IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

Fashion Recommendation System Using Social Media Website

P. Anusha[1], Kandula Nikhil Saradhi[2], Kokkirala Sravan Kumar[3], Marisetty Tejesh[4]
Assistant Professor, Department of CSE[1]
Students, Department of CSE[2,3,4]
Guru Nanak Institute of Technology, Hyderabad, Telangana, India

Abstract: *Fashion knowledge encourages people to properly dress and faces not only physiological necessity of users, but also the requirement of social practices and activities. It usually includes three jointly related aspects of: occasion, person and clothing. Nowadays, social media platforms allow users to interact with each other online to share opinions and information. The use of social media sites such as Instagram has already spread to almost every fashion brand and been evaluated as business take-off tools. With the heightened use of social media as a means of marketing communication for fashion brands, it has become necessary to empirically analyses and extract fashion knowledge from them*

Keywords: Fashion Recommendation System, Social Media Platforms, Fashion Knowledge, Marketing Communication, Instagram

I. INTRODUCTION

Online Social networks are part of every person's life. More than half of the world's population is connected to the internet and has at least one social platform. According to the report carried out by We Are Social of January 2021, in the world there are 7.83 billion people, 66.6% of these have a mobile phone. 4.66 billion People access the internet, an increase of 7.3% compared to January 2020. World internet penetration stands at 59.5%, but the values could be even higher by virtue of problems related to the correct tracking of internet users related to the COVID-19 pandemic. There are 4.20 billion users of social platforms, an increase of 13%. The use of social platforms therefore stands at 53% of the world population.

In particular, social networks have long since changed the way of communicating and perceiving the world: it is therefore no coincidence that fashion, of which communication and perception are two fundamental pillars, is an integral part of this revolution. In fact, the fashion industry is one of the most dynamic in society and in this context social media are fundamental communication tools, in particular Facebook (born in 2004), Instagram (born in 2010) and Tik Tok (born in 2018).

II. LITERATURE SURVEY

T. H. Nobile et. al(2021) This study focuses on the field of digital fashion and its development by providing an overview regarding fashion design and culture. It is part of a larger research that involved a literature review of 491 relevant papers. From the analysis of this corpus, three main categories were identified: Communication and Marketing, Design and Production and Culture and Society. This study focuses on the categories Design and Production and Culture and Society, which collectively gathered indicatively 48% of the selected literature. It presents its relevant studies and sub-categories, providing a rich and varied map of them and contributing to better design in further research in digital fashion.

M. Paolanti and E. Frontoni(2020) Pattern recognition (PR) is the study of how machines can examine the environment, learn to distinguish patterns of interest from their background, and make reliable and feasible decisions regarding the categories of the patterns. However, even after almost 70 years of research, the design of an application based on pattern recognizer remains an ambiguous goal. Moreover, currently, there are huge volumes of data that must be dealt with, which include image, video, text and web documents; DNA; microarray gene data; etc. Among the various frameworks in which pattern recognition has been traditionally formulated, the statistical and machine learning

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

approaches have been most comprehensively studied and employed in practice. Recently, deep learning techniques and methods have been receiving increasing attention. The main objective of this review is to summarize PR applications, departing from the major algorithms used for their design. The PR approaches are subdivided into three main methods: machine learning, statistical, and deep learning. In order to evidence the multidisciplinary aspects of PR applications, attention has been focused on latest PR methods applied to five fields of research: biomedical and biology, retail, surveillance, social media intelligence, and digital cultural heritage. In this paper, we discuss in detail the recent advances of PR approaches and propose the main applications within each field. We also present challenges and benchmarks in terms of advantages and disadvantages of the selected method in each field. A wide set of examples of applications in various domains are also provided, along with the specific method applied.

C. Giri et.al(2019) The enormous impact of artificial intelligence has been realized in transforming the fashion and apparel industry in the past decades. However, the research in this domain is scattered and mainly focuses on one of the stages of the supply chain. Due to this, it is difficult to comprehend the work conducted in the distinct domain of the fashion and apparel industry. Therefore, this paper aims to study the impact and the significance of artificial intelligence in the fashion and apparel industry in the last decades throughout the supply chain. Following this objective, we performed a systematic literature review of research articles (journal and conference) associated with artificial intelligence in the fashion and apparel industry. Articles were retrieved from two popular databases “Scopus” and “Web of Science” and the article screening was completed in five phases resulting in 149 articles. This was followed by article categorization which was grounded on the proposed taxonomy and was completed in two steps. First, the research articles were categorized according to the artificial intelligence methods applied such as machine learning, expert systems, decision support system, optimization, and image recognition and computer vision. Second, the articles were categorized based on supply chain stages targeted such as design, fabric production, apparel production, and distribution. In addition, the supply chain stages were further classified based on business-to-business (B2B) and business-to-consumer (B2C) to give a broader outlook of the industry. As a result of the categorizations, research gaps were identified in the applications of AI techniques, at the supply chain stages and from a business (B2B/B2C) perspective. Based on these gaps, the future prospects of the AI in this domain are discussed. These can benefit the researchers in academics and industrial practitioners working in the domain of the fashion and apparel industry.

Y. Ge et.al(2019) Understanding fashion images have been advanced by benchmarks with rich annotations such as DeepFashion, whose labels include clothing categories, landmarks, and consumer-commercial image pairs. However, DeepFashion has nonnegligible issues such as single clothing-item per image, sparse landmarks (4~8 only), and no per-pixel masks, making it had significant gap from real-world scenarios. We fill in the gap by presenting DeepFashion2 to address these issues. It is a versatile benchmark of four tasks including clothes detection, pose estimation, segmentation, and retrieval. It has 801K clothing items where each item has rich annotations such as style, scale, viewpoint, occlusion, bounding box, dense landmarks and masks. There are also 873K Commercial-Consumer clothes pairs. A strong baseline is proposed, called Match R-CNN, which builds upon Mask R-CNN to solve the above four tasks in an end-to-end manner. Extensive evaluations are conducted with different criterions in DeepFashion2.

III. EXISTING SYSTEM

We propose the Fashion Attributes Recognition Network (FAR Net) to simultaneously recognize three types of clothing attributes, including colors, categories, and patterns, in noisy-labeled images.

FAR Net contains two main components built on top of a CNN image feature extractor. The first component is a Noise Correction Network extended based on the model.

This network corrects noisy labels for images and generates corrected multi-labels of clothing colors and categories.

The second component is a Pattern Classification Network that classifies each image into one of the five clothing patterns. We trained FAR Net using the MTL framework.

Existing System Disadvantages

- We describe our model architecture and the loss functions in this section.
- The Pattern Classification Network uses categorical cross-entropy loss.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

Proposed System

Researchers have proposed several fashion recommender systems in the literature aiming at choosing the right outfit for different occasions.

Companies therefore must try to analyze the information that is spontaneously generated by web users.

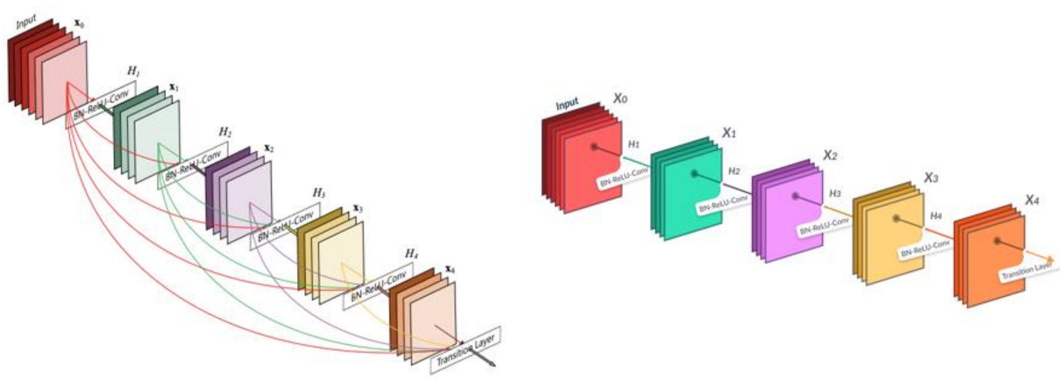
Big Data analysis now makes it possible to predict future trends even before they explode, providing real-time information not only on the volume of sales, but also on that of online searches.

More quickly identifying fabrics, styles and colors for which public interest is growing allows us to satisfy the request in a timely manner and consequently to sell more.

Proposed System Advantages

- ML techniques, companies operating in the fashion sector can identify patterns in data and build models that can predict future results.
- This helps to create a more flexible and faster supply chain and manage inventory in an automated and intelligent way.
- To get more accurate results the keywords have been aggregated.

IV. SYSTEM ARCHITECTURE



DenseNet Structure CNN Structure

$$a^{[l]} = g\left([a^{[0]}, a^{[1]}, a^{[2]}, \dots \dots \dots, a^{[l-1]}]\right)$$

Fig 1.1 System Architecture

The system architecture combines the DenseNet and CNN structures to enhance feature extraction and image classification efficiency. In the DenseNet structure, each layer is densely connected to all preceding layers, ensuring maximum feature reuse and mitigating the vanishing gradient issue by propagating information directly through shortcut connections. This design captures intricate patterns effectively and allows the network to learn robust representations. In contrast, the traditional CNN structure follows a sequential layer design where each layer outputs features to the next, focusing on progressively learning abstract representations. By leveraging DenseNet's dense connectivity and CNN's hierarchical learning, the architecture achieves improved accuracy in tasks such as fashion attribute recognition and recommendation, ensuring a robust and computationally efficient system.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

Methodology

Modules Name:

- Dataset
- Importing the necessary libraries
- Retrieving the images
- Splitting the dataset
- Building the model
- Apply the model and plot the graphs for accuracy and loss
- Accuracy on test set
- Saving the Trained Model

1) Dataset:

In the first module, we developed the system to get the input dataset for the training and testing purpose. We have taken the dataset for fashion classification and product recommendation.

2) Importing the necessary libraries:

We will be using Python language for this. First we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries such as pandas, numpy, matplotlib and tensorflow.

3) Retrieving the images:

We will retrieve the images and their labels. Then resize the images to (200,200) as all images should have same size for recognition. Then convert the images into numpy array.

4) Splitting the dataset:

Split the dataset into train and test. 80% train data and 20% test data.

Convolutional Neural Networks

The objectives behind the first module of the course 4

To understand the convolution operation

To understand the pooling operation

Remembering the vocabulary used in convolutional neural networks (padding, stride, filter, etc.)

Building a convolutional neural network for multi-class classification in images

Computer Vision

Some of the computer vision problems which we will be solving in this article are:

Image classification

Object detection

Neural style transfer

One major problem with computer vision problems is that the input data can get really big. Suppose an image is of the size 68 X 68 X 3. The input feature dimension then becomes 12,288. This will be even bigger if we have larger images (say, of size 720 X 720 X 3). Now, if we pass such a big input to a neural network, the number of parameters will swell up to a HUGE number (depending on the number of hidden layers and hidden units). This will result in more computational and memory requirements – not something most of us can deal with

Building the model:

For building the model we will use sequential model from keras library. Then we will use CNN Model for fashion classification dataset and the DenseNet121 CNN Model for product recommendation dataset which consist of Convolutional layer with 64 filters and a 7x7 kernel size, with stride of 2 and padding of 3.

Apply the model and plot the graphs for accuracy and loss:

We will compile the model and apply it using fit function. Then we will plot the graphs for accuracy and loss.

Accuracy on training set:

We got an accuracy of 99.2% on training set.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

Saving the Trained Model:

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or .pkl file using a library like pickle .Make sure you have pickle installed in your environment. Next, let's import the module and dump the model into.pkl file

V. IMPLEMENTATION

In the existing system, the Fashion Attributes Recognition Network (FAR Net) was utilized to identify clothing attributes such as colors, categories, and patterns using noisy-labeled images. While it provided a foundation, its architecture relied on standard CNN components and categorical cross-entropy loss functions, resulting in certain limitations. For example, the ability to handle intricate patterns or varying lighting conditions was restricted, making the system less robust in real-world scenarios with complex fashion data.To address these challenges, we introduced a more sophisticated approach leveraging Convolutional Neural Networks (CNNs) and DenseNet121 models. CNNs are particularly adept at image recognition tasks due to their ability to automatically and hierarchically extract features from images. DenseNet121, an extension of CNNs, further enhances feature extraction by connecting each layer to every other subsequent layer in a dense manner. This design reduces the vanishing gradient problem, optimizes computational efficiency, and ensures better feature reuse, leading to more accurate classification and predictions.In our implementation, CNNs were employed for general fashion classification, providing a structured method to identify clothing features. DenseNet121 was integrated specifically for recommendation tasks due to its capability to handle intricate patterns and diverse datasets with improved accuracy. The combination of these techniques allowed us to overcome the limitations of the existing system, such as difficulty in distinguishing similar clothing classes or managing deformations and occlusions in images.

By using these advanced models, we achieved significant improvements in the system's ability to process and classify fashion data accurately and efficiently. The CNN-based architecture streamlined the analysis of large-scale datasets, while DenseNet121 ensured precise recommendations even in challenging scenarios, such as cluttered backgrounds or subtle variations in clothing designs. This holistic approach not only addressed the initial drawbacks but also enhanced the user experience by delivering faster and more reliable outputs, thereby paving the way for future advancements in fashion analytics.

Algorithm Used

Existing Algorithm

Clustering algorithm:

The second column lists the number of clusters for each clustering algorithm.The number of clusters derived from DBSCAN is 45, which is the highest among all clustering algorithms**.**The number of clusters derived from DBSCAN is 45, which is the highest among all clustering algorithms**.**We clustered the street fashion images in each subset of Rich Wear by year in order to discover fashion trends**.**

Proposed Algorithm

CNN & DenseNet121:

Ml and dl techniques bring great benefits to image recognition and classification in the fashion environment.

In fact, they can help to improve the user experience, which is a fundamental factor for the calculation of the key performance indicator (kpi), which can be measured through factors such as the time spent by the user in front of the computer, the purchase volume and average checkout value.Deep Learning methods, and in particular Convolutional Neural Networks, can help the user to have a more pleasant experience on the site, being able to make a quicker and more convenient search of the products.

VI. EXPERIMENTAL RESULTS

This Paper is implements like application using python and the Server process is maintained using the SOCKET & SERVERSOCKET and the Design part is played by Cascading Style Sheet.

Home page:

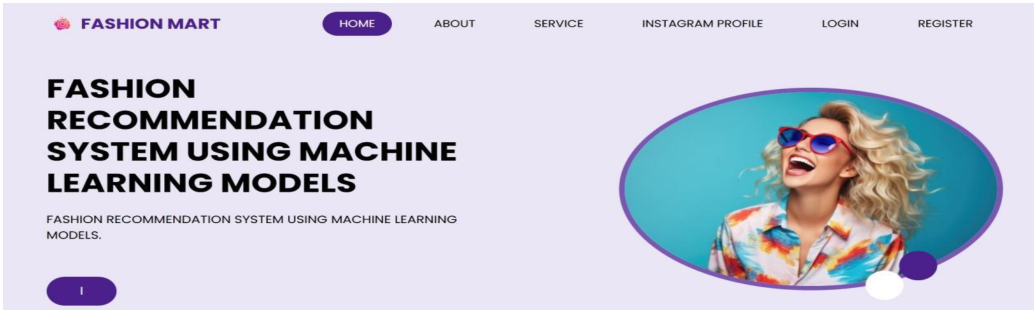


Fig: 2 Home Page

The home page is the main landing page of a website, serving as the gateway for users to explore its content and features. It typically includes a welcoming message and a clean,visually appealing design that reflects the brand identity.

Registration Page:

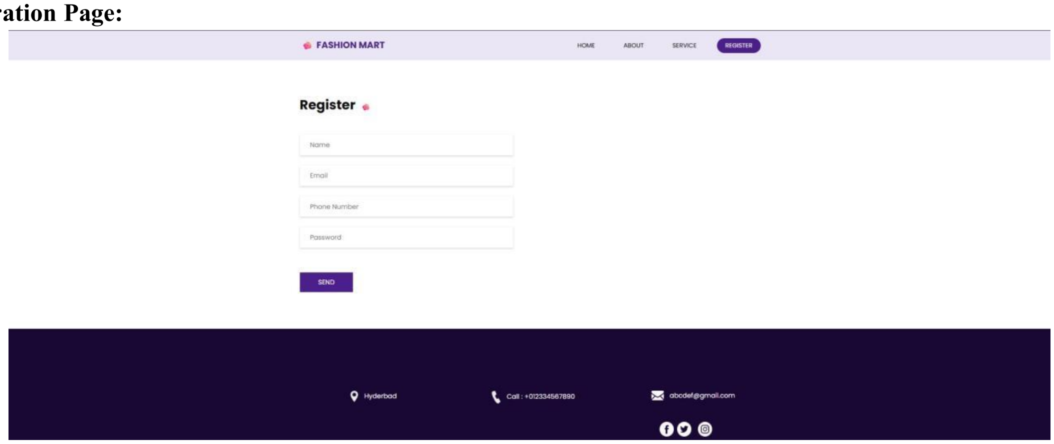


Fig 3 Registration Page

The registration page is a user interface designed to facilitate the process of creating a new account. It typically features input fields for gathering essential information from the user, such as their name, email address, and a secure password.

Login Page:

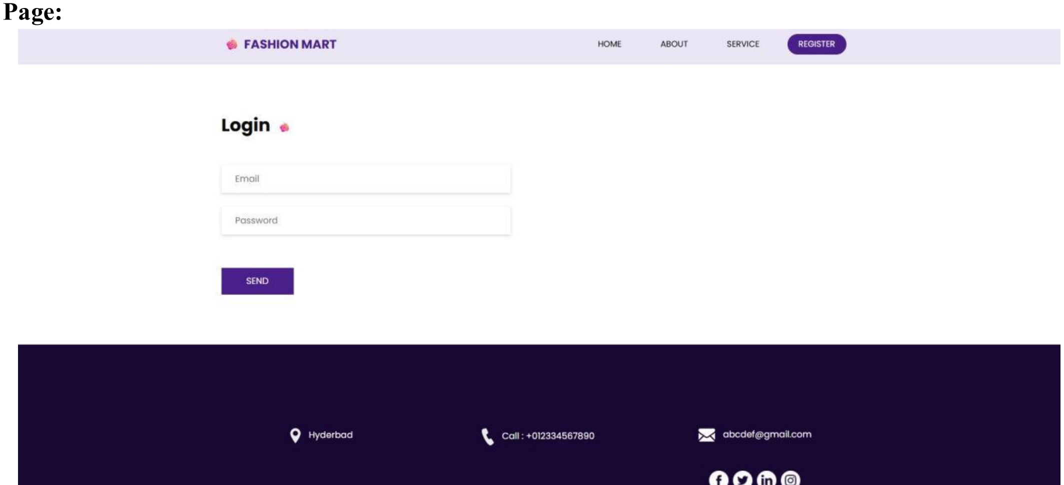


Fig: 4 login Page

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

The login page is a user interface that allows users to securely access their accounts. It typically includes input fields for entering a username and password, as well as a button to submit the login credentials. The page may also include options for recovering a forgotten password or creating a new account.

Instagram page:

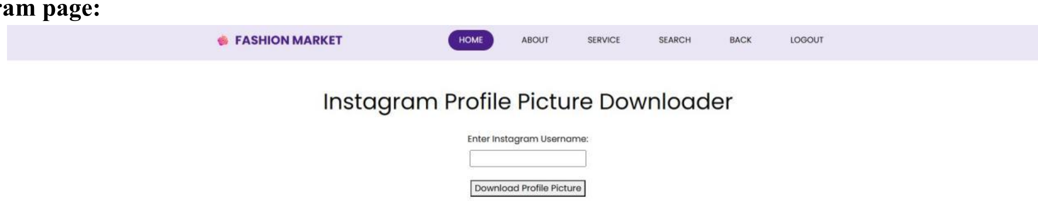


Fig: 5 Instagram Page

This webpage is a simple Instagram profile picture downloader. Users enter an Instagram username into a text field. Clicking "Download Profile Picture" presumably retrieves and downloads the corresponding profile image. Which can be further used for giving input for recommendation system

Input Page:

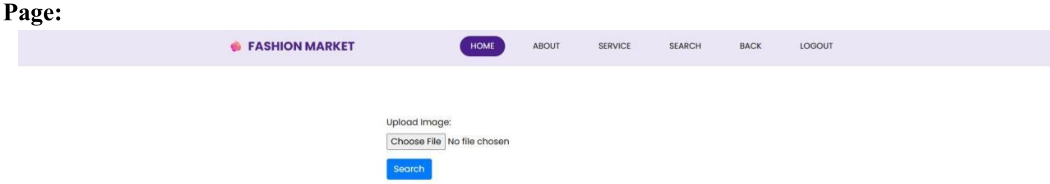


Fig: 6 Input Page

In the input page, user is asked to upload the image downloaded using the Instagram profile picture downloader and the model predicts the fashion of the user using the provided Instagram profile picture and gives recommendations

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, November 2024

Result page:

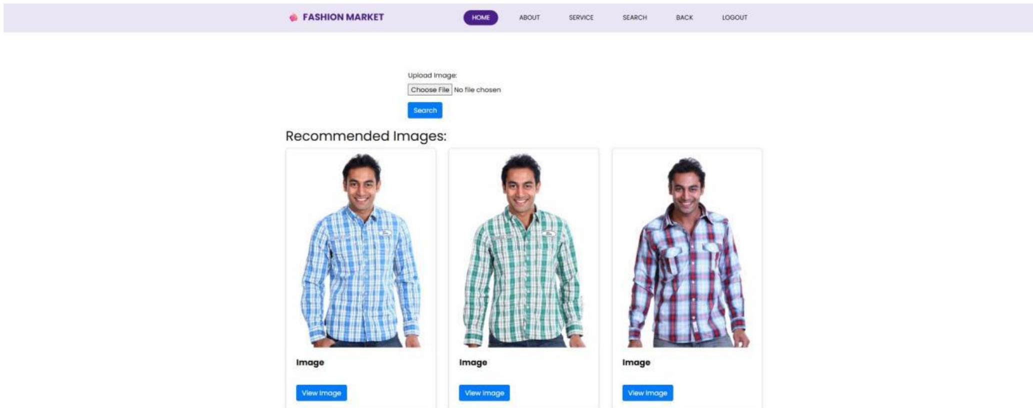


Fig: 7 Result Page

Based on the user's Instagram profile picture, his clothing is processed through the dataset using the algorithms like cnn and densenet and a set of similar clothes is recommended to the user. This is the result page based on the users input

VII. CONCLUSION

Valued at over 3 trillion dollars, the global fashion industry contributes to a healthy 2% of the global Gross Domestic Product (GDP). For this reason, fashion companies are increasingly trying to invest in the world of artificial intelligence to be able to satisfy the customer 100%. In particular, social media have long since changed the way of perceiving the world of fashion by the costumers: in this context social networks are fundamental communication tools, in particular Facebook and Instagram. Above all, the Instagram social network has become of fundamental importance for companies as the influencer sponsoring products is paid by companies to influence consumer preferences.

VIII. FUTURE ENHANCEMENT

Future research directions include the improvement of the algorithms to use other comprehensive features, thereby achieving better performance

REFERENCES

[1] A. Adewumi, A. Taiwo, S. Misra, R. Maskeliunas, R. Damasevicius, R. Ahuja, and F. Ayeni, ''A unified framework for outfit design and advice,'' in Data Management, Analytics and Innovation. Springer, 2020.

[2] T. H. Nobile, A. Noris, N. Kalbaska, and L. Cantoni, ''A review of digital fashion research: Before and beyond communication and marketing,'' Int. J. Fashion Des., Technol. Educ., pp. 1–9, May 2021.

[3] M. Paolanti and E. Frontoni, ''Multidisciplinary pattern recognition applications: A review,'' Comput. Sci. Rev., vol. 37, Aug. 2020.

[4] X. Gu, F. Gao, M. Tan, and P. Peng, ''Fashion analysis and understanding with artificial intelligence,'' Inf. Process. Manage., vol. 57, no. 5, Sep. 2020.

[5] C. Giri, S. Jain, X. Zeng, and P. Bruniaux, ''A detailed review of artificial intelligence applied in the fashion and apparel industry,'' IEEE Access, vol. 7, pp. 95376–95396, 2019.

[6] L. Q. Lomas, A. G. Elordi, A. A.Escondrillas, and D. L. De Ipina Gonzalez De Artaza, ''A systematic literature review of artificial intelligence in fashion retail B2C,'' in Proc. 6th Int. Conf. Smart Sustain. Technol. (SpliTech), Sep. 2021.

[7] S. Chakraborty, M. Hoque, N. Rahman Jeem, M. C. Biswas, D. Bardhan, and E. Lobaton, ''Fashion recommendation systems, models and methods: A review,'' Informatics, vol. 8, no. 3, p. 49, 2021.

[8] K. Yamaguchi, M. H. Kiapour, L. E. Ortiz, and T. L. Berg, ''Parsing clothing in fashion photographs,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2012.

[9] J. Dong, Q. Chen, W. Xia, Z. Huang, and S. Yan, ''A deformable mixture parsing model with parselets,'' in Proc. IEEE Int. Conf. Comput. Vis., Dec. 2013.

[10] K. Yamaguchi, M. H. Kiapour, and T. L. Berg, ''Paper doll parsing: Retrieving similar styles to parse clothing items,'' in Proc. IEEE Int. Conf. Comput. Vis., Dec. 2013.

[11] W. Yang, P. Luo, and L. Lin, ''Clothing co-parsing by joint image segmentation and labeling,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014.

[12] S. Liu, J. Feng, C. Domokos, H. Xu, J. Huang, Z. Hu, and S. Yan, ''Fashion parsing with weak color-category labels,'' IEEE Trans. Multimedia, vol. 16, no. 1, pp. 253–265, Jan. 2013.

[13] B. Loni, L. Y. Cheung, M. Riegler, A. Bozzon, L. Gottlieb, and M. Larson, ''Fashion 10000: An enriched social image dataset for fashion and clothing,'' in Proc. 5th ACM Multimedia Syst. Conf. (MMSys), 2014.

[14] J. Huang, W. Xia, and S. Yan, ''Deep search with attribute-aware deep network,'' in Proc. 22nd ACM Int. Conf. Multimedia, Nov. 2014.

[15] A. Yu and K. Grauman, ''Fine-grained visual comparisons with local learning,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014.

[16] X. Liang, S. Liu, X. Shen, J. Yang, L. Liu, J. Dong, L. Lin, and S. Yan, ''Deep human parsing with active template regression,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 37, no. 12, pp. 2402–2414, Dec. 2015.

[17] X. Liang, C. Xu, X. Shen, J. Yang, S. Liu, J. Tang, L. Lin, and S. Yan, ''Human parsing with contextualized convolutional neural network,'' in Proc. IEEE Int. Conf. Comput. Vis., Jun.2015.

[18] J. Huang, R. Feris, Q. Chen, and S. Yan, ''Cross-domain image retrieval with a dual attribute-aware ranking network,'' in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Dec. 2015.

[19] M. H. Kiapour, X. Han, S. Lazebnik, A. C. Berg, and T. L. Berg, ''Where to buy it: Matching street clothing photos in online shops,'' in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Dec. 2015.

[20] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, ''DeepFashion: Powering robust clothes recognition and retrieval with rich annotations,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016.

[21] Z. Liu, S. Yan, P. Luo, X. Wang, and X. Tang, ''Fashion landmark detection in the wild,'' in Proc. Eur. Conf. Comput. Vis. Springer, 2016.