SMART FASHION RECOMMENDER APPLICATION

A PROJECT REPORT Submitted by

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17/11/2022

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ABSTRACT

In recent years, the huge amount of information and users of the internetservice, it is hard to know quickly and accurately what the user wants. This phenomenonleads to an extremely low utilization of information, also known as the information

overloadproblem. Traditonally, keywords are used to retrieve images, but such methods require al otofannotatonsontheimagedata, which will lead to serious problems such as inconsistent, inaccurate, and incomplete descriptons, and a huge amount of work. To solvethis problem, Content Based Information Retrieval (CBIR) has gradually become a researchhotspot. CBIR retrieves picture objects based entrely on the content. The content of animage needs by features to be represented that represent its uniqueness. anypictureobjectcanberepresented by its specific shapes, colours, and textures. These visual characteristcs of the image are used as input conditions for the query system, and aresult 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 imageswith clothes to learn the user's clothing style and preferences. These atributes are providedto the correspondence model to retrieve the contguous related images for recommendation. Based on data-driven, this thesis uses convolutional neural network as a visual extractor ofimageobjects. This experimental

modelshowsandachievesbeterresultsthantheonesofthepreviousschemes.

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 prefer ences. These preferences are being predicted using two approaches frstcontentwhich involves characteristics of based approach an secondcollaborativeflteringapproacheswhichconsidersuser'spastbehaviourtoevalu ate its choices. This thesis proposes a fashion recommendation systemwhich will images of the recommend clothing supported the style sort 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 createdour own datasets through web scrapping of different ecommerce websites. In thispaper we have come up with an idea to build a content-based recommendation systemusing ResNet-50 convolutional neural network.

Keywords:ClothRecommendation,ConvolutionalNeuralNetwork,SimilarityMeasure.

Introduction

During the last years, online shopping has been growing. In 2013, the total turnover forecommerce in Europe expanded with 17% in contrast to the 12 months before and hugeorganizatons can have hundreds and hundreds of products or even more from which wecan select on websites. Both the customer and the business enterprise desire the client toeasily 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 amonth,and1%saytheydonotbuyfrominternet,asindicatedbyacurrentreportbyWalkerSands.F romalltheclientslookingforitemsontheweb,63%ofthembuygarments(Burke,2002),thesebeing, quitepossibly, the most purchase ditems. The information uncover that women are more likely tobuy on-line, with71% of ladies doingthis, contrasted with 52% of men. Studies on clothing are in a growing development ingeneral as a result of the tremendous market related to dress. In China, the serviceablemarket crushed 20 billion US dollars in 2016. Picture recovery can be depicted as theerrand of looking out for pics in a picture data set. This is present not an astute thought, inlight of everything. It has been explored on account of the that the 1970s way joinedinformatonalcollectonassociatonswithPCvision,lookingintotheissueasindicatedthrough two uncommon perspectives, the frst being text-based and the second one beingvisualbased. From the outset, the developments have been made only through informationannotations that have been saved in a database to work the retrieval step, however, whenthe dimension of the image collectons started to amplify the efort required to label themused to be as soon as unsustainable, to solve this issue, during the 1990s, content-basedphotographretrievalwasproposed.Startngnowmany

searched for lines have seemed the use of one or the diferent isolated or combiningthem. Recommendaton systems make recommendatons based on the information they are provided with and in the manner in which they are programmed. details, most of the evaluation applied is independent coming up with a brand-Going into newrecommendationalgorithm, system, or model. However, different researchers useal ready existing work as researchers use an already existing current piece of work tocome up with a new diagram or to truly improve the current one. The present analysismodel focuses on the use of a current algorithmic program and, consequently, the useofanewresearchconceptcomesupwitharecommendersystem. Existngresearchand fashions given us some inspiratons of how to design recommendatonsystems. Nevertheless, they also involve some common drawbacks. Therefore, in this study, our aim to suggest a new method to assist personal choice making throughsupplying images and getsuggestons based on provided contents.

The contributon of the research are follows:

- To design and implement a web-based clothing fashion stylerecommendersystembasedondeeplearning;
- A scheme for improving a person's clothing style by removing thefeatureshe/she doesn'tlike.
- Theseatributesservedtoasimilarmodeltoretrievesimilarimag esasrecommendatons.
- Combined with more common content-based recommendaton systems, our model can help to extendro bustness and performance.

Literaturesurvey

Myntra-MatchingClothesRecommendation:

On selecting a particular item to buy, Myntra automatically suggests a fullsetofclothesthat arematchingtotheselecteditem. For example, onselecting 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 existinits database.

YourCloset:

This is a mobile application that organizes the closet. The user interface isshown in. The application asks customer to input their clothes. It then matcheseach cloth with other clothes. For example, if there are 4 shirts and 4 pants, theapplicationmatcheseachshirtwitheach pantandthusprovides16possibilities. The application does not make matches of clothes depending upon patterns, colorandtexture of clothes. Italso does not have are commendation system.

YourClosetAppMagicCloset:

This system aims to retrieve clothes from online stores that arematching 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 thetoporbottomclothesalongwiththeoccasiontheywantto useitfor. The system will search for clothing that matches the user query and satisfes the criterion of wearing aesthetically and wearing properly.

WhichClothestowearconfdently?:

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

PersonalizedClothingRecommendationBasedonKnowledgeGraph:

This system attempts to exploit the knowledge graph for providing clothing recommendations to the user keeping the user context in mind. Therecommendation is done by calculating the similarity in the clothing ontologysimilar to users collection. Skin and Clothes matching seeded by Color SystemSelection: The main aim of the system is to suggest clothes to user based onskin 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 skincolormatch. An automated system to determine the highest levels of color

suitabilitybetweenskinandclothingwasmade.

DiscerningAdvisor:

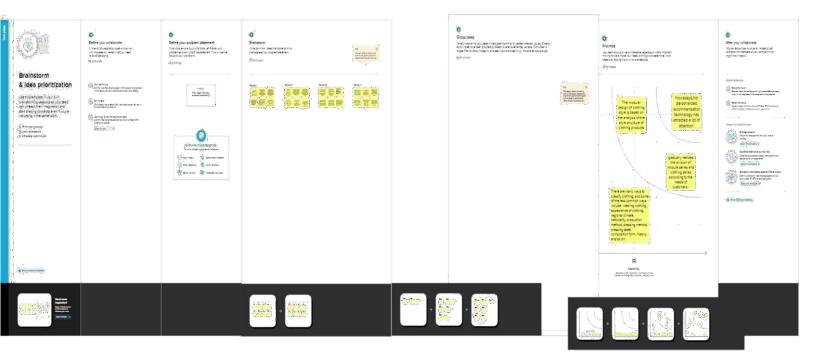
The system tries to recommend clothes based on skin olor of thecustomer. Using a neural network, frst the skin color is detected. Fuzzy logic is used to map askin color to the skin color of a fashion model, and clothes suited to that model are recommended. Garment Detectives: The garment detection is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

IdentifyingCornersofClothesbyImageProcessing:

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

Real-timeClothingRecognitionfromSurveillanceVideos:

It is an analysis system of contents of video which is capable of taggingvarious clothesofd 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 are detected. The system then proceeds to clothing recognition and indicates the type of clothing —skirt, t-shirt, etc.



Proposedsystemarchitecture

The system architecture defines the hardware, sofware and networkenvironment 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 bothhorizontally and vertcally. The architecture used in the system is shown horizontallywhere the Model View Controller is explained as represented in Figure 1. The high-levelpartofthesystemislooked atusingthevertcalway.

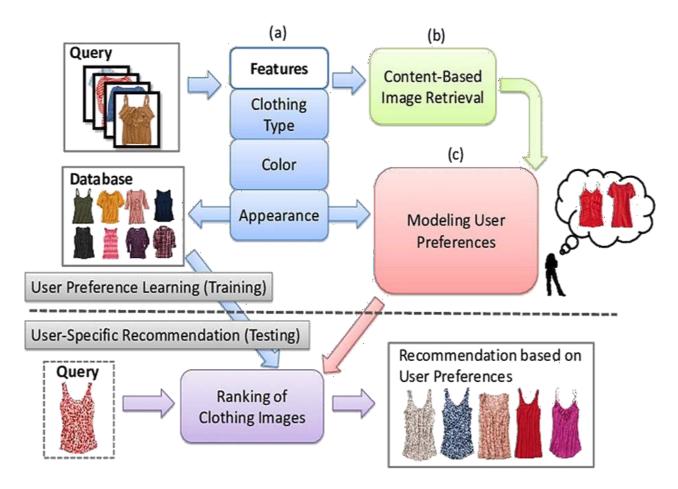


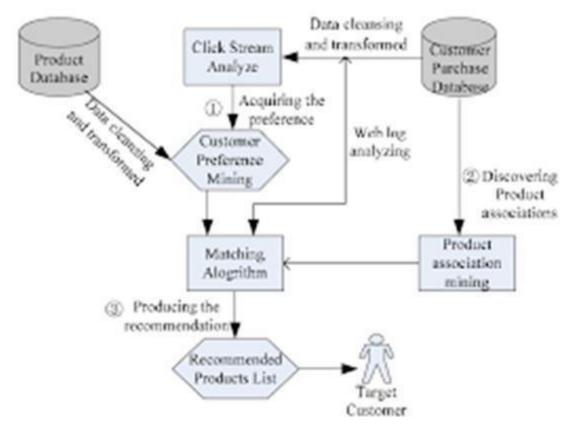
Figure 1. Systemarchitecture.

The system comprises of the Client tre, which is the front end or View mode, middle terwhich is the system controller and the backend tre which is the model. The client side iswhere the users/customers log in in the system, browse for the system interface, provideinputqueryimagetothesystem, and getrecommendation according to the input query. The middle true is responsible for communication between the front end and the backend. It receives user requests and sends them to the back end and in turn accepts responses from the backend and sends them to the user. The internet works to provide access to the site with a strong security check, provided by both frew all and password protecton policy.

Anyunauthorizedaccessisdetectedandpreventedbythefrewall.

a. The vertical classification system model

The recommendation system works with the data set to track user input datafeatures and extracted features from data set upon which new predictions and and available dataset features. Receives Recommendations User Web ServerSendsresponsetouserDatabaseStoresUserinput dataStores datasetfeatures.



Data Recommender Makes Recommendatons Recommender
AlgorithmDetermines 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. Bylooking 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, therecommender flters the data it needs from the repository
using the algorithm. When asignalis senttothe algorithmaboutwhat
dataareneededforfltering,thealgorithm

computes the similarity. The similarity results are then transferred to therecommendersystemwhichinturnsendsrecommendatonstothewebserverandf nallytotherespectveuser.

b. Datasetandclassifcation

In this project, we worked with the Deep Fashion dataset, which isgathered from researchers from the Chinese Hong Kong University. It hasoveronemilliondiversetrendpicsandwealthyannotatonswithadditonaldataab out landmarks, categories, pairs etc. The dataset consists of 5 distnot typesof predictngsubsetsthataretailor-madetowardstheirtasks.

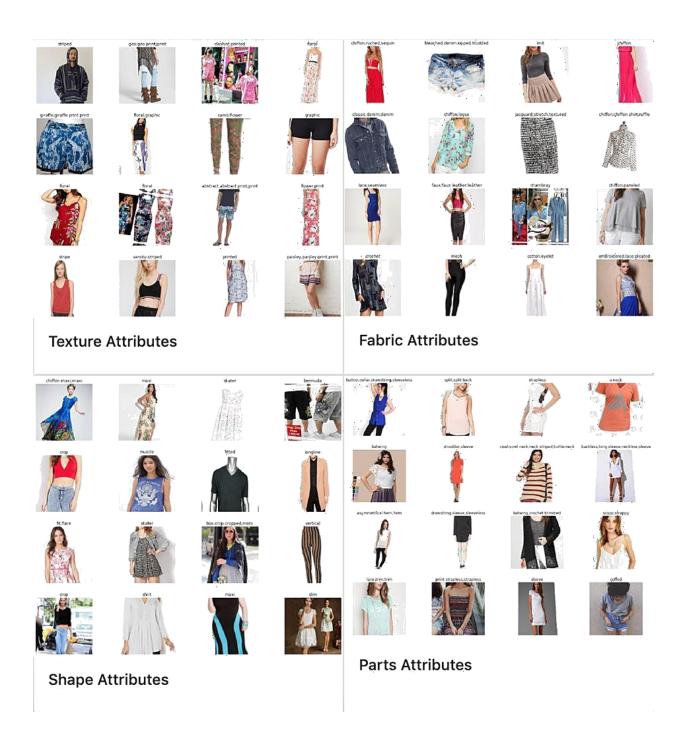
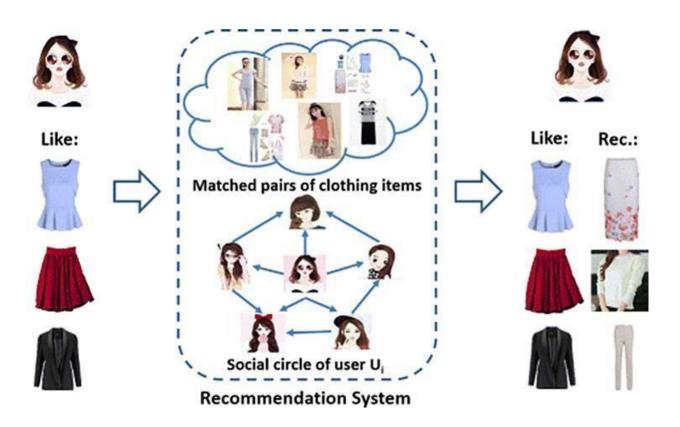


Figure 3. Fashion dataset One subset, known as Atribute Predicton, can beusedforapparelcategoryandatributepredicton. Fromalmost290,000 photos of 50 apparel categories and 1,000 apparel atributes, we randomly picked 18 kimages from different categories and then we classifed them for training and testing. The distribution of labelsis presented in Figure

c. Designofdeeplearningmodule

There are many classifcaton algorithms or classifers in use today. The mostnotablyandthemostimplementedclassifersandfeatureextractorareimplementedt o solve a problem of cloth / fashion recommendaton Design process. (1) are weightvectors, are fully connected output layers that actually perform classifcaton and aretheCNNwithoutthelastlayer. They are used as a feature extractors.



The core network of our model as shown in Figure 4. who presented aconvolutonal neural network in the paper "Very Deep Convolutonal NetworksforLarge-

ScaleImageRecogniton", at the University of Oxford.". Then model is checked for top -5 accuracy on ImageNet.

Results and Evaluation

This secton focuses on evaluating our system and deciding the stage whichitisable tofulfithe purposeforwhichitwascreated the performance of the system is 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 testsystem. In the training implementation module, we are performing the movement throughout the area, freeze the base layers of the organization 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 until the approval exactness set les. We keep the best achievable loads (best on approval exactness) and use it for the suggestion model. The training implementation code is presented below.

Step1:Trainingthe wholenetworkfor5 epochsfrst

Step2:Checkpoint_callback=modelcheckpoint(',/model/vgg_weights_best_patern.hdf5'.St

ep.3: Monitor='val acc', verbose=0

save_best_only=true,save_weights_only=false,mode=auto',period=1)

Step4:Tf_model.ft_generator(Train_generator,Samples_per_epoch=nb_train_sample,N b_epoch=10, Validaton

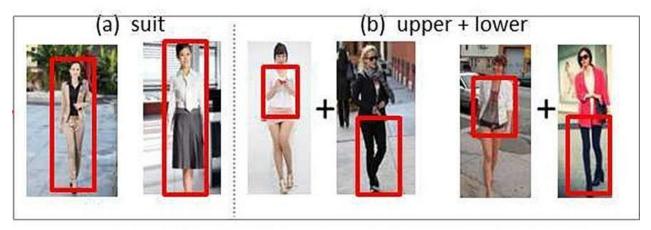
data=validaton_generator,Nb_val_samples=nb_validaton_samples, Verbose=1, Inital_epoch=5,Callbacks=[checkpoint_callback]

Step 5: end

1. Visual recommendation module implementation

To get proposals, we wished to construct a vault of pictures. This archivewould be a unique application. If the suggestion was cultivated for shopping, the storehousewould have contained pictures from online retail locations like Amazon, eBay, Pinterest,Instagram, etc. A subset of patern datasets was used to test our proposed approach. Atthat point, the information had already been cleared of unimportant photos. Then, thephotos were passed by means of the organization and design vector pictures have beencreated from eachphoto. Forthe getingthesuggestion, we frist needed to build the

individual style profle. This is brought out by taking one or more noteworthy picturesoftheclient'sidealatre thingsasthey wereenteredandby making theirstylevector. These vectors are then blended to shape the framework of the individualstyleprofle. The Figure 5 shown Paternrecommendation with similarity score.



Occasion-Oriented Clothing Recommendation Results



Occasion-Oriented Clothing Pairing Results

Figure 5. Patern recommendation with similarity score

The proposed scheme is further below, as follows: we will utlize a closenesscalculaton, which and the designvector of each picture in the vault with the style proflegrid. This gives us as coredependent on the quantity of component coordinates (i.e., how

greatisthedegreeofsimilarity ofapicturetotheindividual'sstyleprofle).

Step1:defsimilarity(feature_data,inp_feature_data):

Step2:nun_samp=inp_feature_data.size

Step3:print(unm_samp)Sim_score=[]foriinrange(1 en(feature_data)):score=0

Step4:show_sample(data_images[i])

Step5: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

Step7:print(score)simScore

Step 8: end

i.Usermanagementservices:

The system provides a plator mthrough which auser can visit the system and provide his sher choices regarding the fashion images for best recommendation.

ii. Fashionvectorforimagesinrepositoryandinputfashionvector:

The system is responsible for making fashion vectors for images intherepositoryandfashionvectorimagesprovidedbytheusertothesystem, for the similarity measures and for making recommendatons. Afermaking the fashion vector, some predictons are made, as illustrated Thesystem is responsible for making recommendatons to users based on theiruserdata. Theuserdata 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=()Foriinrange(len(feature_data));score=0show_sample(data_images[i])print(feature_data[i])RomanianJournalofInformatonTechnology and Automate Control, Vol. 31, No.

4, 123-136, 2021

131http://www.rria.ici.ro Step3: Score_minp_feature_data-

feature_data[i]print(score_m)

 $\textbf{Step4}: Score = num_samp-np.count_nonzero(score_m) Sim_score[i] = scoreprint(score)$

Step5:Returnsim_score

Step3:end

By accessing the system, users are able to access and view their contentbased recommendatons. However, all the recommendatons are made based on thesimilaritybetweenuserinputsanduserinputs. Aslongasthere is alevel of similarity, we make the best recommendatons.

iv. Recommendertothequeryimages indataset:

We can see that our model can capture thebest matching style by including the length, shape, colour, fabric and patern of the cloths, as illustrated in three query images examples. Inthefrstexample, the model captures deep features including the blouse category, fabric, repeated for all patern and the regular ft style. As seen, the fve recommended images display different clothes. The second examples hows that the model captures the wool fabrics, the contrast colour sttches and the turtleneck. The third example shows that the model capture the coton fabrics and the printed leters. The recommendations 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

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

your favourites.

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

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

necklaces... 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 alam fas

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 withhighaccuracy, meaning that our systemachieves its purpose. It can be not ced 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 recommendation and recommend top similar images in different colours, shapes, and styles.

v.Recommendationstothequeryimagesoutsidethedataset:

It's natural to ask if the model you made works with images which are not partofthedataset. We randomly downloaded three online images illustrating expensive clothes. As shown in Figure 8, the model is stll able to capture the style, paternand fabrics of the clothes and recommends imilarones.

The model is checked for different 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 different categories.

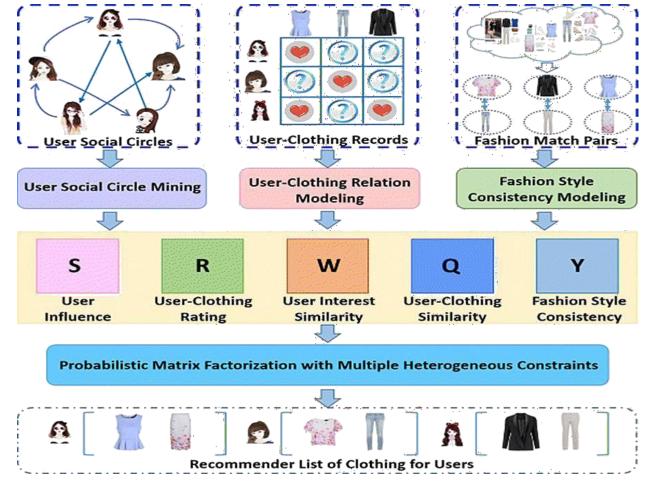


Figure: Outsiderecommendaton dataset

Systemresultandaccuracy:

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

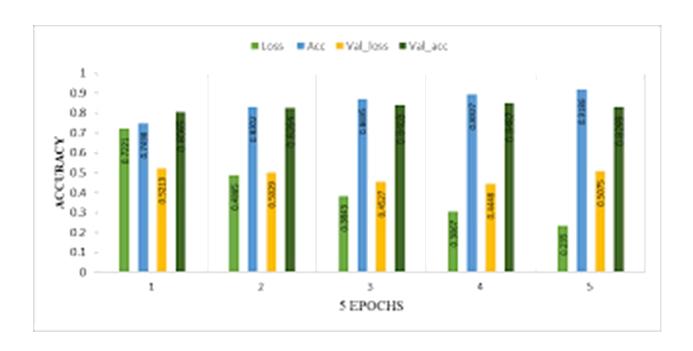


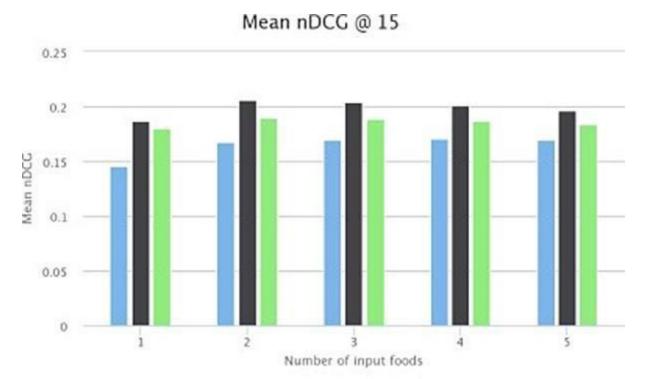
Figure 9. Model accuracy af erfreezing the layers for 5 epochs

Afercalculating themean accuracy for 5 epochs, the obtained results are as follows:

Validaton:accuracy=0.836000;loss=0.489109

This part of the sentence "Afer calculating the mean accuracy for 5 epochs" ismentonedalsobelow, 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.



AssociationRules PairwiseAssociationRules TransactionalItemConfidence Figure10.Modelaccuracyfor5epochs

Afer calculating the mean accuracy for 5 epochs, the final result are as follows: Validation: accuracy=0.864750; loss=0.516400 These values mentioned for accuracy acyand 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 noticed that our model gives a beter accuracy when compared to Alex Net, as shown in Figure 11.

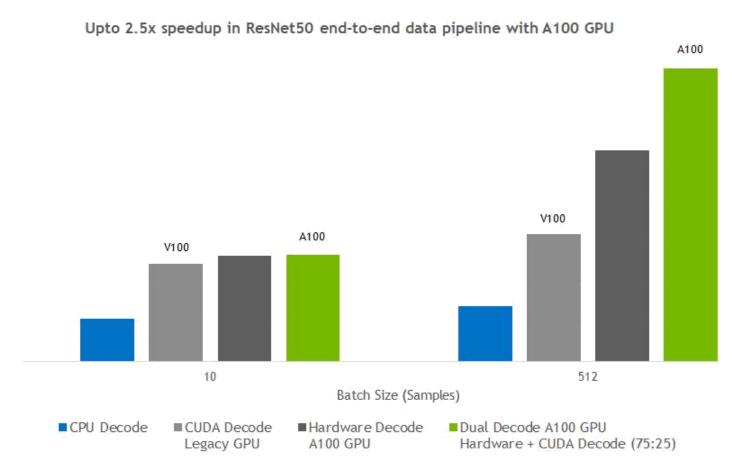


Figure 11. Accuracy and loss

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 solution to the overload of webdata, an important problem afecting 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.

Source Code

fashion.html

```
<html>
  <head>
    <metaname="viewpoint"content="width=device-width,inital-scale=1.0">
    <ttle>FASHIONVIBE</ttle>
    <style>
    *{margi
 n: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:10px10%;
  display:fex;
  align-items:center;
  justfy-content:space-between;
  positon:fxed;
}
.logo{
```

width:200px;

```
height:50px;
  text-
  decoraton:none;text-
  align:
  center;color:#00112
  8;
}
.user-
  pic{width:40
  px;
  border-radius:
  50%;cursor:
  pointer; margin-
  lef:30px;
}
navul{
  width:
  100%;text-align:
  right;font-
  weight:bold;
}
navulli{
  display: inline-
  block;list-style:
  none;margin:10px
  20px;
```

```
}
navullia{
  color:rgb(252,252,5);
  text-decoraton:none;
```

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

```
}
.Adcontent
{
  width:45%;heig
  ht:
  400px;margin-
  lef: 55%;color:
  #7DE5ED;text-
  align:center;pad
  ding:100px;
}
.Adcontent2
  width:45%;heig
  ht:
  400px;margin-
  lef: 5%;
  color:
  #7DE5ED;text-
  align:
  center;padding:
  100px;
}
.columnst
  {foat:lef;margi
```

n-lef:7%;

margin-top:10%;

```
width:230px;
  height:400px;
  background-color:transparent;
  border: 2px solid
  #74bde0;border-
  color:transparent;
}
.column
  {foat:lef;margi
  n-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(25
 2,252,5);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;posito
  n:fxed;
}
.srch{
  width:
  200px;height
  :40px;
  background:#7DE5ED;
  border:2pxsolid#121212;
  margin-top:
  13px;margin-right:13px;
  color:#FCE700;
```

font-size:16px;

```
align-items:
  center;padding:10
  px;
  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
 #00000dd;background:#00
  0000dd;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{outlin
  e:none;
}
.srch:focus{outli
  ne:none;
}
.sub-menu-
  wrap{positon:ab
  solute;top:100%;
  right:
  2%;width:32
  0px;
  max-
  height:0px;overfow:hidde
  n;transiton:max-
  height0.5s;
}
.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:6
  0px;
  border-radius:
  50%;margin-
  right:15px;
}
.sub-menu
  hr{border:
  0;height:
  1px;width:10
  0%;
  background:#525252;
  margin:15px010px;
}
```

.sub-menu-link{

```
display:fex;
  align-items:
  center;text-
  decoraton:
  none;color:
  #525252;margin:12p
  x0;
}
.sub-menu-linkp{
  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:transform0.5s;
.sub-menu-link:hoverspan{
  transform:translateX(5px);
```

```
}
.sub-menu-link:hoverp{
```

```
font-weight:600;
}
.hello{
 margin-botom:
 200px;text-align:
 lef;positon:absolute;ri
 ght: 10px;
}
   </style>
 </head>
 <body>
     <nav>
       <aclass="logo"href="MadFinalhome.html"><h2>FASHION
       VIBE</h2></a>
         <inputclass="srch"type="search"name=""placeholder="TYPETOSEARCH">
        <ahref="#"><butonclass="btn">SEARCH</buton></a>
        <ahref="#">HOME</a><ah
        ref="#">FEATURES</a>
        <ahref="#">ABOUT</a>
```

```
<imgsrc="htps://storagedemo-madzh.s3.jp-tok.cloud-object-</pre>
storage.appdomain.cloud/images/profle.jpeg"
                                                          class="user-
pic"onclick="toggleMenu()">
    <divclass="sub-menu-wrap"id="subMenu">
       <divclass="sub-menu">
         <divclass="user-info">
                            src="htps://storagedemo-madzh.s3.jp-tok.cloud-
object-storage.appdomain.cloud/images/profle.jpeg">
          <h2>NAME</h2>
         </div>
         <hr>
         <ahref="#"class="sub-menu-link">
                            src="htps://storagedemo-madzh.s3.jp-tok.cloud-
object-storage.appdomain.cloud/images/profle.jpeg">
          EDITPROFILE
         </a>
         <ahref="#"class="sub-menu-link">
                            src="htps://storagedemo-madzh.s3.jp-tok.cloud-
                    <imq
```

object-storage.appdomain.cloud/images/setngs.jpeg">

```
SETTING&PRIVACY
        </a>
        <ahref="#"class="sub-menu-link">
                  <img src="htps://storagedemo-madzh.s3.jp-tok.cloud-
object-storage.appdomain.cloud/images/help.jpeg">
          HELP
        </a>
        <ahref="/Login"class="sub-menu-link">
          <img src="htps://cdn-icons-
         png.fatcon.com/512/56/56805.png">LOGOUT
        </a>
      </div>
    </div>
  </nav>
 <divclass="Banner">
                    <divclass="Bannerimg1"><imgimgclass="image"
src="fashionimagebanner.webp"></div>
```

```
<divclass="Adcontent">
     <h1><br>THEJOYOFDRESSINGISANART.</br></h1>
     <br>Let'shave alook on it -----></br>
   </div>
 </div>
 <divclass="rowstart">
               <divclass="columnst"><divclass="depimg"><imgclass="image"sr
c="sarees.webp"></div><div>lass="Botom">WEDDINGSAREES</div></div>
      <divclass="columnst"><divclass="depimg"><imgclass="image"src="Salwarka"
meez.webp"></div><divclass="Botom">SALWARKAMEEZ</div></div>
               <divclass="columnst"><divclass="depimg"><imgclass="image"sr
c="Kurts.webp"></div><divclass="Botom">CASUALKURTIS</div></div>
       <divclass="columnst"><divclass="depimg"><imgclass="image"src="bridalleh"</pre>
enga.webp"> </div><div class="Botom">BRIDAL LEHENGA</div></div>
 </div>
 <divclass="Banner">
                        <divclass="Bannerimg2"><imgimgclass="image"</pre>
src="lovablekidsatre.webp"></div>
   <divclass="Adcontent2">
     <h1class="kids"><br>LOVABLEKIDSATTIRE</br></h1>
```

```
<br>-----
   </div>
 </div>
 <divclass="row">
      <div class="column"> <div class="depimg"> <img
class="image"src="Modernvibe.webp"></div><divclass="Botom">MODERNVIBE<
/div></div>
               <div class="column"> <div class="depimg"> <img
class="image"src="festvemood.webp"></div><divclass="Botom">FESTIVEMOOD
</div></div>
       <div class="column"> <div class="depimg"> <img
class="image"src="skinnydress.webp"></div><divclass="Botom">SKINNYDRESS<
/div></div>
        <div class="column"> <div class="depimg"> <img
class="image"src="Maxgirls.webp"></div><divclass="Botom">MAXGIRLS</
div></div>
 </div>
 <divclass="Banner">
                      <divclass="Bannerimg1"><imgimgclass="image"</pre>
src="mensfashion.webp"></div>
   <divclass="Adcontent">
    <h1><br>HANDSOMEMENATTIRE</br></h1>
    <br>AlwaysDRESSwell,KeepitSIMPLEbutSIGNIFICANT ......
```

```
</div>
 </div>
 <divclass="row">
        <divclass="column"><divclass="depimg"><imgclass="image"src="polotshir")</pre>
ts.webp"></div><divclass="Botom">POLOT-SHIRTS</div></div>
                <div class="column"> <div class="depimg"> <img
class="image"src="menhoodies.webp"></div><divclass="Botom">HOODIES</di
v></div>
         <divclass="column"><divclass="depimg"><imgclass="image"src="menca"</pre>
suals.webp"> </div><divclass="Botom">MENCASUALS</div></div>
        <divclass="column"><divclass="depimg"><imgclass="image"src="formalshi")</pre>
rts.webp"></div> <divclass="Botom">FORMAL SHIRTS</div></div>
 </div>
 <divclass="Banner">
   <divclass="Bannerimg2"><imgclass="image"src="adornments.webp"></div>
   <divclass="Adcontent2">
     <h1><br>PERSONALADORNMENTS</br></h1>
     <br>ADORNMENTis neveranything exceptaREFLECTIONoftheHEART!!!</br>
   </div>
 </div>
```

```
<divclass="rowend">
    <divclass="columnend"><divclass="depimg"><imgclass="image"src="womenor"
nmanets.webp"></div><divclass="Botom">JEWELLERY</div></div>
  <div class="columnend"> <div class="depimg"> <img
class="image"src="watch.jpg"></div><divclass="Botom">WATCHES</di
v></div>
            <div class="columnend"> <div</pre>
class="depimg"><imgclass="image"
src="htps://5.imimg.com/data5/TQ/NK/MY-45888708/men-belts-
500x500.jpg"></div><divclass="Botom">BELTS</div></div>
            <div class="columnend"> <div class="depimg"> <img</pre>
class="image"src="htps://encrypted-
tbn0.gstatc.com/images?q=tbn:ANd9GcQSWDKgpQeZ-3VNR7-
9SfaVGVvqOawrkZiLdNfSpjNNQJNI6hl8cJg0Qs_DZfpJtzUst0&usqp=CAU"></div>
<divclass="Botom">HANDBAGS&CLUTCHES</div></div>
 </div>
<script>
 letsubMenu=document.getElementById("subMenu");fu
 nctontoggleMenu(){
   subMenu.classList.toggle("open-menu");
 }
 window.watsonAssistantChatOptons={
       integrationID: "1a8c11c0-839e-4442-8b03-59f7c12ce5f5",//TheIDofthis
```

```
integraton.
    region: "au-syd", // The region your integration is hosted
     in.serviceInstanceID:"bada3725-51e6-42fe-bccc-3e2603433478",//TheID
 ofyourserviceinstance.
    onLoad:functon(instance){instance.render();}
  };
  setTimeout(functon(){
    constt=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>
</body>
<footer>
  <divclass="footer">
    <divclass="hello">
      <ahref="Feedback.html">feedback</a>
    </div>
    <div>
      <H1>THANKYOUFORPURCHASING....... WELCOMEAGAIN!!!!</H1>
    </div>
  </div>
</footer>
```

```
</html>
```

server.py

```
from fask import Flask,
render_template,request importos
appFlask=Flask(___name___)
picFolder =
os.path.join('statc','images')appFlask.confg['UPL
OAD_FOLDER']=picFolder
@appFlask.route('/')@
appFlask.route('/out')d
ef index():
  returnrender_template("login.html")
@appFlask.route('/login',methods=['POST','GET'])
defmy_forum_post():
  returnrender_template('FashionVibe.html')
@appFlask.route('/index',methods=['POST','GET'])
```

```
defmy_forum_posts():
  returnrender_template('index.html')
@appFlask.route('/Feed',methods=['POST','GET'])d
efmy_forum_posts1():
  returnrender_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:#00112
  8;
}
.user-
  pic{width:40
  px;
  border-radius:
  50%;cursor:
  pointer; margin-
  lef:30px;
}
navul{
  width:
  100%;text-align:
```

right;font-

weight:bold;

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

lef;width:5

0%;

```
height:400px;
  background-color:#525252;
}
.Bannerimg2
  foat:
  right;width:50
  %;height:400
  px;
  background-color:#525252;
}
.Adcontent
  width:45%;height
  : 400px;margin-
  lef: 55%;color:
  #7DE5ED;text-
  align:
  center;padding:1
  00px;
.Adcontent2
  width:45%;hei
  ght:
  400px;margin-
```

lef:5%;

```
color:
 #7DE5ED;text-
  align:
  center;padding:1
  00px;
}
.columnst
  {foat:lef;margi
 n-lef:7%;
  margin-top:10%;
 width:230px;
  height:400px;
  background-color:transparent;
  border: 2px solid
 #74bde0;border-
  color:transparent;
}
.column
  {foat:lef;margi
  n-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: 230 px; he
  ight: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;posito
  n: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:10
  px;
  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:2pxsolid#00000dd;

```
background:#00000dd;
  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{outlin
  e:none;
}
.srch:focus{outli
  ne:none;
}
.sub-menu-
 wrap{positon:ab
  solute;top:100%;
  right:
  2%;width:32
  0px;
```

```
max-
  height:0px;overfow:hidde
  n;transiton:max-
  height0.5s;
}
.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-infoimg{
```

```
width:60px;
  border-radius:
  50%;margin-
  right:15px;
.sub-menu
  hr{border:
  0;height:
  1px;width:10
  0%;
  background:#525252;
  margin:15px010px;
}
.sub-menu-
  link{display:f
  ex;
  align-items:center;
  text-
  decoraton:none;colo
  r:
  #525252;margin:12
  px0;
}
.sub-menu-linkp{
  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:transform0.5s;
}
.sub-menu-link:hoverspan{
  transform:translateX(5px);
}
.sub-menu-link:hover
  p{font-weight:600;
}
.hello{
  margin-botom:
  200px;text-align:
  lef;positon:absolute;ri
  ght: 10px;
```

```
<script>
   letsubMenu=document.getElementById("subMenu");fu
   nctontoggleMenu(){
      subMenu.classList.toggle("open-menu");
    }
   window.watsonAssistantChatOptons={
           integrationID: "1a8c11c0-839e-4442-8b03-59f7c12ce5f5", // The ID
  ofthisintegraton.
      region:"au-syd",//Theregionyourintegratonis hostedin.
       serviceInstanceID: "bada3725-51e6-42fe-bccc-3e2603433478", // The
  IDofyourserviceinstance.
      onLoad:functon(instance){instance.render();}
   };
   setTimeout(functon(){
      constt=document.createElement('script');
         t.src="htps://web-
  chat.global.assistant.watson.appdomain.cloud/versions/"+(window.watsonAssista
  ntChatOptons.clientVersion || 'latest') +"/WatsonAssistantChatEntry.js";
      document.head.appendChild(t);
   });
 </script>
chat.js
<script>
   let subMenu =
   document.getElementById("subMenu");functontoggle
   Menu(){
```

```
subMenu.classList.toggle("open-menu");
  }
  window.watsonAssistantChatOptons={
         integrationID:"1a8c11c0-839e-4442-8b03-
 59f7c12ce5f5",//TheIDofthisintegration.
    region:"au-syd",//Theregionyourintegratonis hostedin.
     serviceInstanceID:"bada3725-51e6-42fe-bccc-
 3e2603433478",//TheIDofyourserviceinstance.
    onLoad:functon(instance){instance.render();}
  };
  setTimeout(functon(){
    constt=document.createElement('script');
        t.src="htps://web-chat.global.assistant.watson.appdomain.cloud/versions/"
 +(window.watsonAssistantChatOptons.clientVersion
                                                                 'latest')
                                                          \parallel
                                                          +"/WatsonAssistantC
 hatEntry.js";
    document.head.appendChild(t);
  });
</script>
```

DISCUSSION

This scholarly artcle has provided a comprehensive review of the methods, algorithmic models and fltering techniques used in the recent fashion recommendation-based research papers. However, this review paper has some limitations too. Primarily, the focus of this comprehensive review paper was to explore fashion recommendation-based artcles published in last decade that

explicitlydescribedtheirframeworks, algorithms, and fltering techniques. To achieve this goal, the artcles were searched using keywords relevant to the topicttle instead of using the PRISMA technique. However, it did not afect the artcleextracton methodology, because the authors included and studied all the research papers relevant to the research focus. However, future researchers could conduct a systematic literature review on the same topic. The initial keywords earching did not include "garment" and "outit"; however, this did not infuence these arch results because we also studied the fashion recommendation articles that contained these keywords. The future research can also conduct a review of the datasets that have been used in fashion recommendation-based research articles. Additionally, further reviews of fashion recommendation systems can apply our proposed potental algorithms to any of the available fashion image datasets to evaluate the performance of the recommender systems.

CONCLUSION

Recommendation systems have the potential to explore new opportunities forretailers 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 statof-the-

artalgorithmshavebeendevelopedtorecommendproductsbasedonusers'interactonswit htheirsocialgroups. Therefore, research onembedding social media images within fashion recommendaton systems has gainedhugepopularityinrecenttmes. Thispaperpresented are view of the fashion recommission of the fashion recommiss endaton systems, algorithmic models and fltering techniques based on theacademicartclesrelatedtothistopic. Thetechnical aspects, strengths and weaknesses of the fitering techniques have been discussed elaborately, which willhelp future researchers gain an indepth understanding of recommendersystems. However, the proposed prototypes should be tested in commercial applications to understand their feasibility and accuracy in the retail market, becauseinaccuraterecommendatonscanproduceanegatveimpactonacustomer. Moreo ver, future research should concentrate on including tme series analysis and accurate categorization of product images based on the variation in color, trendand

clothingstyle inorder to developanefectverecommendatonsystem.

FUTURE SCOPE

Online selling and purchasing ofer innumerable benefts to both sellersand buyers, and these advantages are also the reasons for the rising scope ofeCommerceWell, 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 alreadyinvesteda greatdeal, especially with its 49% stake in the Future Group.

Indian online retail giant Flipkart has already opened a few ofine storesand plans more stores in smaller cites. They plan to combine online and ofinestores to maximize their selling potental. Google and Tata Trust have launched ajoint program 'Saathi' to increase internet and mobile penetraton among ruralwomen. The Government of India is also making a huge push for Ecommerce byproviding numerous sops to startups, cyberparks, and so on through its DigitalIndia program. As of now, there are close to 20,000 Ecommerce companies inIndia, withmany more expected to join the bandwagon everymonth.

REFERENCE

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