SMART FASHION RECOMMENDER APPLICATION

A PROJECT REPORT

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Project Report Format

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ABSTRACT

In recent years, the huge amount of informaton and users of the internet service, it is hard to know quickly and accurately what the user wants. This phenomenon leads to an extremely low utlizaton of informaton, also known as the informaton overload problem. Traditonally, keywords are used to retrieve images, but such methods require alot of annotatons on the image data, which will lead to serious problems such as inconsistent, inaccurate, and incomplete descriptons, and a huge amount of work. To solve this problem, Content Based Informaton Retrieval (CBIR) has gradually become a researchhotspot. CBIR retrieves picture objects based entrely on the content. The content of an image needs to be represented by features that represent its uniqueness. Basically, any picture object can be represented by its specifc shapes, colours, and textures. Thesevisual characteristcs of the image are used as input conditons for the query system, and a result the system will recommended nearest images and data set. This research designs and implements two-stage deep learning-based model that recommends a clothing fashionstyle. This model can use deep learning approach to extract various atributes from images with clothes to learn the user's clothing style and preferences. These atributes are providedto the correspondence model to retrieve the contguous related images for recommendaton.Based on data-driven, this thesis uses convolutonal neural network as a visual extractor of image objects. This experimental model shows and achieves beter results than the ones of the previous schemes.

Recommendation systems are the techniques that are used to predictthe rating one individual will give to an item or social entity. The items can includebooks, movies, restaurants and things on which individuals have different preferences. These preferences are being predicted using two approaches frst content-based approach which involves characteristics of an item and second collaborative fltering approaches which considers user's past behaviour to evaluate its choices. This thesis proposes a fashion recommendation system which will recommend clothing images supported the style sort of the provided clothing images. In this work, we focus on the images of upper body as well as the lower body clothing and with human model in the images. We have created our own datasets through web scrapping of different ecommerce websites. In thispaper we have come up with an idea to build a content-based recommendation system using ResNet-50 convolutional neural network.

Keywords: Cloth Recommendation, Convolutional Neural Network, Similarity Measure.

1. Introduction

During the last years, online shopping has been growing. In 2013, the total turnover for ecommerce in Europe expanded with 17% in contrast to the 12 months before and huge organizatons can have hundreds and hundreds of products or even more from which we can select on websites. Both the customer and the business enterprise desire the client to easily discover applicable products or items both throughout search and when they are searching, and this is where recommender systems come into the picture. The greater part (62%) of US buyers with Web access presently shop on-line, to some degree, at least a month, and 1% say they do not buy from internet, as indicated by a current report byWalker Sands. From all the clients looking for items on the web, 63% of them buy garments (Burke, 2002), these being, quite possibly, the most purchased items. Theinformaton uncover that women are more likely to buy on-line, with 71% of ladies doing this, contrasted with 52% of men. Studies on clothing are in a growing development in general as a result of the tremendous market related to dress. In China, the serviceable market crushed 20 billion US dollars in 2016. Picture recovery can be depicted as the errand of looking out for pics in a picture data set. This is present not an astute thought, in light of everything. It has been explored on account of the way that the 1970s joined informatonal collecton associatons with PC vision, looking into the issue as indicatedthrough two uncommon perspectves, the frst being text-based and the second one being visual-based. From the outset, the developments have been made only through informaton annotatons that have been saved in a database to work the retrieval step, however, when the dimension of the image collectons started to amplify the efort required to label them used to be as soon as unsustainable, to solve this issue, during the 1990s, content-based photograph retrieval was proposed. Startng now many searched for lines have seemed the use of one or the diferent isolated or combining them. Recommendaton systems make recommendatons based on the informaton they are provided with and in the manner in which they are programmed. Going into details, most of the evaluaton applied is independent coming up with a brand-newrecommendaton algorithm, system, or model. However, diferent researchers use already existng work as researchers use an already existng current piece of work to come up with a new diagram or to truly improve the current one. The present analysis model focuses on the use of a current algorithmic program and, consequently, the use of a new research concept comes up with a recommender system. Existng research and fashions have given us some inspiratons of how to design fashion recommendatonsystems. Nevertheless, they also involve some common drawbacks. Therefore, in this study, our aim to suggest a new method to assist personal choice making through supplying images and get suggestons based on provided contents.

The contributon of the research are follows:

- To design and implement a web-based clothing fashion stylerecommender system based on deep learning;
- A scheme for improving a person's clothing style by removing thefeatures he/she doesn't like.
- These atributes served to a similar model to retrieve similarimages as recommendatons.
- Combined with more common content-based recommendatonsystems, our model can help to extend robustness and performance.

1.1 PROJECT OVERVIEW

The Fashion industry is one of the larger industries around the world. One of the things that have remained constant throughout human civilization is humans covering their bodies with a piece of cloth. Initially, this cloth was worn as protection from the harsh climates of those ages. Later on, as we humans learned to fend for ourselves from the unforgiving climates, the cloth started to serve a different purpose. Fashion these days showcases the individuality of the person. There are many things that can be said about a person based on their fashion sense.

1.2 PURPOSE

There is currently no existing system that is capable of recommending clothes based on the occasion. Different occasions call for different clothing. Moreover, a lot of fashion is basedon the color combinations of outfits. A person with no or little fashion sense will have a hard time to decide on clothes that leave a lasting impression. The proposed Fashion Recommendation System is intended to be used by individual users in order to store images of the clothes that they own in what is called a digital wardrobe and also to get recommendations by the system on what clothes to wear for a given occasion. The main aim of the project is to recommend the most appropriate clothes for a given occasion based on the clothes existing in the user's wardrobe to relieve the user of the burden of making decisions about what clothing to wear. Such a system should be capable of helping someone who has no fashion sense to wear clothes that leave a good impression on others. The system should be such that it is easily accessible and easy to take advantage of the various features that it provides. One of the features should be the ability to store images that the user uploads into a wardrobe. A wardrobe is a very useful entity that the user can use to view and manage the images of clothes that they have uploaded. This feature can also be used by the recommendation algorithm to recommend the clothes. Another feature is the classification of the type and color of the clothing that is uploaded by the user. The system should be capable of handling the 4 basic clothing types: Shirt, T-Shirt, Pants and Shoes.

2. Literature survey

Myntra-Matching Clothes Recommendation:

On selecting a particular item to buy, Myntra automatically suggests a full set of clothes that are matching to the selected item. For example, on selecting aparticular t-shirt, the system automatically generates a combination of watches, shoes, pants, etc. that are matching to the selected t-shirt. This system does not take into consideration private qualities of customers like skin color and existing clothes. It will only suggest clothes that already exist in its database.

Your Closet:

This is a mobile application that organizes the closet. The user interface is shown in. The application asks customer to input their clothes. It then matches each cloth with other clothes. For example, if there are 4 shirts and 4 pants, the application matches each shirt with each pant and thus provides 16 possibilities.The application does not make matches of clothes depending upon patterns, color and texture of clothes. It also does not have a recommendation system.

Your Closet App Magic Closet:

This system aims to retrieve clothes from online stores that are matching to the input clothes. These clothes must be ft to a particular occasion. In this system, the user takes a photo of them specifying if they want to use the top or bottom clothes along with the occasion they want to use it for. The systemwill search for clothing that matches the user query and satisfes the criterion of wearing aesthetically and wearing properly.

Which Clothes to wear confdently?:

The basic problem the system addresses is: From the two given images corresponding to a pair of clothes, we have to determine if the pair of clothes matches or not. While there may be several aesthetics espoused by dierent individuals, it takes a simplistic approach in this problem. An example ofshirts and ties is used. Various machine learning methods are used to classify ifthe clothes are matching or not such as Ridge Regression, Standard Neural Network and Siamese Neural Network.

Personalized Clothing Recommendation Based on Knowledge Graph:

This system attempts to exploit the knowledge graph for providing clothing recommendations to the user keeping the user context in mind. The recommendation is done by calculating the similarity in the clothing ontology similar to users collection. Skin and Clothes matching seeded by Color SystemSelection: The main aim of the system is to suggest clothes to user based on skin color. The paper frst fnds out which color scheme is best suited to represent skin colors and then tries to fnd a way to recommend if clothes and skin color match. An automated system to determine the highest levels of color suitability between skin and clothing was made.

Discerning Advisor:

The system tries to recommend clothes based on skin olor of the customer. Using a neural network, frst the skin color is detected. Fuzzy logic is used to map a skin color to the skin color of a fashion model, and clothes suitedto that model are recommended. Garment Detectives: The garment detection isto detect the presence of clothes in images and somewhat locate their extents, where the localization can be defned from coarse (image) level to fne (pixel) level. A unifed system is proposed for detecting and recognizing clothes in customer photos.

Identifying Corners of Clothes by Image Processing:

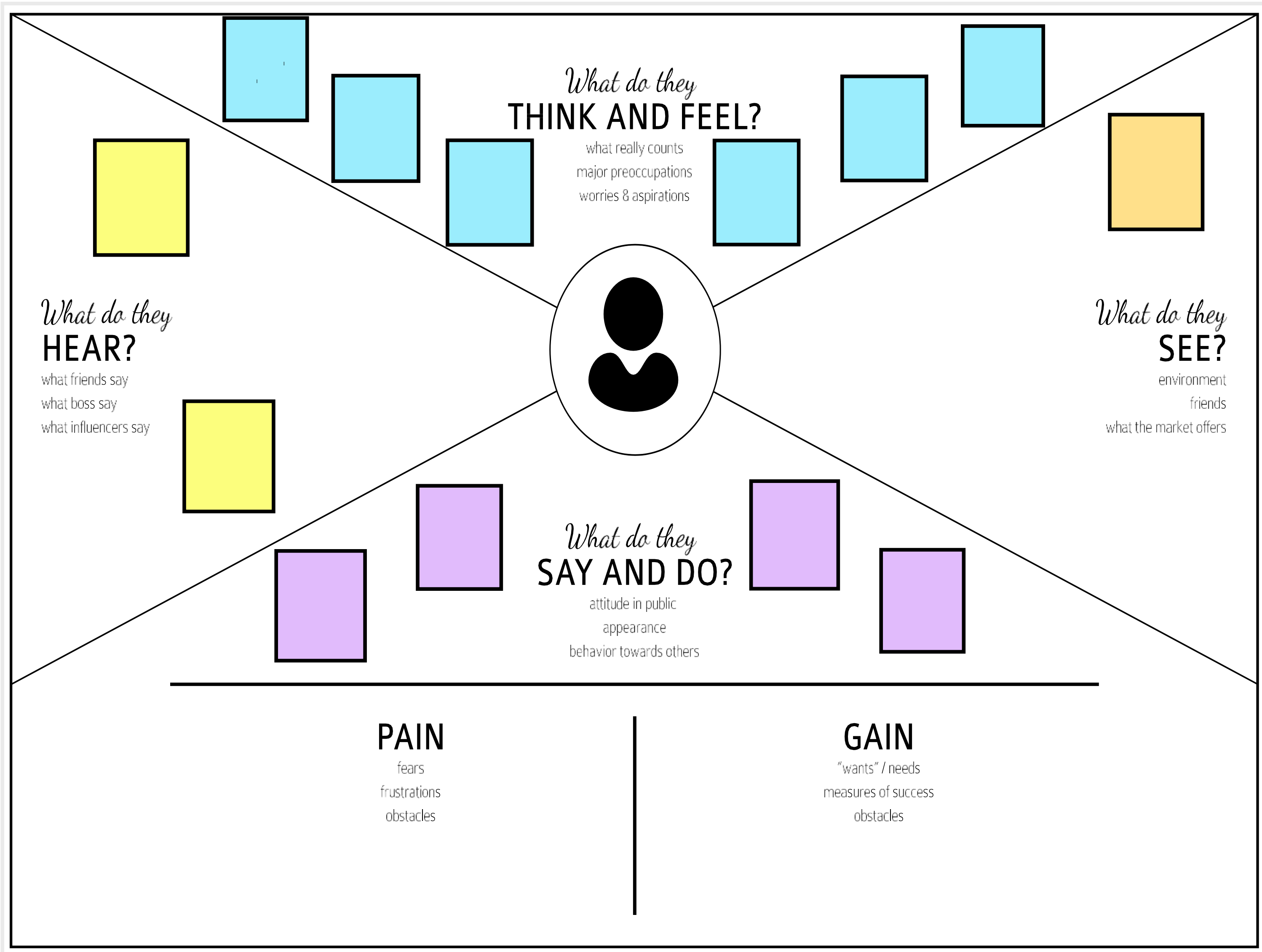
This system aims to fnd the edges of the clothes for clothes manipulation. This system achieves this by fnding pixels that represent the clothes. This system frst accepts user image and then performs several imageprocessing operations to improve the efciency of edge detection. It then uses certain criterion to decide whether a pixel represents an image or not.

Real-time Clothing Recognition from Surveillance Videos:

It is an analysis system of contents of video which is capable of tagging various clothes of different persons is created. First, face detection and tracking is performed and each frame is aligned. The system then proceeds to clothing segmentation using a variant of region growing method. Through this, clothes aredetected. The system then proceeds to clothing recognition and indicates the type of clothing – skirt, t-shirt, etc.

3. IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP



3.2 Proposed Solution

S. No.	Parameter	Description
1.	Problem Statement	In shopping apps navigating to the desired product is very difficult and no proper assistance will be provided.
2.	Idea/Solution Description	A proper assistance will be provided which offers a rich set of interactions that help improve preference elicitation and interact with users through natural language. chatbots can provide mechanisms to capture contextual information, as what has been intended by the so-called context-aware recommender systems.
3.	Novelty/Uniqueness	Customers can purchase the products without any search. The chatbot recommend their present based on their histories.
4.	Social Impact/Customer Satisfaction	The proposed model can recommend products that are more suitable to the customer. It can directly do online shopping based on customer choice without any search. It can also save a lot of time.
5.	Business Model (Revenue Model)	Due to market dynamics and customer preferences, there is a large vocabulary of distinct fashion products, as well as high turnover. This leads to sparse purchase data, which challenges the usage of traditional recommender systems. Better experience and Feasibility.

3.3 Problem Solution fit

Who is your customer?

- Chatbot Shoppers:

Shoppers who prefer the ease of contacting a chatbot to buy a product instead of search.

- Website shoppers:

Shoppers who browse online to buy products.

- Discount seeking customers who often seek for discount in the product.

CUSTOMER CONSTRAINTS

What constraints prevent your customers from taking action or limit their choices of solutions?

- Available of similar sites with good discount
- Website speed and search function
- Quick finding of customer related products.
- Reviews and ratings can distract customers
- Customers cannot bargain

AVAILABLE SOLUTIONS

Which solutions are available to the customers when they face the problem or need to get the job done? What have they tried in the past? What pros & cons dothese solutions have?

- FAQ's to sort out queries of customers.
- Availability of refund and return option
- Search for a specific product through search bar.
- Showing similar product of selected product
- Category wise product arrangement.

JOBS-TO-BE-DONE / PROBLEMS

Which jobs-to-be-done (or problems) do you address for your customers?

- Presence of chatbot can help in asking and resolving customer queries.
- Customer review of a product.
- Availability of sort and filter option to show products relevant to customer.
- Showing a comparison between products.
- Showing products that are most relevant to them.
- Availability of refund and return policies.
- Track order option.

PROBLEM ROOT CAUSE

What is the real reason that this problem exists? What is the back story behind the need to do this job?

- Network issue so that product could not load fast.
- Long delivery
- Poor Tracking
- Product research and cross shopping.

BEHAVIOUR

What does your customer do to address the problem and get the job done?

- Cross check and compare with other sites
- Purchase the product and write a review
- Dispose goods and services over the internet
- Monitoring and evaluation
- Identify the issues

TRIGGERS

- Easy return and refund policy
- Time consuming
- Social proof and novelty

EMOTIONS: BEFORE / AFTER

Before: Want to buy products on huge rush and frequently ask the vendor to show more products.
After: Anywhere anytime shopping and can easily see any number of products even if they don't buy.

YOUR SOLUTION

- Chatbot will recommend products related to the shoppers searching for.
- Get detailed information about the product and the product care.
- Availability of review and rating option to give their feedback about the product bought.
- Can compare products with various brands.

CHANNELS of BEHAVIOUR

ONLINE

Chat with chatbot
Buy products
Track and pay for the purchased products

OFFLINE

In place search for a relevant shop
Search for products by walk

4. REQUIREMENT ANALYSIS

4.1 Functional Requirements:

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through mail Registration through Gmail
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	User Login	Login using username & Password
FR-4	Personal Details	Personal details through Form Personal details through UI Tab
FR-5	Delivery Confirmation	Confirmation via Email Confirmation via Phone

4.2 Non Functional Requirements

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	Ease of use of the application for the user
NFR-2	**Security**	User privacy is the highest priority of the application. Security measures are undertaken for the user
NFR-3	**Reliability**	It can handle more than 2000 users at a time. It can process and initialize most functions.
NFR-4	**Performance**	The application can handle complex tasks and supports multi-tasking.
NFR-5	**Availability**	It is a free web and application available on all platforms.
NFR-6	**Scalability**	With higher workloads the user will experience a 10 to 17% drop in performance.

5. PROJECT DESIGN

5.1 Solution & Technical Architecture

The system architecture defnes the hardware, sofware and network environment of the structure. The system will be web-based meaning that the usersneed to run the URL in order to run the system. The system will run both horizontally and vertcally. The architecture used in the system is shown horizontallywhere the Model View Controller is explained as represented in Figure 1. The high-level part of the system is looked at using the vertcal way.

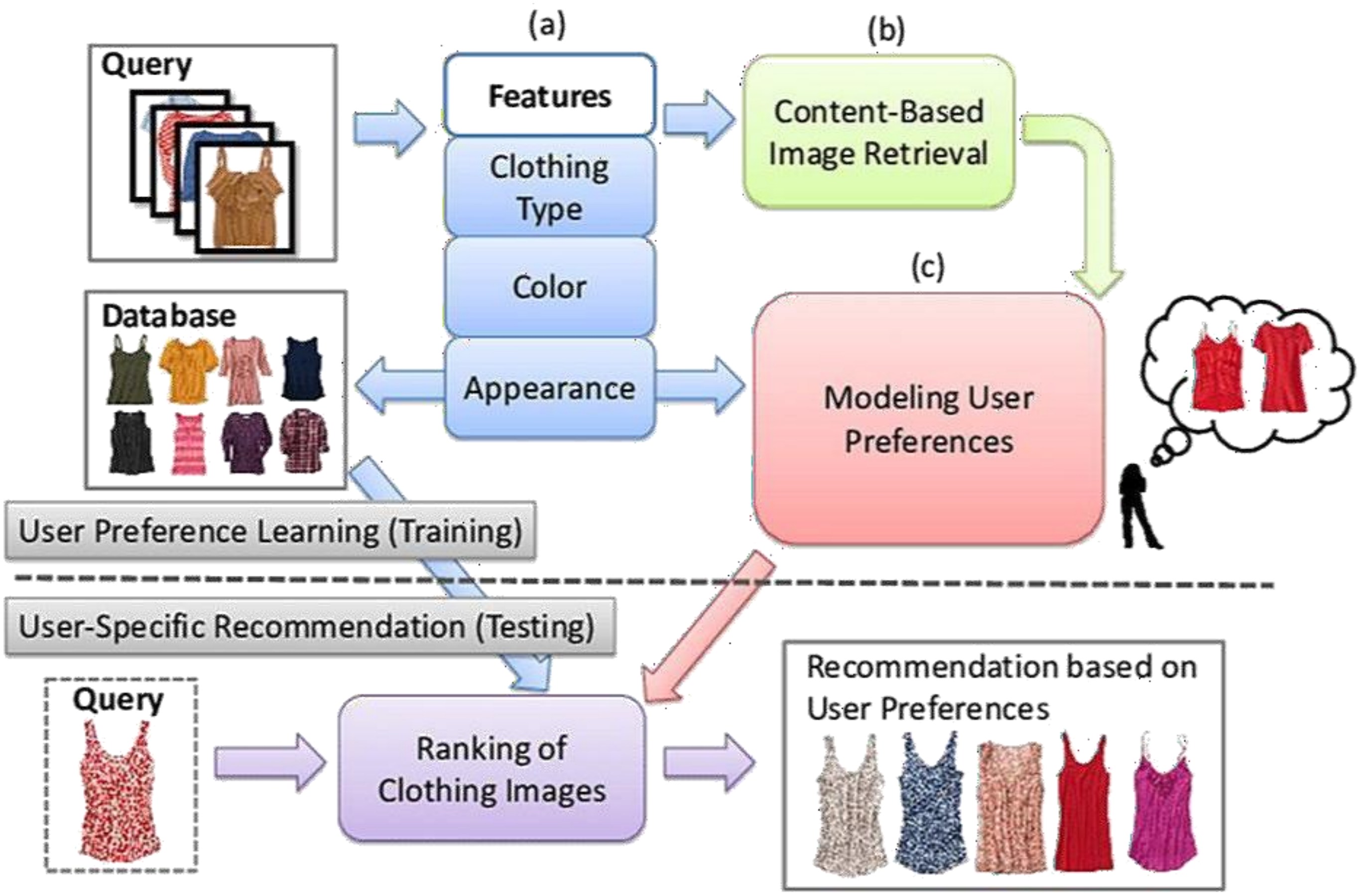


Figure 1. **System architecture**.

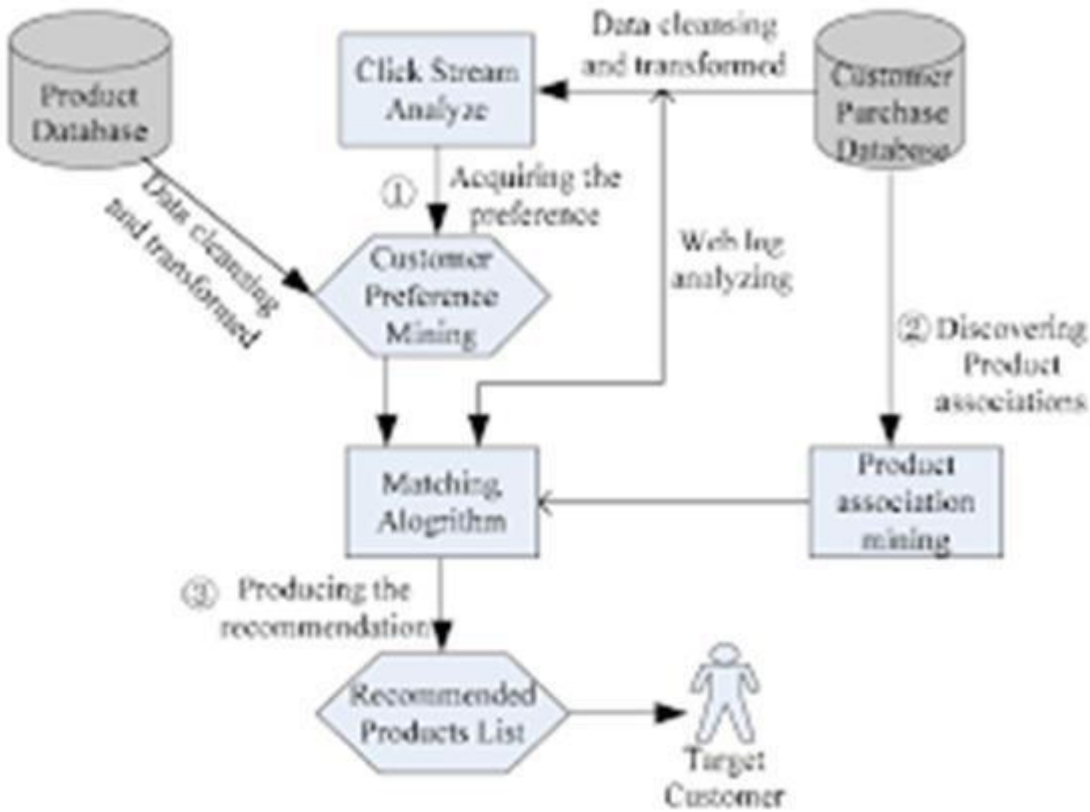
The system comprises of the Client tre, which is the front end or View mode, middle ter which is the system controller and the backend tre which is the model. The client side is where the users/customers log in in the system, browse for the system interface, provide input query image to the system, and get recommendaton according to the input query.

The middle true is responsible for communicaton between the front end and the back end. Itreceives user requests and sends them to the back end and in turn accepts responses fromthe back end and sends them to the user. The internet works to provide access to the site with a strong security check, provided by both frewall and password protecton policy.

Any unauthorized access is detected and prevented by the frewall.

a. The vertical classifcation system model

The recommendaton system works with the data set to track user input datafeatures and extracted features from data set upon which new predictons and recommendatons are made. The recommendaton browses the dataset for user data and available dataset features. Receives Recommendatons User Web ServerSends response to user Database Stores User input data Stores dataset features.



Data Recommender Makes Recommendatons Recommender Algorithm Determines the Similarity between cloths Figure 2. Vertcal architecture of the system.It uses the algorithm to go over the input user data and determine similarites betweenusers input data and stored dataset features. Finally, it makes recommendatons. By looking at Figure 1 and Figure 2, we realize that the recommender system does not interact directly with the users at any point. When the repository stores data, the recommender flters the data it needs from the repository using the algorithm. When asignal is sent to the algorithm about what data are needed for fltering, the algorithm computes the similarity. The similarity results are then transferred to the recommender system which in turn sends recommendatons to the webserverand fnally to the respectve user.

b. Dataset and classifcation

In this project, we worked with the Deep Fashion dataset, which is gathered from researchers from the Chinese Hong Kong University. It has over one million diverse trend pics and wealthy annotatons with additonal dataabout landmarks, categories, pairs etc. The dataset consists of 5 distnct typesof predictng subsets that are tailor-made towards their tasks.

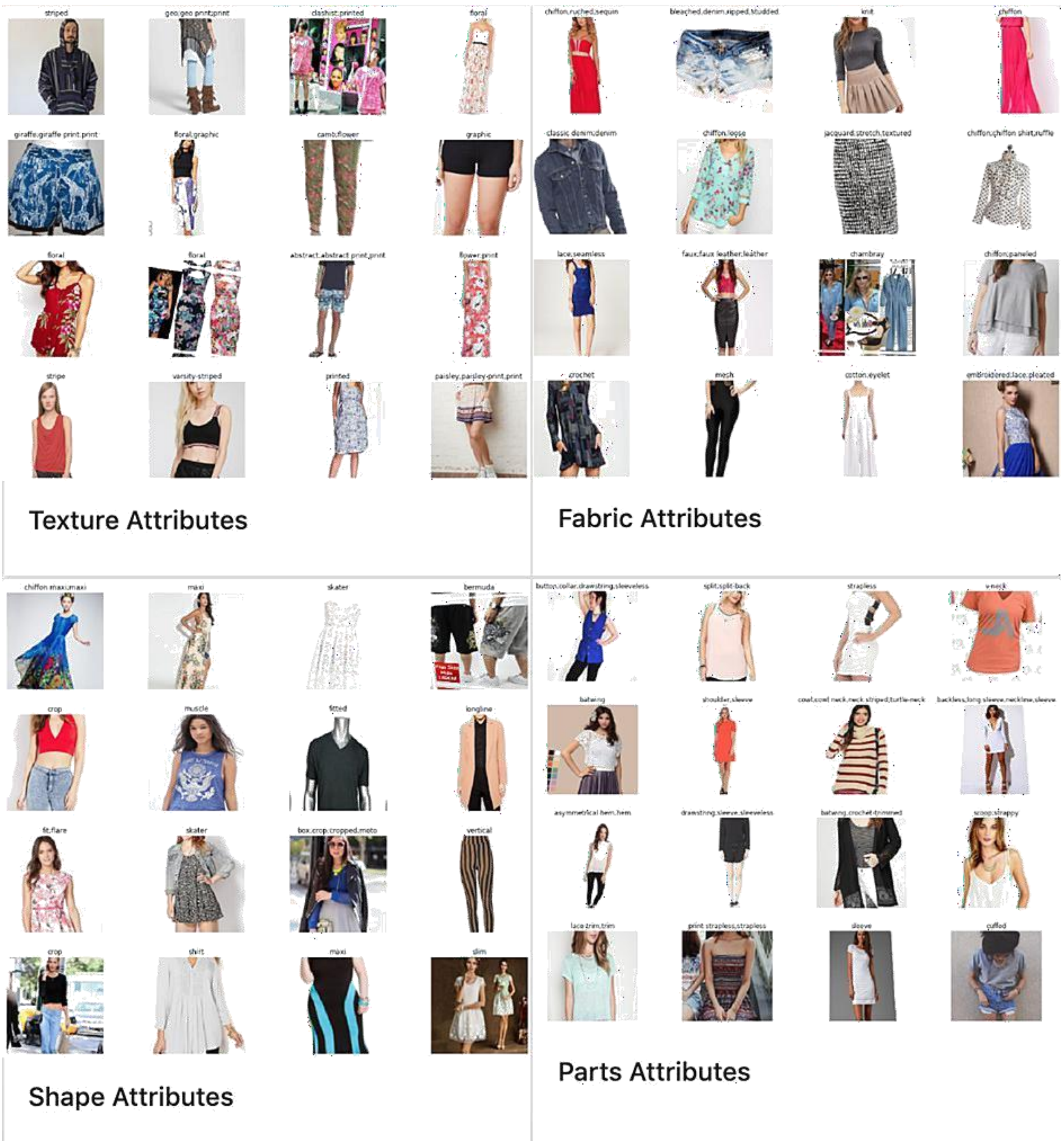
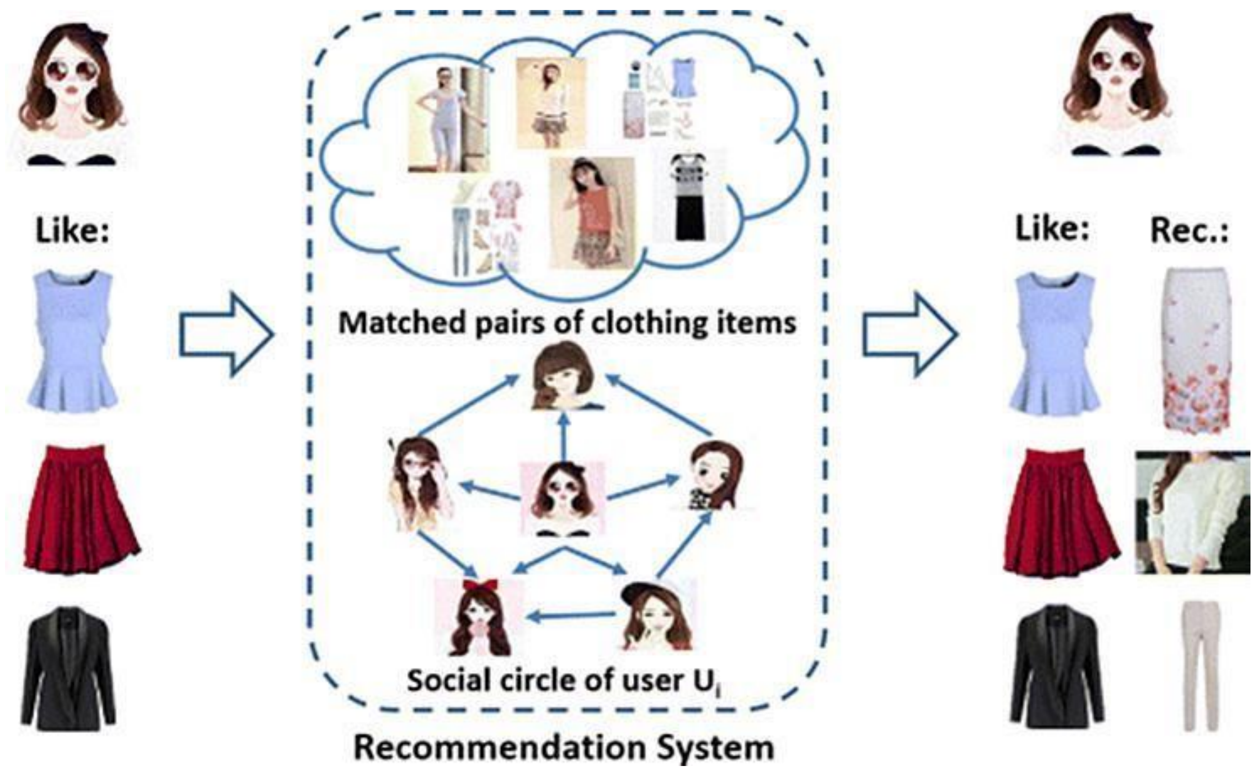


Figure 3. Fashion dataset One subset, known as Atribute Predicton, can be used for apparel category and atribute predicton. From almost 290,000 photos of50 apparel categories and 1,000 apparel atributes, we randomly picked 18k images from diferent categories and then we classifed them for training and testng. The distributon of labels is presented in Figure

c. Design of deep learning module

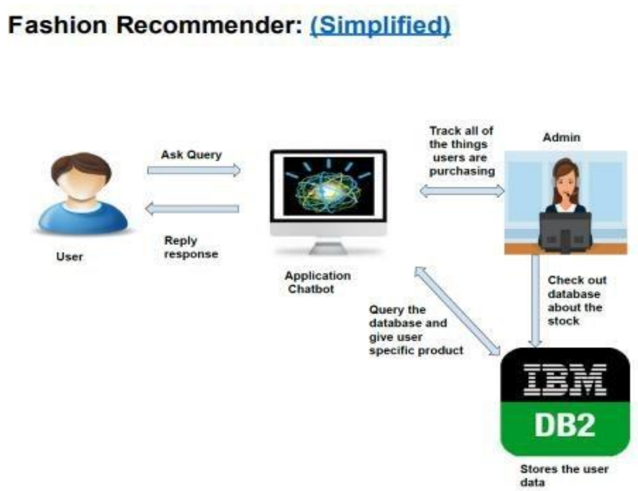
There are many classifcaton algorithms or classifers in use today. The most notably and the most implemented classifers and feature extractor are implementedto solve a problem of cloth / fashion recommendaton Design process. (1)are weightvectors, are fully connected output layers that actually perform classifcaton and arethe CNN without the last layer. They are used as a feature extractors.

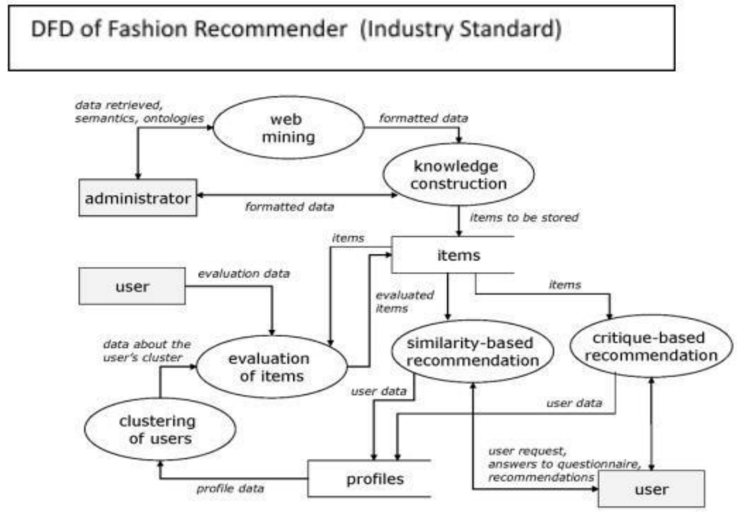


The core network of our model as shown in Figure 4. who presented a convolutonal neural network in the paper “Very Deep Convolutonal Networksfor Large-Scale Image Recogniton”, at the University of Oxford.”. Then modelis checked for top-5 accuracy on ImageNet.

5.2 Data flow diagram

5.3





6 PROJECT PLANNING & SCHEDULING

6.1 Sprint delivery plan

Product Backlog, Sprint Schedule, and Estimation (4 Marks)

Use the below template to create product backlog and sprint schedule

Project Tracker, Velocity & Burndown Chart:

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 gothrough the products available on the website	20	High	AJITH E RANJITHKUMAR GSAVIO A SAJITH RAM S
Sprint-2	Admin panel	USN-2	The role of the admin is to check out the database about the stock and have a trackof all the things that the users are purchasing.	20	High	AJITH E RANJITH KUMAR G SAVIO A SAJITH RAM S
Sprint-3	Chat Bot	USN-3	The user can directly talk to Chatbot regarding the products. Get the recommendations based on informationprovided by the user.	20	High	AJITH E RANJITH KUMAR G SAVIO A SAJITH RAM S
Sprint-4	final delivery	USN-4	Container of applications using docker kubernetes and deployment the application. Create the documentation and final submit the application	20	High	AJITH E RANJITH KUMAR G SAVIO A SAJITH RAM S

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 Nov 2022		05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022		12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022		19 Nov 2022

Velocity:

Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let’s calculate the team’s average velocity (AV) periteration unit (story points per day)

$$AV = \frac{\textit{sprint duration}}{\textit{velocity}} = \frac{20}{10} = 2$$

7.CODING & SOLUTIONING

7.1Fashion.html

```
<html>
   <head>
      <meta name="viewpoint" content="width=device-width, inital-scale=1.0">
      <ttle>FASHION VIBE</ttle>
      <style>
       *{ margin: 0;

   padding: 0;
     font-family:"Century Gothic", CenturyGothic, AppleGothic, sans-serif,'CourierNew',
    Courier, monospace;
   box-sizing: border-box;background: fxed;


}



.footer
{
   width:100%;height: 20%;display:fex;

   background:#121212;margin-top:  5%; color: #7DE5ED; padding-lef: 22%;
```

```
    align-items: center;text-align: center;


}
.hero{
    width: 100%;height: auto;

    background-color:#8f8f8f;color: #525252;


}
nav{
    background: #7DE5ED;width: 100%;

    padding: 10px 10%;
    display: fex;
    align-items: center;
    justfy-content: space-between;
    positon: fxed;



}
.logo{



    width:200px;
```

```
    height:50px;
    text-decoraton:none;text-align: center; color:#001128;

}
.user-pic{ width: 40px;

    border-radius: 50%;cursor: pointer; margin-lef: 30px;

}
nav ul{
    width: 100%; text-align: right; font-weight: bold;

}
nav ul li{
    display: inline-block;list-style: none; margin: 10px 20px;

}
nav ul li a{
    color: rgb(252, 252, 5);

    text-decoraton: none;
```

```
}
.Banner
{
   foat:lef; width: 100%;
   height: 400px;
   background-color: #121212;
   color: #7DE5ED;margin-top: 10%;text-align: center;
}
.Bannerimg1
{
   foat: lef; width:50%; height: 400px;
   background-color: #525252;
}
.Bannerimg2
{
   foat: right; width:50%; height: 400px;
   background-color: #525252;
```

```
}
.Adcontent
{
   width:45%; height: 400px; margin-lef: 55%;color: #7DE5ED;text-align: center;padding:
   100px;
}
.Adcontent2
{
   width:45%; height: 400px; margin-lef: 5%;
   color: #7DE5ED;text-align: center;padding: 100px;
}

.columnst { foat:lef; margin-lef:7%;
   margin-top: 10%;
```

```
width:230px; height:400px;
background-color:transparent;
border: 2px solid #74bde0;border-color:transparent;


}
.column { foat:lef; margin-lef:7%;
margin-top: 10%;width:230px; height:400px;
background-color:transparent; border: 2px solid #74bde0; border-color:transparent;
}
.columnend
{
foat:lef; margin-lef:7%;
margin-top: 10%;
margin-botom: 10%;width:230px;
```

```
    height:400px;
    background-color:transparent; border: 2px solid #74bde0; border-color:transparent;


}
.Botom
{
    height:50px;width:230px;

    text-align: center;margin-top:300;

    background: #000000e8;color: rgb(252,252,5); padding: 5%;

}
.depimg
{
    foat:lef; width:228px; height:300px;

    background-color:transparent; border: 2px solid #74bde0; border-color:transparent;
```

```
}
.image
{
   width: 100%;
   height: 100%; object-ft: contain;

}
.search{
   width: 330px; margin-lef: 40%;color: #7DE5ED;positon:fxed;

}


.srch{
   width: 200px;height: 40px;

   background: #7DE5ED;
   border: 2px solid #121212;margin-top: 13px; margin-right:13px ;

   color: #FCE700;
   font-size: 16px;
```

```
  align-items: center;padding: 10px;

  border-botom-lef-radius: 25px;
  border-top-lef-radius: 25px; border-botom-right-radius: 25px;border-top-right-radius:

  25px;


}


.btn{
  width: 60px; height: 40px;

  border: 2px solid #000000dd;background:#000000dd; margin-top: 13px;

  color: rgb(252, 252, 5);align-items: center; font-size: 15px;

  border-botom-lef-radius: 25px;border-top-lef-radius: 25px; border-botom-right-radius:

  25px;border-top-right-radius: 25px;

}
```

```
.btn:focus{ outline: none;

}


.srch:focus{ outline: none;

}
.sub-menu-wrap{ positon:absolute;top: 100%;

   right: 2%; width: 320px;

   max-height:  0px; overfow: hidden; transiton: max-height 0.5s;


}
.sub-menu-wrap.open-menu{
   max-height: 400px;

}
.sub-menu{ background:rgb(252, 252, 5);padding: 20px;

   margin: 10px;
```

```
    border-radius: 8%;


}
.user-info{ display: fex;

    align-items: center;

}
.user-info h3{
    font-weight: 500;

}
.user-info img{width: 60px;

    border-radius: 50%;margin-right: 15px;

}
.sub-menu hr{ border: 0; height: 1px; width: 100%;

    background: #525252;
    margin: 15px 0 10px;

}


.sub-menu-link{
```

```
    display: fex;
    align-items: center; text-decoraton: none;color: #525252; margin: 12px 0 ;

}
.sub-menu-link p{

    width: 100%;

}
.sub-menu-link img{ width: 40px; background: #e5e5e5;border-radius: 50%; padding:

    8px;

    margin-right: 15px;

}
.sub-menu-link span{font-size: 22px;

    transiton: transform 0.5s;

}
.sub-menu-link:hover span{
    transform: translateX(5px);

}
.sub-menu-link:hover p{
```

```
   font-weight: 600;
}
.hello{
   margin-botom: 200px;text-align: lef; positon:absolute; right: 10px;


}



      </style>
   </head>



   <body>



         <nav>
            <a class="logo" href="MadFinalhome.html"><h2>FASHIONVIBE</h2></a> <ul>

                <li><input class="srch" type="search" name="" placeholder="TYPE TO
    SEARCH">
               <a href="#"><buton class="btn">SEARCH</buton></a></li>
               <li><a href="#">HOME</a></li> <li><ahref="#">FEATURES</a></li>

               <li><a href="#">ABOUT</a></li>
```

```
</ul>
        <img src="https://storagedemo-madzh.s3.jp-tok.cloud-object-
storage.appdomain.cloud/images/profle.jpeg"          class="user-pic"
onclick="toggleMenu()">

    <div class="sub-menu-wrap" id="subMenu">
      <div class="sub-menu">
        <div class="user-info">
            <img    src="https://storagedemo-madzh.s3.jp-tok.cloud-object-
storage.appdomain.cloud/images/profle.jpeg">
          <h2>NAME</h2>
        </div>
        <hr>

        <a href="#" class="sub-menu-link">
            <img    src="https://storagedemo-madzh.s3.jp-tok.cloud-object-
storage.appdomain.cloud/images/profle.jpeg">
          <p>EDIT PROFILE</p>

        </a>

        <a href="#" class="sub-menu-link">
            <img    src="https://storagedemo-madzh.s3.jp-tok.cloud-object-
storage.appdomain.cloud/images/setngs.jpeg">
```

```
<p>SETTING & PRIVACY</p>


</a>


<a href="#" class="sub-menu-link">
<img src="https://storagedemo-madzh.s3.jp-tok.cloud-object-
storage.appdomain.cloud/images/help.jpeg">
<p>HELP</p>


</a>


<a href="/Login" class="sub-menu-link">
<img src="https://cdn-icons- png.fatcon.com/512/56/56805.png">

<p>LOGOUT</p>


</a>
</div>
</div>


</nav>


<div class="Banner">
<div class="Bannerimg1"> <img img class="image"
src="fashionimagebanner.webp"></div>
```

```html
    <div class="Adcontent">
      <h1><br>THE JOY OF DRESSING IS AN ART.</br></h1>
      <br>Let's have a look on it ------></br>
    </div>
  </div>


  <div class="rowstart">
                <div class="columnst"> <div class="depimg"><img class="image"
src="sarees.webp"> </div> <div class="Botom">WEDDING SAREES</div> </div>

        <div class="columnst"> <div class="depimg"><img class="image" src="Salwar
kameez.webp"> </div> <div class="Botom">SALWAR KAMEEZ</div> </div>

                <div class="columnst"> <div class="depimg"><img class="image"
src="Kurts.webp"> </div> <div class="Botom">CASUAL KURTIS</div> </div>

        <div class="columnst"> <div class="depimg"><img class="image" src="bridal
lehenga.webp"> </div> <div class="Botom">BRIDAL LEHENGA</div> </div>
  </div>


  <div class="Banner">
                          <div class="Bannerimg2"> <img img class="image"
src="lovablekidsatre.webp"></div>
    <div class="Adcontent2">
      <h1 class="kids"><br>LOVABLE KIDS ATTIRE</br></h1>
```

```
        <br>-------Smiles are always in FASHION------ </br>
      </div>
    </div>


    <div class="row">


            <div class="column"> <div class="depimg"><img class="image" src="Modern
vibe.webp"> </div> <div class="Botom">MODERN VIBE</div> </div>

                          <div class="column"> <div class="depimg"><img class="image"
src="festvemood.webp"> </div> <div class="Botom">FESTIVE MOOD</div> </div>

              <div class="column"> <div class="depimg"><img class="image" src="skinny
dress.webp"> </div> <div class="Botom">SKINNY DRESS</div> </div>

               <div class="column"> <div class="depimg"><img class="image" src="Max
girls.webp"> </div> <div class="Botom">MAX GIRLS</div> </div>
    </div>


    <div class="Banner">
                                       <div class="Bannerimg1"> <img img class="image"
src="mensfashion.webp"></div>
      <div class="Adcontent">
        <h1><br>HANDSOME MEN ATTIRE</br></h1>
        <br>Always DRESS well, Keep it SIMPLE but SIGNIFICANT ... </br>
```

```
    </div>
  </div>


  <div class="row">
            <div class="column"> <div class="depimg"><img class="image" src="polo t
shirts.webp"> </div> <div class="Botom">POLO T-SHIRTS</div> </div>

                     <div class="column"> <div class="depimg"><img class="image"
src="menhoodies.webp"> </div> <div class="Botom">HOODIES</div> </div>

             <div class="column"> <div class="depimg"><img class="image" src="men
casuals.webp"> </div> <div class="Botom">MEN CASUALS</div> </div>

            <div class="column"> <div class="depimg"><img class="image" src="formal
shirts.webp"> </div> <div class="Botom">FORMAL SHIRTS</div> </div>
  </div>


  <div class="Banner">
    <div class="Bannerimg2"> <img class="image" src="adornments.webp"></div>
    <div class="Adcontent2">
      <h1><br>PERSONAL ADORNMENTS</br></h1>
      <br>ADORNMENT is never anything except a REFLECTION of the HEART!!!</br>

    </div>
  </div>
```

```
<div class="rowend">
    <div class="columnend"> <div class="depimg"><img class="image" src="women
ornmanets.webp"> </div> <div class="Botom">JEWELLERY</div> </div>

 <div class="columnend"> <div class="depimg"><img class="image"src="watch.jpg">
</div> <div class="Botom">WATCHES</div> </div>

                <div class="columnend"> <div class="depimg"><img class="image"
src="https://5.imimg.com/data5/TQ/NK/MY-45888708/men-belts-500x500.jpg"> </div>
<div class="Botom">BELTS</div> </div>


                <div class="columnend"> <div class="depimg"><img class="image"
src="https://encrypted-tbn0.gstatc.com/images?q=tbn:ANd9GcQSWDKgpQeZ-3VNR7-
9SfaVGVvqOawrkZiLdNfSpjNNQJNI6hl8cJg0Qs_DZfpJtzUst0&usqp=CAU"> </div>
<div class="Botom">HANDBAGS & CLUTCHES</div> </div>


</div>



<script>
  let subMenu = document.getElementById("subMenu");functon toggleMenu(){

     subMenu.classList.toggle("open-menu");

  }
  window.watsonAssistantChatOptons = {
             integratonID: "1a8c11c0-839e-4442-8b03-59f7c12ce5f5", // The ID of this
```

```
integraton.
    region: "au-syd", // The region your integraton is hosted in. serviceInstanceID:
      "bada3725-51e6-42fe-bccc-3e2603433478", // The ID
of your service instance.
    onLoad: functon(instance) { instance.render(); }
  };
  setTimeout(functon(){
    const t=document.createElement('script');
        t.src="https://web-chat.global.assistant.watson.appdomain.cloud/versions/" +
(window.watsonAssistantChatOptons.clientVersion || 'latest') +
"/WatsonAssistantChatEntry.js";
    document.head.appendChild(t);
  });
</script>
</body>
<footer>
  <div class="footer">
    <div class="hello">
      <a href="Feedback.html">feedback</a>
    </div>
    <div >
      <H1>THANK YOU FOR PURCHASING..... WELCOME AGAIN!!!!</H1>
    </div>
</div>
</footer>
```

```
</html>
```

7.2 server.py

```
from fask import Flask, render_template,request import os

appFlask = Flask(__name__)

picFolder = os.path.join('statc','images') appFlask.confg['UPLOAD_FOLDER'] = picFolder

@appFlask.route('/') @appFlask.route('/out')def index():
   return render_template("login.html")

@appFlask.route('/login',methods = ['POST', 'GET'])
def my_forum_post():
   return render_template('FashionVibe.html')
@appFlask.route('/index',methods = ['POST', 'GET'])
```

```
def my_forum_posts():
   return render_template('index.html')


@appFlask.route('/Feed',methods = ['POST', 'GET'])def my_forum_posts1():
   return render_template('Feedback.html')



 if__name__== "__main__":
appFlask.run(debug=True)
```

fashion.css

```
{
   margin: 0;
   padding: 0;
     font-family:"Century Gothic", CenturyGothic, AppleGothic, sans-serif,'CourierNew',
    Courier, monospace;
   box-sizing: border-box;background: fxed;


}


.footer
{
```

```
    width:100%;height: 20%;display:fex;
    background:#121212;margin-top:  5%; color: #7DE5ED; padding-lef: 22%; align-items:
    center; text-align: center;


}
.hero{
    width: 100%;height: auto;
    background-color:#8f8f8f;
    color: #525252;


}
nav{
    background: #7DE5ED;width: 100%;
    padding: 10px 10%;display: fex;
```

```
    align-items: center;
    justfy-content: space-between;
    positon: fxed;


}
.logo{


    width:200px;height:50px;
    text-decoraton:none;text-align: center; color:#001128;
}
.user-pic{ width: 40px;
    border-radius: 50%;cursor: pointer; margin-lef: 30px;
}
nav ul{
    width: 100%; text-align: right; font-weight: bold;
```

```
}
nav ul li{
   display: inline-block;list-style: none; margin: 10px 20px;
}
nav ul li a{
   color: rgb(252, 252, 5);text-decoraton: none;
}
.Banner
{
   foat:lef; width: 100%;
   height: 400px;
   background-color: #121212;
   color: #7DE5ED;margin-top: 10%;text-align: center;
}
.Bannerimg1
{
   foat: lef; width:50%;
```

```
    height: 400px;
    background-color: #525252;
}
.Bannerimg2
{
    foat: right; width:50%; height: 400px;
    background-color: #525252;
}
.Adcontent
{
    width:45%; height: 400px; margin-lef: 55%; color: #7DE5ED;text-align: center;padding:
    100px;
}
.Adcontent2
{
    width:45%; height: 400px; margin-lef: 5%;
```

```
    color: #7DE5ED;text-align: center;padding: 100px;
}


.columnst { foat:lef; margin-lef:7%;
    margin-top: 10%;
    width:230px; height:400px;
    background-color:transparent;
    border: 2px solid #74bde0;border-color:transparent;


}
.column { foat:lef; margin-lef:7%;
    margin-top: 10%;width:230px; height:400px;
    background-color:transparent;
```

```
    border: 2px solid #74bde0;border-color:transparent;
}
.columnend
{
    foat:lef; margin-lef:7%;
    margin-top: 10%;
    margin-botom: 10%;width:230px; height:400px;
    background-color:transparent;
    border: 2px solid #74bde0;border-color:transparent;


}
.Botom
{
    height:50px;width:230px;
    text-align: center;margin-top:300;
    background: #000000e8;
    color: rgb(252,252,5);
```

```
    padding: 5%;
}
.depimg
{
    foat:lef; width:228px; height:300px;
    background-color:transparent; border: 2px solid #74bde0; border-color:transparent;


}
.image
{
    width: 100%;
    height: 100%; object-ft: contain;
}
.search{
    width: 330px; margin-lef: 40%;color: #7DE5ED;positon:fxed;
}
```

```
.srch{
   width: 200px;height: 40px;
   background: #7DE5ED; border: 2px solid #121212;margin-top: 13px;
   margin-right:13px ;color: #FCE700; font-size: 16px; align-items: center;padding: 10px;
   border-botom-lef-radius: 25px;border-top-lef-radius: 25px; border-botom-right-radius:
   25px;border-top-right-radius: 25px;


}


.btn{
   width: 60px; height: 40px;
   border: 2px solid #000000dd;
```

```
    background:#000000dd;margin-top: 13px;
    color: rgb(252, 252, 5);
    align-items: center;font-size: 15px;
    border-botom-lef-radius: 25px;
    border-top-lef-radius: 25px; border-botom-right-radius: 25px;border-top-right-radius:
    25px;
}

.btn:focus{ outline: none;
}

.srch:focus{ outline: none;
}
.sub-menu-wrap{ positon:absolute;top: 100%;
    right: 2%; width: 320px;
```

```
    max-height:  0px; overfow: hidden; transiton: max-height 0.5s;


}
.sub-menu-wrap.open-menu{
    max-height: 400px;
}
.sub-menu{ background:rgb(252, 252, 5);padding: 20px;
    margin: 10px;
    border-radius: 8%;


}
.user-info{ display: fex;
    align-items: center;
}
.user-info h3{
    font-weight: 500;
}
.user-info img{
```

```
    width: 60px;
    border-radius: 50%;margin-right: 15px;
}
.sub-menu hr{ border: 0; height: 1px; width: 100%;
    background: #525252;
    margin: 15px 0 10px;
}

.sub-menu-link{display: fex;
    align-items: center;
    text-decoraton: none;color: #525252; margin: 12px 0 ;
}
.sub-menu-link p{
    width: 100%;
}
.sub-menu-link img{width: 40px;
```

```
background: #e5e5e5;border-radius: 50%; padding: 8px;
margin-right: 15px;
}
.sub-menu-link span{font-size: 22px;
transiton: transform 0.5s;
}
.sub-menu-link:hover span{
transform: translateX(5px);
}
.sub-menu-link:hover p{font-weight: 600;
}
.hello{
margin-botom: 200px;text-align: lef; positon:absolute; right: 10px;


}
```

test.js

```
<script>
  let subMenu = document.getElementById("subMenu");functon toggleMenu(){
    subMenu.classList.toggle("open-menu");
  }
  window.watsonAssistantChatOptons = {
        integratonID: "1a8c11c0-839e-4442-8b03-59f7c12ce5f5", // The ID ofthis
  integraton.
    region: "au-syd", // The region your integraton is hosted in.
     serviceInstanceID: "bada3725-51e6-42fe-bccc-3e2603433478", // The IDof your
  service instance.
    onLoad: functon(instance) { instance.render(); }
  };
  setTimeout(functon(){
    const t=document.createElement('script');
      t.src="https://web-chat.global.assistant.watson.appdomain.cloud/versions/" +
  (window.watsonAssistantChatOptons.clientVersion || 'latest') +
  "/WatsonAssistantChatEntry.js";
    document.head.appendChild(t);
  });
 </script>
```

chat.js

```
<script>
  let subMenu = document.getElementById("subMenu");functon toggleMenu(){
```

```
    subMenu.classList.toggle("open-menu");
  }
  window.watsonAssistantChatOptons = {
          integratonID: "1a8c11c0-839e-4442-8b03-59f7c12ce5f5", // The ID ofthis integraton.
    region: "au-syd", // The region your integraton is hosted in.
     serviceInstanceID: "bada3725-51e6-42fe-bccc-3e2603433478", // The IDof your service instance.
    onLoad: functon(instance) { instance.render(); }
  };
  setTimeout(functon(){
    const t=document.createElement('script');
        t.src="htps://web-chat.global.assistant.watson.appdomain.cloud/versions/" + (window.watsonAssistantChatOptons.clientVersion || 'latest')+ "/WatsonAssistantChatEntry.js";
    document.head.appendChild(t);
  });
</script>
```

8 TESTING

8.1 User Acceptance Testing

Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the Smart Fashion Recommender Application project at the time of the release to User Acceptance Testing (UAT).

Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and howthey were resolved

Resolution	Severit y 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	5	5	2	3	21
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	24	14	13	26	77

Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	Not Tested	F ail	P as s
Login	5	0	0	5
Register	7	0	0	7
Home Page	2	0	0	2
Order page	3	0	0	3
Order products	9	0	0	9
Final Report Output	4	0	0	4
Version Control	2	0	0	2

9 Results and Evaluation

This secton focuses on evaluatng our system and deciding the stage whichit is able to fulfl the purpose for which it was created the performance of the systemis analysed in detail through several tests, from small scale to large scale. Firstly, the unit tests are done at the lower stages and then we proceed to the whole test system. In the training implementaton module, we are performing the movement throughout the area, freeze the base layers of the organizaton i.e., the VGG16 layers, and train the model on the dataset for 5 epochs. This trains the external layers to fgure out how to characterize the pictures. We then unfreeze the lower layers and train the model for 5-7 epochs untl the approval exactness setles. We keep the best achievable loads (best on approval exactness) and use it for the suggeston model. The training implementaton code is presented below.

Step 1: Training the whole network for 5 epochs frst

Step 2: Checkpoint_callback=modelcheckpoint(‘, /model/vgg_weights_best_patern.hdf5’.**Step.3**: Monitor=’val_acc’, verbose=0 save_best_only=true, save_weights_only=false, mode=auto’, period=1)

Step 4: Tf_model.ft_generator(Train_generator, Samples_per_epoch=nb_train_sample, Nb_epoch=10, Validaton data=validaton_generator,

Nb_val_samples=nb_validaton_samples, Verbose=1, Inital_epoch=5, Callbacks=[checkpoint_callback]
Step 5: end

1. Visual recommendation module implementation

To get proposals, we wished to construct a vault of pictures. This archive would be a unique applicaton. If the suggeston was cultvated for shopping, the storehousewould have contained pictures from online retail locatons like Amazon, eBay, Pinterest, Instagram, etc. A subset of patern datasets was used to test our proposed approach. At that point, the informaton had already been cleared of unimportant photos. Then, the photos were passed by means of the organizaton and design vector pictures have been created from each photo. For the getng the suggeston, we frst needed to build the individual style profle. This is brought out by taking one or more noteworthy pictures of the client's ideal atre things as they were entered and by making their style vector. These vectors are then blended to shape the framework of the individual style profle. The Figure 5 shown Patern recommendaton with similarity score.

Figure 5. Patern recommendaton with similarity score

The proposed scheme is further below, as follows: we will utlize a closeness calculaton, which and the design vector of each picture in the vault with the style profle grid. This gives us a score dependent on the quantty of component coordinates (i.e., how great is the degree of similarity of a picture to the individual's style profle).

Step 1: def similarity (feature_data, inp_ feature_data):

Step 2: nun_samp=inp_feature_data. size

Step 3: print (unm_samp) Sim_score = [] for i in range (1 en (feature_data)): score=0

Step 4: show_sample (data_images[i])

Step 5: print (feature_data[i]) score _m = inp_feature_data - feature_data[i]

Step 6: print (Soore_ m) score= nun_samp-np. Count_nonzero (score_m)sim_score [i]=score

Step 7: print (score) sim Score

Step 8: end

i.User management services:

The system provides a platorm through which a user can visit the system andprovide his/her choices regarding the fashion images for best recommendaton.

ii. Fashion vector for images in repository and input fashion vector:

The system is responsible for making fashion vectors for images in the repository and fashion vector images provided by the user to the system, for the similarity measures and for making recommendatons. Afer making the fashion vector, some predictons are made, as illustrated The system is responsible for making recommendatons to users based on their user data. The user data compiled in the dataset is fltered by the recommender system through the recommender algorithm.

Step1: Def similarity (feature_data, inp_feature_data); Num_samp=inp_feature_data.size **Step2:** print (num_samp) Sim_score = () For i in range (len (feature_data)); score = 0show_sample (data_images[i]) print(feature_data[i]) Romanian Journal of InformatonTechnology and Automatc Control, Vol. 31, No. 4, 123-136, 2021 131 http://www.rria.ici.ro **Step3:** Score_m inp_feature_data-feature_data[i] print (score_m)

Step4:Score=num_samp-np.count_nonzero(score_m) Sim_score[i]=score print(score)

Step 5: Return sim_score

Step 1: Similarites=similarity(feature_data,inp_feature_data)

step.2.items(),

```
key=operator.itemegter(1),reverse=(true)
Num_reco=30data=feature_data.size
For I in range(num_reco) Ind = sorted_similarites[i][0]
print (sorted_similarites)

Print (“score:”, sorted_similartes[i][1])Show_sample(data_images[ind])
```

Step 3: end

By accessing the system, users are able to access and view their content-based recommendatons. However, all the recommendatons are made based on the similarity between user inputs and user inputs. As long as there is a level ofsimilarity, we make the best recommendatons.

iv. Recommender to the query images in dataset:

We can see that our model can capture the best matching style by including the length, shape, colour, fabric and patern of the cloths, as illustrated in three query images examples. In the frst example, the model captures deep features including the blouse category, fabric, repeated foral patern and the regular ft style. As seen, the fve recommended images display diferent clothes. The second example shows that the model captures the wool fabrics, the contrast colour sttches and the turtleneck. The third example shows that the model can capture the coton fabrics and the printed leters. The recommendatons can be seen in Figure.

DESCRIBING CLOTHES AND STYLE

CLASSY

Your style is elegant and,
with clean, simple lines, softly tailored not usually mix and match.
Never trendy, faddish or severe,
Textures such as silk, soft woolen fabrics, cotton are among your favourites.

FUNKY ROCK

This look is edgy, a fashion style expressed by bold hair styles and colors, accessories, black leather jackets and shirts with funky designs.

ETNIC

The easiest way to wear the look is a print. If prints aren't your thing, then you can still indulge in the ethnic /tribal fashion trend by way of accessories.

GIRLY GLAM

Your outfits hug Your body tightly and are full of pink, loud and sparkly accessories, high stilettos and platforms. It is a style that exposes some of your body and brings out a flirty, feminine and sexy look.

BOHO CHIC

It a vintage inspired style with earthy tones, loose fitting clothes, and combining certain looks to appeal to an eclectic vibe.
This trend is a mix of luxurious textures and contrasting fabrics, big purses, casual, long necklaces...

TRENDY

You love the big city and adore your uniform of all black with stiletto boots, pumps, or sandals.
You love to dress up, be in all the latest trends. You know which pieces make the whole look appear expensive.

PREPPY/GIRLY

Polo shirts, or Oxford shirts, dresses and T shirts all either in pastel or bright colors.
jeans, khakis, slacks, or Bermuda shorts. Oxford shoes, tennis shoes, ballet flats make the look.

CASUAL

A cute, sweat suit is your go-to outfit .If an evening activity is on the agenda, a quick change to slacks or jeans and a sweater or nice T-shirt does the trick. Your color navy, gray, and black

PUNK

A lot of punk clothing has a DIY (do it yourself) look to it.
Flight jackets, skinny jeans, leather, studs, are the things to wear together with classic accessories like, arm warmers, bullet belts, and wristbands with pyramid studs, stars or spikes.

MOD

Dresses and skirts are A-line and either mid-thigh length or just below the knee.
Go for crazy patterns or stripes with lines that pop.
Typical colors are white and black, but you can incorporate others.
Mod shoes are chunky knee- or ankle-high boots

SKATER

Their look is more put together and creative then you'd think.
Strategic layers (long and short sleeve Tees) and smart yet accessories (necklaces, etc.) are the basis of this look.

HIPSTER

Wear skinny jeans, basically, the tighter, the better.
Wear glasses and dress vintage.
Hipster shoes include cowboy boots, Converse, and a range of flats.
Wearing things that don't match together is also very hipster.

HOBO

Hobo's clothes must be either painfully small or comically large.
Hobo Shoes can cover a wide range of styles, as long as they are beaten up and battered, fingerless gloves and hats give you the look too.

GOTH GLAM

Goth glam fashion is now a classy version of gothic.
It still retains dark and gloomy colors like black, navy and burgundy.

ROMANTIC

You like to wear soft colors and fabrics like chiffon and silk that drape graciously on your body.
You also go for ruffle or skirt and dresses with floral prints, lace, crocheted tops, cameos and antique jewelry.

EMO

Tight clothing is still your thing, though much of it has taken a more modern look now.
Stripes are popular as stars, hearts, skulls, nautical stars, and sparrows. Hair still black.

As shown in Figure, our model can capture the style with high accuracy, meaning that our system achieves its purpose. It can benotced that our system can perform for all the involved categories like patern, style, fabric etc. The highest similarity score shows that the input images and the recommended ones are similar. This fgure also illustrates that the system can work best for patern recommendaton and recommend top similar images in diferent colours, shapes, and styles.

v.Recommendations to the query images outside the dataset:

It's natural to ask if the model you made works with images which are not part of the dataset. We randomly downloaded three online images illustratng expensive clothes. As shown in Figure 8, the model is stll able to capture the style, patern and fabrics of the clothes and recommend similar ones.

The model is checked for diferent categories like patern, style, fabric. The highest score show that the image is more similar to the input query. So, our model obtains high similarity score for diferent categories.

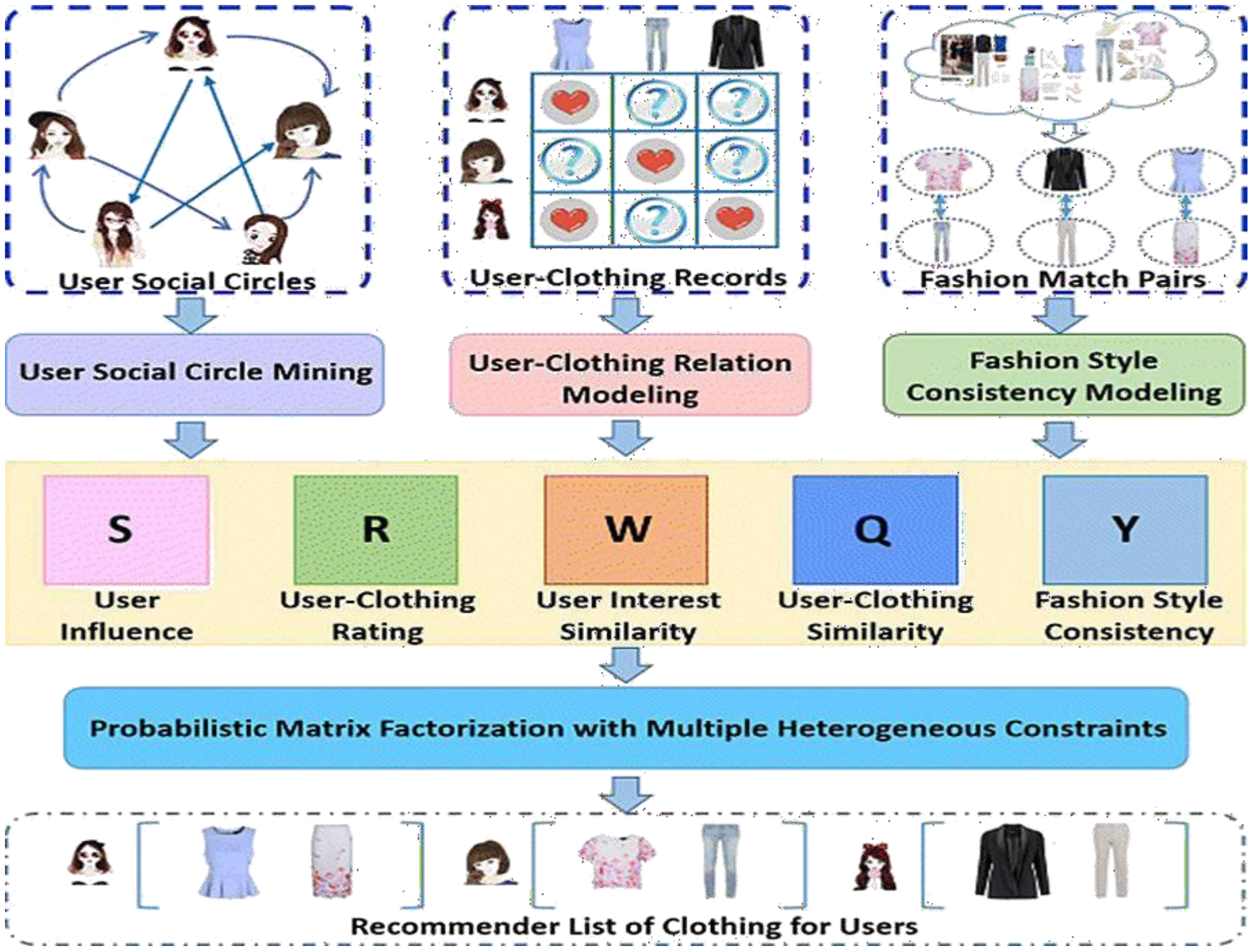


Figure: Outside recommendaton dataset

System result and accuracy:

Finally, this subsecton evaluates the system and shows the testng results and the accuracy of our model. Afer adding the model on top of the convolutonal base, freezing the weights of all layers except of the top ones, and training the model for 5 epochs, the following accuracy was obtained, as shown in Figure.

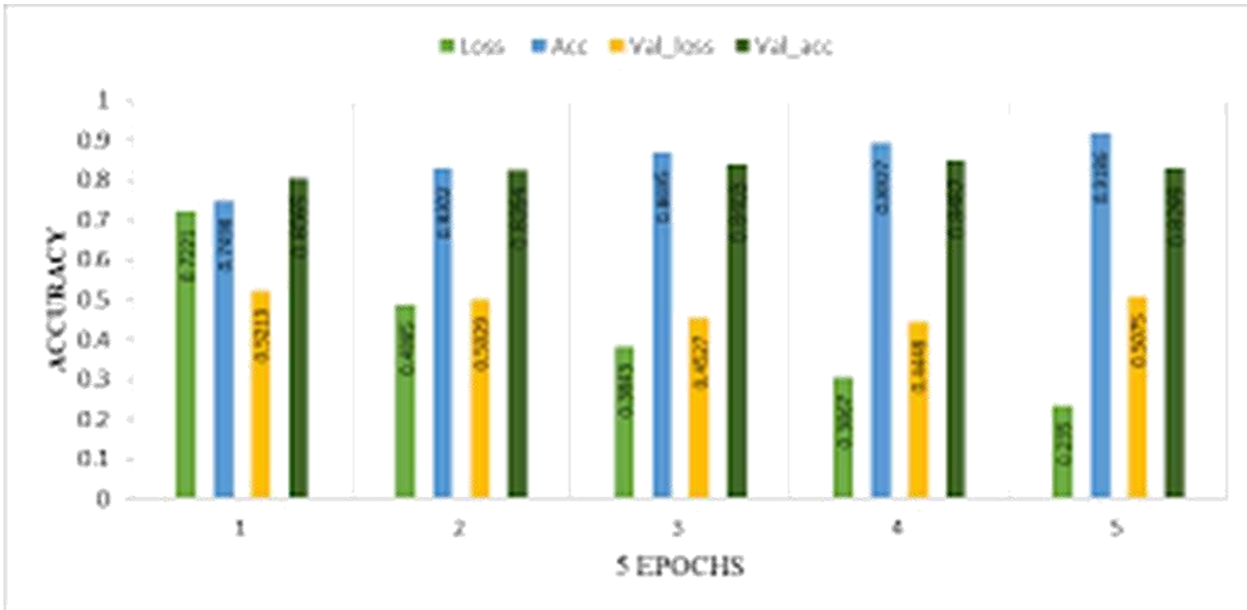


Figure 9. Model accuracy afer freezing the layers for 5 epochs

Afer calculatng the mean accuracy for 5 epochs, the obtained results areas follows:

Validaton: accuracy = 0.836000; loss = 0.489109

This part of the sentence “Afer calculatng the mean accuracy for 5 epochs” is mentoned also below, afer Figure 10, and these values mentoned for accuracy and loss (0.836000 and 0.489109) are not illustrated in Figure 9, but in Figure.

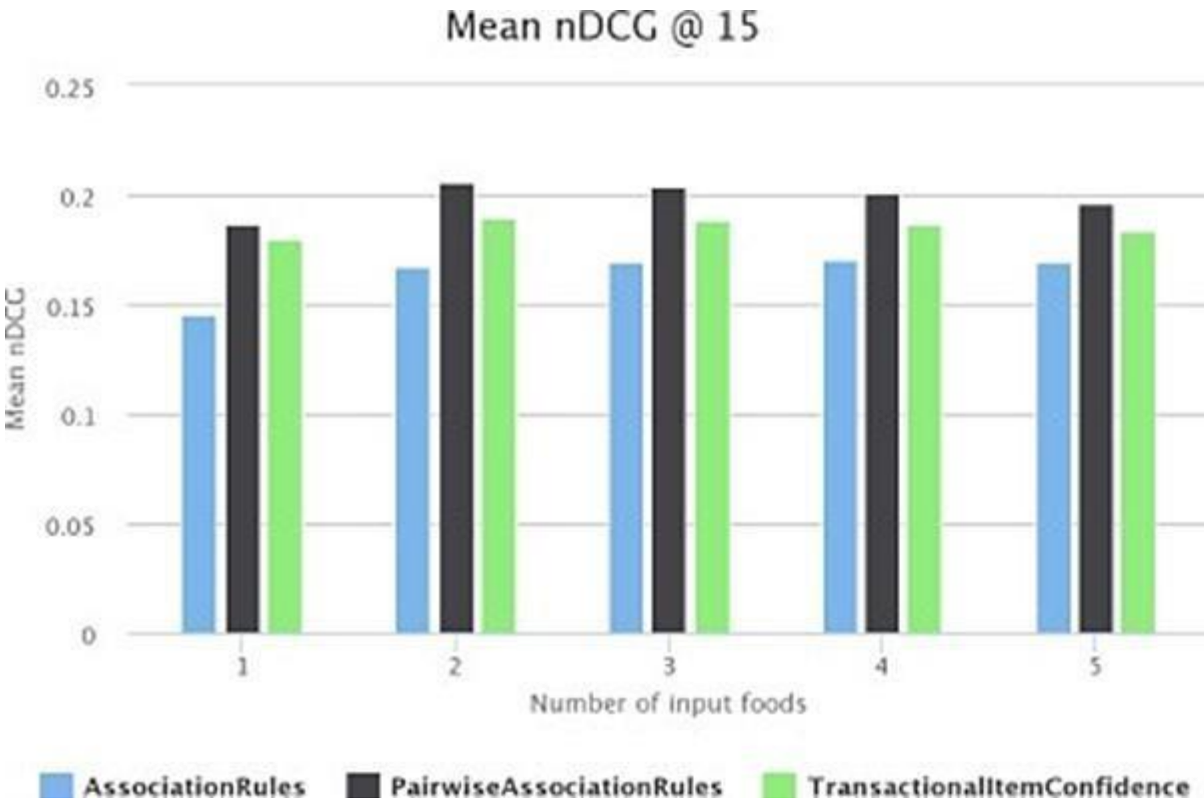


Figure 10. Model accuracy for 5 epochs

Afer calculatng the mean accuracy for 5 epochs, the fnal result are as follows: Validaton: accuracy = 0.864750; loss = 0.516400 These values mentoned for accuracy and loss (0.864750 and 0.516400) are not illustrated in Figure 10.

The accuracy of our model was compared with the one of Alex Net model. It can be clearly notced that our model gives a beter accuracy when compared to Alex Net, as shown in Figure 11.

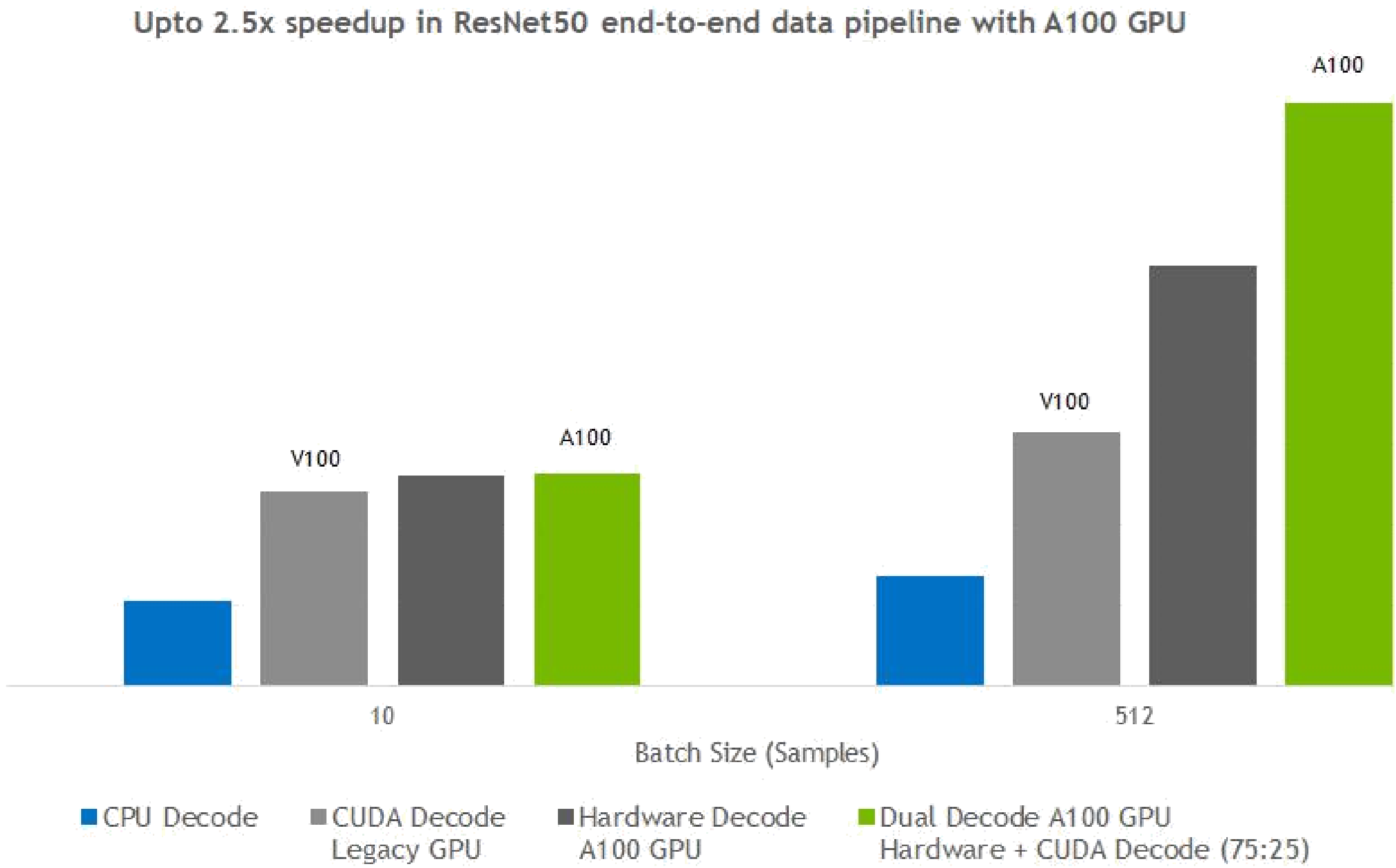


Figure 11. Accuracy and loss

Recommender systems are stll developing and, as extra research is beingdone, extra areas and weaknesses that need greater study are also developing. Recommender systems have proved to be a great soluton to the overload of web data, an important problem afectng the users. With the ever-growing records and choices, recommender systems enable the customers to access the data they need within minutes, just by a mere mouse click or by a single key stroke. Table 2 shows the comparison with other models regarding the accuracy and the loss values.

10 DISCUSSION

This scholarly artcle has provided a comprehensive review of the methods, algorithmic models and fltering techniques used in the recent fashion recommendaton-based research papers. However, this review paper has some limitatons too. Primarily, the focus of this comprehensive review paper was to explore fashion recommendaton-based artcles published in last decade that explicitly described their frameworks, algorithms, and fltering techniques. To achieve this goal, the artcles were searched using keywords relevant to the topic ttle instead of using the PRISMA technique. However, it did not afect the artcle extracton methodology, because the authors included and studied all the research papers relevant to the research focus. However, future researchers could conduct a systematc literature review on the same topic. The inital keywordsearching did not include “garment” and “outit”; however, this did not infuence the search results because we also studied the fashion recommendaton artcles that contained these keywords. The future research can also conduct a review of the datasets that have been used in fashion recommendaton-based research artcles.Additonally, further reviews of fashion recommendaton systems can apply our proposed potental algorithms to any of the available fashion image datasets to evaluate the performance of the recommender systems.

11 CONCLUSION

Recommendaton systems have the potental to explore new opportunites for retailers by enabling them to provide customized recommendatons to consumers based on informaton retrieved from the Internet. They help consumers to instantlyfnd the products and services that closely match with their choices. Moreover,diferent stat-of-the-art algorithms have been developed to recommend products based on users’ interactons with their social groups. Therefore, research on embedding social media images within fashion recommendaton systems has gainedhuge popularity in recent tmes. This paper presented a review of the fashion recommendaton systems, algorithmic models and fltering techniques based on the academic artcles related to this topic. The technical aspects, strengths and weaknesses of the fltering 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 applicatons to understand their feasibility and accuracy in the retail market, because inaccurate recommendatons can produce a negatve impact on a customer. Moreover, future research should concentrate on including tme series analysis and accurate categorizaton of product images based on the variaton in color, trend and clothing style in order to develop an efectve recommendaton system.

12 FUTURE SCOPE

Online selling and purchasing ofer innumerable benefts to both sellers and buyers, and these advantages are also the reasons for the rising scope of eCommerceWell, 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 alreadyinvested a great deal, especially with its 49% stake in the Future Group.

Indian online retail giant Flipkart has already opened a few ofine stores and plans more stores in smaller cites. They plan to combine online and ofine stores to maximize their selling potental.Google and Tata Trust have launched a joint program ‘Saathi’ to increase internet and mobile penetraton among rural women.The Government of India is also making a huge push for Ecommerce by providing numerous sops to startups, cyberparks, 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.

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