SMART FASHION RECOMMENDER APPLICATION

A PROJECT REPORT

Submitted by

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GNANAMANI COLLEGE OF TECHNOLOGY

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It was a great learning experience. We would like to take this opportunity to express our gratitude.

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TITLE

1. INTODUCTION

In recent years, the textile and fashion industries have witnessed an enormous amount of growth in fast fashion. On e-commerce platforms, where numerous choices are available, an efficient recommendation system is required to sort, order, and efficiently convey relevant product content or information to users. Image-based fashion recommendation systems (FRSs) have attracted a huge amount of attention from fast fashion retailers as they provide a personalized shopping experience to consumers. With the technological advancements, this branch of artificial intelligence exhibits a tremendous amount of potential in image processing, parsing, classification, and segmentation. Despite its huge potential, the number of academic articles on this topic is limited. The available studies do not provide a rigorous review of fashion recommendation systems and the corresponding filtering techniques.

1.1 Project Overview

Clothing is a kind of symbol that represents people’s internal perceptions through their outer appearance. It conveys information about their choices, faith, personality, profession, social status, and attitude towards life. Therefore, clothing is believed to be a nonverbal way of communicating and a major part of people’s outer appearance . Recent technological advancements have enabled consumers to track current fashion trends around the globe, which influence their choices. Additionally, consumers’ clothing choices and product preference data have become available on the Internet in the form of text or opinions and images or pictures. Since these images contain information about people from all around the world, both online and offline fashion retailers are using these platforms to reach billions of users who are active on the Internet. Therefore, e-commerce has become the predominant channel for shopping in recent years. The ability of recommendation systems to provide personalized recommendations and respond quickly to the consumer’s choices has contributed significantly to the expansion of e-commerce sales. According to different studies, e-commerce retailers, such as Amazon, eBay, and Shopstyle, and social networking sites, such as Pinterest, Snapchat, Instagram, Facebook, Chictopia, and Lookbook, are now regarded as the most popular media for fashion advice and

recommendations. Therefore, the purpose of this paper is to present an integrative review of the research related to fashion recommendation systems. Moreover, Guan et al. cited research published until 2015. Therefore, the first objective of this paper is to review the most recent research published on this topic from 2010 to 2020. The previous study did not provide an in-depth analysis of the computational methods or algorithms corresponding to the fashion recommendation systems. This review study aims to fulfill this research gap and rigorously study the principles underlying, the methods used by, and the performance of the state-of-the-art fashion recommendation systems. To the best of our knowledge, this in-depth study is first of its kind. It includes research articles related to image parsing, clothing and body shape identification, and fashion attribute recognition, which are critical parts of fashion recommendation systems (FRSs). This review paper also provides a guideline for a research methodology to be used by future researchers in this field. The first section of this review discusses the history and background of FRSs. This review paper has identified state-of-the art algorithms and filtering techniques that have high potential to become more popular in the future. The sections of this paper are arranged in the order of the important FRS components, so that the reader can gain a substantial understanding of components such as algorithmic models before moving to other important components such as filtering techniques.

1.2 Purpose

The era of recommendation systems originally started in the 1990s based on the widespread research progress in Collective Intelligence. During this period, recommendations were generally provided to consumers based on their rating structure. The first consumer-focused recommendation system was developed and commercialized by Goldberg, Nichols, Oki and Terry in 1992. Tapestry, an electronic messaging system was developed to allow users only to rate messages as either a good or bad product and service. However, now there are plenty of methods to obtain information about the consumer's liking for a product through the Internet. These data can be retrieved in the forms of voting, tagging, reviewing and the number of likes or dislikes the user provides. It may also include reviews written in blogs, videos uploaded on YouTube or messages about a product.

LITERATURE SURVEY

2.1 Existing problem

To put this survey in context, we identified and present related review and survey articles to explain in which ways our article differs from and extends earlier work. In a recent work, a survey of fashion recommender application, i.e., visual, audio, and/or textual features. The domains studied in this survey include various ones such as media streaming for audio and video recommendation, e-commerce for recommending different products including fashion items, news, and information recommendation, social media, and so forth. While fashion RS were also discussed, the authors only included a small portion of the topics and papers in this domain. Here, we discuss and present a comprehensive survey of significant tasks, challenges, and types of content used in the fashion RS field. We have also identified surveys [29, 170] where the authors present a literature review of techniques at the intersection of fashion and computer vision (CV) and/or natural language processing (NLP). While we find these works relevant to this article, they remain largely different from the review presented here as those systems are not focused on RS but on other aspects of the fashion domain, such as text generation from images or pose estimation. Moreover, as another point of difference, we also provide recent techniques dealing with item visual and textual content representation exploited by RS approaches. Perhaps the most relevant work to our current survey is a recent book chapter by Jaradat et al. [75] on fashion RS. This chapter focuses on discussing the state of the art of fashion recommendation systems; in particular, the authors affirm that deep learning represented a turning point with respect to the canonical approaches and therefore the authors examined four different tasks that use this new approach. Additionally they provided examples and possible problems and their evaluation. In particular the authors focused their review on tasks related to social media and the size recommendation

2.2REFERENCES

CASE STUDY I

TITLE

A Systematic Study on the Recommender Systems in the E-Commerce

AUTHOR

Pegah Malekpour Alamdari, N. J. Navimipour, M. Hosseinzadeh: 2020

PROJECT DESCRIPTION

Electronic commerce or e-commerce includes the service and good exchange through electronic support like the Internet. It plays a crucial role in today's business and users' experience. Also, e-commerce platforms produce a vast amount of information. So, Recommender Systems (RSs) are a solution to overcome the information overload problem. They provide personalized recommendations to improve user satisfaction. The present article illustrates a comprehensive and Systematic Literature Review (SLR) regarding the papers published in the field of e-commerce recommender systems. We reviewed the selected papers to identify the gaps and significant issues of the RSs' traditional methods, which guide the researchers to do future work. So, we provided the traditional techniques, challenges, and open issues concerning traditional methods of the field of review based on the selected papers. This review includes five categories of the RSs' algorithms, including Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic-Based Filtering (DBF), hybrid filtering, and Knowledge-Based Filtering (KBF).

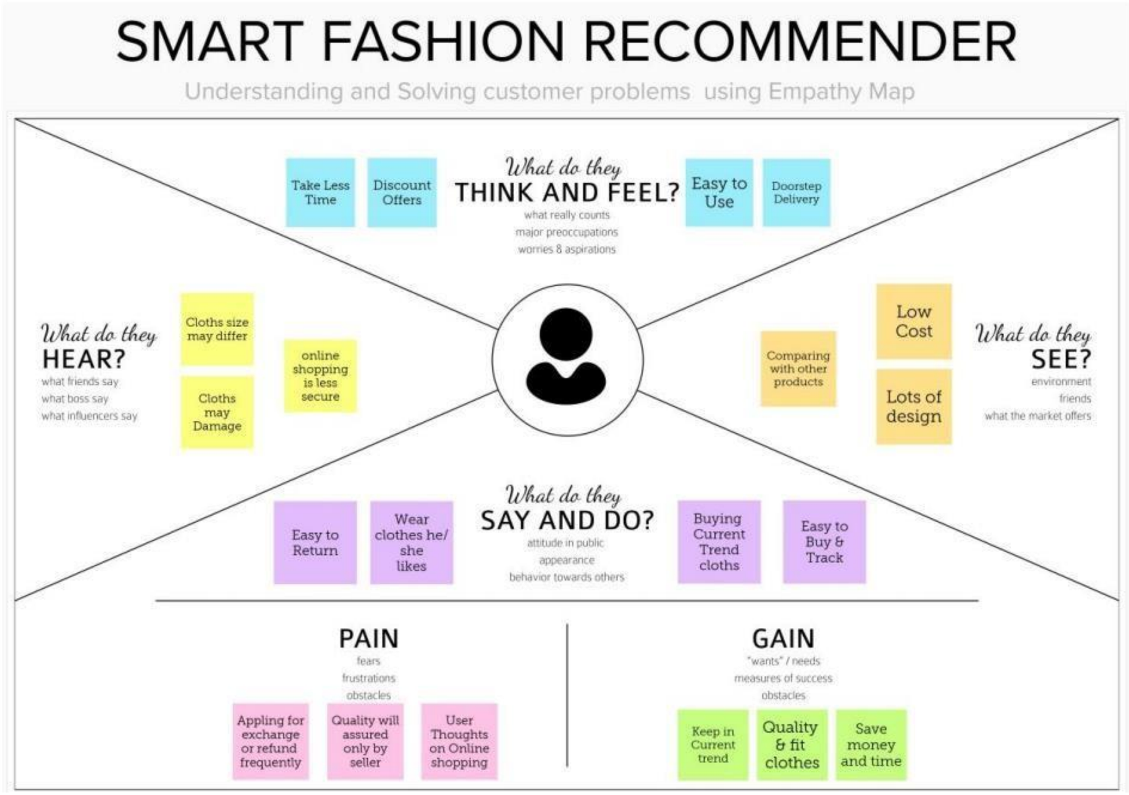
2.3 PROBLEM STATEMENT DEFINITION

If the recommender systems is to be provide recommendations based on recorded information on the users preferences. High level fashion analysis includes recommendation, fashion synthesis, seeks a wide perspective on the generality of fashion and has not focused on image based .

3.IDEATION AND PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS

Empathy Map Canvas:



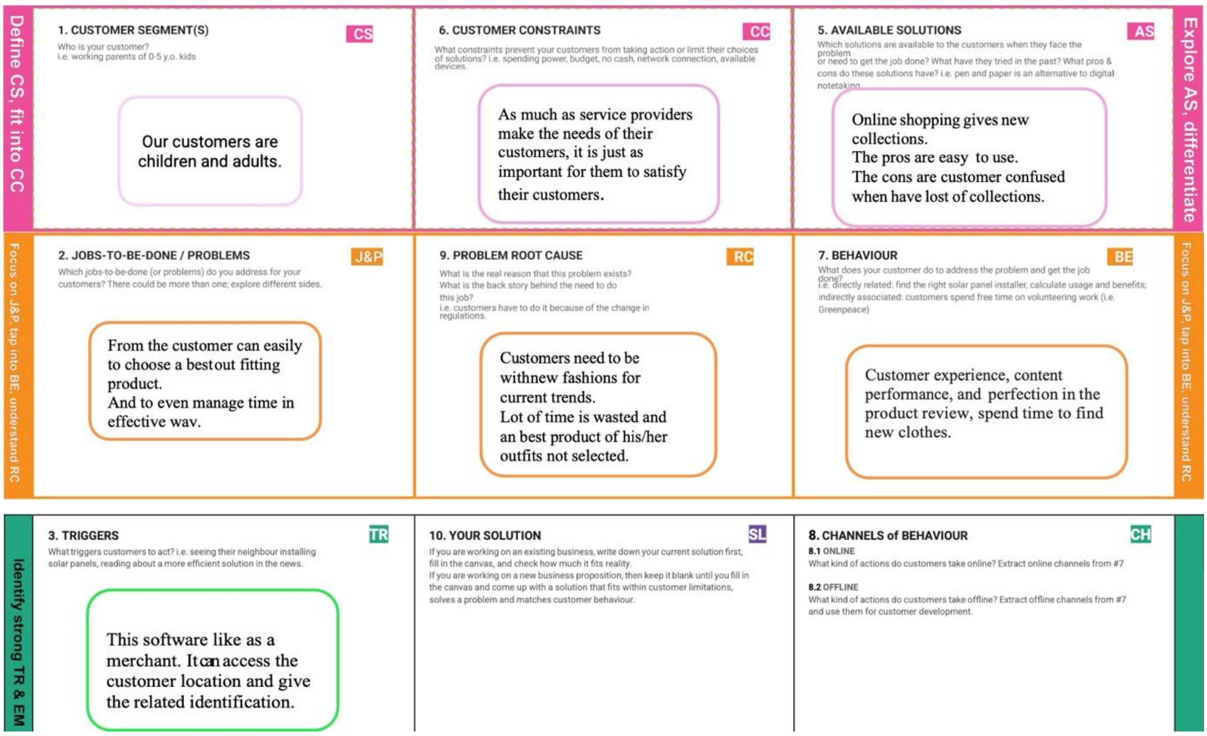
3.2 IDEATION AND BRAINSTORMING

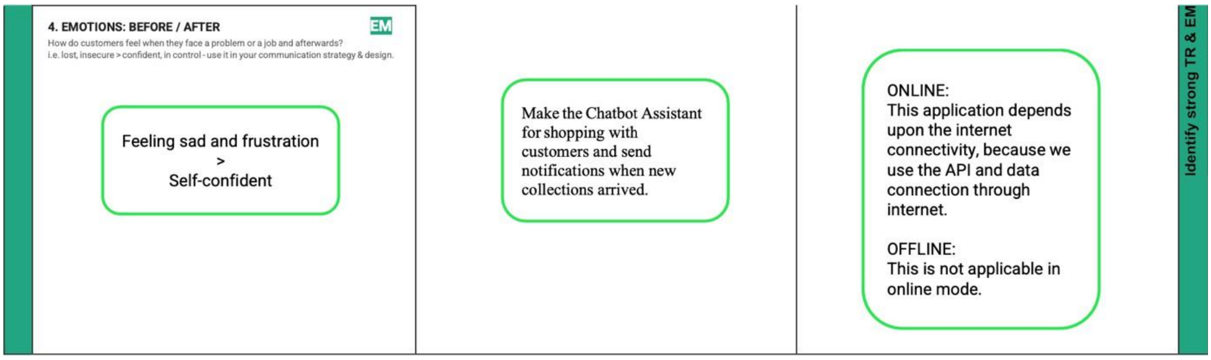
3.3 PROPOSED SOLUTION

Proposed Solution :

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	Customers feels difficult when Search many websites to find Fashion clothes and accessories.
2.	Idea / Solution description	Customers directly make online shopping based on customer choice without any search.
3.	Novelty / Uniqueness	The customer will talk to Chat Bot regarding the Products. Get the recommendations based on information provided by the user
4.	Social Impact / Customer Satisfaction	The user friendly interface, Assistants form chat bot finding dress makes customer satisfied.
5.	Business Model (Revenue Model)	The chat bot sells our Products to customer. Customers buy our products and generate revenue
6.	Scalability of the Solution	We can easily scalable our Applications by increases the items and products

3.4 PROBLEM SOLUTION FIT





4. REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENT

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Delivery confirmation	Confirmation via email and phone number
FR-4	Assistance	Bot is integrated with the application to make theusability simple

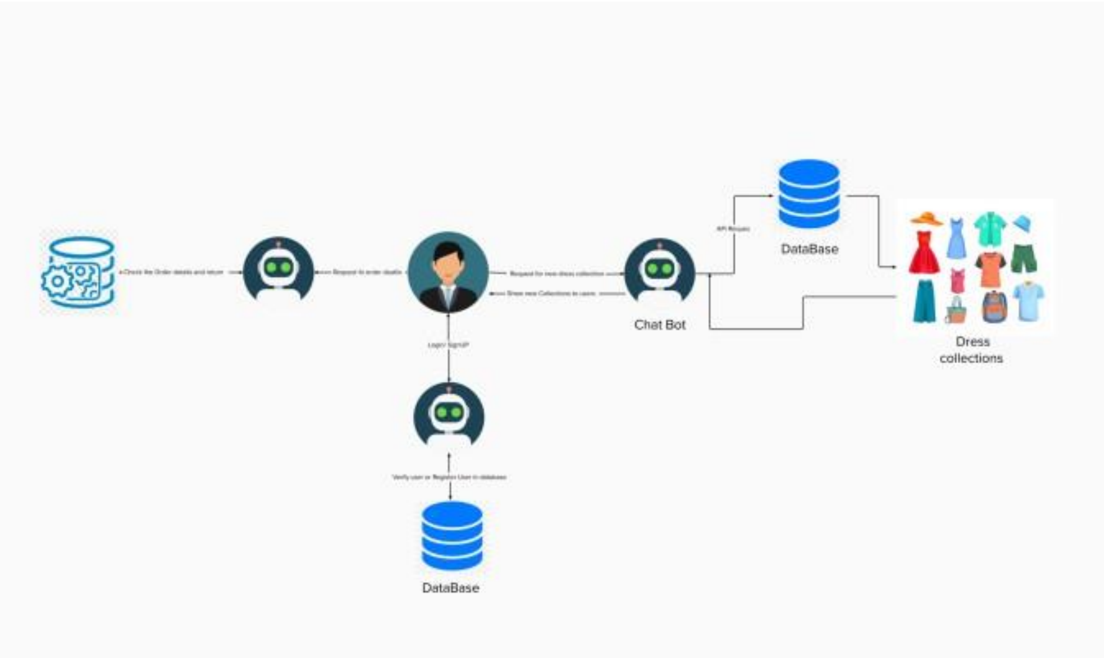
4.2 NON-FUNCTIONAL REQUIREMENTS

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	A user-friendly interface with chat bot to make usability efficient
NFR-2	**Security**	Secured connection HTTPS should be established for transmitting requests and responses
NFR-3	**Reliability**	The system should handle excepted as well as unexpected errors and exceptions to avoid termination of the program
NFR-4	**Performance**	The system shall be able to handle multiple requests at any given point in time and generate an appropriate response.
NFR-5	**Availability**	It is a cloud based web application so user can access without any platform limitations ,just using a browsers with a internet connection is enough for use the application
NFR-6	**Scalability**	It has a quick request and response time, high throughput, enough network resources and so on.

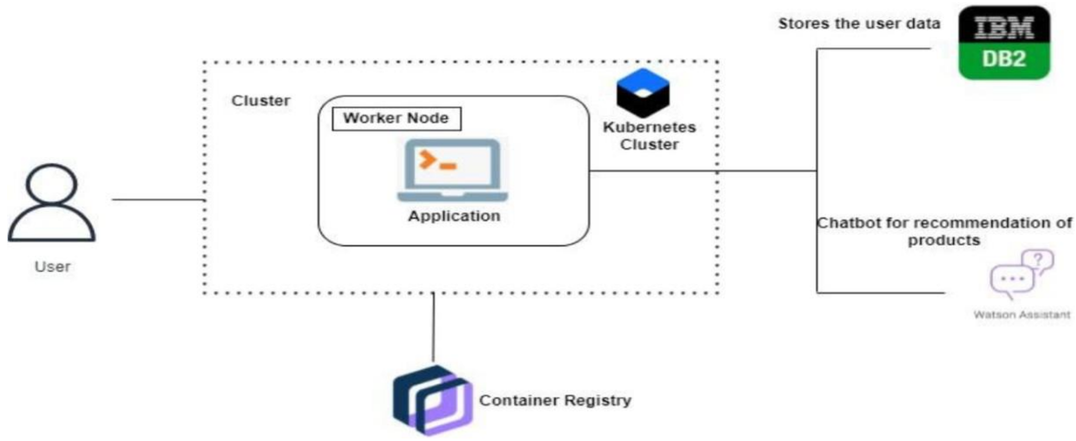
5.PROJECT DESIGN FLOW

5.1 DATA FLOW DIAGRAMS

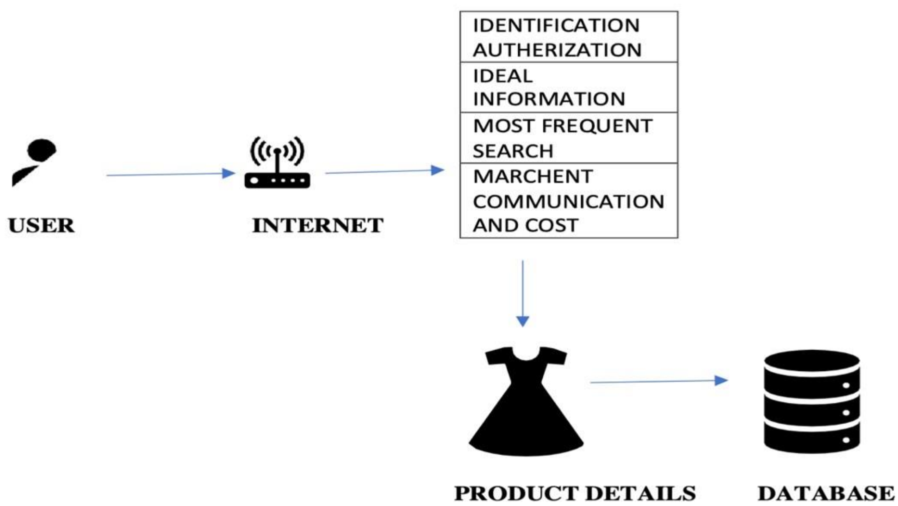
A Data Flow Diagram (DFD) is a traditional visual representation of the informationflows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leavesthe system, what changes the information, and where data is stored.



5.2 SOLUTION ARCHITECTURE



Example - Solution Architecture Diagram:



5.3 USER STORIES

User Stories

Use the below template to list all the user stories for the product.

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through Facebook	I can register & access the dashboard with Facebook Login	Low	Sprint-2
		USN-4	As a user, I can register for the application through Gmail		Medium	Sprint-1
	Login	USN-5	As a user, I can log into the application by entering email & password	I can access my data by login	High	Sprint-1
	Dashboard	USN-6	As a user , I can view the dashboard and by products		High	Sprit -2
Customer (Web user)	Registration / Login	USN-7	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard		Sprint -1
Customer Care Executive	Contact with Customers	USN-8	As a Customer customers care executive, I solve the customer Requirements and feedback	I can receive calls from customers	High	Sprint-1
Administrator	Check stock and Price , orders	USN_9	As a Administrator , I can Check the database And stock details and buying and selling prices	I am the administrator of the company	High	Sprint -2

6. PROJECT PLANNING AND SCHEDULING

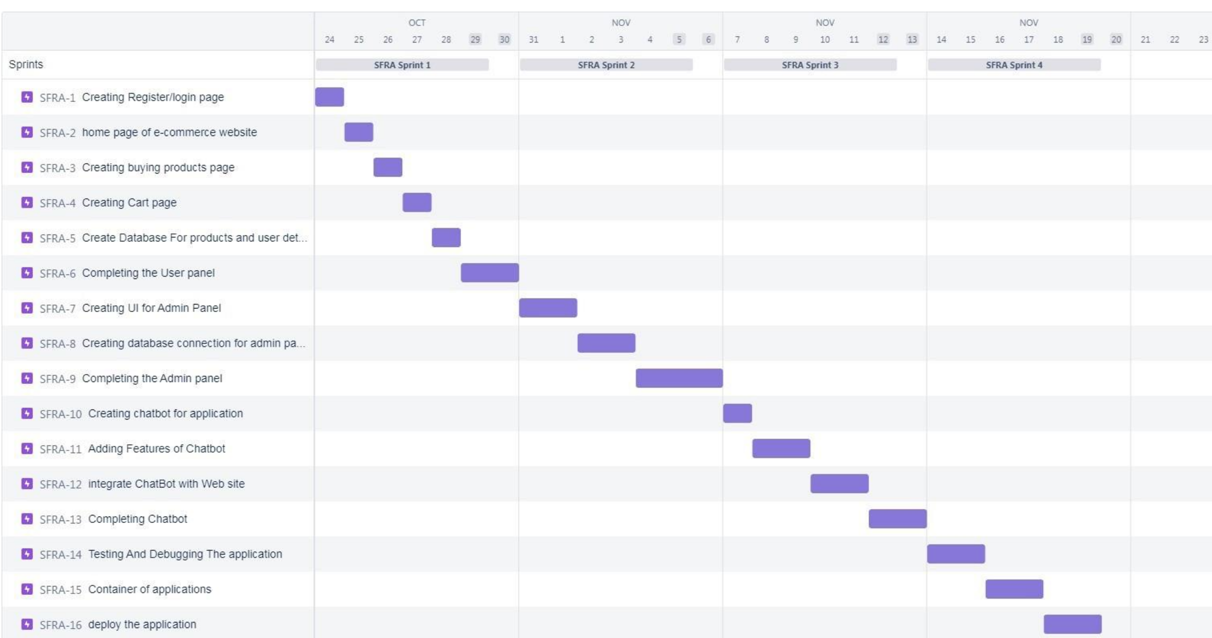
6.1 SPRINT PLANNING AND ESTIMATION

Sprint	Functional Requirement(Epic)	User Story Number	User Story /Task	Story Points	Priority	Team Members
Sprint-1	User Panel	USN-1	The user will login into the website and go through the products available on the website.	20	High	Subhashree. B Manjula. S Jeevanandhini.M Suvetha. M
Sprint-2	Admin Panel	USN-2	The role of the admin is to check out the database about the stock and have a track of all the things that the users are purchasing.	20	High	Subhashree. B Manjula. S Jeevanandhini.M Suvetha. M
Sprint-3	Chat Bot	USN-3	The user can directly talk to Chat bot regarding the products. Get the recommendations based on information provided by the user.	20	High	Subhashree.B Manjula.S Jeevanandhini.M Suvetha.M

Sprint-4	Final Delivery	USN-4	Container of applications using docker kubernetes and deployment the application. Create the documentation and final submit	20	High	Subhashree. B Manjula. S Jeevanandhini.M Suvetha. M
			the application			

6.2 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date(Planned)	Story Points Completed(as on Planned End Date	Sprint Release Date(Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022		29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Oct 2022		05 Oct 2022
Sprint-3	20	6 Days	07 Oct 2022	12 Oct 2022		12 Oct 2022
Sprint-4	20	6 Days	14 Oct 2022	19 Oct 2022		19 Oct 2022



7. CODING AND SOLUTIONING

7.1 FEATURE 1

```
<script>

 window.watsonAssistantChatOptions =

 {

  integrationID: "614a4315-ff80-4187-8fe4-2fd9b506b723", // The ID of this

  integration. region: "au-syd", // The region your integration is hosted in.

  serviceInstanceID: "9670dcf8-789f-4609-8d7a-6e25c412a9ec", // The ID of your

  service instance. onLoad: function(instance) { instance.render(); }

 };

 setTimeout(function(){

  const t=document.createElement('script');

  t.src="https://web-chat.global.assistant.watson.appdomain.cloud/versions/" +
(window.watsonAssistantChatOptions.clientVersion || 'latest') +
"/WatsonAssistantChatEntry.js";

  document.head.appendChild(t);

 });

</script>
```

7.2 FEATURE 2

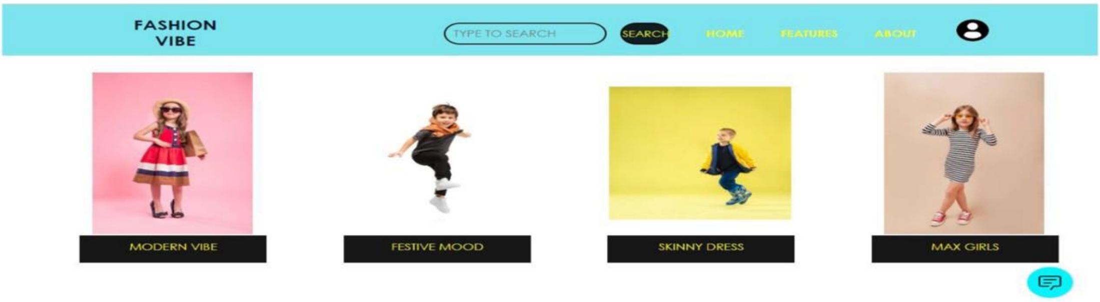
```
import stream lit as
st import tensor
flow import pandas
as pd from PIL
import Image
import pickle
import numpy as np
from tensor flow.keras.preprocessing import image
from tensor flow.keras.applications.resnet50 import ResNet50,
preprocess_input from tensor flow.keras.layers import
GlobalMaxPooling2D
from tensor flow.keras.models import
Sequential from numpy.linalg import norm
from sklearn.neighbors import Nearest
Neighbors import os
```

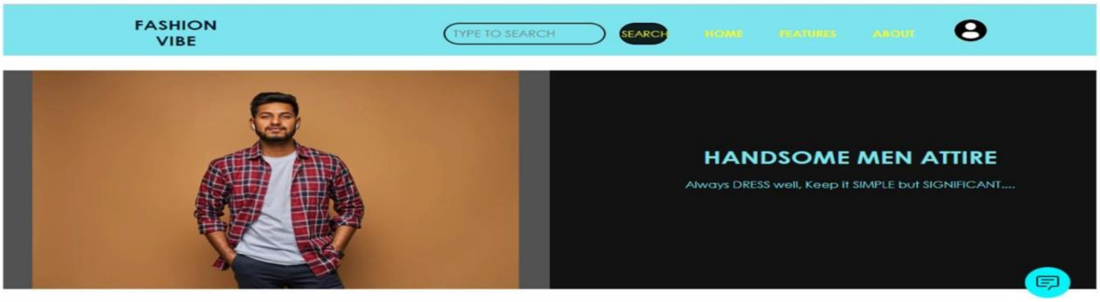
```
features_list =
pickle.load(open("image_features_embedding.pkl", "rb"))
img_files_list = pickle.load(open("img_files.pkl", "rb"))

model = ResNet50(weights="imagenet", include_top=False, input_shape=(224, 224, 3))
model.trainable = False
model = Sequential([model,

GlobalMaxPooling2D()])st.title('Clothing

recommender system')


def
   save_file(uploaded_file
   ):try:
      with open(os.path.join("uploader", uploaded_file.name),
         'wb') as f:f.write(uploaded_file.getbuffer())
         return
   1except:
      return 0


def extract_img_features(img_path, model):
   img            =            image.load_img(img_path,
   target_size=(224,        224))       img_array        =
   image.img_to_array(img)
   expand_img  =  np.expand_dims(img_array,
   axis=0)             preprocessed_img             =
   preprocess_input(expand_img)
   result_to_resnet                                  =
   model.predict(preprocessed_img)
   flatten_result = result_to_resnet.flatten()
   # normalizing
   result_normlized       =       flatten_result       /

   norm(flatten_result)return result_normlized


def recommendd(features, features_list):
   neighbors = NearestNeighbors(n_neighbors=6, algorithm='brute', metric='euclidean')
   neighbors.fit(features_list)

   distence, indices =

   neighbors.kneighbors([features])return
```

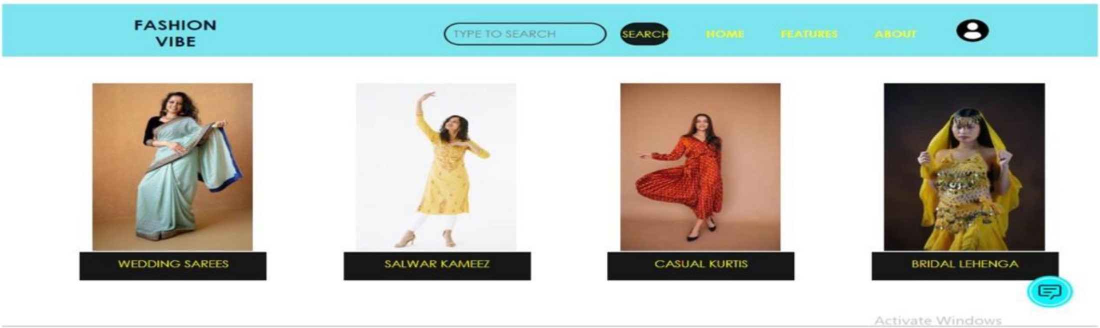
```
    indices

uploaded_file = st.file_uploader("Choose your image")
```

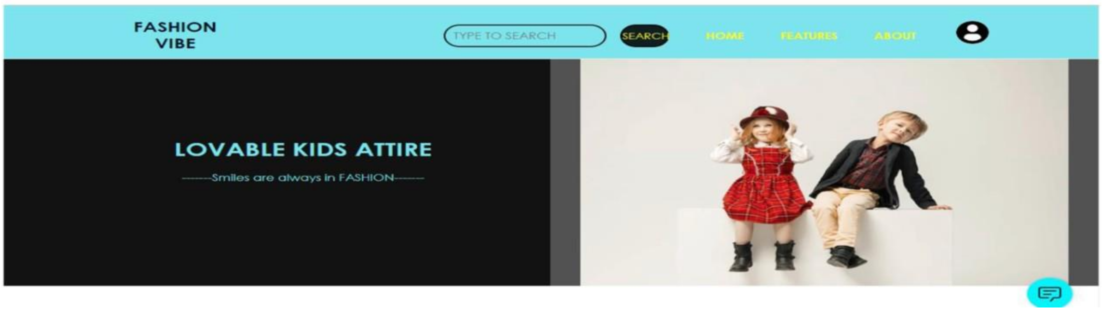
```
if uploaded_file is not
  None: if
  save_file(uploaded_fi
  le):
    # display image
    show_images =
    Image.open(uploaded_file)size =
    (400, 400)
    resized_im = show_images.resize(size)
    st.image(resized_im)
    # extract features of uploaded image
    features = extract_img_features(os.path.join("uploader", uploaded_file.name),
    model)#st.text(features)
    img_indicess = recommendd(features,
    features_list)col1,col2,col3,col4,col5 =
    st.columns(5)

    with col1:
      st.header(
      "I")
      st.image(img_files_list[img_indicess[0][0]])

    with col2:
      st.header(
      "II")
      st.image(img_files_list[img_indicess[0][1]])

    with col3:
      st.header("
      III")
      st.image(img_files_list[img_indicess[0][2]])

    with col4:
      st.header("
      IV")
      st.image(img_files_list[img_indicess[0][3]])

    with col5:
      st.header(
      "V")
      st.image(img_files_list[img_indicess[0][4]])
  else:
    st.header("Some error occur")
```

7.3 DATABASE SCHEMA (IF APPLICABLE)









8. TESTING

8.1 TESTING CASES

```
 import pickle
import numpy
as np
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.resnet50 import ResNet50,
preprocess_inputfrom tensorflow.keras.layers import
GlobalMaxPooling2D
from tensorflow.keras.models import
Sequentialfrom numpy.linalg import norm
from sklearn.neighbors import
NearestNeighborsimport cv2
```

```
features_list =
pickle.load(open("image_features_embedding.pkl", "rb"))
img_files_list = pickle.load(open("img_files.pkl", "rb"))

print(np.array(features_list).shape)

model = ResNet50(weights="imagenet", include_top=False, input_shape=(224, 224,
3))model.trainable = False

model = Sequential([model, GlobalMaxPooling2D()])

img =
image.load_img('sample/shoes.jpg',target_size=(224,224))
img_array = image.img_to_array(img)
expand_img =
np.expand_dims(img_array,axis=0)
preprocessed_img =
preprocess_input(expand_img)
result_to_resnet =
model.predict(preprocessed_img)
flatten_result = result_to_resnet.flatten()
# normalizing
result_normlized = flatten_result / norm(flatten_result)

neighbors = NearestNeighbors(n_neighbors = 6, algorithm='brute', metric='euclidean')
neighbors.fit(features_list)

distence, indices =

neighbors.kneighbors([result_normlized])

print(indices)

 for file in
    indices[0][1:6]:
    print(img_files_list
    [file])
    tmp_img =
    cv2.imread(img_files_list[file])
    tmp_img =
    cv2.resize(tmp_img,(200,200))
    cv2.imshow("output", tmp_img)
    cv2.waitKey(0)
```

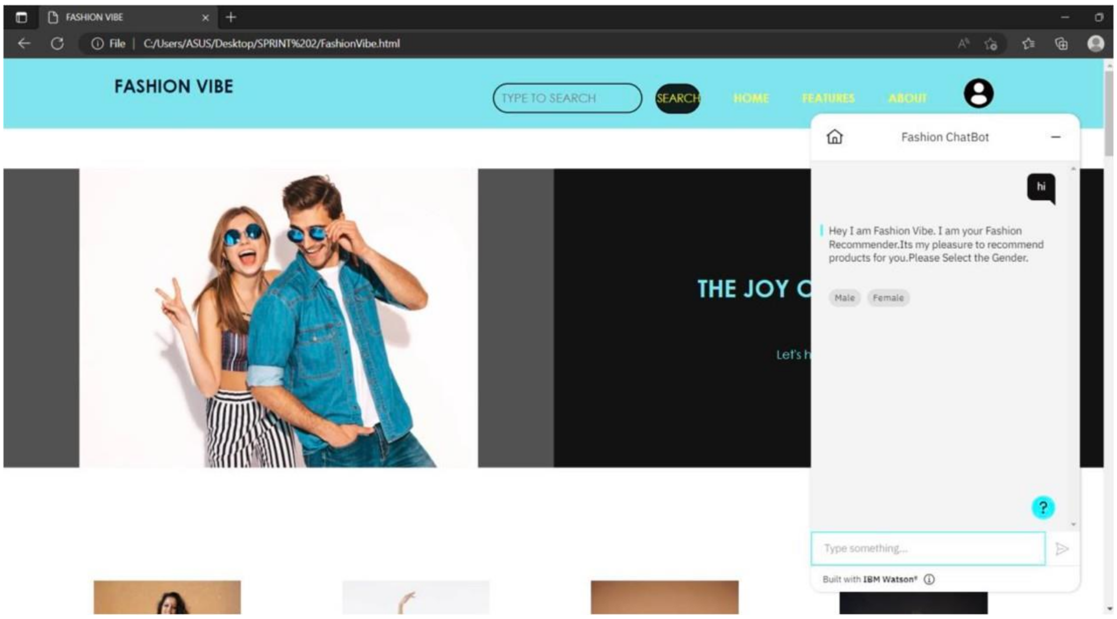
8.2 TESTING CASES

```
from tensorflow.keras.preprocessing import image
from tensorflow.keras.layers import GlobalMaxPooling2D
from tensorflow.keras.applications.resnet50 import ResNet50,
preprocess_inputfrom tensorflow.keras.models import Sequential
import numpy as np
from numpy.linalg
import normimport os
from tqdm
import tqdm
import pickle

model = ResNet50(weights="imagenet", include_top=False, input_shape=(224, 224,
3))model.trainable = False

model = Sequential([model, GlobalMaxPooling2D()])
#model.summary()

def extract_features(img_path,model):
    img =
    image.load_img(img_path,target_size=(224,224))
    img_array = image.img_to_array(img)
    expand_img =
    np.expand_dims(img_array,axis=0)
    preprocessed_img =
    preprocess_input(expand_img)
    result_to_resnet =
    model.predict(preprocessed_img)
    flatten_result =
    result_to_resnet.flatten()
    # normalizing
    result_normlized = flatten_result / norm(flatten_result)

   return result_normlized
#print(os.listdir('fashion_small
/images'))img_files = []

for fashion_images in os.listdir('fashion_small/images'):
    images_path = os.path.join('fashion_small/images',
    fashion_images)img_files.append(images_path)

# extracting image
features
image_features =
[]

for files in tqdm(img_files):
    features_list =
```

```
    extract_features(files, model)
    image_features.append(features_
    list)

pickle.dump(image_features,
open("image_features_embedding.pkl", "wb"))
pickle.dump(img_files, open("img_files.pkl", "wb"))
```

9. RESULTS

9.1 PERFORMANCE METRICS



10. ADVANTAGES AND DISADVANTAGES

Advantages:

For customers, recommender systems can **help them find items which they are interested in**. For enterprises, recommender systems can improve the loyalty of their customers by enhancing the user experience and further convert more browsers to consumers.

Disadvantages:

Lack of Data

Perhaps the biggest issue facing recommender systems is that they need a lot of data to effectively make recommendations. It's no coincidence that the companies most identified with having excellent recommendations are those with a lot of consumer user data: Google, Amazon, Netflix.

11. CONCLUSION

Recommendation systems have the potential to explore new opportunities for retailers by enabling them to provide customized recommendations to consumers based on information retrieved from the Internet. They help consumers to instantly find the products and services that closely match with their choices. Moreover, different stat-of-the-art algorithms have been developed to recommend products based on users' interactions with their social groups. Therefore, research on embedding social media images within fashionrecommendation systems has gained huge popularity in recent times. This paper presented a review of the fashion recommendation systems, algorithmic models and filtering techniques.

Based on the academic articles related to this topic. The technical aspects, strengths and weaknesses of the filtering techniques have been discussed elaborately, which will help future researchers gain an in- depth understanding of fashion recommender systems. However, the proposed prototypes should be tested in commercial applications to understand their feasibility and accuracy in the retail market, because inaccurate recommendations can produce a negative impact on a customer. Moreover, future research should concentrate on including time series analysis and accurate categorization of product images based on the variation in color, trend and clothing style in order to develop an effective recommendation system.

12. FUTURE SCOPE

Online selling and purchasing offer innumerable benefits to both sellers and buyers, and these advantages are also the reasons for the rising scope of e Commerce Well, to put it bluntly, the scope of e-business in the near future looksto be ever-increasing and growing, because the trend has really caught on here. E-commerce giant Amazon is keen to conquer the Indian market and has already invested a great deal, especially with its 49% stake in the Future Group.

Indian online retail giant Flipkart has already opened a few offline stores and plans more stores in smaller cities. They plan to combine online and offline storesto maximize their selling potential. Google and Tata Trust have launched a joint program 'Saathi' to increase internet and mobile penetration among rural women. The Government of India is also making a huge push for Ecommerce byproviding numerous sops to startups, cyber parks, and so on through its Digital India program. As of now, there are close to 20,000 E-commerce companies in India, with many more expected to join the bandwagon every month.

13. APPENDIX

'Guan, C.; Qin, S.; Ling, W.; Ding, G. Apparel recommendation system evolution:

An empirical review. Int. J. Cloth. Sci. Technol. 2016, 28, 854–879, doi:10.1108/ijcst-09-2015-0100.

′ Hu, Y.; Manikonda, L.; Kambhampati, S. What we Instagram: A first analysis of Instagram photo content and user types. Available online: http://www.aaai.org (accessed on 1May 2014).

Gao, G.; Liu, L.; Wang, L.; Zhang, Y. Fashion clothes matching scheme based on SiameseNetwork and AutoEncoder. Multimed. Syst. 2019, 25, 593–602, doi:10.1007/s00530-019-
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SOURCE CODE GITHUB: PYTHON, FLASK

PROJECT DEMO LINK:

https://drive.google.com/drive/folders/1UpqAizxRZUi-8gAOUHMOL7zUyx3Ypu8N