignment-Free Approach [3]
    - This Technique uses PCA+LDA to give an accuracy of 92%, but PCA+LDA is computationally heavy

LITERATURE SURVEY

Table 2.1 Literature Survey Comparison

Paper Name	Publisher	Approach	Disadvantages
Age Group Estimation and Gender Recognition Using Face Features[1]	**The International Journal of Engineering and Science**	**Support vector machine (SVM)**	**Lacks accuracy compared to deep learning model.**
An Image Mining System for Gender Classification & Age Prediction Based on Facial Features[2]	**e ISSN: 2278 Volume 10, Issue 6 (May. – Jun. 2013)**	**Adaboost tool for feature selection. Viola's method.**	**AdaBoost can be sensitive to noisy data and outliers.**
Partial Face Recognition: Alignment-Free Approach[3]	**IEEE transactions on pattern analysis**	**PCA + LDA & LBP Canny edge detector.**	**PCA +LDA is computationally heavy.**

2.2 Limitation of existing systems

Phoenix Market City mall has a very static system. This system requires manual interaction of the customers with it and does not deliver personalized experience for the users.

In this manner the customers are not recommended shops according to their characteristics. The existing system is not able to predict and recommend a retailer for the user, because it only tends to provide the list of retailers.

Thus, the experience for the customer is not pleasant as they have to consider all shops for their shopping needs.

The Offline retail shops don't have any means by which it can compete with the personalized experience of their counterparts i.e. online retailers, Online retailers have been ruling the markets since the bloom of personalization and search recommendations, which provide customer with a much better experience as compared to offline retail shops.

Also the methods that have been applied before have their own disadvantages such as:

- Age Group Estimation and Gender Recognition Using Face Features [1]

  It uses Support Vector Machine thus lacks the accuracy of Deep Learning Models.

- An Image Mining System for Gender Classification & Age Prediction Based on Facial Features [2]

  It uses Adaboost which can be sensitive to noisy data and outliers.

- Partial Face Recognition: Alignment-Free Approach [3]

  It uses a combination of PCA+LDA which can be computationally heavy.

Chapter – Three

METHODOLOGY

3.1 Architecture

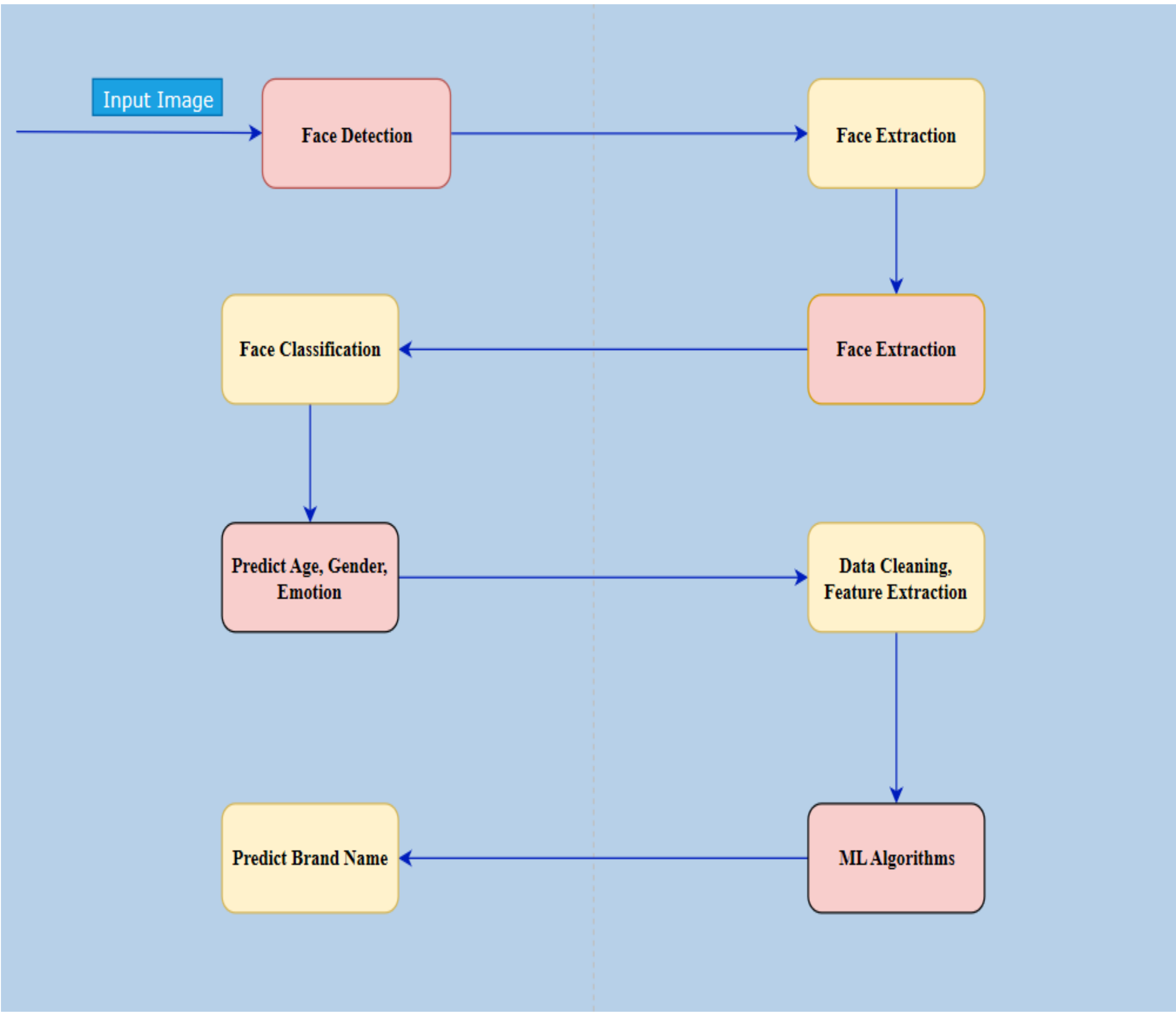


Figure 3.1.1. Architectural design of proposed system

3.1 Architecture

- Face Detection: It is done by using opencv2 to detect the face through webcam interface which can capture live feed.

- Face Extraction: Using opencv2 Deep Neural Network method readnet which will extract data from the files opencv_face_detector which will help us to compare the features with live feed.

- Face Classification: Using Convolution Neural Network we will classify the image on the basis of gender and age group.

- Predict Age and Gender: Using previously build open models and new image we can classify the person into his/her gender and age group and this is then feed into a word document.

- Dataset Cleaning: We will impute the missing values in dataset with the mean values for continuous variables, and median for categorical variables.

- Predicting Brand Name: Using ML algorithms such as Decision Tree and Random Forrest we the output of brand is given

- Output: The Output Screen will suggest users the Brand Outlet they should visit with the top 6 recommendations.

3.2 Hardware requirements

- Laptop
  Laptop will be the computing mobile machine through which users can interact with the system.

- Webcam
  Webcam should be enabled on a laptop so that it can be used to detect the face of people as well as show what is their gender and age range.

- RAM 8GB(Minimum)
  Deep Learning Networks such as Convolutional Network are very heavy on the system and consume lot of RAM, thus a minimum of 8GB RAM is recommended, 16GB is ideal.

- HDD 512GB and SDD 128GB(Minimum)
  HDD will be required to store images and data and SDD will be required to retrieve it quickly thus minimum of 128GB SDD and 512GB HDD is recommended.
  A storage of 1TB SDD is ideal.

3.3 Software requirements

- Operating System- Windows 10
  Operating System on the mobile laptop must be Windows 10.

- Python 3.5 or higher
  The coding of the project is done in Python and has most of the libraries which are being used from the v3.5.

- Anaconda
  Anaconda IDE is recommended because it already has a good interface to incorporate Python and Spyder.

- SPYDER Integrated Development Environment
  We will be using SPYDER to run our code.

Chapter – Four

IMPLEMENTATION

4.1 Working

- The Webcam is used as an interface which is used to detect the facial features of the Customer

- Using opencv2 Deep Neural Network method readnet which will extract data from the files opencv_face_detector which will help us to compare the features that have been already trained with the facial features that has been captured by webcam.

- We will use two steps of Machine learning Algorithm. The first will be used to give us output of age and gender, this output will be feed to second stage of Machine Learning Algorithm where it will be used to predict Brand and Products.

- Using Convolution Neural Network we will classify the image on the basis of gender and age group, this will give us the required age group and gender.

- Now we will clean the already gathered Survey Data by imputing missing, erroneous values

- The Categorical Feature ie age group will be converted to Numerical for prediction by using Label Encoding

- We divide Survey data into train and test and train the above data using Decision Tree and Random Forrest algorithm

- The new input ie the prediction of age group and gender is passed through the trained model to give us Recommended Brand and top product suggestions.

4.1 Working

UML Use Case Diagram

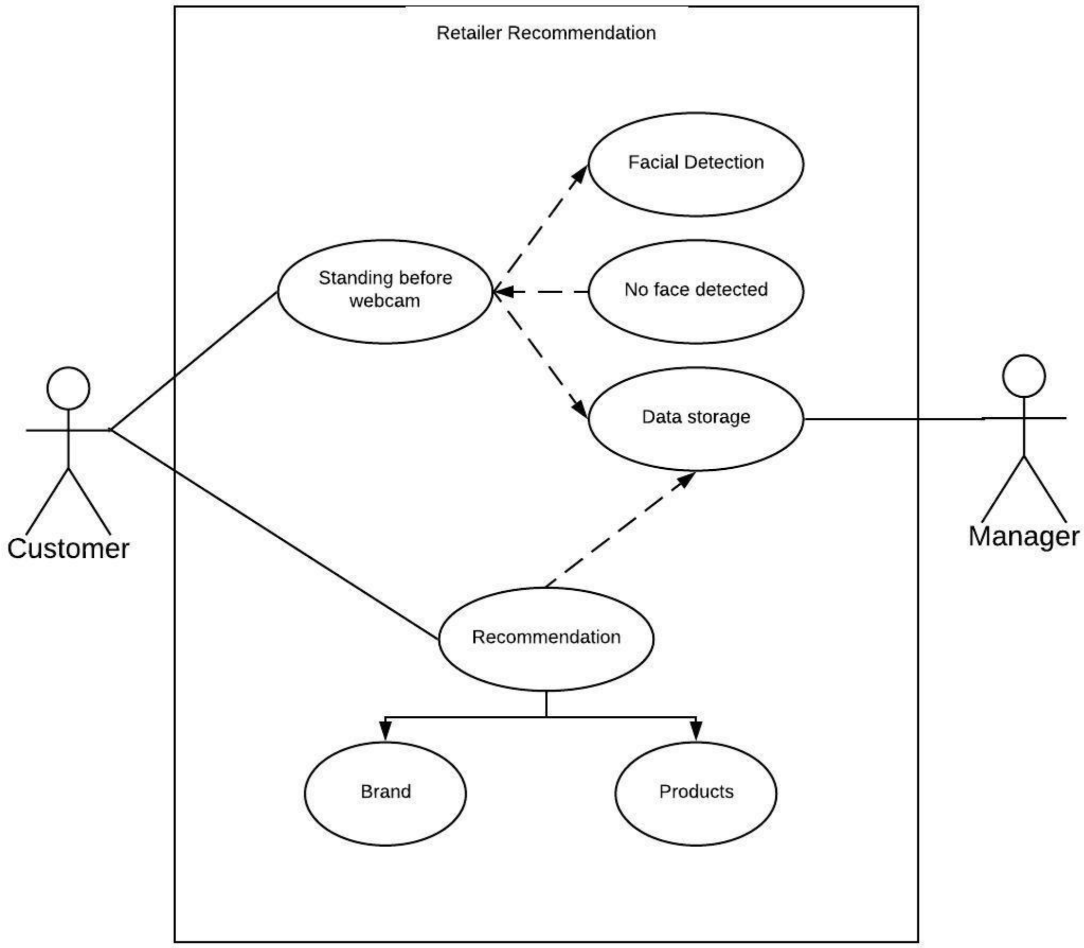


Fig 4.1.1 Use Case Diagram

Fig 4.1.1 shows us the use case diagram and the relation of main actor ie customer between different entities such as webcam and prediction output and the relation between the secondary actor ie manager between data storing.

4.2 Algorithms

1) Convolution Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

Input : Images/Videos

Output : Age , Gender.

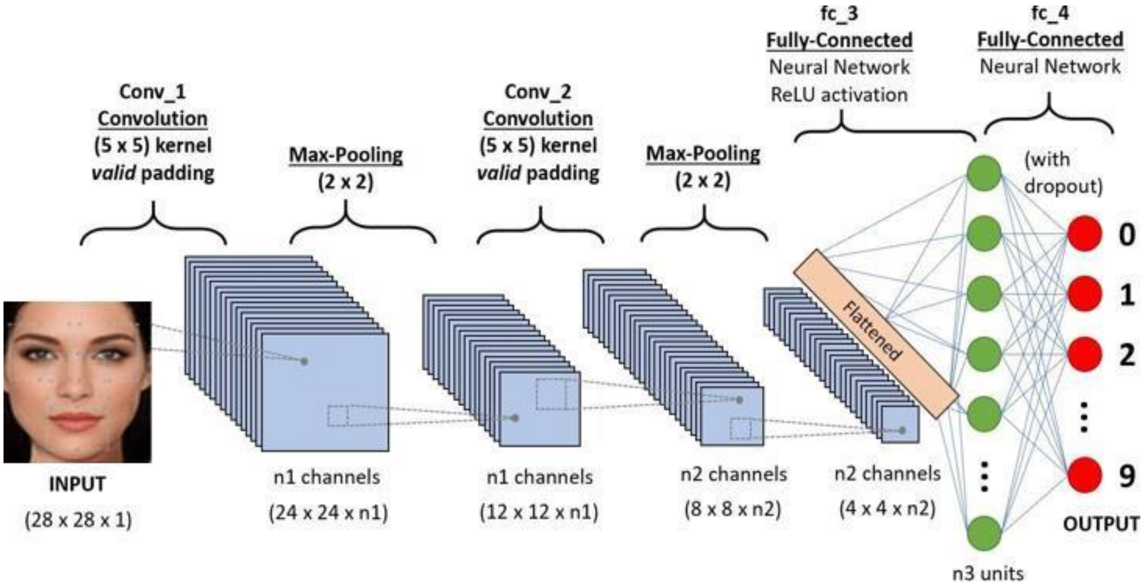


Fig 4.2.1 CNN Working

The convolutional neural network for this python project has 3 convolutional layers:

- Convolutional layer; 96 nodes, kernel size 7
- Convolutional layer; 256 nodes, kernel size 5
- Convolutional layer; 384 nodes, kernel size 3

It has 2 fully connected layers, each with 512 nodes, and a final output layer of softmax type.

In the first phase of project, we will:

- Detect faces
- Classify into Male/Female
- Classify into one of the 8 age ranges
- Put the results on the image and display it

For face detection, we have a .pb file- this is a protobuf file (protocol buffer); it holds the graph definition and the trained weights of the model. We can use this to run the trained model. And while a .pb file holds the protobuf in binary format, one with the .pbtxt extension holds it in text format. These are TensorFlow files. For age and gender, the .prototxt files describe the network configuration and the .caffemodel file defines the internal states of the parameters of the layers.

2. We use the argparse library to create an argument parser so we can get the image argument from the command prompt. We make it parse the argument holding the path to the image to classify gender and age for.

3. For face, age, and gender, initialize protocol buffer and model.

4. Initialize the mean values for the model and the lists of age ranges and genders to classify from.

5. Now, use the readNet() method to load the networks. The first parameter holds trained weights and the second carries network configuration.

6. Let's capture video stream in case you'd like to classify on a webcam's stream. Set padding to 20.

7. Now until any key is pressed, we read the stream and store the content into the names hasFrame and frame. If it isn't a video, it must wait, and so we call up waitKey() from cv2, then break.

8. Let's make a call to the highlightFace() function with the faceNet and frame parameters, and what this returns, we will store in the names resultImg and faceBoxes. And if we got 0 faceBoxes, it means there was no face to detect.

Here, net is faceNet- this model is the DNN Face Detector and holds only about 2.7MB on disk.

- Create a shallow copy of frame and get its height and width.
- Create a blob from the shallow copy.
- Set the input and make a forward pass to the network.
- faceBoxes is an empty list now. for each value in 0 to 127, define the confidence (between 0 and 1). Wherever we find the confidence greater than the confidence threshold, which is 0.7, we get the x1, y1, x2, and y2 coordinates and append a list of those to faceBoxes.
- Then, we put up rectangles on the image for each such list of coordinates and return two things: the shallow copy and the list of faceBoxes.

9. But if there are indeed faceBoxes, for each of those, we define the face, create a 4-dimensional blob from the image. In doing this, we scale it, resize it, and pass in the mean values.

10. We feed the input and give the network a forward pass to get the confidence of the two class. Whichever is higher, that is the gender of the person in the picture.

11. Then, we do the same thing for age.

12. We'll add the gender and age texts to the resulting image and display it with imshow().

2)Random Forest

Decision trees leave you with a difficult decision. A deep tree with lots of leaves will over fit because each prediction is coming from historical data from only the few houses at its leaf. But a shallow tree with few leaves will perform poorly because it fails to capture as many distinctions in the raw data.

The random forest uses many trees, and it makes a prediction by averaging the predictions of each component tree for regression problems.

Input : Age , Gender, (This are O/P of Facial Recognition)

Output : Brand Name .

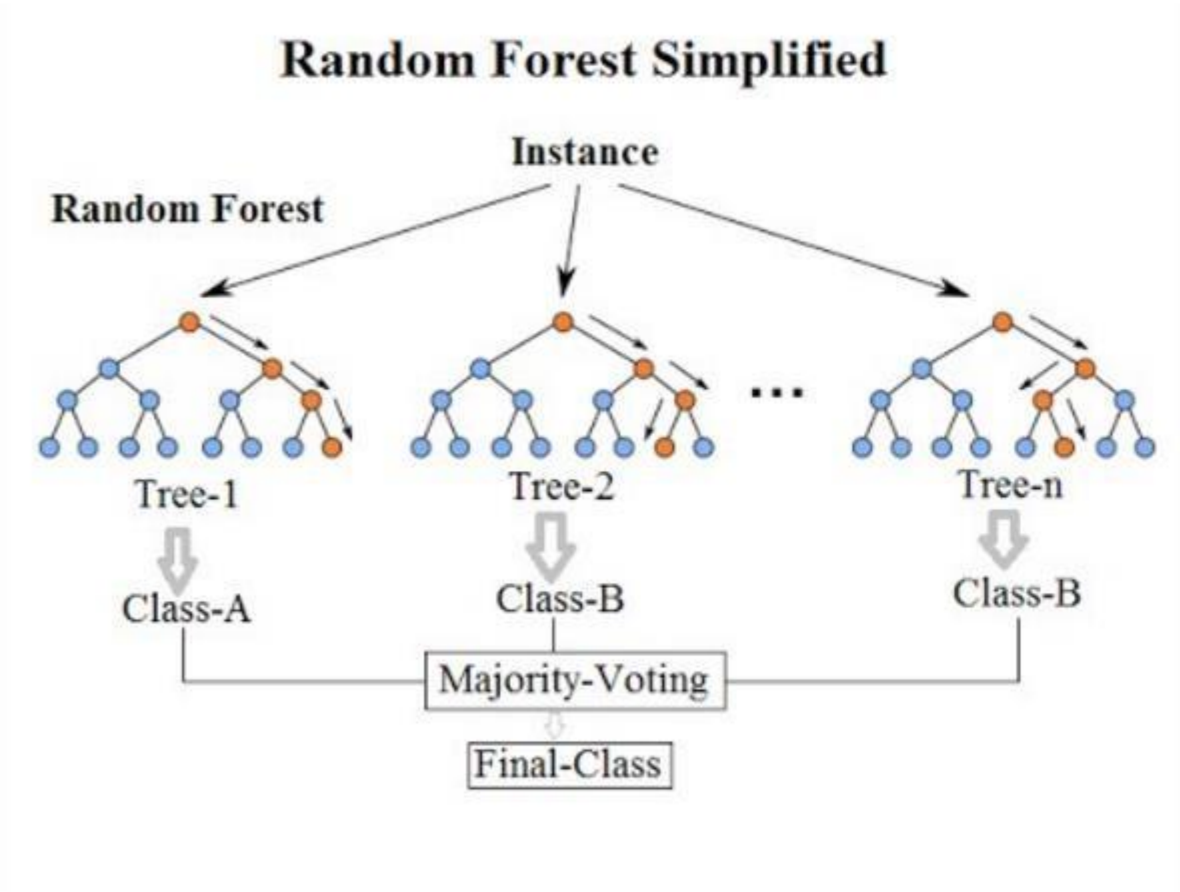


Fig 4.2.2 Random Forest Working

In the second phase of project we will:

1. We import data from Project.csv file which contains Age and Gender and Brand Recommendation.
2. We have 21,961 data points which we have imported.
3. Age and Gender being categorical variables have to be converted into numerical equivalence thus we use Dummies method on this variable, while we use Label Encoding for Output Variable.
4. Not the Dataframe which has 21,961 datapoints is divided into training and test data in the ratio of 80:20 by using the method train_test_split.
5. Now we will use RandomForrestClassifier which will learn from it's fitting and learning on training data.
6. RandomForrestClassifier is an improved variant of Decision trees where a large number of learning trees are used to predict an Output.
7. The Problem with decision trees can be that they can overfit and hence produce some errors, so a large number of trees which have different parameters can average out the errors and hence give us better results, hence we have used RandomForrestClassifier.
8. For choosing the next node we can use methods such as Gini Index or Entropy Gain, we will be using Gini Index over here.
9. The average of all the trees can be taken using Soft Voting method or Hard Voting method, we will be using the default Soft Voting method to get our Output i.e. Brand Name.
10. But this Output is label encoded, thus we perform Inverse Transform to get the Output.

Chapter – Five

CONCLUSION

Main purpose of the proposed system is to provide business advantage to retail industry. By moving the recommender technology to offline stores, an excess of possibilities would be opened for entrepreneurs and retail stores. By serving their customers with personalised offers, they increase their customer loyalty and their sales. This equips them to effectively combat the major online retailers like Flipkart, SnapDeal, Amazon etc. Thus, we conclude that by using our model, the sale and the user experience can be significantly improved.

The offline retailers can go toe to toe with the online retailers and can have major say in the market share.

Offline stores are an integral part of any economy and this project will help them to survive the battle with online retailers.

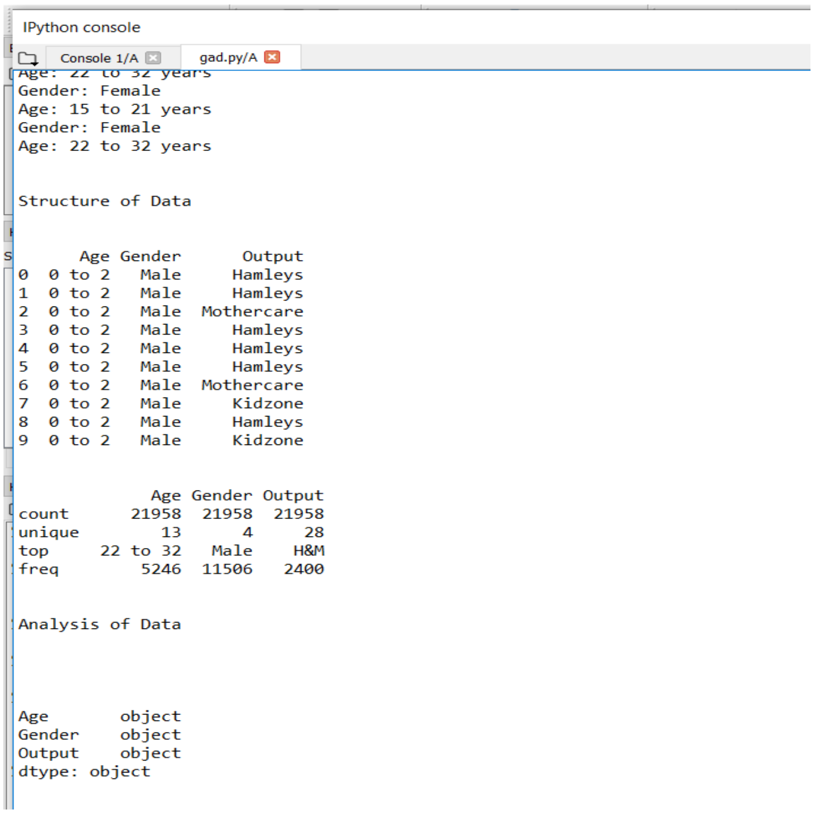
Future Scope: The project can be improved and implemented by adding some more features such as emotion, seasons etc which will enable better prediction.

Chapter – Six

APPENDIX

Working model Screenshots

1) Data Structure and Analysis



```
IPython console
Console 1/A    gad.py/A
Age: 22 to 32 years
Gender: Female
Age: 15 to 21 years
Gender: Female
Age: 22 to 32 years


Structure of Data


      Age Gender      Output
0  0 to 2   Male     Hamleys
1  0 to 2   Male     Hamleys
2  0 to 2   Male  Mothercare
3  0 to 2   Male     Hamleys
4  0 to 2   Male     Hamleys
5  0 to 2   Male     Hamleys
6  0 to 2   Male  Mothercare
7  0 to 2   Male     Kidzone
8  0 to 2   Male     Hamleys
9  0 to 2   Male     Kidzone


             Age Gender Output
count      21958  21958  21958
unique        13      4     28
top     22 to 32   Male    H&M
freq        5246  11506   2400


Analysis of Data



Age       object
Gender    object
Output    object
dtype: object
```

Fig 6.1.1 Structure and Analysis

From Fig 6.1.1, we can see that the structure of data has 21958 input data points, which have 3 attributes namely Age, Gender and target variable Output.
There are 13 unique Age categories,4 Gender categories and 28 Output Brands.
Age, Gender and Output all belong to object data type, hence all of them are categorical.

Working model Screenshots

2) Data Cleaning

(i) Age and Gender

```
22 to 32        5246
33 to 45        3784
15 to 21        3368
46 to 59        2144
60 and above    2124
0 to 2          1952
3 to 7          1200
8 to 14         1048
3 to 7           952
36                40
25                36
28                36
78                28
Name: Age, dtype: int64
Male      11506
Female     9772
F           628
M            52
Name: Gender, dtype: int64
```

Fig 6.2.1.1 Age and Gender Before Cleaning

```
Male      11558
Female    10400
Name: Gender, dtype: int64
22 to 32        5318
33 to 45        3824
15 to 21        3368
3 to 7          2152
60 and above    2152
46 to 59        2144
0 to 2          1952
8 to 14         1048
Name: Age, dtype: int64
```

Fig 6.2.1.2 Age and Gender After Cleaning

Fig 6.2.1.1 Shows data before cleaning we can see that the Age Category is unclean 36 belongs to category 33 to 45, 25 belongs to 22 to 32 and so on, Similarly Gender category also has farce data such as F which stands for Female hence should be merged together and M which stands for Male and are one and the same.

Fig 6.2.1.2 Shows data after cleaning where the erroneous data has been cleaned and merged as per requirement.

Working model Screenshots

2)Data Cleaning

ii)Brands

```
Name: Gender, dtype: int64
H&M              2400
Zara             2228
Levi             1892
Hamleys          1704
Adidas           1416
Nike             1410
Nyka             1372
Kidzone          1344
Mothercare       1292
Starbucks        1024
Crossword        1020
Myo Thai Spa     1016
Peter England    1004
Nike              872
McDonalds         452
Max               360
Inox              256
Smaash            216
Westside          144
Louis Vuitton     108
Thai Spa           80
Armani             80
LEVI               72
Van Heusen         64
Ptr England        52
Vans               40
Levi               36
NYKA                4
Name: Output, dtype: int64
```

Fig 6.2.2.1 Brands Before Cleaning

```
H&M              2400
Nike             2282
Zara             2228
Levi             2000
Hamleys          1704
Adidas           1416
Nyka             1376
Kidzone          1344
Mothercare       1292
Myo Thai Spa     1096
Peter England    1056
Starbucks        1024
Crossword        1020
McDonalds         452
Max               360
Inox              256
Smaash            216
Westside          144
Louis Vuitton     108
Van Heusen        104
Armani             80
Name: Output, dtype: int64
```

Fig 6.2.2.2 Brands After Cleaning

Fig 6.2.2.1 Show the Output Target Brands, we can see that while imputation for survey the users have made many mistakes LEVI and Levi are one and the same, so are NYKA and Nyka, Ptr England and Peter England, Thai Spa and Myoi Thai Spa and so on

Fig 6.2.2.2 Thus we have merged and cleaned the data into their respective categories.

Working model Screenshots

3) Univariate Analysis

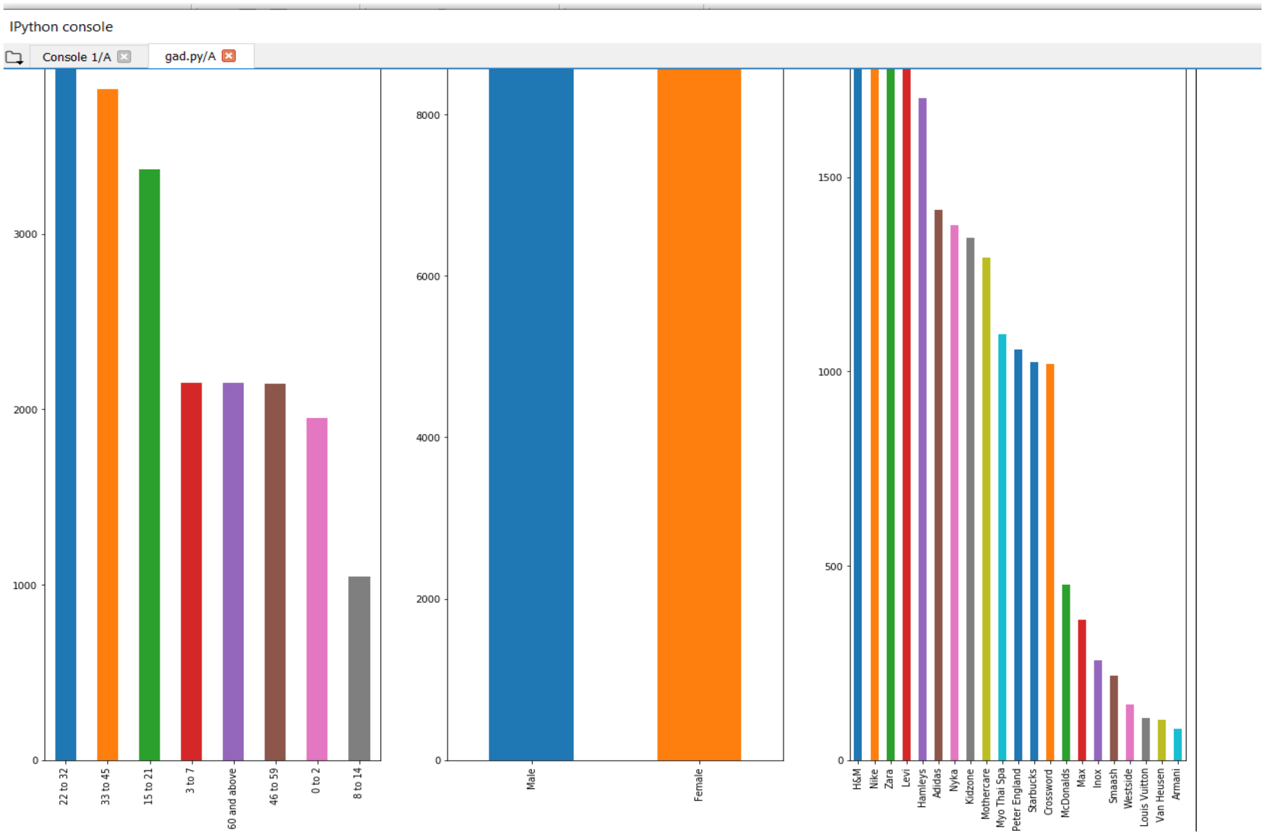


Fig 6.3.1 Distribution of Age Groups, Gender, Brands

Fig 6.3.1 shows the univariate analysis which shows the distribution of data

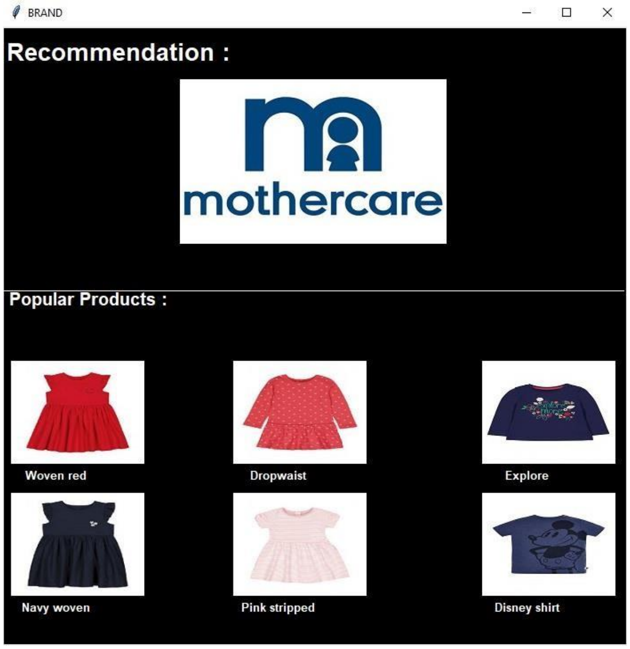
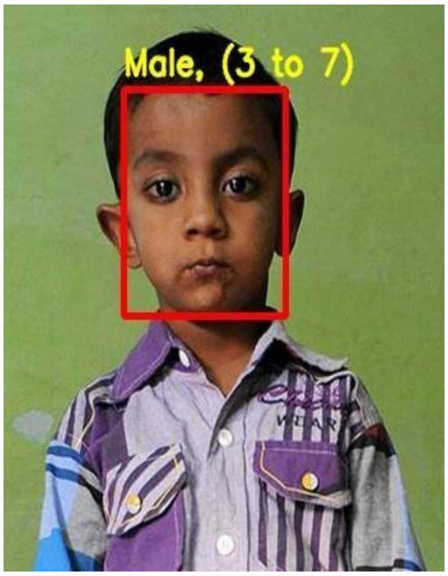
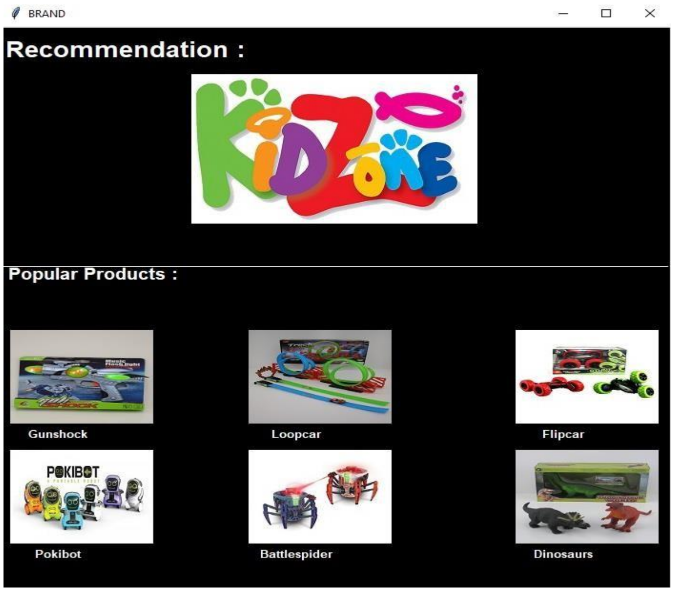
This shows that the age bracket of 22 to 32 is most likely to visit mall since they are young and have achieved spending power right now, hence ads and offers should be targeted towards them. It also shows that both men and women visit Malls on a regularly basis, there is no gender disparity.

It also shows H&M, Nike and Zara to be the most popular choices.

Working model Screenshots

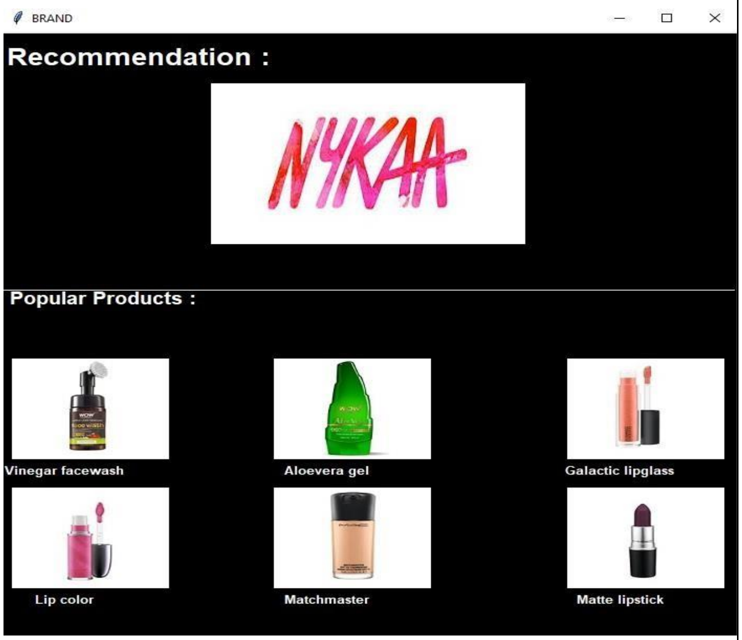
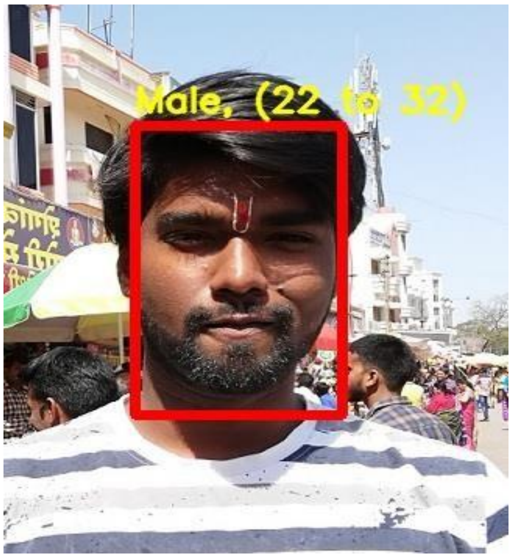
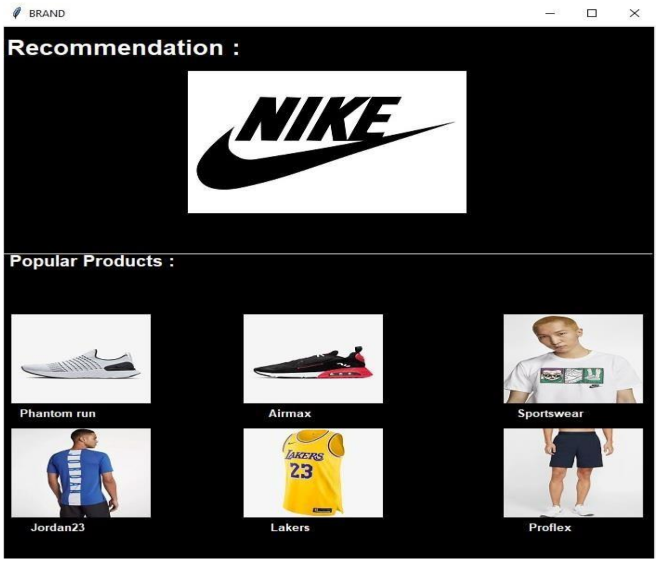
4) Output

Table 6.4.1 Brand recommendation of various age groups

Facial Recognotion	Brand Recommendation
	
	

Working model Screenshots

4) Output

<table>
<tr><th>Facial Recognotion</th><th>Brand Recommendation</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>
</td><td>
</td></tr>
</table>

Working model Screenshots

4) Output

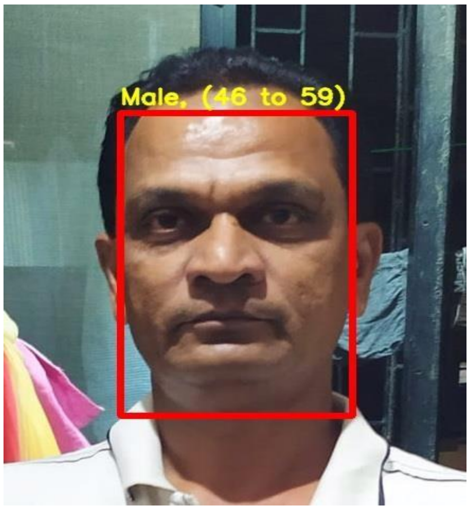
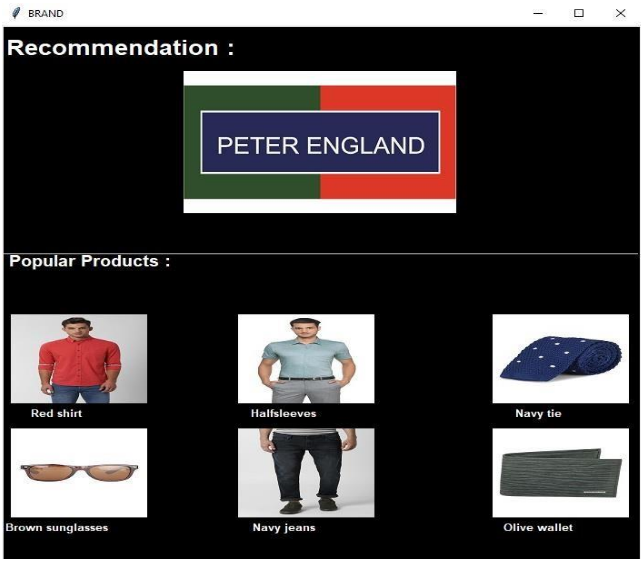
Facial Recognotion	Brand Recommendation
	

Table 6.4.1 shows us the Output of Facial recognition and recommendation of brand for that Gender and Age category.

We have also added top 6 product recommendations of the brand according to the Age and Gender category of the respective person, so as to provide him with options to buy.

Facial Recognition is the first part of Output where we get the Age and Gender category, Brand and Product recommendation is the second part.

Working model Screenshots

5) Accuracy

```
IPython console
gad.py/A

Levi             2000
Hamleys          1704
Adidas           1416
Nyka             1376
Kidzone          1344
Mothercare       1292
Myo Thai Spa     1096
Peter England    1056
Starbucks        1024
Crossword        1020
McDonalds         452
Max               360
Inox              256
Smaash            216
Westside          144
Louis Vuitton     108
Van Heusen        104
Armani             80
Name: Output, dtype: int64


Univariate Analysis


Accuracy Score on test data:  83.9936247723133
Accuracy Score on test data:  83.9936247723133



['Nike']
Nike
        Age Gender Output
0  22 to 32   Male   Nike
```

Fig 6.5.1 Accuracy

Fig 6.5.1 shows us the Accuracy on new test data by using Random Forrest algorithm, which comes out to be 83.99%

Chapter – Seven

REFERENCES

[1] Age Group Estimation and Gender Recognition Using Face Features in The International Journal of Engineering and Science (IJES) || Volume || 7 || Issue || 7 Ver. I|| Pages || PP01-07 || 2018 || ISSN (e): 2319 – 1813 ISSN (p): 23-19 – 1805 Prajakta A. Mélange , Dr. G. S. Sable.

[2] An Image Mining System for Gender Classification & Age Prediction Based on Facial Features in e-ISSN: 2278 Volume 10, Issue 6 (May. - Jun. 2013) Ms.Dhanashri Shirkey , Prof.Dr.S.R. Gupta .

[3] Partial Face Recognition: Alignment-Free Approach in IEEE transactions on pattern analysis Shengcai Liao, Anil K. Jain, Fellow, IEEE and Stan Z. Li .

Chapter – Eight

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