INTERACTIVE SYSTEM FOR FASHION CLOTHING RECOMMENDATION

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, ***Interactive System for Fashion Clothing Recommendation***, in partial fulfillment of the requirements for the award of degree of *Master of Technology* in *Computer Science and Applications* submitted in Computer Science and Engineering Department of Thapar Institute of Engineering and Technology, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Shreelekha Pandey* and refers other researcher's work which are duly listed in the reference section. The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ABSTRACT

An interactive system for fashion clothing recommendation is upcoming and exploring area that deals with image retrieval. Basically it aims to have efficient online shopping systems that take clothes image as an input and automatically retrieve similar clothing images from massive collection of clothing image dataset. In addition, such systems are trained to generate relevant style tags or annotations for the query image. Existence of factors like heterogeneous style attributes, body poses and appearances, background, etc. generate several challenges for both the tasks. Past few years have identified part-based representations as useful tool in this domain. A survey of such systems is presented in this manuscript drawing attention towards their contribution. An attempt is also made to summarize must have features of fashion clothing recommendation systems thus presenting the future directions in this domain.

Based on the inferences drawn, an image based fashion clothing retrieval system is designed as well as implemented. It works with two features (color histogram and attribute descriptor) and is divided into two main modules. One retrieves matching clothing pair and second allows user the flexibility to change a few style related attributes that helps in result refinement as per the user requirement. It effectively uses the concepts of neural networks and its applicability is validated using a sub-set of self-collected image dataset with 1,100 images from freely available DeepFashion dataset. The developed system is evaluated using visual examination of retrieved images and is observed to achieve satisfactory accuracy values.

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LIST OF ABBREVIATIONS

ATTR	Attribute Descriptor
BOW	Bag of Words
CNN	Convolutional Neural Network
DARN	Dual Attribute-aware Ranking Network
GDP	Gross Domestic Product
GUI	Graphical User Interface
HOG	Histogram of Oriented Gradients
HT	Hybrid Topic
IIP	Index of Industrial production
LBP	Local Binary Pattern
MTCT	Multi-Task Curriculum Transfer
SGD	Stochastic Gradient Descent
SURF	Speeded Up Robust Features
SVM	Support Vector Machines
ReLU	Rectified Linear Unit Activation
ResNet	Residual Neural Network

Chapter 1

INTRODUCTION

“***Fashion is about dreaming and making other people dream***”

Donatella Versace

India is illustrious for the richness in its clothing, their made, and various textile heritages. It's actually a surprise to experience enormous traditional customs as each and every region of Asian nation has its own exclusive native apparel and ancient attire. Most of the agricultural population still wears ancient garments. Urban Asian nation is dynamical quick with new path breaking international brands mirrored by the young and excited youth, within the multi-ethnic major cities of Asian nation. Indian industry is nothing however spirited. It’s still a rising business where several new models and designers are waiting within the wings to showcase their skills to the globe. Though in textile planning, the probability that a designer gets good recognition depends largely on the weaver and his/her skills.

One can easily observe that the current state of Indian fashion is a colorful blend of better styles from Indian as well as western fashion. Moreover, fusion of fashion in Asian country with world is mostly witnessed within urban elements of India. As a consequence, big brand names like Vero Moda, Tommy Hilfiger, Benetton, Diesel, Z3, Calvin Klien, and many more have come across a tremendous experience in a great escalation in sales rate. Among all brands a few like Zara, Uniqlo, Forever21, and Armani outstands in Indian youth market [1]. Similarly Asian country is also doing its half by giving several noted accessories to the western world ranging from a simple *Bindi*, *Heena* (*Mehendi*), *Bangles* to clothing styles as well as fabrics. Indian Fashion Industry has great potential to make the mark on the world stage. Foreign celebrities can be seen to wear Asian accessories with pride [2].

Asian country is additionally hosting many fashion shows of world category standards thus contributing a bit more. Also, fashion industry is growing at rapid pace with International developments, such as Indian Fashion Week which is gaining popularity day by day. Indian textile industry statistics in terms of gross domestic product (GDP) and Index of Industrial production (IIP) further clarify the things. This industry currently estimates approximately 108 billion dollar and most probably will reach to around 223 billion dollar by 2021. Also, it contributes 5% to India's GDP and 14% to overall IIP [1]. Looking at India's export, then Indian textile industry contributes 13.5% to total export. Apart from this, one of the fastest growing economies, i.e. Indian economy, is also witnessing major shifts in client preferences. One of the survey reports states that 46% global consumers have purchased books (the highest) and surprisingly the second highest figure is 41% which is for clothing online [3].

The chapter represents the motivation behind the chosen work and the opted objectives in addition to the basics of image based clothing systems. Chapter starts with a briefing of fashion scenario then gives motivation in Section 1.1. Basics of image based fashion search systems are discussed in Section 1.2. Objectives focused are listed in Section 1.3. Concepts required understanding discussed systems are briefed in Section 1.4. Lastly, the organization of the thesis is specified in Section 1.5.

1.1. Motivation

The entire business state of affairs of the style retail business within the Indian market has encountered a major amendment. Competition among the business giants is among the prime reasons behind the changes that have occurred within the past few years. The retailers related to the style business bit by bit started counting on the web taking it as an alternate commerce channel.

Increasing popularity of e-commerce web-sites and advances in mobile computing not only explodes number of web images but also opens several challenges related to application of image processing techniques in domain of online shopping. Shop anywhere anytime convenience associated with online shopping particularly clothes

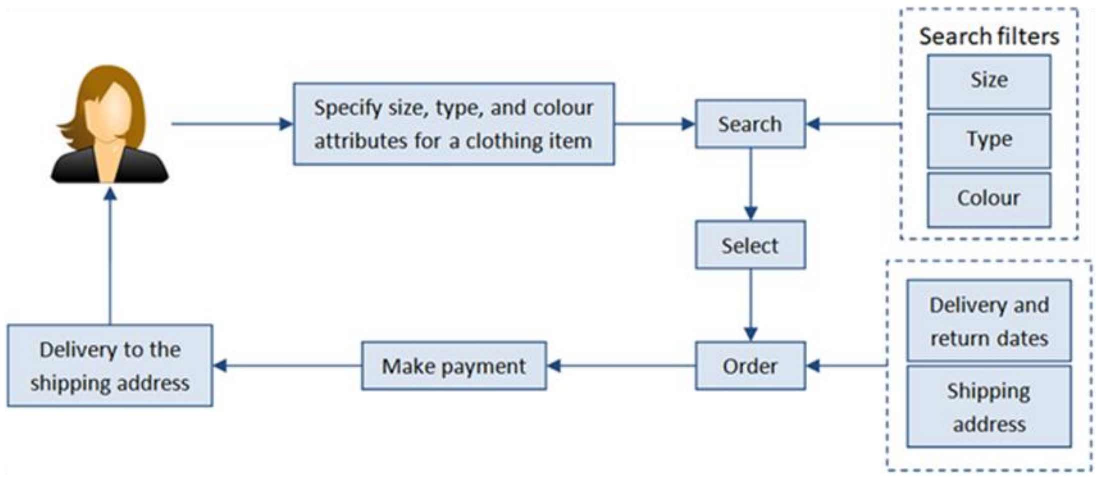

Figure 1.1. Basic process flow of a keyword based online clothing search system.

Figure 1.2. Top 10 images retrieved from www.myntra.com using text query as "Black top".

has attracted a large crowd thus making it a huge market. Online clothing shopping model continues to gain popularity in the present era due to easily available products and attractive deals. Most of the shopping websites, like Amazon.com, shopstyle.com, etc. facilitates keyword based search to find favorite clothing easily [4-5]. The basic process flow of such systems is shown in Fig. 1.1 and an example from www.myntra.com is shown in Fig. 1.2. These keywords typically belong to an attribute vocabulary (some-times erroneous as well as incomplete) whose size is too small and is thus unable to characterize existing visual diversity in clothing properly.

1.2. Online Clothing System - An Image Based Fashion Search System

The past few years have observed an effective search and annotation of clothing images using image processing concepts an active research area [5]. Style is identified as an important clothing description in addition to colors and patterns. Also defining a style is easier using similar looking product images than descriptive words. Image based fashion search is retrieving fashion products based on query images that reflect users needs such as those containing clothes [6-7].

A differentiating characteristic of the fashion category is that a user's buying decision is primarily influenced by the product's visual appearance. Traditional recommender systems depend just on client click/buy movement and totally disregard the image content [8-9]. Hence researchers tried to develop recommender systems that work on

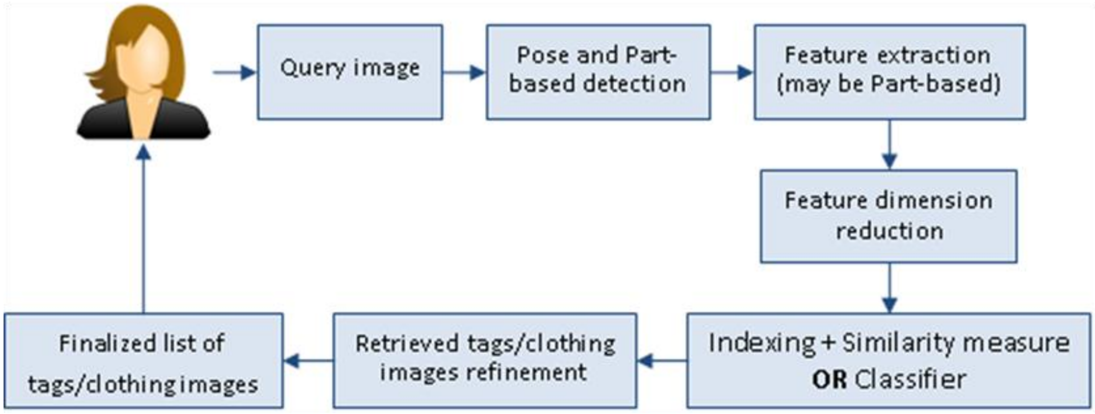

Figure 1.3. Basic process flow of an image based clothing/tags retrieval system.

combination of image and text processing principles. Such systems follow some basic sequence of steps as is shown in Fig. 1.3. Firstly in addition to basic preprocessing different regions in clothing images are localized, mostly using bounding boxes or convolution neural network (CNN), visual features like histogram of oriented gradients (HOG), local binary patterns (LBP), color histogram, etc. are extracted, training is then performed using style attributes and extracted visual features [10]. Optionally these systems have modules like pose estimation which is observed to enhance the systems performance greatly. Similarly, the obtained features are gone through dimension reduction phase to speed up the computation speed in later steps. During retrieval the obtained images or clothing suggestions or attributes (tags) with fixed set of attributes, e.g. color, length, material, etc. are obtained and may experience refinement and then finally presented to the users. A few provides flexibility to modify these attributes for further refinement of results. Instead of classifiers indexing structures like KD-trees or hashing combined with suitable similarity measures may also replace the classifier module in these systems.

1.3. Objectives

Image based retrieval provides a convenient way for users to search for products with rich details that are hard to describe either verbally or comprehensively. Thus, the work presented in this dissertation mainly focuses on the implementation of an image based system with the following objectives:

- To study image based fashion search online clothing systems.
- To study various neural network architectures with respect to clothing image datasets.

- To implement a two phase image based system that:
    - Searches and recommends a matching clothing pair given a query image.
    - Allows style manipulation to refine results obtained in phase one.
- To analyze the results obtained with the implemented system.

1.4. Background Concepts

Image is worth of thousand words, as a result an image based system are gaining popularity by making querying process more efficient for a user. In fashion industry description in terms of product image is easier as compared to corresponding verbal narration. Moreover product images play significant role in driving buying decisions of customers. But, image based clothing retrieval systems are still in developing stage and thus there exists no standardized architecture. Clothing dataset usually contain images covering a wide range of fashion and are not so prominent sometimes. Several approaches are developed to deal with the existing heterogeneity in a dataset and to get desired performance. A few modules, as shown in Fig. 1.3, are identified which may or may not be a part of clothing retrieval systems. Such systems take fashion clothing or any real world image depicting user demand as an input ***query image***. Most of these systems then ***determine the pose***, for which researchers have proposed several approaches [11]. It's difficult to describe a dress by concentrating on look of a single part; therefore ***part-based*** approach is generally followed which means considering different cues as well as viewpoints. Image is divided into poselets, i.e. a part of an image capturing some clothing pattern for a particular viewpoint. Identified poselets are analyzed separately for better accuracy [12]. Concept of bounding box is very popular for this purpose; however segmentation followed by clustering is equally efficient.

Image based systems work on visual space which is generated by ***extraction of appropriate features*** of an image or identified poselets. Incorporating style attributes in the obtained visual feature space is commonly practiced in the past few years and is observed to give better system performance. Automatic feature extraction using deep learning models usually leads to desired results [13]. Other commonly used features in this domain are histogram of oriented gradients (HOG), speeded up robust features (SURF), local binary pattern (LBP), color histograms, etc. Skin and style attribute descriptors are also proposed and utilized purposefully. The extracted feature descriptor can either be used directly or undergoes a ***feature dimension reduction*** process. Dimensional reduction approaches obtain a set of principle or uncorrelated dimensions of the obtained feature thus decreasing its size. Visualizing a training set in the presence of several features is difficult. Prominent features can easily be identified using some standard feature selection methods, like filter, wrapper, and embedded methods. Statistical filter methods, like correlation coefficient score, information gain, chi square test, etc., rank features with a score to decide its presence in the visual space. Contrary, wrapper methods, like recursive feature elimination, prepare, evaluate, and compare different combinations of features based on the accuracy values reported by utilized analytical model. Embedded methods, like regularization, ridge regression, etc., select features based on their contribution to the model's best accuracy when it is being created. Also known as penalization methods as they add constraints to optimize predictive algorithm and reduce complexity.

Once features are finalized, they are either arranged using an ***indexing*** structure or are fed into a ***classification*** model. Some studies employed trees for indexing which are combined with a suitable ***similarity measure*** for effective searching. But most of the works utilize a basic convolutional neural network (CNN) to present a novel architecture for accurate recognition. As said earlier CNN is utilized for extraction of features which are found to report better accuracy (nearly 100%) than other common features, like SURF. There are only few layers within a CNN that are suitable for image feature extraction. A convolutional neural network has multiple hidden layers between the input and output layers. It consists of units (neurons), organized in layers, that convert input vector into some output. Every layer takes an input, applies operation to generate output, and passes it on to consecutive layer. Weights are applied to the signals passing from one layer to another. These weighs are tuned during training to adapt the actual downside at hand. A CNN

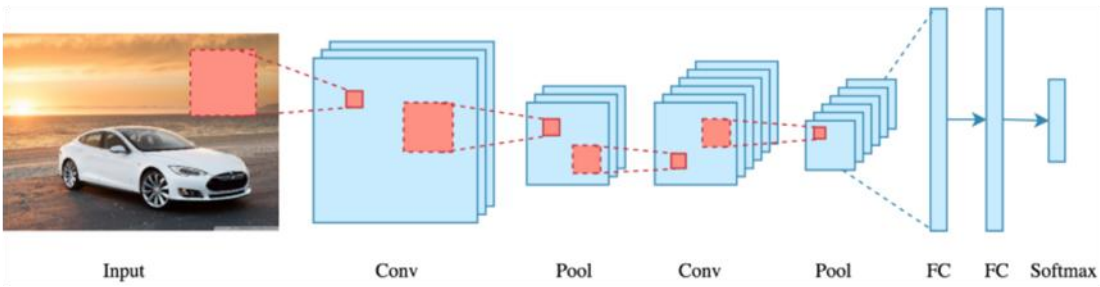

Figure 1.4. Commonly used architecture in CNN models [14].

architecture shown in Fig. 1.4 is the one usually followed by all CNN models. It has series of convolution and pooling layers, then a number of fully connected layers. In case of multiclass classification, the output is softmax. CNNs are broadly utilized as a part of example and picture acknowledgment issues as they have various favorable circumstances contrasted with different strategies [15-16]. In recent years, CNN has been used with unprecedented success for object recognition [17-20].

1.5. Thesis Organisation

The rest of the thesis is organized as follows:

Chapter 2 presents related studies in the domain of fashion clothing recommendation system and lists observations made during the survey along with the discussions.

Chapter 3 introduces some well-known CNN architectures and discusses the image based fashion clothing retrieval system presented in this dissertation. It include all the details related to the dataset used for system validation.

Chapter 4 describes the implementation details of the developed image based fashion clothing retrieval system. Describing interface details, the chapter presents complete functionality of the system.

Chapter 5 concludes the work presented in this dissertation along with the summary and a quick look at the future of this work.

Chapter 2

LITERATURE SURVEY

Incorporating technology within fashion helps in two ways; it connects consumers to big brands and commits conspicuous shopping experiences too. Fusion of technology with innovation, changes functioning of fashion industries which directly affect the way clothing products interact with consumers. Researches pertaining to development of streamlined and efficient web-based clothing systems with modernized operations are done in the past few years. Concepts of machine learning, image/voice processing, artificial intelligence, data analytics, augmented reality, and social media tools are competently utilized in guiding purchasing decisions [21]. In addition to enhancing user shopping experience, growing fashion industry demands automatic annotation, attribute prediction, classification, and retrieval of clothing articles so as to valuably employ the above said concepts in this domain [20, 22-25]. Work presented in this dissertation analyses several such systems highlighting their major contributions.

Image processing approaches are mainly used to retrieve and annotate similar clothing images automatically in the domain of clothing images. The annotation task is difficult when it comes to clothing images due to numerous style attributes covering appearances and body poses. Background variations complicate this task further. Thus studies have explored part-based clothing and found it to be a valuable and meaningful task. However, factors like huge collection of clothing items, varying viewpoints and lighting conditions create several challenges [26].

The contents in this chapter are organized as follows. Section 2.1 discusses various existing clothing systems highlighting their main points. Section 2.2 presents a summary and a few observations made during the study.

2.1. Existing Clothing Systems

The problem of attribute classification for people is considered to be important but challenging too as it has many practical applications [27]. A simple and efficient system utilizing histogram of oriented gradients (HOG) features from image patches is trained with support vector machine (SVM) classifier. It is robust against discriminatory camera views, occlusions, and communications. The system is capable enough to gain cues at any scale from body parts without any explicit inference

A man with short hair and long sleeves | A person with long pants | A woman with long hair, glasses and long pants

Figure 2.1. Description in natural language generated for a given image of a person [27].

related to pose or leverage of alignment power. Results are presented using a dataset consisting of 9 annotation attributes for 8035 people. Fig. 2.1 shows a natural language description obtained for a given query image using attributes predicted by the developed system. Attributes with lower confidence values are automatically skipped by the system like attribute “person” may be used in place of either “man” or “woman”. The system is flexible and can easily be extended to more attributes and visual categories. Another work uses SVM and develops 'magic closet' which is an occasion oriented and practical clothing pairing system [28]. It works on wearing properly as well as wearing aesthetically principles. Rules matching visual features with respective clothing attributes are described using SVM to suggest the most apposite clothing provided a specific occasion automatically. The system is quite accurate but unable to detect a few clothing in the photo album mainly due to the employed human detectors. Although with the maturity in state-of-the-art methods for feature detection systems performance can be improved. Fig. 2.2 shows an interface of the developed system ‘magic closet’. Its Kinect based and allows users to try and check suitability of suggested clothing given occasion or reference clothing.

A scalable, fast, and fully automatic clothing detection and suggestion system working on Fashionista dataset with million’s of products is developed [29]. It distinguishes variations and styles within clothing class using attributes and considers

Figure 2.2. The client server mechanism used by 'magic closet' [28].

co-occurrences among classes during training for better detection and lesser misclassifications. The example shown in Fig. 2.3 depicts output (images on right) generated by the application for real world image as a query (image on left). Product images from online shopping databases are presented in the output and are based on

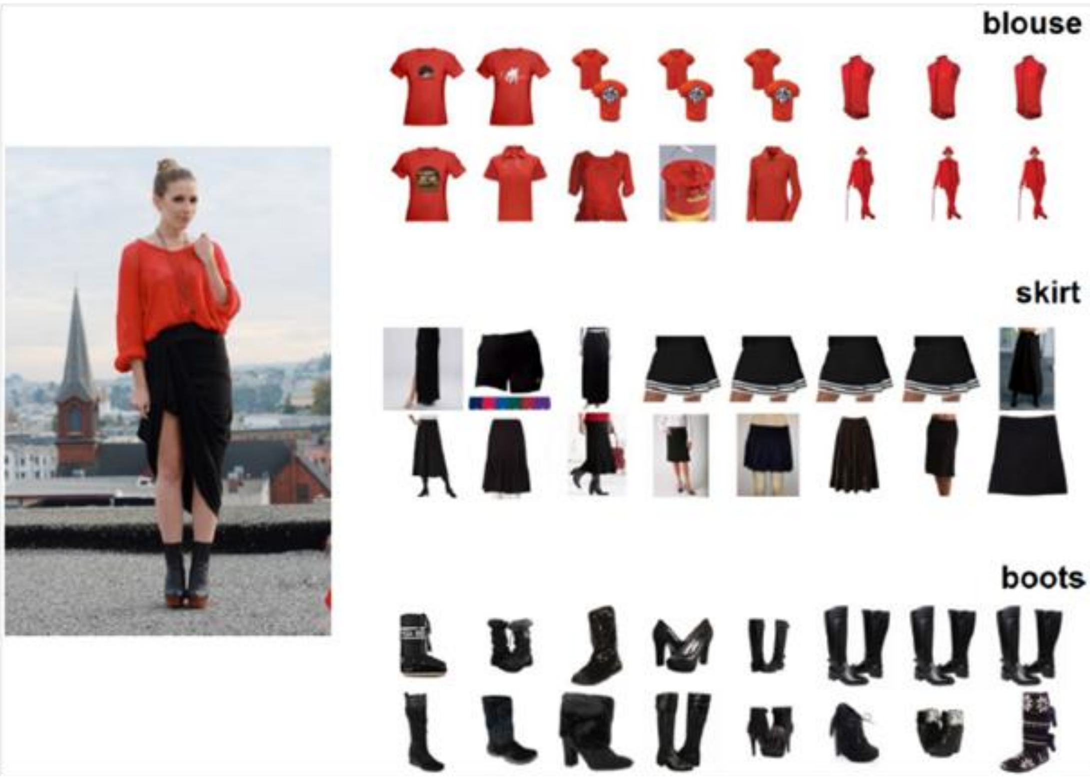

Figure 2.3. Query image from real world and suggestions generated for the detected clothing product classes [29].

Figure 2.4. (a) Tags generated automatically by the system, and (b) Top 8 results retrieved for the attribute “material” as Has-fur, Leather, and Is-shiny [4].

the classes identified in the query image along with their visual appearances. It outperforms state-of-the-art approaches in terms of speed (50 times faster) and reports equivalent performance too. It can easily be scaled to hundred product categories having millions of images. Model can further be generalized by including attributes and gender data for clothing class recognition along with the proposed suggestion stages. In fact it can also be successfully employed for gender classification. Suggestions generated by the system can either be utilized directly or used to support annotators in integrated semi-automatic annotation surroundings, thus help in speeding up the expensive annotation method. A generalized approach employing transfer learning, applicable to a range of fashion style categories as well as datasets with different domains is presented [4]. It utilizes aspect classifiers to allow searching based on attribute/stylistic element as well as to automatically generate tags or descriptions based on detected attributes. Fig. 2.4 shows results obtained by the developed system for both the said tasks, i.e. automatic generation of description (Fig. 2.4 (a)) and image retrieval for a specific style (Fig. 2.4 (b)). The work provides Women’s Fashion Coat dataset with fine grained clothing classes and also presents study of distinctive classifiers for every style attribute which are basically visual characteristics associated with a collection of style. In future, multiple binary visual aspects help in category-level classification and development of other methods.

One more work attempts to approximate influence of social factors and content illustrations based on vision to approximate fashion photos quantitatively [30].

(a)

(b)

Figure 2.5. Images predicted by the learned model based on popularity (a) The most popular, and (b) The least popular [30].

Content illustrations are prepared taking benefits from natural speech processing, computer vision, and network data repositories. It utilizes information namely user identity, number of comments, and user expertise. Specifically a sparse vector for user identity and a scalar feature for number of earlier comments from similar user with respect to expertise are employed. Statistical evidences as well as subjective measures (aesthetics from social content) are effectively evaluated and analyzed that prove the significance of system in comparison to other state of the art systems in judging leaders with good social power. An example of images identified as the most and the least popular by the developed prediction model is shown if Fig. 2.5. Focusing on cross-domain scenario, a practical approach suitable for clothing retrieval in real-world application based on ranking network of dual attributes is presented [31]. Fig. 2.6 shows the cross-domain retrieval results where query image is from street and the output is from a large-scale gallery of online shopping images. Its characteristic learning phase encloses semantic features and visual correspondence force simultaneously to effectively model irregularities. Results show significant improvement over the baseline approaches. In addition, the work provides a distinct large-sized clothing dataset that can be used in other applications like person re-identification in surveillance videos.

Figure 2.6. Clothing images retrieval in a cross-domain feature using daily photo as query image (leftmost) and top-6 results from online shopping dataset [31].

Another unique retrieval system, 'Particular Street to Shop' based on convolution neural network (CNN) and selective search method is presented [32]. Classification is achieved using CNN and selective search is a refinement to take out set of relevant images from shop dataset. It introduces a new dataset too and evaluates three techniques to learn a correspondence between street and shop domains. Retrieval results (quantitative as well as qualitative) are exceptionally good and the presented system is an attempt to allow precise retrieval of clothing stuff from on-line owners. Fig. 2.7 shows retrieval results obtained with the developed system considering an article within the bounding box as a query image in any real world image. Performance can further be improved by developing techniques for better alignment of street and shop objects. In an attempt to improve clothing annotation and retrieval accuracy, a model using concepts of pose detection and part-based features is developed [33]. Study establishes the importance of part-based representative tags in

Figure 2.7. Top 8 images retrieved for the article selected in the query image [32].

Figure 2.8. Image retrieval results based on image and part-based search [33].

clothing photos; also it presents an analysis to estimate associations between images and tags based on intra- and inter-clusters clothing key parts. List of tags is improved by combining search based image annotation structure with part-based significant tag removal. Effective results are obtained for millions of clothing images with fashion models from Taobao as compared to state-of-the-art methods. Fig. 2.8 compares the results retrieved using an image based search and those obtained by the part-based model. In future, model can be investigated for automatic annotation of all kinds of clothing photos and performance improvements are expected using deep learning methods too.

A two-level system aiming for better personalized interaction of customers is presented based on image retrieval technology [34]. It allows modification of original query descriptors, particularly color, texture, shape and attribute, to handle semantic gap. Fig. 2.9 shows retrieval results for the query image with changes in attribute values as per the user requirement. Clothing descriptors are converted to bag of words (BOW) formats to ease descriptors modifications and effective use of topic model for semantic analysis. Later, a probabilistic network based hybrid topic model combines multi-channel descriptors to depict each image. Contrarily, each topic is described as distributions over various codewords. Results show improvement by 24% and are found to be promising. Recently, an out of the way study focus on the development of CNN based system that can learn effectively even in the presence of erroneous or incomplete clothes labels as well as category imbalances [35]. The presented multi-

Figure 2.9. Images retrieved based on user requirements [34].

weight deep convolutional neural network utilizing the concepts of multi-label and multi-task outperforms and shows enhanced retrieval results. Working with limited training dataset, a multi-task curriculum transfer (MTCT) network for fine grained clothing attributes is formulated [26]. It optimally utilizes the concepts of transfer learning in specific scenario, i.e. orderly source domain with large labeled information and a noisy target domain. It consists of two main components, multitask deep learning and curriculum transfer deep learning, which helps in dealing all the issues related to small training dataset. Experiments are performed on a dataset collected from a wide source ranging from images via web retailers to in-the-wild street images. Fig. 2.10 (a) shows the attributes generated automatically by the system for real world images. Fig. 2.10 (b) shows matching pair of images from two domains (in-the-wild and clean shop/model samples) retrieved automatically. Effective attribute recognition results as well as accurate image retrieval results are clearly showcased for unconstrained images from the street views.

2.2. Summary

Table 1 list the main objectives along with the solution proposed by researchers for all the studies considered in this work. Following are some observation for the literature survey. Most of the studies in this domain focus on human psychology while designing a clothing retrieval system to appropriately satisfy their demands.

(a) (b)

Figure 2.10. (a) Tags retrieved by the system for images in clutter, and (b) Cross domain clothing detection results [26].

Architectures like support vector machines (SVM) and different versions of neural networks are noticed to outperform any other architecture. Inclusion of semantic attributes during learning in any of the proposed work seems to improve the retrieval performance. Scalability as well as speed are two important properties of such systems. Recently, Dual Attribute-aware Ranking Network (DARN) is developed which is found to solve several issues related to cross-domain image retrieval, like street to shop image retrieval system. Majority of related works have observed that the utilization of concepts, like person detection and pose estimation, greatly helps in achieving quite accurate results.

Although the researchers are on their way to success and have achieved a few milestones in this domain, but still there are some fundamental challenges associated with clothing images. Diversity of style, in terms of sleeves, collar, length, texture, cuts, etc. can easily confuse a person and thus any computer system too. Thus, knowledge about style annotations is extensively used along with low level features for enhanced recognition, retrieval, and classification of clothing images. Similarly it’s common to have dissimilarity in human postures and attaining a clear frontal view of clothes always is critically difficult. Background variations are quite common due to easy availability of cameras these days as people click images at any place. In fact having clear background scenario is rare and objects clutter is general. Lack of standard datasets is another point of concern. Very recently Deep Fashion dataset is introduced which is a large scale dataset with rich annotations.

Table 2.1. Summarization of objectives focused and the solutions proposed in existing studies.

Reference	Objectives	Solution Proposed
2011 [27]	Recognize gender and other attributes like hair style, style of clothes. Effective recognition and segmentation.	Extracts HOG features and trains SVM classifier using Bourdev method and combines together in discriminative model.
2012 [28]	Recommend suitable clothing for occasions by retrieving the most matched ones with the reference clothing image from online shops.	Uses latent SVM model to aesthetically pair reference clothing that are suitable for specified occasion.
2013 [29]	Develop a finer clothing detection approach using image retrieval techniques to detect and retrieve visually similar products belonging to each class present in query image.	Develops a fast and scalable clothing product suggestion framework based on detected classes and visual appearances. Works for hundreds of product classes and millions of product images. Performance is 50 times better.
2013 [4]	Recognize and retrieve similar fashion imagery as given in a query like suit, dress, sweater, etc. Return a ranked list of related items that has same visual attributes.	Applies individual classifier for each style attribute and trains attribute classifiers on fined grained clothing. Defines a set of style-related visual attributes and provides attribute-oriented image retrieval. Accepts either a query image or target attribute group specification.
2015 [30]	Analyze effects of visual, textual, and social factors on popularity in real-world networks focusing fashion. Utilize social factor for research involving social network photos.	Presents a new feature for style based on clothing parsing. Does a large-scale empirical study on how social vs. content influences popularity on a real-world uncontrolled fashion network.
2015 [31]	Retrieve similar clothing items from a large-scale gallery of professional online shopping images. Create a dataset containing tens of thousands of online and offline clothing pairs obtained from user review pages.	Develops a Dual Attribute-aware Ranking Network (DARN) for retrieval and feature learning. It simultaneously embeds semantic attribute information and visual similarity constraints into the feature learning stage.

Table 2.1. (Contd…) Summarization of objectives focused and the solutions proposed in existing studies.

Reference	Objectives	Solution Proposed
2015 [32]	Match real-world garment item to the same item in an online shop. Collect large dataset by pairing of exactly matching items worn in a street.	Achieves similarity measures between the street and shop domains that enable more accurate retrieval of clothing items from online shops.
2016 [33]	Address part-based clothing image annotation.	Proposes effective and efficient clothing image retrieval system based on pose detection and part-based feature alignment.
2016 [34]	Allow users to specify query inputs as image and keywords too. Also multi-dimensional requirements are flexible and can be refined by editing visual features and attributes.	Proposes a Hybrid Topic (HT) model, a probabilistic network integrating multi-channel descriptors into a unified framework. It uses bag of words (BOW) format.
2017 [35]	Use deep convolutional neural networks for imbalance learning as images labeled by shop retailers from web pages are largely erroneous or incomplete.	Proposes multi-weight deep convolutional neural networks for coping with the noisy and imbalanced clothing image data in real world.
2017 [26]	Recognize clothing characteristics in detail, termed as fine-grained attributes in real world cluttered images.	Develops a novel deep learning based Multi Task Curriculum Transfer architecture that utilizes multi-labeled annotations from different web sources with fine-grained attributes.

Most of the existing systems are based on retrieval of similar clothing. A very few of them has incorporated the concept of recommending a matching pair corresponding to a given query. Also the commonly used architecture in these systems is some variation of a popular convolutional neural network. The work attempted in this dissertation thus focuses on the development and implementation of one such system based on the concept of neural networks. The system tries enhancing user experience by searching for matching clothing pairs, i.e. provided either a "top" or a "bottom" in the query image the system retrieves an appropriate complementing pair from the offline dataset. The result is then shown as the recommendation to the user. In addition the user is provided with the flexibility to change a fixed set of attributes so as to effectively refine the obtained results further while accommodating user requirements appropriately.

Chapter 3

METHODOLOGY

The clothing system being studied in this work has to deal with fashion objects which are characterized by diversity, variations in appearances, textures, styles, etc. Clothing images are difficult to segment as well as recognize, however convolutional neural networks are shown to report good accuracy values as per the survey. Before presenting the actual image based clothing retrieval system developed in this work, understanding of a few known CNN architecture is necessary. Thus the objectives focused in this chapter include the study of several existing CNN architectures. After this a discussion on design of the developed system is followed.

The contents in this chapter are organized as follows. A discussion on existing CNN architectures is included in Section 3.1. Section 3.2 discusses process flow of the developed image based fashion clothing system. Details of neural network architecture and attribute descriptor employed are included in Section 3.3 and Section 3.4, respectively. The complete process for dataset collection and preparation is illustrated in Section 3.5. Lastly, Section 3.6 presents the chapter summary.

3.1. Existing Convolutional Neural Networks

LeNet-5 is developed by LeCun et al in 1998. It's a novel 7-level CNN, works with an input image which is digitized to 32x32 pixels in grey scale. It is capable to classify digits, hence many banks has used LeNet-5 in recognizing hand-written numbers on cheques. Processing higher resolution images demands more hidden layers and larger network, thus computing resources limits applicability of LeNet-5. Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever developed **AlexNet** in 2012 which splits up in two pipelines. Its architectural design is similar to LeNet with much deepness, stacked convolutional layers, and additional filters per layer. It It has 11x11, 5x5, 3x3, convolutions, max pooling, dropout, and data augmentation. It utilizes stochastic gradient descent (SGD) with momentum. Each of the convolutional and fully-connected layers is followed by rectified linear unit (ReLU) activation. Another architecture **ZFNet** is developed by proper tuning of AlexNet's hyper-parameters. Looking at its architecture then it mirrors AlexNet with a few more deep learning elements.

Google's **GoogleNet**, also known as Inception, is introduced in 2014. It is known to perform very close to human perception. Another CNN motivated from LeNet outperforming GoogleNet is also introduced which simulates inception in a novel way via image distortions, batch normalization, and RMSprop optimizer. It has 22 layers and uses 4 million parameters only by using many smaller convolutions. In the same year **VGGNet** by Simonyan and Zisserman comes in limelight because of its very consistent architecture of 16 convolutional layers. It structure is simple with only 3x3 convolutions and many filters, but has 138 million parameters, i.e. quite a large number to handle. VGGNet is commonly used for image feature extraction these days. Also one can easily find several applications and challenges working on freely available VGGNet weight configuration. The most recent CNN architecture, termed as Residual Neural Network (**ResNet**) is proposed in 2015 by Kaiming He et al. This architecture innovatively uses heavy batch normalization with gated recurrent units or skip connections to train 152 neural network layers that to with lesser complexity than VGGNet. ResNet also performs very close to human perception.

3.2. The Developed Fashion Clothing System

The block diagram showing the complete process flow of the developed fashion clothing system is shown in Fig. 3.1. It mainly consists of two modules: first one retrieves a matching clothing pair and second allows user the flexibility to change a few style related attributes that helps in result refinement as per the user requirement. Processing starts with the user specification of reference apparel (upper or lower) followed by corresponding reference image selection. Once the input query image is picked, the system adaptively generates a few appropriate matching pairs coordinating the most with the reference apparel from the employed clothing image dataset. Aim is to return a set of apparels that can elegantly be combined with the given query image. Neural network based architecture is designed and implemented to get the matching set of apparels. The developed system gives a multimodal description to each garment in the dataset for better accuracy. The network is trained using color histogram feature extracted in RGB color space [26-27, 31, 36] and an attribute descriptor. Attribute descriptor is a computer vision feature which is inspired from the features suggested in some studies [6, 37]. The attribute descriptor is basically extracted from the keywords or the textual description associated with dataset images. Such attributes help to efficiently retrieve images matching the style features as specified by the user.

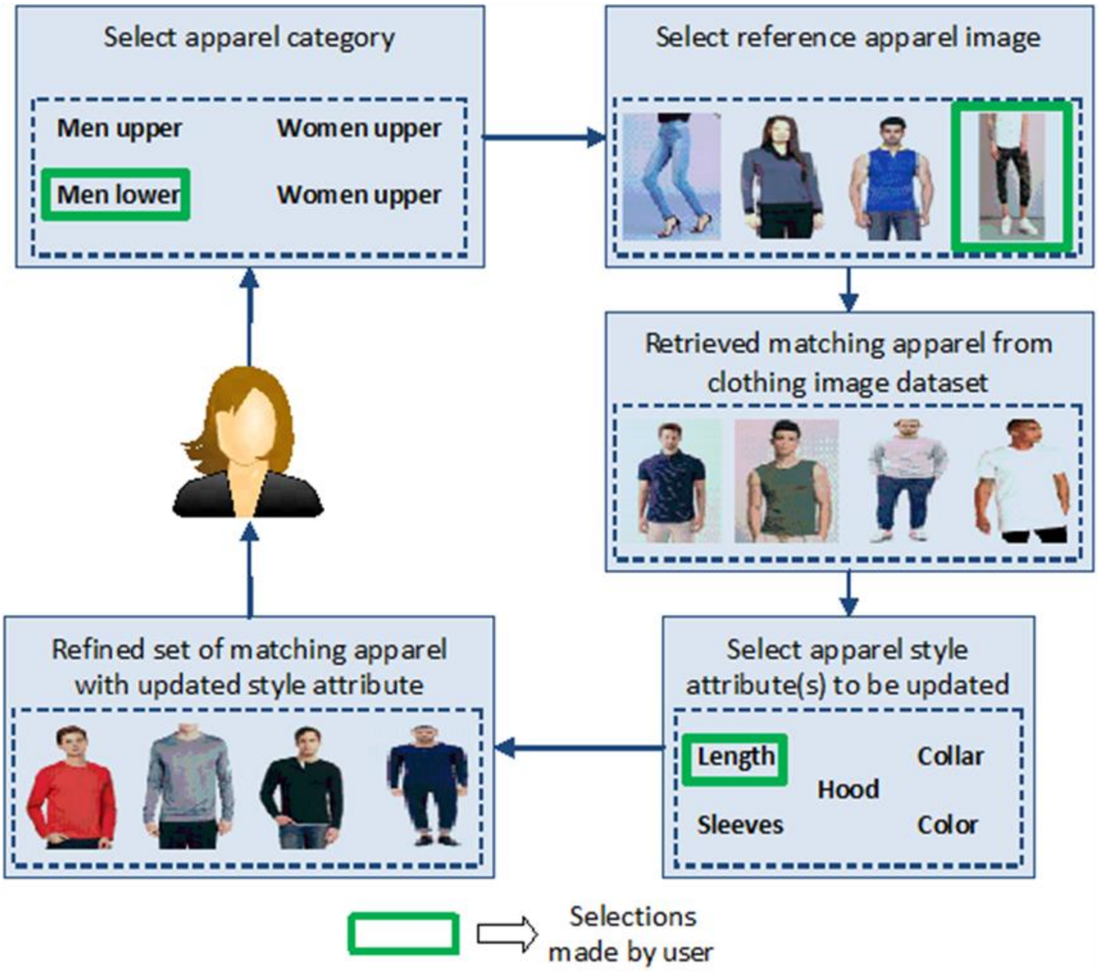

Figure 3.1. Process flow of the developed fashion clothing system.

The architecture used in this work is discussed in Section 3.3. Advantage of using color feature is to retrieve maximum suggestions in the first module of the system so that later attribute manipulation can effectively be done.

The second module comes in picture if user wishes to update a few of the style attributes and thus refine the results obtained from first module as per his/her requirement. Only the second feature that is attribute descriptor is utilized in this part of the system. Finally the refined set of images is picked and shown as an output to the user. The system is flexible enough and allows user to modify as many style attributes as are supported by the system.

3.3. Neural Network Architecture Employed in the System

The employed neural network is meant to interleave the hidden idea of visual similarity across the diverse clothing categories and thus becomes capable to accommodate clients' multi-dimensional requirements effectively. A feed forward network based on supervised learning is utilized in the system developed in this work. Supervised feed forward neural networks are well-known for modeling, classification, recognition, and prediction. Looking at basic main of the system, i.e. to retrieve similar kinds of matching clothing pairs and change attributes according to users' requirement, neural networks are observed as the best candidate. Neural network with six input neurons, one output neuron and ten hidden layers is designed to effectively portray clothing apparel using multimodal features.

3.4. Attribute Descriptor

Attribute descriptor is one of the commonly used features in image based clothing retrieval systems [6, 37]. It basically contains a list of style attributes and maps them to the allowed corresponding sets. Such descriptors are useful but are highly dynamic due to existing heterogeneity in clothing styles. As a result there exists a huge variety of parameters that can form a part of these descriptors. Dataset considered and purpose of the developed system also play significant role while finalizing the attribute descriptor. Frequently exercised style attributes are Coat, Collar, Sleeves, Length of Sleeve, Feather dress, Cardigan, Pantsuits, Leggings, Size of pantsuits, Waistband, Skirts, Size of skirts, Thickness, Season, Shade, Crowd, Style, Gender, Color, Wool Thickness, Leather material, Pattern, etc. Each of the style attribute also has a set of allowed values which varies from one scenario to another. The dataset employed in this work does not contain images that belong to the specified style attributes, thus the sub-set consisting of five different style attributes is considered. The attributes and their allowed values are given in Table 3.1.

Table 3.1. List and allowed values of style attributes employed.

Style Attribute	**Allowed set of values**
Collar	With collar (1 or 'C') and Without collar (0 or 'W')
Color	Red (1 or 'R'), Green (2 or 'G'), Blue (3 or 'B'), Black (4 or 'X'), White (5 or 'W'), and Grey (6 or 'Y')
Gender	Male (0 or 'M') and Female (1 or 'F')
Hood	With hood (1 or 'Y') and Without hood (0 or 'N')
Length	Long (1 or 'L') and Short (0 or 'S')
Sleeves	Without sleeves (0 or 'WS'), Full sleeves (1 or 'FS'), and Half sleeves (2 or 'HS')

3.5. Dataset Description

Many of the studies have not only proposed a novel approach but have prepared a dataset too containing a wide variety of clothing images selected carefully with attribute labels from fashion websites mostly [19, 38, 39]. These datasets are meant for evaluating algorithms designed for estimating either clothing attributes or retrieving similar clothing, but they are not freely available. Moreover, the work focused here depicts matching pair given a query and no such dataset satisfies this requirement to the best of author's knowledge. Thus, to evaluate the developed system a sub-set of images is vigilantly selected from recently introduced freely available clothing dataset, termed as DeepFashion [40]. This clothing dataset contains images belonging to 11 categories covering a range of styles for women as well as men. The actual category labels and the corresponding count of the dataset used to create the sub-set are tabulated in Table 3.2. Out of these 11 clothing categories, 7 are selected for women and only 5 are selected for men. This selection is basically driven by the attribute descriptor employed in this work as aim is to have a good number of images corresponding to each said attribute (Collar, Color, Gender, Hood, Length, and Sleeves length). The selected categories are divided into upper and lower for both women and men as is shown in Table 3.3. All the selected categories are suitably

Table 3.2. Actual category labels and the corresponding count of DeepFashion dataset used to create a sub-set for system evaluation.

Women		**Men**	
Category	**# of Images**	**Category**	**# of Images**
Cardigans	242	Coats	378
Denim	70	Denim	261
Dresses	1274	Hoodies	99
Graphic Tees	294	Jackets	167
Jacket Coats	361	Pants	367
Leggings	64	Shirts	600
Pants	300	Shorts	278
Shorts	469	Suiting	200
Skirts	288	Sweaters	100
Sweaters	600	Sweatshirts	188
Top	1407	Tees	312

Table 3.3. Selected categories from DeepFashion dataset for system evaluation.

	Upper	**Lower**
Women	Dresses Graphic Tees Top	Denim Pants Shorts Skirts
Men	Shirts Tees	Pants Shorts Suiting

picked and divided too for system evaluation. Division is done to ease user experience and also to reduce system's complexity a bit. Typically the system is generating suggestions for matching pairs (either upper or lower) given a corresponding lower or upper query image separately for both the genders. Thus the considered categories are broadly divided into four parts, namely Women Upper, Men Upper, Women Lower, and Men Lower.

3.5.1. Dataset Preparation

The DeepFashion dataset contains many types of apparel for a category and corresponding to each apparel images are present depicting its various views, viz. front, side, back, full, and additional. Men category has one more view termed as flat. Picking images for as all the views makes no sense for proper functioning of the system developed in this work, so based on visual examination of the dataset only images belonging to flat, additional, and front views are selected for data preparation. Fig. 3.2 shows images from all the views for two apparel categories, i.e., Men Pants and Women Top. The ones shown within green box are only selected. Clearly pictures for side or back poses can safely be dropped for better performance of the system. This also eases better and accurate feature extraction. Moreover, putting proper results via comprehensible clothing images helps in developing a user friendly system too. Repeating this procedure for each of the category shown in Table 3.3, a dataset with a total of 1100 images is collected. 600 images are selected from categories of women apparel and remaining 500 images from men apparel. Thus images in the dataset comprise of a large set of clothing image pairs depicting user requirements and the corresponding similar garments.

Figure 3.2. Representative images depicting different views for two apparel categories (a) Men Pants and (b) Women Top from DeepFashion dataset.

3.5.2. Image Attribute Description

After finalizing images in the dataset, the attribute descriptor as discussed in Section 3.4 is prepared for each of the 1100 images. Fig. 3.3 and Fig. 3.4 show values for each of the considered style attribute for a few images, covering all the possibilities, from the dataset considered for experimentation in this work. The system maintains the attribute description for all the images in the form of a table as is shown in Table 3.4 to ease implementation.

3.6. Summary

This chapter details the design of image based fashion clothing retrieval system developed in this work. The in depth explanation of all the techniques utilized while designing the system is followed by the description of features employed. Details of the style attribute are properly explained. The rest of the chapter discusses one of the most important part of the system developement, i.e. dataset collection and its preparation. Images are carefully selected considering most effective views. After

Collar: Yes
Color: Black
Hood: No
Length: Short
Sleeves: Half

Collar: No
Color: Black
Hood: No
Length: Long
Sleeves: Without

Collar: No
Color: Black
Hood: No
Length: Short
Sleeves: Full

Collar: No
Color: Black
Hood: Yes
Length: Short
Sleeves: Full

Collar: No
Color: Blue
Hood: No
Length: Long
Sleeves: Full

Collar: No
Color: Blue
Hood: Yes
Length: Short
Sleeves: Half

Collar: Yes
Color: Blue
Hood: No
Length: Short
Sleeves: Half

Collar: No
Color: Blue
Hood: No
Length: Short
Sleeves: Without

Collar: No
Color: White
Hood: No
Length: Short
Sleeves: Full

Collar: No
Color: White
Hood: Yes
Length: Short
Sleeves: Without

Collar: No
Color: White
Hood: No
Length: Long
Sleeves: Half

Collar: Yes
Color: White
Hood: No
Length: Short
Sleeves: Full

Figure 3.3. A few representative images from the self-collected dataset and their corresponding attribute descriptor for Gender as “Male”.

finalizing images attributes are required to be attached with each and every image in the dataset. Also, these are maintained in proper format for better and easy functioning of the system.

Table 3.4. Images and the corresponding attribute description maintained by the system to ease implementation.

				
Collar	0	0	0	1
Color	4	5	5	6
Gender	1	1	0	0
Hood	0	0	1	0
Length	0	0	0	0
Sleeves	0	0	1	1

Figure 3.4. A few representative images from the self-collected dataset and their corresponding attribute descriptor for Gender as “Female”.

Chapter 4

SYSTEM IMPLEMENTATION AND RESULTS

The image based fashion clothing retrieval system developed in this work is evaluated using visual examination instead of any quantitative measure. User interface details are first included followed by the results. The obtained results for all the functionalities of the developed system are also visually analyzed.

The chapter starts with a description of experimental setup in Section 4.1 followed an introductory description of the developed system's user interface in Section 4.2. Section 4.3 discusses the results with respect to the different functionalities of first module of the system and subsequently evaluates them using visual examination approach. Lastly, Section 4.4 presents functionality of second module of the system, i.e. result refinement, on the same lines as of Section 4.3.

4.1. Experimental Setup

The image based fashion clothing retrieval system developed in this work is implemented using MATLAB R2017a on a PC with Intel Core i5 2.40 GHz processor, 4GB RAM, 1TB HDD, and Windows 10 64-bit operating system. MATLAB® offers a user friendly point-and-click environment and suggestive Toolbox to develop computer applications with an attractive graphical user interface.

Training. The system is trained using 50% of images chosen randomly from the self-collected dataset (Section 3.5). Scaled conjugate gradient algorithm with random data division is employed to train the neural network module of the system for 1000 iterations. The value of gradient used is 9.319.

Validation. The trained network is then validated to get an optimized model after code validation and error generation in case any of the properties are not defined. 10% of images from self-collected dataset are used in this phase. The best validation performance reported by the developed system is 0.011398 at epoch 47. Network validation helps in reducing over fitting. If accuracy over training data set increases, but decreases or stays same over validation data, then the network is over fitted and training is ought to be stopped.

Reference Positive In-class negative Out-of-class

Figure 4.1. An example to showcase the importance of visual examination.

Testing. The actual predictive power of the network is confirmed using remaining 40% of the images from self-collected dataset for testing. A quantitative performance parameter measuring suitability of a set of matching clothing pair generated by the developed system given a query image cannot give proper evaluation, thus the system is examined using a visual approach. An example is shown in Fig. 4.1, assume that a user is searching for apparel looking similar to that of an image marked as ‘reference’. In response to this image the system has retrieved three images as shown in Fig. 4.1. Clearly an image marked as ‘positive’ is the best retrieved one, the one marked as ‘in-class negative’ can be considered as somewhat similar from different user perspectives, however the last one marked as ‘out-of-class’ is just the one which is not required at all. Similar results, discussed later in this chapter, are generated for matching clothing pairs by the developed system and thus the relevance of retrieved images are better judged by visual examination, as is clear from the discussed example. Thus all the results are presented in qualitative form in this dissertation.

4.2. User Interface

Fig. 4.2 shows the user interface, i.e. the first screen shown to the user once the application executes. The major functionality of the system is implemented and provided in an easily accessible form to the user by means of four buttons: Initialization, Select Item, Suggestions, and Change Attributes. The two drop-down lists are also provided to select appropriate category and style attribute to be changed.

Initialization button is used to get the system in the working state by loading the clothing image dataset and all other required tables so that the information can be extracted easily. In present state of the system this button seems to be not of much use but in later versions the system can be extended to work on more than one clothing

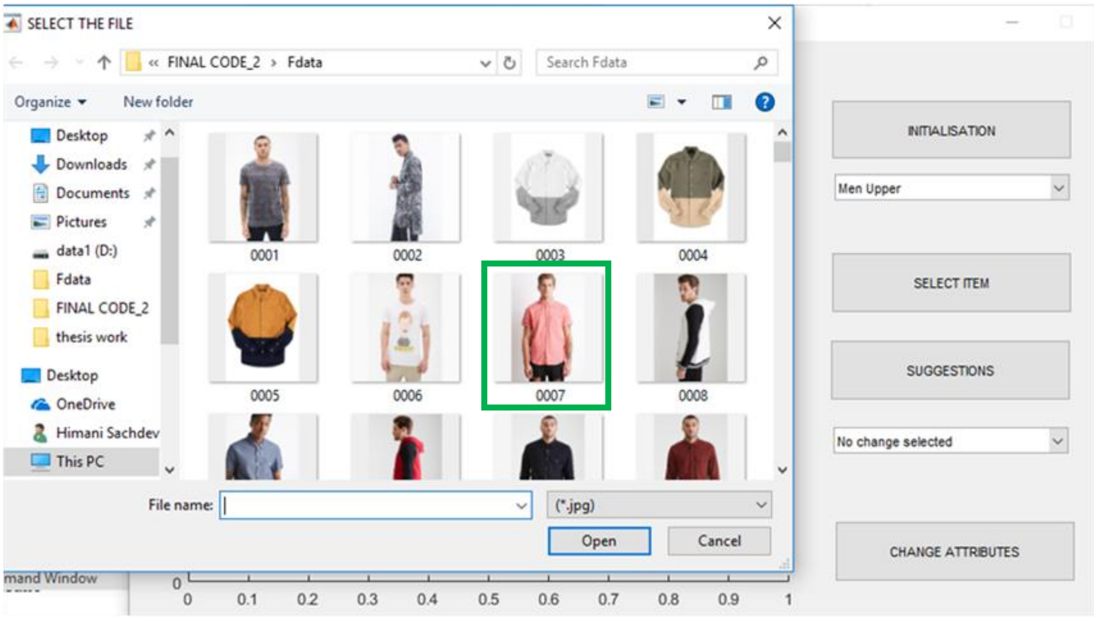

Figure 4.2. User interface of the developed clothing image retrieval system.

image dataset. Thus, this button helps user to choose any dataset of his/her choice to be utilized for retrieval of clothing images.

Next is the drop-down list that provides four options: Women Upper, Men Upper, Women Lower, and Men Lower, to choose from. This categorization helps in reducing the complexity of the system a bit and also eases user. The images displayed to the user, from which one is to be chosen as a query image, depends on this selection. Women Upper option includes images from women apparel categories like Dresses, Graphic Tees, and Top. Men Upper option comprises images from men apparel categories like Shirts and Tees. Similarly, Women Lower allows user to opt from women apparel categories like Denim, Pants, and Skirts. Finally, Men Lower covers images from men apparel categories like Denim and Pants.

Clicking Select Item button presents a set of images to the user depending upon the category selected in the drop-down list. Among the images presented to the user, the one to be opted as a reference is picked on a simple mouse click. Suggestions button is used to feed the selected image as a query to the trained and validated neural network. The response generated in the form of a set of matching clothing pair images is presented to the user. For example, opting for a black color trouser, the system may recommend matching Tees of various colors like red, grey, or white. Similarly with all the categories matching images will be retrieved. In case user is not satisfied with the results and wishes to change something related to style then a click on button Change Attributes is to be done. This will help user to refine the retrieved as per the user requirement. Five style attributes that a user is allowed to change is listed in the second drop-down list at the bottom, specifically Collar (With Collar or Without Collar), Color (Red, Blue, Green, Black, Grey, or White), Hood (With Hood or Without Hood), Length (Long or Short), and Sleeves (Full Sleeves, Half Sleeves, or Without Sleeves). Any number of attributes can be changed to get as refined set of matching pairs as possible satisfying the user's requirements.

4.3. Results

As said earlier the system is evaluated based on visual examination, thus in this section results are presented for various possible combinations of style attributes for upper and lower apparel categories both for women as well as men.

Scenario 1: Choosing Men Upper.

After initialization, Men Upper is selected from the first drop-down list. Now a click on Select Item button results in displaying many men upper images from the dataset on as is shown in Fig. 4.2. Let an image selected by the user is the one shown within a green box. The system then displays that image just for user confirmation (see Fig. 4.3). Now a click on the Suggestions button will display the matching lower pairs (see Fig. 4.4) retrieved for the image shown in Fig. 4.3.

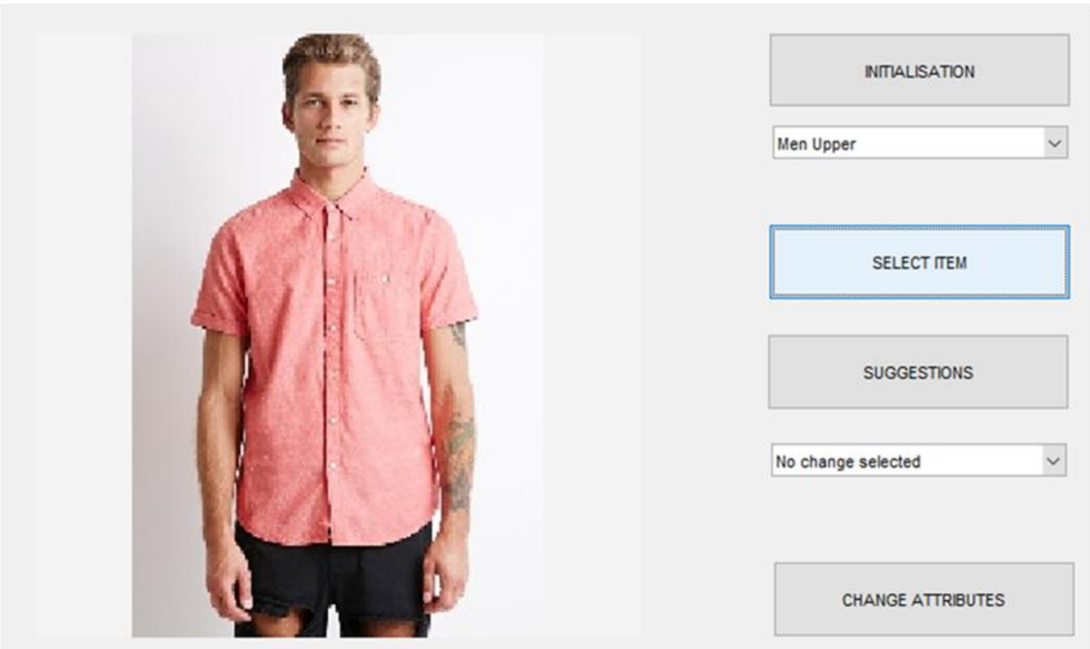

Figure 4.3. System interface showing the Men Upper image selected by the user.

Figure 4.4. Images retrieved as matching lower for the men upper image shown in Fig. 4.3.

Scenario 2: Choosing Women Upper.

Now Women Upper is selected from the first drop-down list and a click on Select Item button results in displaying many women upper images from the dataset. Let an image is selected by the user and then the system displays that image (see Fig. 4.5). Now a click on the Suggestions button will display the corresponding matching lower pairs (see Fig. 4.6) retrieved for the image shown in Fig. 4.5.

Scenario 3: Choosing Men Lower.

Similar to the previous two scenarios, here Men Lower is selected from the first drop-down list and a click on Select Item button results in displaying many men lower images from the dataset. Let an image is selected by the user and then the system

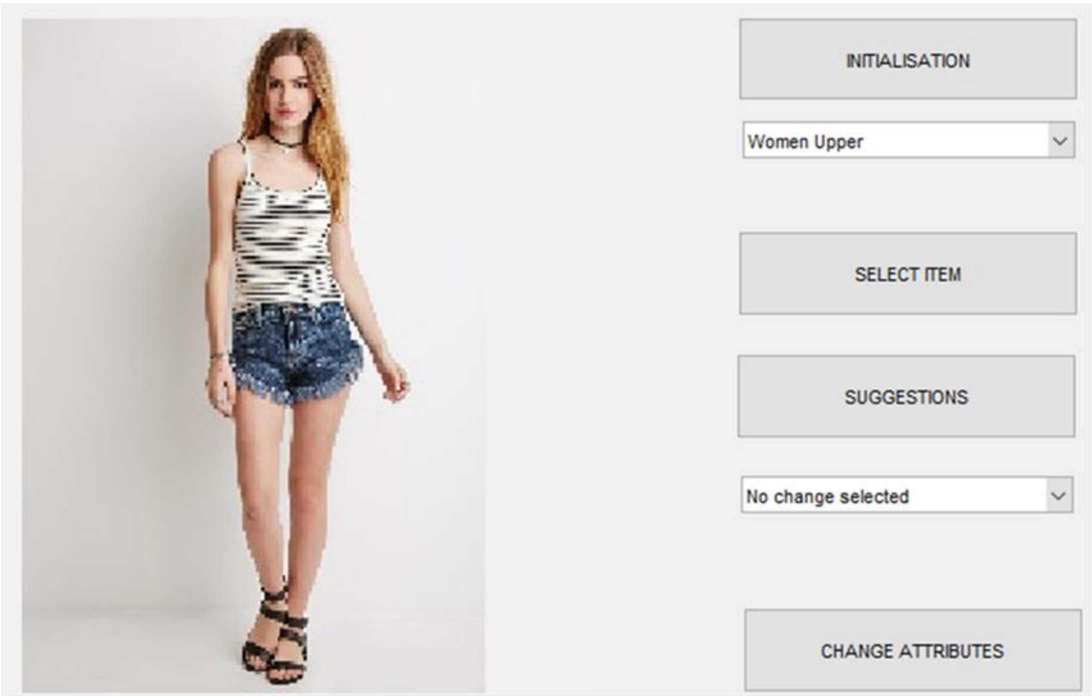

Figure 4.5. System interface showing the Women Upper image selected by the user.

Figure 4.6. Images retrieved as matching lower for the women upper image shown in Fig. 4.5.

displays that image (see Fig. 4.7). Now a click on the Suggestions button will display the corresponding matching upper pairs (see Fig. 4.8) retrieved for the image shown in Fig. 4.7.

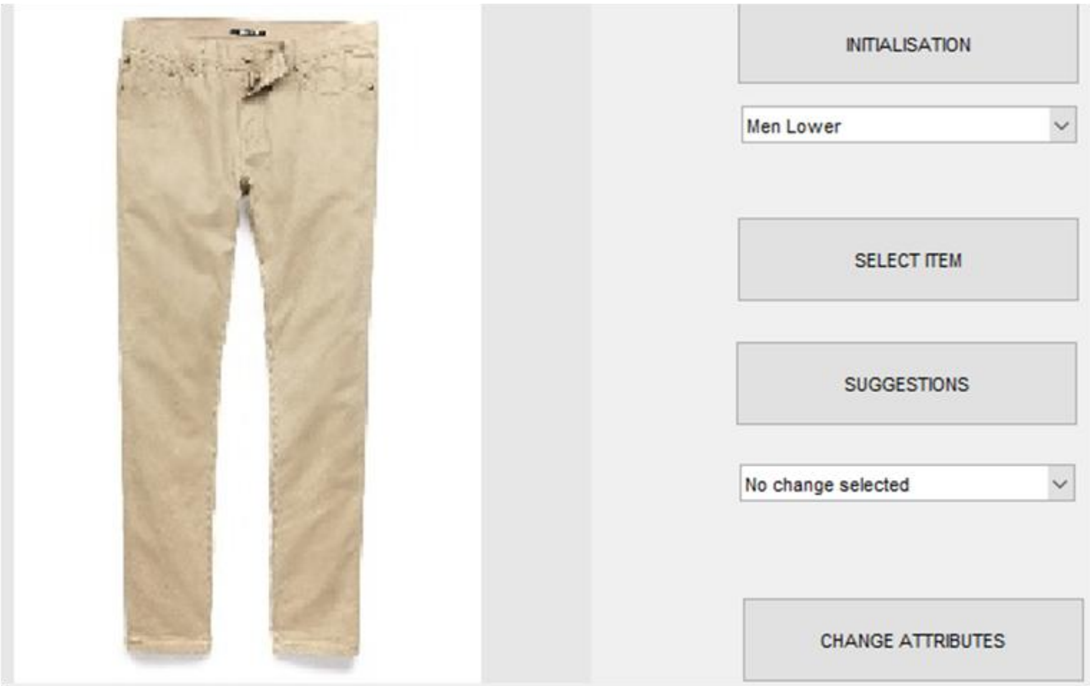

Figure 4.7. System interface showing the Men Lower image selected by the user.

Figure 4.8. Images retrieved as matching upper for the men lower image shown in Fig. 4.7.

Scenario 4: Choosing Women Lower.

Last option to be selected is Women Lower from the first drop-down list and a click on Select Item button results in displaying many women lower images from the dataset. Let an image is selected by the user and then the system displays that image (see Fig. 4.9). Now a click on the Suggestions button will display the corresponding matching upper pairs (see Fig. 4.10) retrieved for the image shown in Fig. 4.9.

Analysis of results by visual examination.

Results presented in all the four scenarios clearly demonstrate capability of the system in retrieving the best possible matching pair for the given query image. One thing to be noticed is that the number of images retrieved in response will vary from one

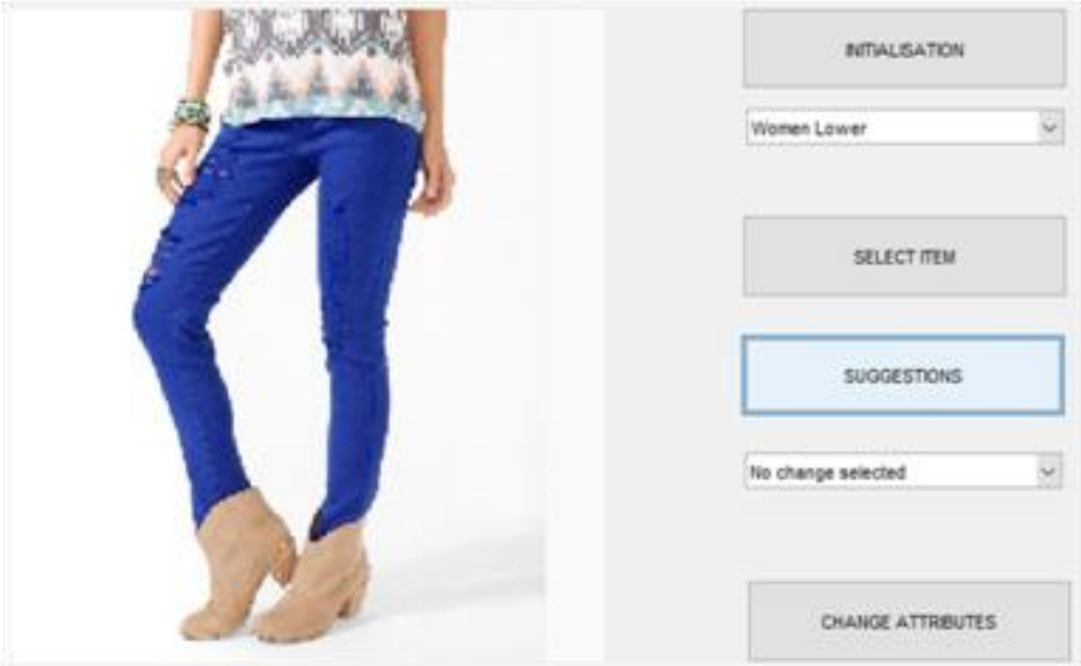

Figure 4.9. System interface showing the Women Lower image selected by the user.

Figure 4.10. Images retrieved as matching upper for the women lower image shown in Fig. 4.9.

scenario to another depending upon the number of images satisfying the matching criteria. In scenario 1 only three images satisfy the constraints and thus are retrieved while in rest of the scenarios there are four images suiting the criteria. Overall it can be said that the system in performing quite well as in all the cases two or three out of four retrieved images are perfectly matching with the supplied query image.

4.4. Result Refinement – Update Attribute Descriptor

Next major functionality of the developed system is the attribute descriptor update feature with the help of which user can refine the obtained results. For example, suppose user wish to refine images shown in Fig. 4.10, he/she wishes to have a top with collar. This requirement can easily be accommodated by selecting Collar style attribute in the second drop-down and changing it to With Collar by clicking on Change Attributes button. For this example the refined results generated by the system are shown in Fig. 4.11, although the last two images are not that much satisfactory looking at the bottom used as the query, but images retrieved as top two images are matching almost perfectly. Thus system's accuracy can be computed as 50% in this case.

The system is flexible enough and allows user to change as many attributes as possible. This functionality is demonstrated using a Women Bottom image shown in Fig. 4.12. Images retrieved by the first module of the system are shown in Fig. 4.13. Now to change style attribute Sleeves to Full Sleeves, one has to simply pick it from the second drop-down menu and click on Change Attributes to get a user interface shown in Fig. 4.14. Putting the appropriate option in the pop-up window and clicking Ok button generate a refined set of images. Results obtained for this particular example are shown in Fig. 4.15. If user now wants to add Hood to the results retrieved in Fig. 4.13, then pick style attribute Hood from the second drop-down menu and

Figure 4.11. Images retrieved as matching upper for the women lower image shown in Fig. 4.9 with style attribute Collar as "With Collar".

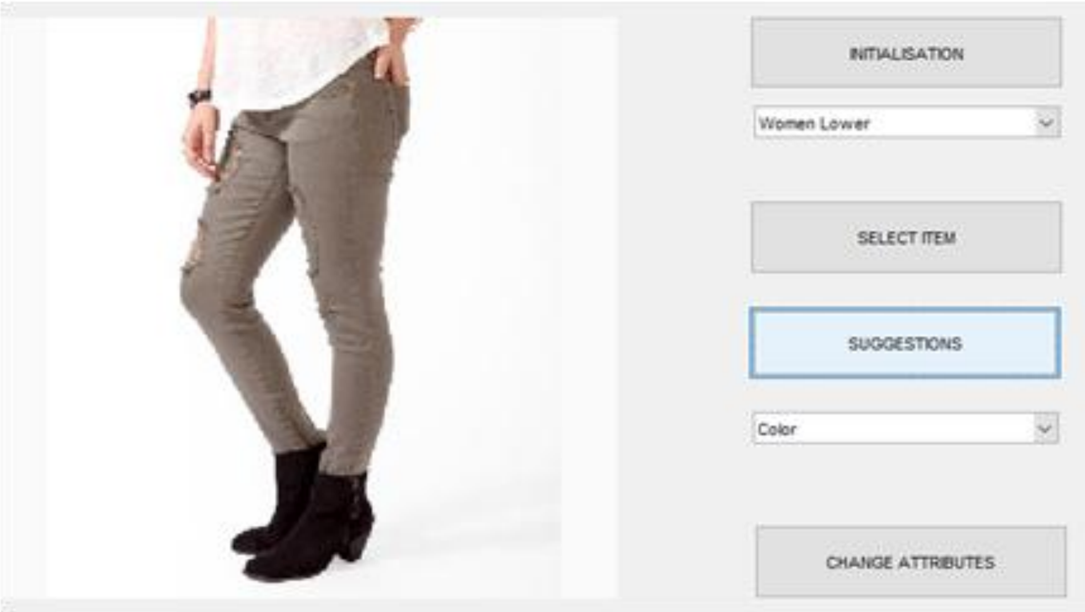

Figure 4.12. System interface showing the Women Lower image, a grey color trouser, selected by the user.

Figure 4.13. Images retrieved as matching upper for the women lower image shown in Fig. 4.12.

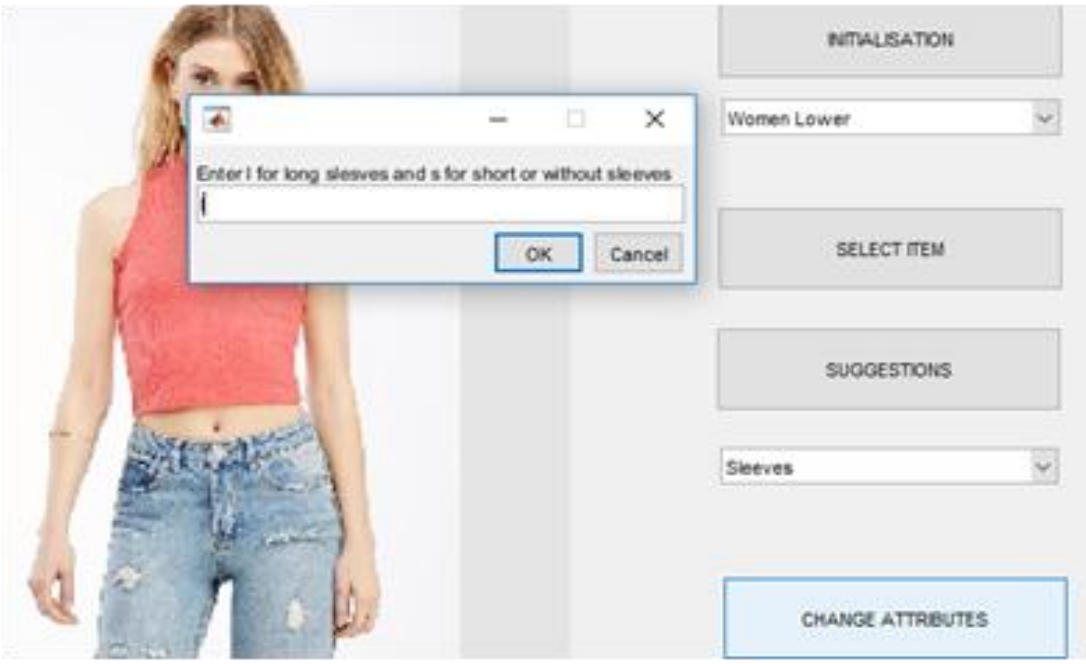

Figure 4.14. System interface to change style attribute Sleeves. Enter the required value in the appeared dialogue box and click OK else Cancel.

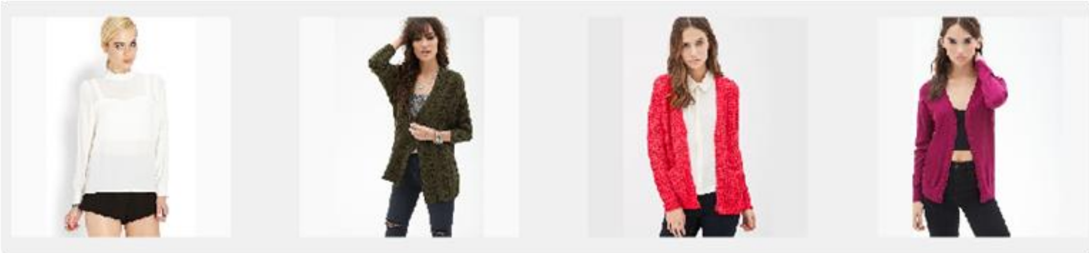

Figure 4.15. Images retrieved with style attribute Sleeves as “Full Sleeves”, for the women lower image shown in Fig. 4.12.

click on Change Attributes to get a user interface shown in Fig. 4.16. In the pop-up window, put the appropriate option and click Ok button to generate a refined set of images as shown in Fig. 4.17. One can observe the number of images retrieved in the initial stage by the system and those retrieved with each refinement placed as per the user requirement, for Full Sleeves four images but for With Hood only one image is retrieved. These numbers clearly focus the adaptive nature of the system, i.e. it is not biased to the number of images instead will display images only if constraints are satisfied. In will not be surprising if the developed system does not generate even a single matching pair for some image because in that scenario none of the images in the dataset is satisfying the required criteria.

Similarly, Fig. 4.18 shows a maroon color Men Lower selected by the user, in response the system has retrieved only a single image shown in Fig. 4.19. Evidently

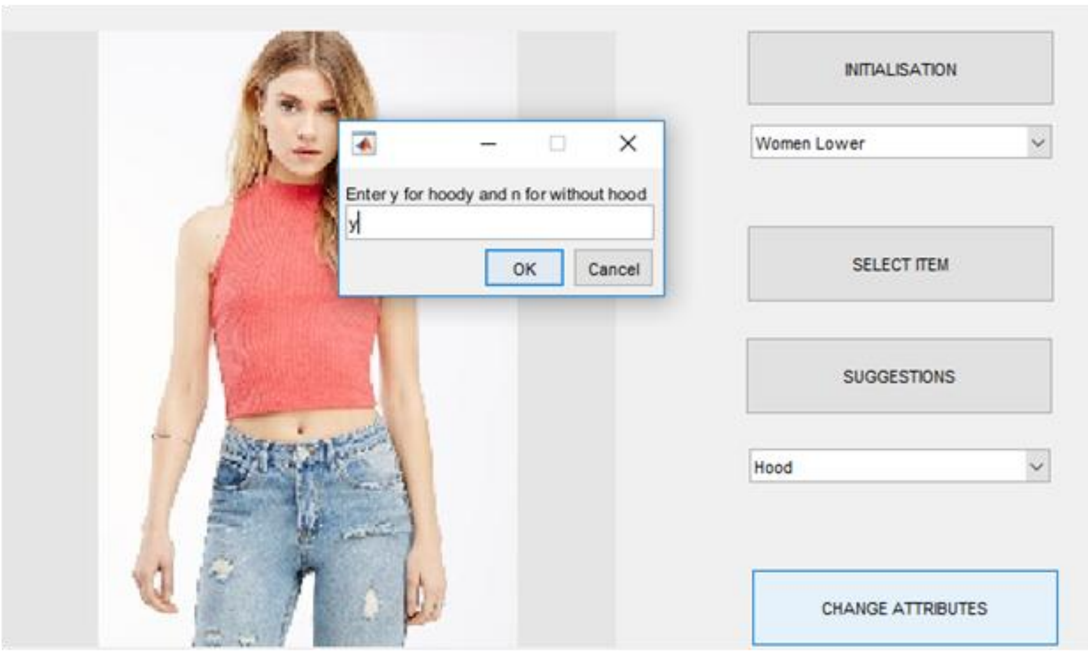

Figure 4.16. System interface to change style attribute Hood. Enter the required value in the appeared dialogue box and click OK else Cancel.

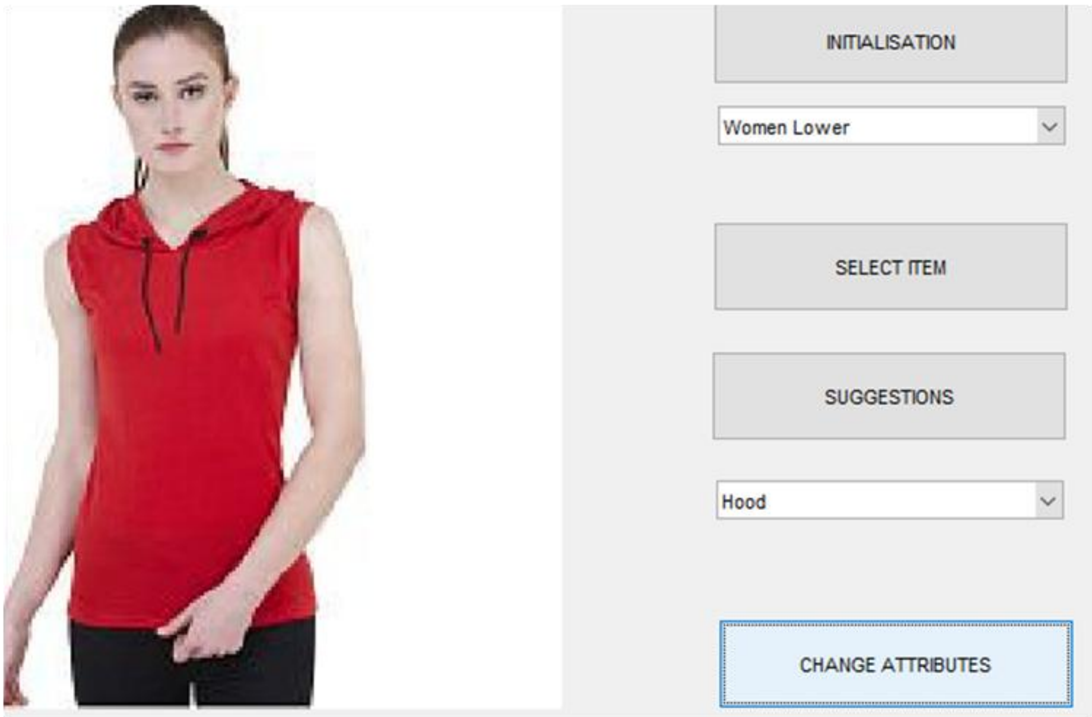

Figure 4.17. Image retrieved with style attribute Hood as "With Hood", for the women lower image shown in Fig. 4.12.

the retrieved matching pair has collar but user wishes to have a clothing with no collar, thus updating the required style attribute is to be opted. The final refined results retrieved are as shown in Fig. 4.20. Again visual examination of final retrieved

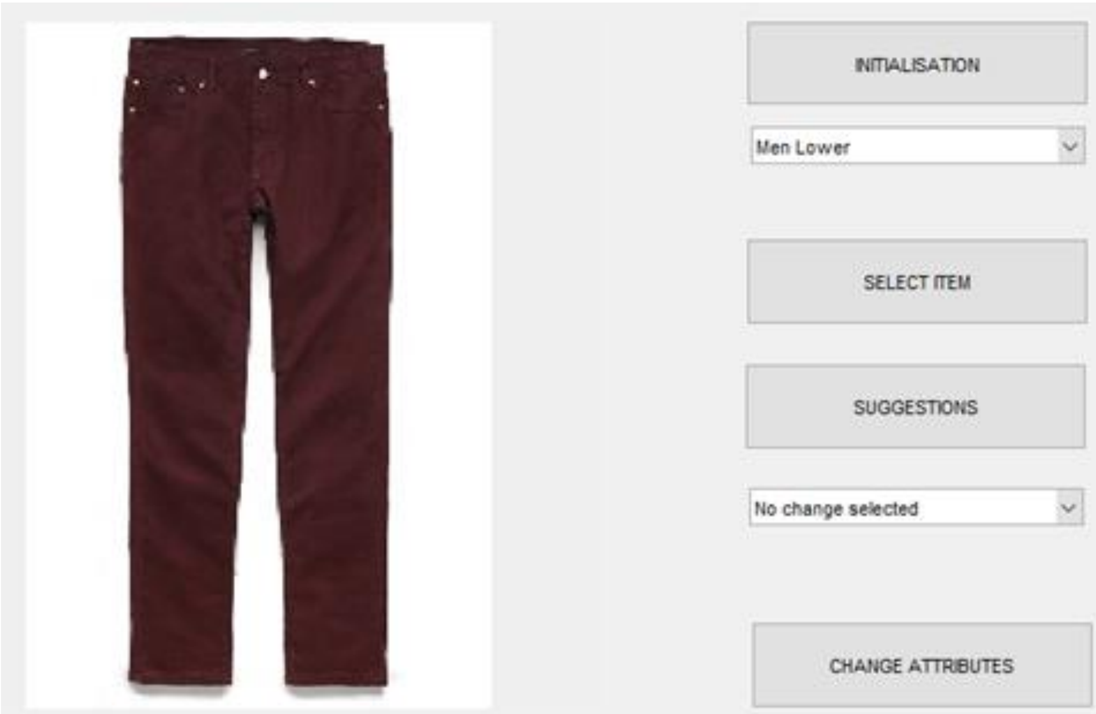

Figure 4.18. System interface showing the Men Lower image, a maroon color trouser, selected by the user.

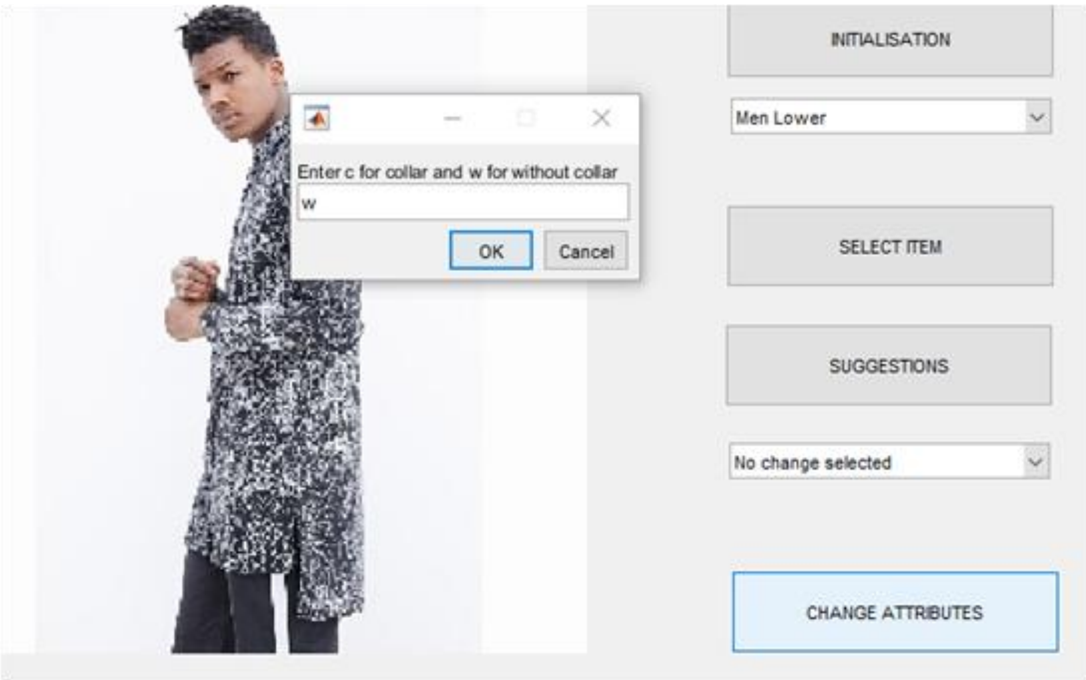

Figure 4.19. System interface to change style attribute Collar. Enter the required value in the appeared dialogue box and click OK else Cancel.

Figure 4.20. Images retrieved as matching upper for the men lower image shown in Fig. 4.18 with style attribute Collar as "Without Collar".

images computes accuracy of the system to be three out of four. Moreover, improvement in the retrieved results in comparison to that shown in Fig. 4.19 is considerably noticeable.

In the next example user wishes to choose a short sleeves shirt for the provided reference image of a green colored Men Lower. Fig. 4.21 shows the selected lower, user interface to change style attribute Sleeves to Half Sleeves is given in Fig. 4.22, and the refined set of images retrieved as per the user requirement is displayed in Fig. 4.23. The system has not chosen any single shirt with short sleeves in the first module, instead only one image that too with half sleeves is retrieved. It is one of those images

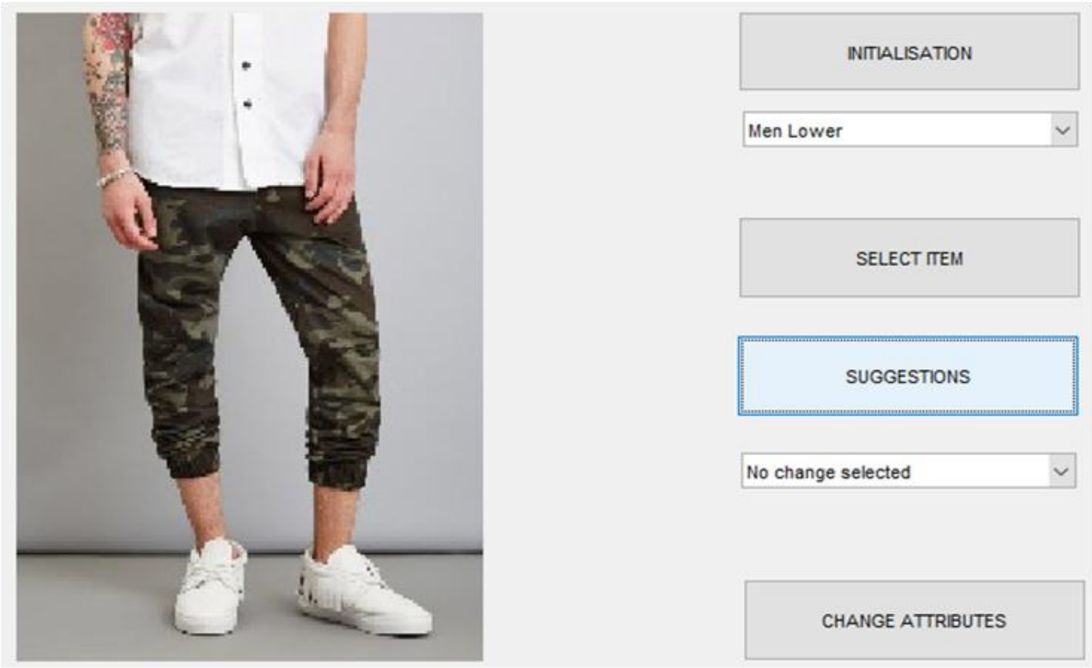

Figure 4.21. System interface showing the Men Lower image, a green color trouser, selected by the user.

where the suggestions prepared by the developed system are not so good. So the accuracy will vary with user perspective.

Rest all the examples showcase systems capability in retrieving similar color image for the provided reference image. Without worrying about the retrieval suggested by

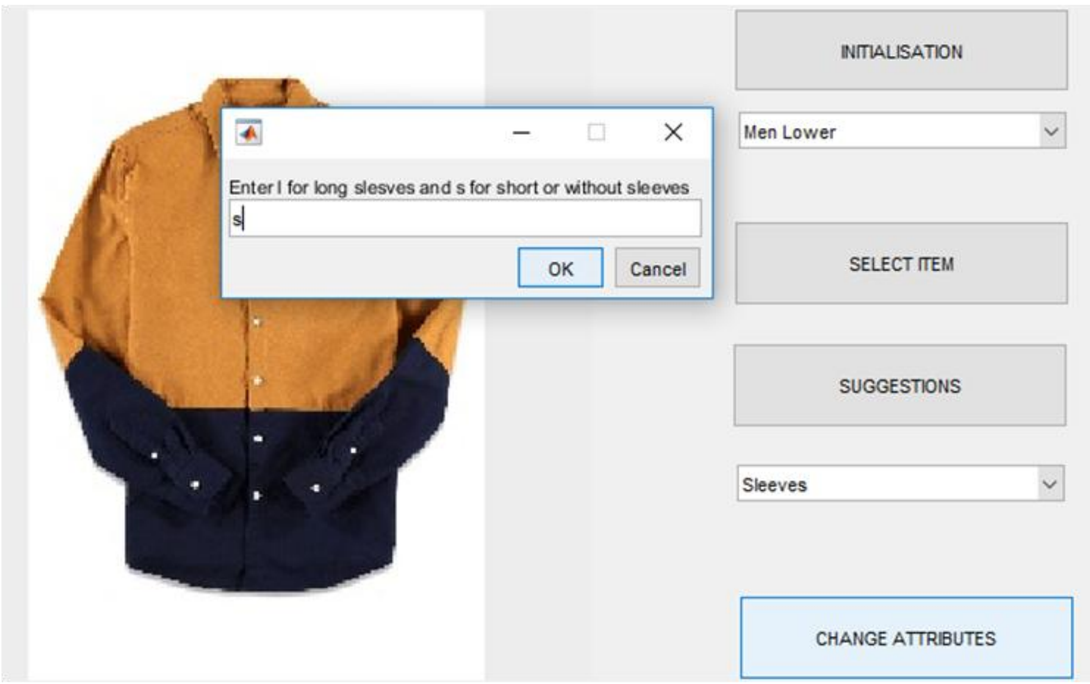

Figure 4.22. System interface to change style attribute Sleeves. Enter the required value in the appeared dialogue box and click OK else Cancel.

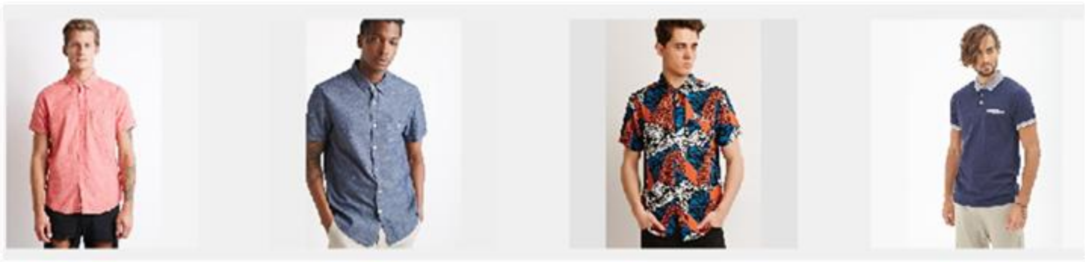

Figure 4.23. Images retrieved with style attribute Sleeves as “Half Sleeves”, for the men lower image shown in Fig. 4.21.

the first module of the system, assumption is that the user is searching for matching apparel of a particular color with any style attribute. Visual examination of all the results presented here after show distinguishing performance of the developed system as one can compute accuracy as near to 100% in most of the examples covered.

Fig. 4.24, Fig. 4.26, and Fig. 4.28 shows the system interface where user has respectively selected Men Lower as blue color jeans (looking for black color upper), blue color trouser (looking for grey color upper), and black color trouser (looking for white color upper and then for green color upper). The corresponding refined retrieved results for black, grey, white, and green color upper are shown in Fig. 4.25, Fig. 4.27, Fig. 4.29, and Fig. 4.30. These results again showcase the adaptive nature

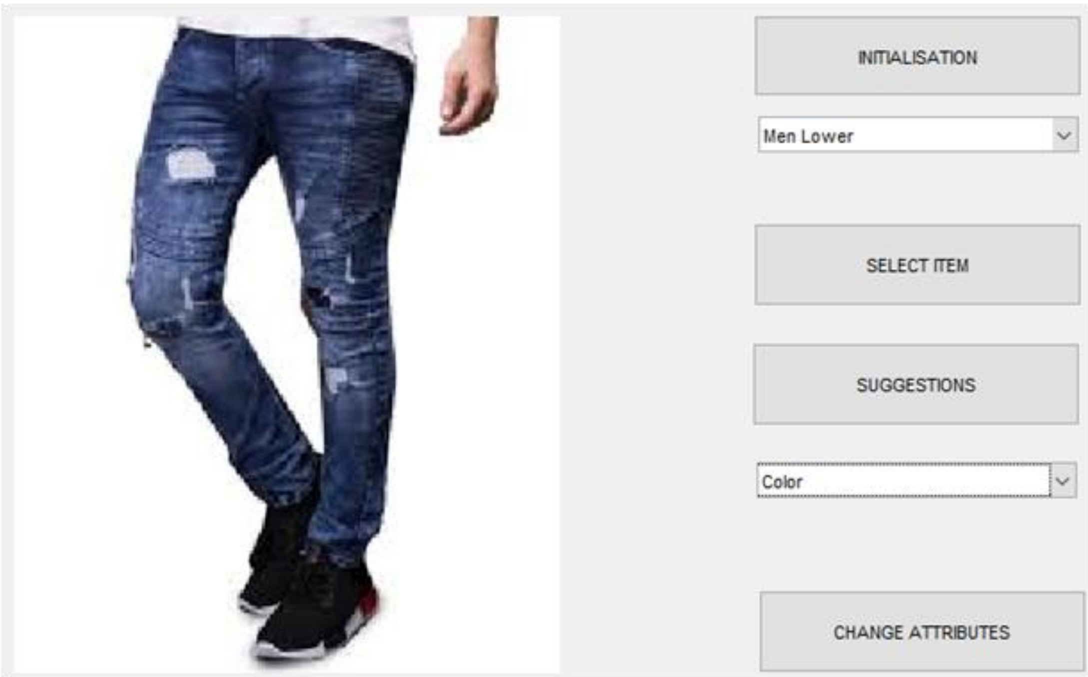

Figure 4.24. System interface showing the Men Lower image, a blue color jeans, selected by the user.

Figure 4.25. Images retrieved with style attribute Color as “Black”, for the men lower image shown in Fig. 4.24.

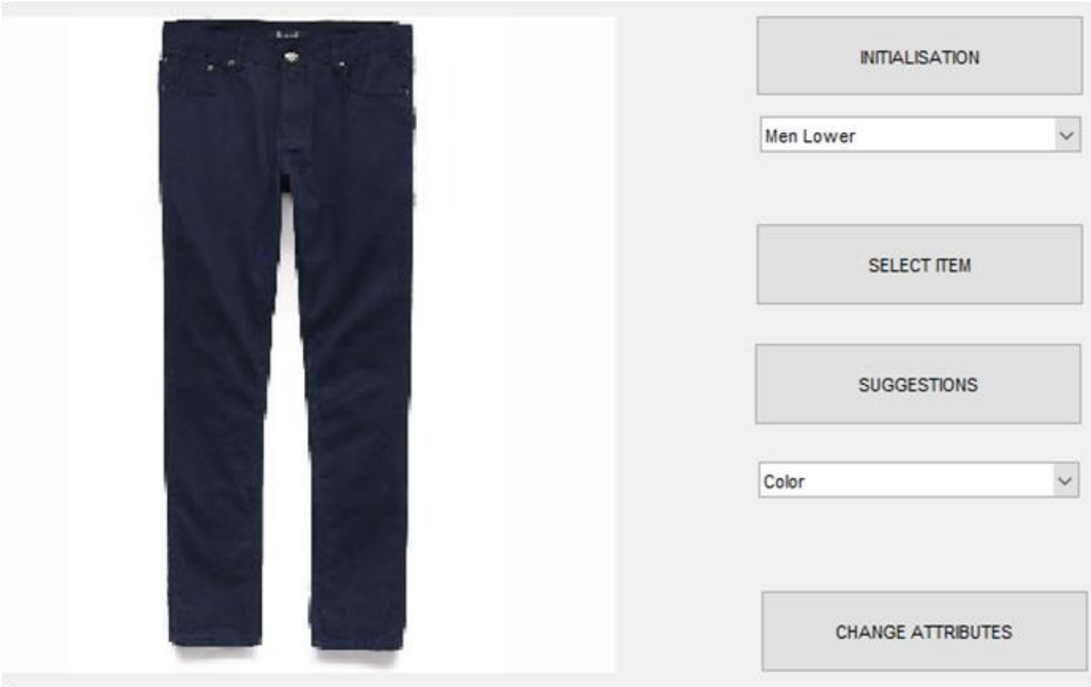

Figure 4.26. System interface showing the Men Lower image, a blue color trouser, selected by the user.

Figure 4.27. Images retrieved with style attribute Color as “Grey”, for the men lower image shown in Fig. 4.26.

of the developed system. The dataset used in this work contains several images of each color but retrieved are only those which satisfy the said criteria with respect to the reference image and one can observe variations in the number of retrieved images.

Similar to the previous examples for Men Lower, next there are a few more examples for Women Lower category. Fig. 4.31, Fig. 4.33, and Fig. 4.35 shows the system

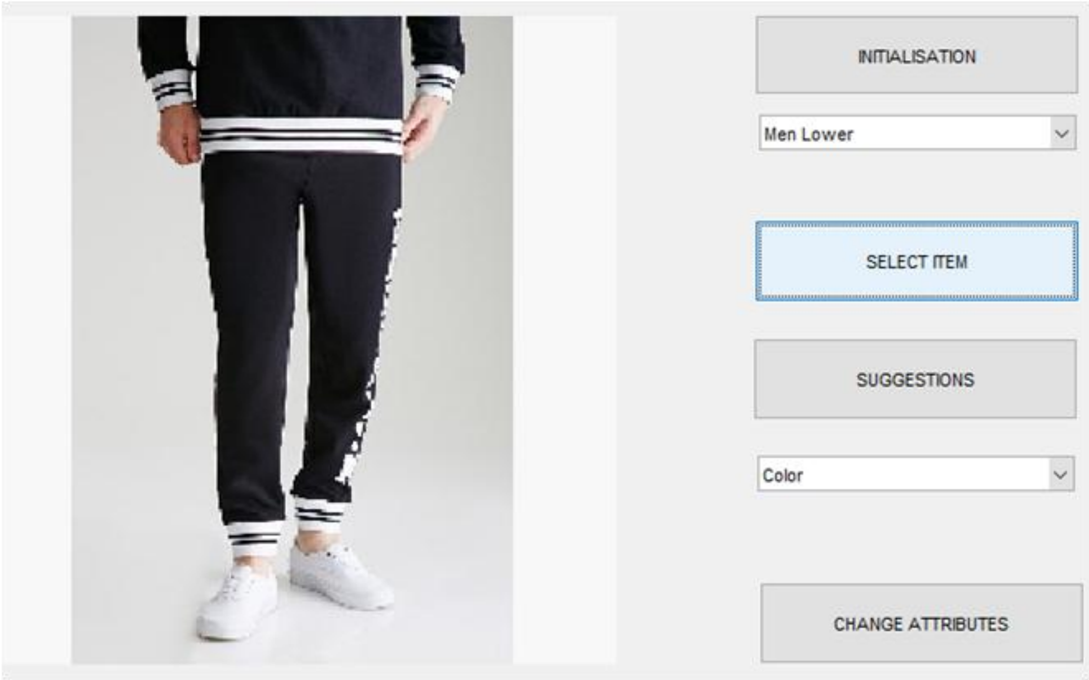

Figure 4.28. System interface showing the Men Lower image, a black color trouser, selected by the user.

Figure 4.29. Images retrieved with style attribute Color as "White", for the men lower image shown in Fig. 4.28.

Figure 4.30. Images retrieved with style attribute Color as "Green", for the men lower image shown in Fig. 4.28.

interface where user has respectively selected blue color capree (looking for black color upper), blue color denim (looking for grey color upper), and black color denim (looking for white color upper) as Women Lower. The corresponding refined retrieved results for black, grey, and white color upper are shown in Fig. 4.32, Fig.

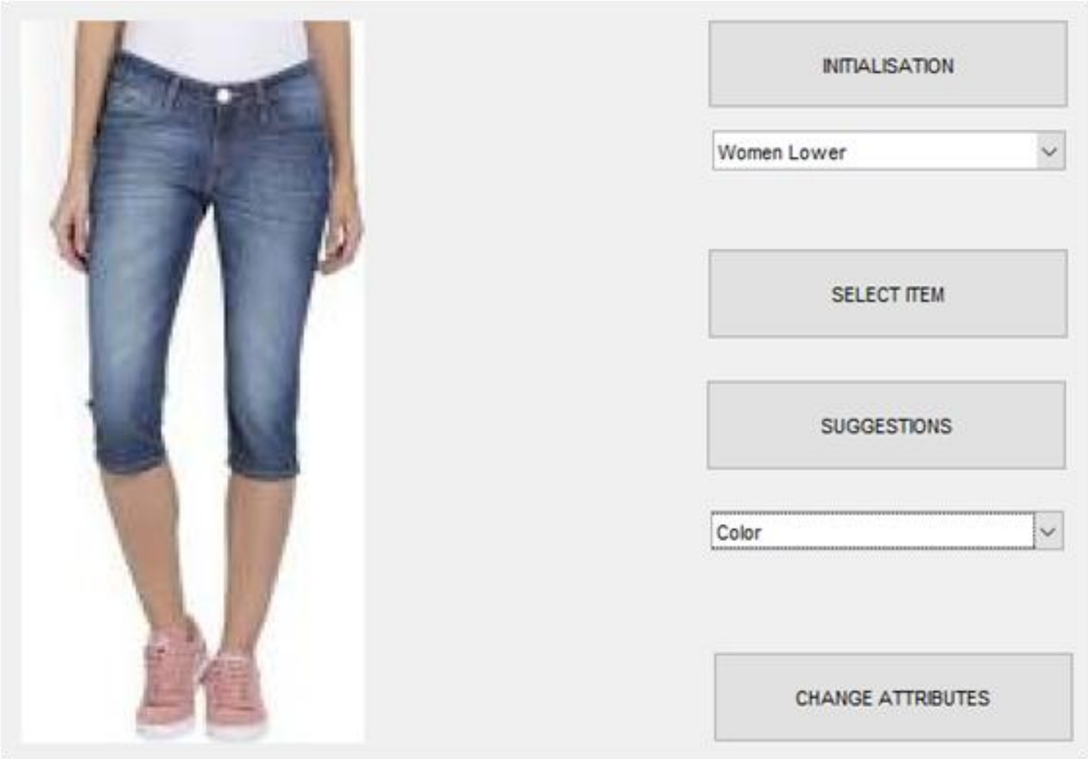

Figure 4.31. System interface showing the Women Lower image, a blue color capree, selected by the user.

Figure 4.32. Images retrieved with style attribute Color as "Black", for the women lower image shown in Fig. 4.31.

4.34, and Fig. 4.36. Similar observations as in the previous examples can be drawn here too. That is adaptive nature of the developed system with respect to the number of retrieved images.

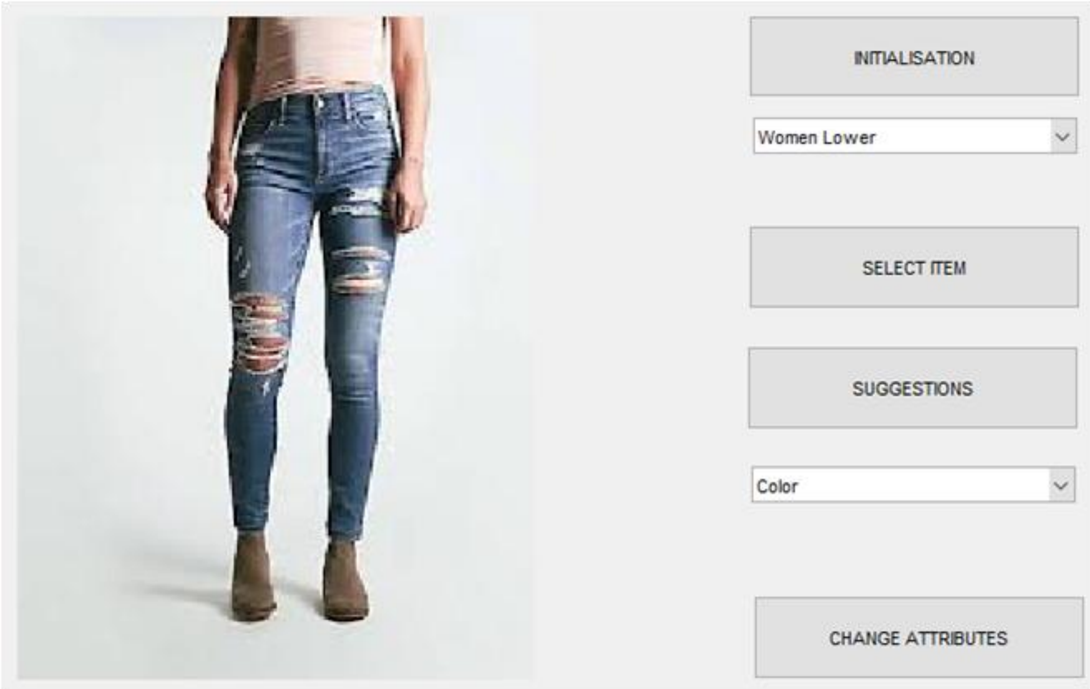

Figure 4.33. System interface showing the Women Lower image, a blue color denim, selected by the user.

Figure 4.34. Images retrieved with style attribute Color as “Grey”, for the women lower image shown in Fig. 4.33.

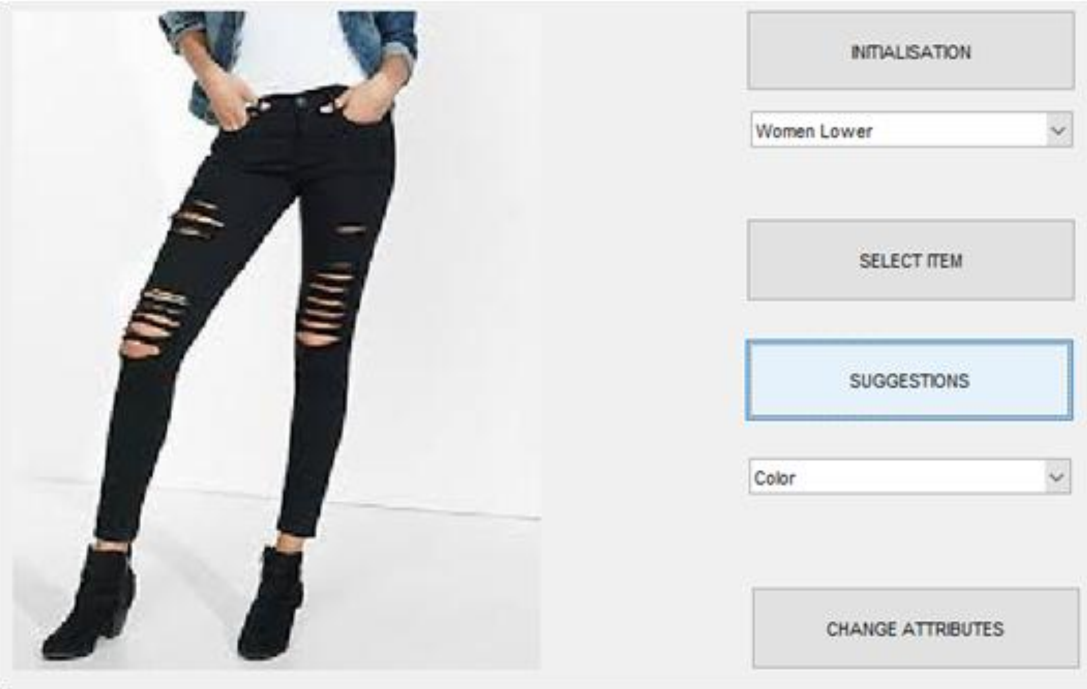

Figure 4.35. System interface showing the Women Lower image, a black color denim, selected by the user.

Figure 4.36. Images retrieved with style attribute Color as “White”, for the women lower image shown in Fig. 4.35.

Chapter 5

CONCLUSIONS AND FUTURE SCOPE

5.1. CONCLUSIONS

Most of the existing systems are based on retrieval of similar clothing. A very few of them has incorporated the concept of recommending a matching pair corresponding to a given query. In past few years, researchers have tried to develop a flexible system to enhance user performance, where performance is measured how well retrieved images can match a fixed set of attributes. The system is designed so that efficient results can be achieved in less time. The images can be retrieved according to users' desires and accuracy is achieved.

In view of these observations and focusing on effective visual recommendations, i.e. retrieval of exact as well as similar matches, an image based fashion clothing retrieval system is presented in this work. It effectively combines the concepts of neural network with color histogram and attribute descriptor features. It is capable to retrieve matching clothing pair for a given reference image and provides feature of style attribute update for refinement of retrieved results according to the user requirement. Currently four broad categories, namely Women Upper, Men Upper, Women Lower, and Men Lower are used. Similarly, six style attributes (Collar, Color, Gender, Hood, Length, and Sleeves) are defined. Based on visual examination results it is well said that the developed system is performing closer to human perception. The system is user friendly and easy to use. It has many benefits in day-to-day life as most of the times one wastes so much time in finding matching clothing pairs for several occasions like weddings, birthdays or a simple get to together. Existence of such systems would assist users in not only finding pairs but also to have an idea about different dressing styles.

5.2. FUTURE SCOPE

Although the system developed in this dissertation is working quite well, as can be observed from the obtained results. But there exists several points on which it can easily be improved. The dataset used is too small consisting of only 1,100 images in comparison to the number of the fashion images available these days. It can be extended for larger datasets by employing a range of suitable machine learning algorithms and feature extraction techniques too. Employing more than one feature for image depiction can also be explored. Lastly, only five style attributes are considered in the present implementation, this list can easily be extended to support better performance for large image datasets.

As it is very dynamic domain, a system would be much more accurate, user experience would be increased, and efficient results would be achieved in less period of time. The most important thing is that such systems should be much more close to human psychology. Development of the system is still on their way. New techniques are being introduced everyday whose incorporation may lead to better results.

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LIST OF PUBLICATIONS

Himani Sachdeva, Shreelekha Pandey, “Interactive Systems for Fashion Clothing Recommendation”, Third International Conference on Computer Vision & Image Processing (CVIP-2018), Paper Code: 152, Madhya Pradesh, India, September 29 – October 01, 2018 (Submitted).

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