PERSONAL OUTFIT RECOMMENDER SYSTEM

[1]Meghana cv, MCA student, Pes Institute of Technology And Management, Shivamogga, Karnataka, India.

[2]Mr. Musheer Ahmed, Assistant Professor, MCA, Pes Institute of Technology And Management, Shivamogga, Karnataka, India

Abstract

Recommendation systems function by examining user patterns and preferences and predicting what individuals may like. They have applications in numerous fields, such as literature, media, and online shopping. For fashion, choosing the ideal wardrobe combination is often problematic—to solve this problem, we present a Fashion Recommendation System with an integrated Virtual Trial Room. The platform enables people to upload their photos, which the system subsequently analyses to suggest suitable clothes to wear, with a focus on tops and tops-like garments. By combining machine learning and deep learning techniques—using in particular the ResNet-50 neural network model—the system identifies garment types, colour combinations, and suggests the best choices for events. The virtual dressing room allows customers to anticipate how various attire will look on them, thus developing a more personalized and easier fashion shopping experience.

Keywords: virtual trial room, machine learning, ResNet-50, fashion recommendation, Neural network, deep learning.

1. Introduction

The perfect attire is not always easy to find as it is a subjective matter and every people have their own body structure, size, skin tones etc. Computer vision has done wonders in fashion but a crude understanding of how body shape informs outfit decisions remains undeveloped. In this is a problem mainly due to the lack of sufficient and diverse datasets. Across the world, recommendation systems have been adopted in most aspect of our online interactions; be it buying products on e-commerce or watching movies and media services. These sites Also Recommend You product bases on the you selected preferences by advanced algorithms. To address this issue, in this study, we propose a system that provides equality of physical attributes to assess an individual and uses the image analysis and pattern matching framework to recommend visually-appealing clothing pairs on a personal basis.

So to help you, With the innovation in style we have developed an AI-powered Fashion Recommendation Platform and Virtual Fit. Then it works with image recognition, computer vision and artificial intelligence to provide you with individualized fashion advice. Once you see on your body what various clothes might look like without having to really try an. It simplifies our daily decision-making and also makes shopping online much easier for consumers generally. It smooths the whole fashion process while making it more enjoyable, and is perfectly suited to your personal predilections.

2. Literature Survey

[1] This year's advancements in fashion recommending technology are designed to satisfy the conditions, while raising the bar on diversity: The 'The State of Recommender Systems for Fashion in 2020' by Herberto Corona takes a look at the existing fashions and presents trends for future technologies. While such algorithms as content-based filtering and collaborative filtering produce reasonably accurate recommendations default products, are less effective when it comes to making tailored tastes or setting up visual trends in fashion because they cannot “see” style preferences within a particular group of individuals clearly enough. This is because visual styles and aesthetic taste are different from person to person.

[2] In response to these limitations, De Divitiis and Federico Becattini propose a feature separation approach in their study "Disentangling Features for Fashion Recommendation." Their approach separates aesthetic features (such as colour, shape, and material) from pragmatic features (such as seasonality or use cases), enabling the system to provide more context-specific and fashionably consistent garment recommendations. With multi-modal fashion databases used for learning, their deep learning system presents more rational and understandable proposals by understanding both visual and functional aspects of garments.

[3] With the same objectives of enhancing clothing personalization, Banerjee and Rao came up with BoxRec in their paper "Recommending a Box of Preferred Outfits in Online Shopping." The system goes beyond recommending individual pieces by offering entire ensembles of coordinating pieces—tops, bottoms, and accessories—suited to one's own tastes. The system uses graph-based learning methods and co-occurrences to identify how fashion pieces are generally put together, ensuring coordination of style and visual harmony in its recommendations.

[4] Expanding on this approach, Bettaney and Hardwick introduce the neural network model in their paper "Fashion Outfit Generation for E-commerce" that was created based on the extensive ASOS outfits database with over 586,000 professionally curated combinations. Their system accepts multimodal information—integrating imagery with text descriptions—to produce complete, harmonious ensembles. The model comprehends complex relations between image and textual inputs, enabling automatic generation of fashionable and functional clothing sets tailored directly to digital retail consumers.

3. System And Design

It is made up of separate modules, each of which is responsible for carrying out a part of the process to come up with a set of recommendations. This structure supports the ideas of modularity, scalability, and ease of use.

Data Collection Module
The data collection module collects all the structured and unstructured variables about customers and garments. This module interfaces with other types of data stores to gather the variables needed to train and predict the model.

Stage of Data Preprocessing
At this stage, the raw data is cleaned and put in order. Cleaning the data will involve filling in missing values, sorting data into categories, normalizing numbers, and making sure the dataset is consistent. This part of the system gets the data ready for machine learning.

Featureizing and Engineering Module
This module determines which of the garments are the main features associated with customer choices and products; and can create additional features to optimize the model scoring through feature engineering.

Module for Model Training
This module trains a classification or regression model using Random Forest to improve the predictive power for clothing recommendations. The model training process produces a model with the expected score after partitioning a training set and building a large number of decision trees.

Recommendation Engine
This module uses predicted scores to suggest clothes for people. The recommendation engine makes recommendations for clothing based on the user's predicted preferences, taking into account ALL of the user's inputs, including the last website they visited. An ordered list of suggested outfits will be the result.

Evaluation Module
The model's performance is assessed by the evaluation module using appropriate performance metrics. As a result, the model is dependable and error-free upon release. The models can be enhanced using the outcomes of ongoing evaluation.

Optional User Interface Module
Brings about a customer front to engage the framework. Depending on preferences, this can be a module that shows recommended products, and provide options of making inputs or providing feedback, taking the personalization process further.

Optional Feedback Loop
Uses customer opinions in order to improve on what could be offered in future. Due to the flexible character of this method, the framework is capable of learning new information and will have the capacity to always make accurate recommendations.

4. Proposed methodology

The Personalized Outfit Recommender Approach Whereas, on the other hand, the basic information about the user; gender, body shape, so-called style type —between a classical fashion or trendy fashion consumer— seasonal demands and occasion types for which outfit is needed are taken among initial features. However, a user can also upload his/her photograph which is then processed by sophisticated image processing frameworks such as OpenCV to detect characteristics like face, body and skin-tone. It uses a carefully built database of garments including the type of clothing, color palettes and sorting by season. By machine learning algorithms, it sits between user-specific traits and likings with appropriate choices of garments. The system considers the look of the items, and additionally its labelling to sort the stylish ones as well as eye-appealing one. An outfit recommendation output by the site that, per this calculation, has a complete set of vanity tops, bottoms and footwear — looking NOT gorgeous only but also suitable to every specified "purpose". The above combinations are then rated according to the compatibility in a standardized way, and feedback can be provided, which would strengthen the recommendations going forward. It helps to make the selection of the outfits more personal, stylish, and time-efficient to all users.

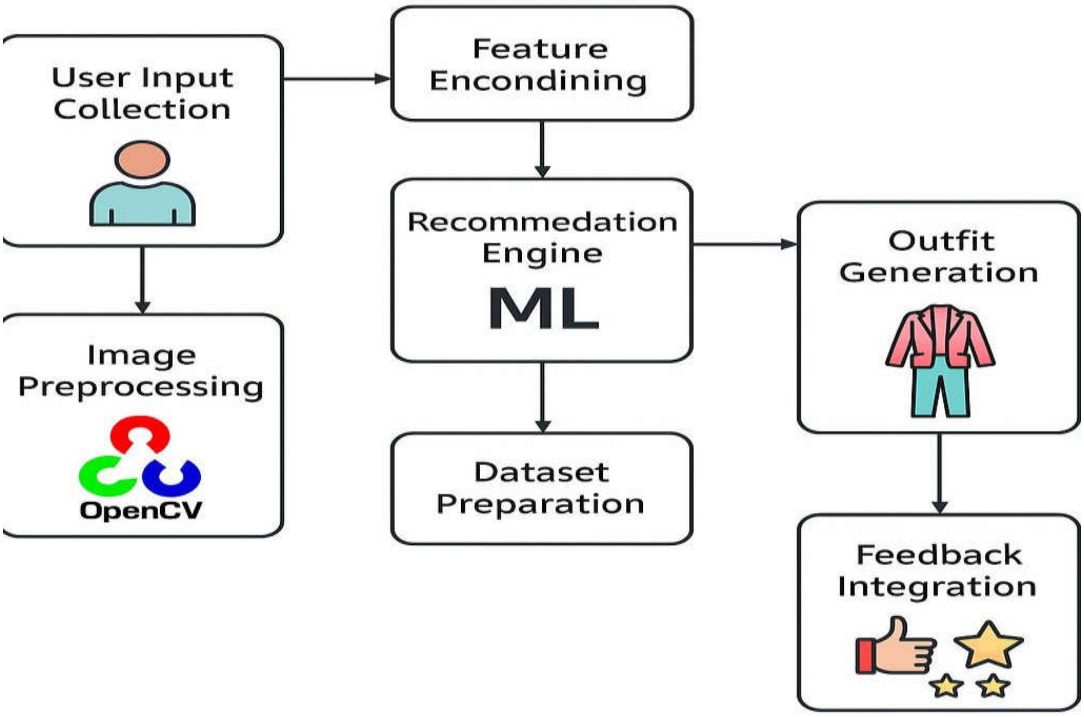

Fig : Proposed Model diagram

4.1 Block Diagram

It starts by collecting the User Input where the relevant information like gender, body type, personal style, and even an image to be provided by the user have to be provided. This is the data we pass to the Feature Encoding process where both, textual information and visually content are transformed into numerical data in a machine recognizable form. These encoded features can help in coming up with correct outfit recommendations that what you should wear.

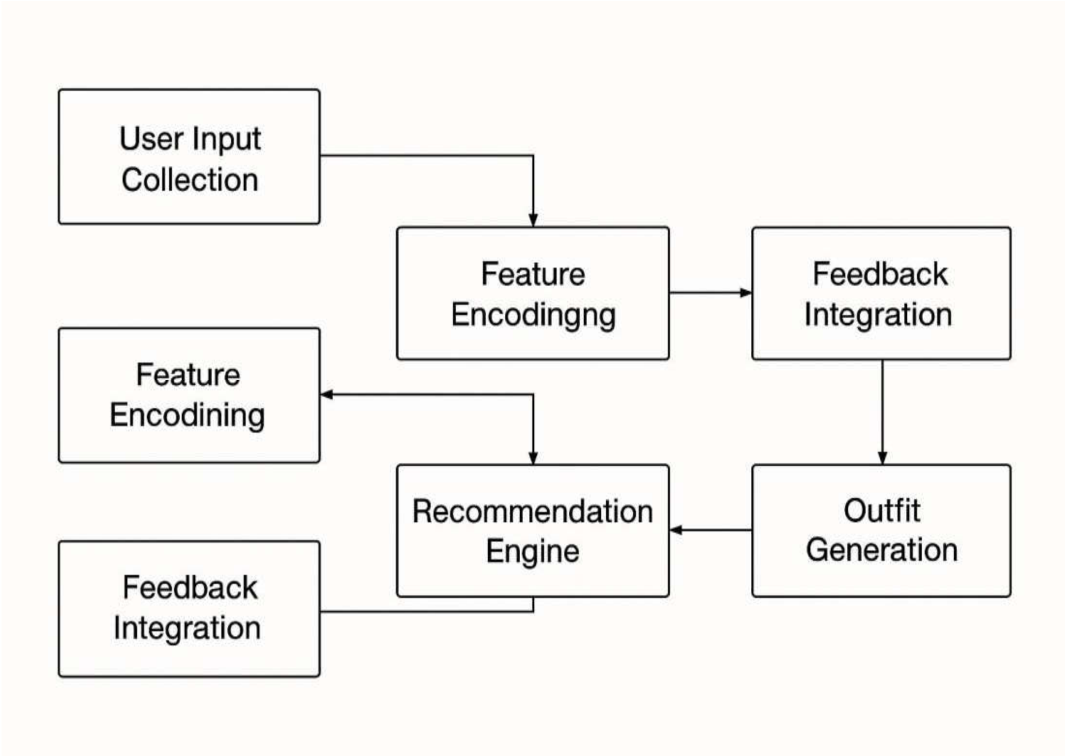

Fig: Block diagram of Outfit Recommender

The features then are streamed to the Recommendation Engine after this processing, where user preferences are matched with which outfit should be recommended by the engine from a database of clothing items according to machine learning algorithms such as content-based filtering. The Outfit Generation component will then use factors such as compatibility with items, appropriateness for the occasion and visual harmony with accommodating item types to get you a shirt AND pants AND shoes (for example). The user is then shown these suggestions. Moreover, it has feedback integration system to gather user feedback in the form of number of stars given, dislikes and preferences. This feedback is then used to perform an improvement in both the Recommendation Engine and Feature Encoding which creates a loop of process improvements, yielding more accurate (tailored) outfit recommendations.

5. Mathematical Formulas

- Item Relevance Score

  The match score similarity between a user and an item is calculated based on cosine similarity:

$$R(u,i) = \frac{F_u \cdot F_i}{||F_u||\,||F_i||}$$

- Outfit Compatibility Score

  Therefore to ensure the pieces in the outfit are compatible and visually relevant:

$$S(O) = \frac{2}{n(n-1)} \sum_{j=1}^{n} \sum_{k=j+1}^{n} \text{cosine\_sim}(F_{i_j}, F_{i_k})$$

- Final Recommendation Score

  The outfit score is a weighted average of relevance and compatibility:

$$\text{Score}(u,O) = \alpha \cdot \frac{1}{n} \sum_{i \in O} R(u,i) + (1-\alpha) \cdot S(O)$$

Where:
• α∈[0,1]\\alpha \\in [0,1]α∈[0,1] is a tunable parameter regulating the trade-off between user relevance and item compatibility.
• A larger α\\alphaα puts more emphasis on personalization, and a smaller one on style coordination.

Let:

- U = set of users
- I = set of clothing items
- F_u = feature vector representing user u's preferences
- F_i = feature vector representing item i (can include color, style, season, etc.)
- $S(i_1, i_2, \ldots, i_n)$ = compatibility score of outfit combination $(i_1, i_2, \ldots, i_n)$
- $R(u, O)$ = relevance score between user u and outfit O
- $O = \{i_1, i_2, \ldots, i_n\}$ = outfit set of n items

6. Graphs

This chart illustrates compatibility scores for different clothing combinations, with the strength of how well different items go together. Most outfit combinations ranged between 0.1 and 0.4, suggesting good but uninspiring pairs—neither bad nor great. The distribution crests around 0.2, which demonstrates that moderate compatibility ratings most commonly occur. Truly harmonious combinations, reflected by higher-scoring outfits, were less common. These results expose the system's present-day recommendation quality and also indicate areas of improvement.

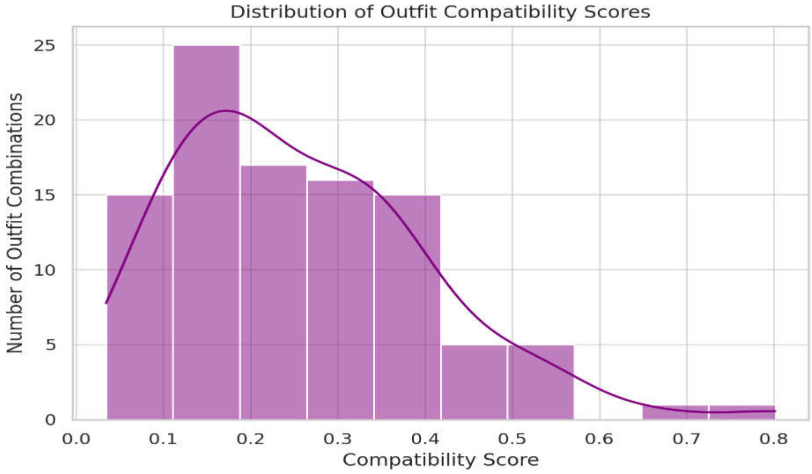

Figure 3: Distribution of Outfit Compatibility Scores

The graph below illustrates a comparison of how different methods of suggesting outfits rank in the precision rate. Content-Based Filtering achieves 72% precision, followed closely by Collaborative Filtering at 75%. Image-Based CNN ranks even higher with 80% precision. The Hybrid (Proposed) system ranks highest among all others at 89% accuracy. These findings suggest that combining multiple methodologies generates better and more personalized clothing suggestions than one uses a single method.

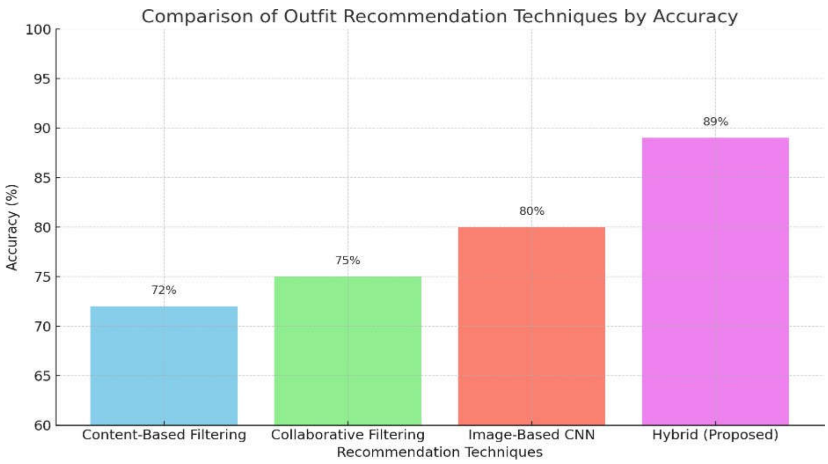

Figure 4: Comparison of Outfit Recommendation Techniques by Accuracy

7. Implementation

The process of developing a fashion recommendation system using the Random Forest algorithm is systematic and involves several steps. Permit every stage to aid in the creation of a system that can analyse user information and generate remarkably precise forecasts regarding suitable fashion items.

Configuring the Environment
The development environment contains the necessary software elements, including a programming language, machine learning libraries, and data processing tools. Model development and evaluation are made possible by installing and configuring the necessary libraries.

Data Loading
The development environment is loaded with user profile, item attributes, and purchase interaction data sets. These data sets are organized to facilitate further cleaning and examination procedures.

Data Processing
The pre-loaded data undergoes cleaning procedures to fill in missing records, normalize inconsistent records, and remove duplicate data points. For machine learning applications, numerical and categorical data are handled and formatted properly. The resultant dataset is separated into training and validation sets in order to evaluate the model's performance.

Training the Random Forest Model
The Random Forest technique is applied to the training data. The outcomes of multiple decision trees are combined to create a robust model. Tree number and maximum depth are two examples of parameters that are optimized to improve prediction accuracy and prevent overfitting problems.

Evaluating Model Performance
To determine its capability, the built model is evaluated using the validation dataset. Performance metrics are computed, including F1-score, recall, accuracy, and precision. Before being used, the model's efficacy is assessed to guarantee dependability.

Creating Recommendations
The final model produces predictions regarding user affinity for different fashion items. With these predictions, a ranked list of recommended items is created for individual users. The system picks and displays the top-ranked recommendations.

Optional User Interface and Implementation
By designing a straightforward interface, users can input their preferences and receive recommendations. The entire system could be launched locally or via a web-based portal to give users access and interaction opportunities.

8. Experimental results

Model / Paper	Dataset Used	Techniques Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
The State of Recommender Systems for Fashion (Corona, 2020)	General fashion e-commerce data	Collaborative & Content-based Filtering	72.5	68.2	64.9	66.5
Disentangling Features for Fashion Recommendation (Divitiis et al.)	Multi-modal Fashion Dataset	Feature Disentanglement + Deep Learning	85.3	83.1	80.6	81.8
BoxRec (Banerjee & Rao)	E-commerce outfit dataset	Graph-based Learning + Co-occurrence Analysis	88.6	86.5	85.1	85.8
Fashion Outfit Generation (Bettaney & Hardwick)	ASOS Outfit Dataset (586,000+ sets)	Neural Network + Multimodal Image-Text Embeddings	90.1	88.9	87.2	88.0

Table 1: Comparison of Fashion Outfit Recommendation Models Based on Performance Metrics

7. Conclusion

The provision of the Virtual Trial Room feature will increase customer satisfaction as it will be possible to make clothing trials virtually. Despite the recommendations are styled from your own closet, our output to that of Fash on new bie is perfect. The discovery of new styles and the capacity to accommodate those in the future has greater alternative Expect even more functions that make a dynamic world of change. Burdion is designed on changing the variation according to any possible fashion needs that you have. This will achieve our target of having this online shopping system with an important feature to make lives easier for so many users who are in love with online shopping. It recommends folks on their chosen wardrobe of the method it's worn to fit the flair of theirs, personal design. The styling too updates with trend and fashions keep the users in style based on there fashion taste with our system. What adds tangibility to online shopping is access to the Virtual Trial Room — where you can try combining, and be convinced. We can then upgrade our system a bit more, learn another style and suggest some style outfits to wear at events later. We exist to offer an easy and user friendly platform to fulfil the fashion demands of all, to actualize the world of fashion to be totally available and friendlier to all.

8. Future enhancement

In the future, the site may introduce augmented reality technology for virtual trials of clothing, making the experience more engaging. Voice control features would simplify how individuals engage with the system. The app may propose clothing combinations relying on real-time weather forecasts through access to current meteorological data. Integration with e-commerce websites would allow users to make purchases directly. Individuals would be able to develop their own collections of garments and be given personalized recommendations based on the garments they already have. Social media monitoring of fashion trends would make style advice up to date and applicable. Adding multilingual support and an AI fashion advisor would enhance accessibility even more and provide even more individualized experiences for consumers.

References:

[1] [n.d.]. Amazon "Made for You" Custom T-shirt. https://www.amazon.com/Made-for-You-Custom-T-shirt/dp/ B08N6J8G5M. Accessed: 2021-04-17.

[2] Mohammed Al-Rawi and Joeran Beel. 2021. Probabilistic Color Modelling of Clothing Items. Recommender Systems in Fashion and Retail 734 (2021), 21

[3] Elaine M Bettaney, Stephen R Hardwick, Odysseas Zisimopoulos, and Benjamin Paul Chamberlain. 2019. Fashion outfit generation for E-commerce. arXiv preprint arXiv:1904.00741 (2019). https://arxiv.org/abs/1904.00741 ar5iv.labs.arxiv.org+2

[4] Humberto Corona. [n.d.]. The State of Recommender Systems for Fashion in 2020. https://towardsdatascience.com/thestate-of-recommender-systems-for-fashion-in-2020-180b3ddb392f/. Accessed: 2021-13-19.

[5] Lavinia De Divitiis, Federico Becattini, Claudio Baecchi, and Alberto Del Bimbo. 2023. Disentangling features for fashion recommendation. ACM Transactions on Multimedia Computing, Communications and Applications 19, 1s (2023), 1–21. https://dl.acm.org/doi/10.1145/3531017.

[6] Debopriyo Banerjee, Krothapalli Sreenivasa Rao, Shamik Sural, and Niloy Ganguly. 2020. Boxrec: recommending a box of preferred outits in online shopping. ACM Transactions on Intelligent Systems and Technology (TIST) 11, 6 (2020), 1ś28. 10.1145/3408890.

[7] GloablInfoResearch: Global Fast Fashion Apparel Market 2021 by Key Countries, Companies, Type and Application. GloablInfoResearch, HongKong, 2021.

[8] Hou, M., Wu, L., Chen, E., Li, Z., Zheng, V. W., & Liu, Q.: Explainable fashion recommendation: A semantic attribute region guided approach. In Proceedings of the 28th Twenty-Eighth International Joint Conference on Artificial Intelligence, 2019; pp. 4681- 4688.

[9] Hidayati, S. C., Hsu, C. C., Chang, Y. T., Hua, K. L., Fu, J., & Cheng, W. H.: What Dress Fits Me Best? Fashion Recommendation on the Clothing Style for Personal Body Shape. In Proceedings of the 26th ACM International Conference on Multimedia (MM '18). Association for Computing Machinery, New York, NY, USA, 2018; pp. 438-446.

[10] Sattar, H., Pons-Moll, G., & Fritz, M.: Fashion is taking shape: Understanding clothing preference based on body shape from online sources. In Proceedings of IEEE Winter Conference on Applications of Computer Vision, 2019; pp. 968- 977.

[11] Hsiao, W. L., & Grauman, K.: Creating capsule wardrobes from fashion images. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018; pp. 7161-7170.

[12] Li, Y., Cao, L., Zhu, J., & Luo, J.: Mining fashion outfit composition using an end-to-end deep learning approach on set data. IEEE Transactions on Multimedia, 19(8), 1946-1955, 2017.

[13] Cardoso, Â., Daolio, F., & Vargas, S.: Product characterisation towards personalisation: learning attributes from unstructured data to recommend fashion products. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2018; pp. 80-89.

[14] Kang, W. C., Fang, C., Wang, Z., & McAuley, J.: Visually-aware fashion recommendation and design with generative image models. In Proceedings of 2017 IEEE International Conference on Data Mining (ICDM), 2017; pp. 207- 216.

[15] Tan, Z., Hu, Y., Luo, D., Hu, M., & Liu, K.: The clothing image classification algorithm based on the improved Xception model. Computational Science and Engineering 23, pp. 214-223, 2020.

[16] CHEN, Q. H. "Clothing image classification based on multi-scale SEXception.," Journal of ZheJiang University (Engineering Science), 54(9), 1727- 1735, 2020.

[17] Wang, W., Xu, Y., Shen, J., & Zhu, S. C.: Attentive fashion grammar network for fashion landmark detection and clothing category classification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018; pp. 4271-4280.

[18] Quintino Ferreira, B., Costeira, J. P., Sousa, R. G., Gui, L. Y., & Gomes, J. P.: Pose Guided Attention for Multi-Label Fashion Image Classification. In Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops. 2019; pp.1-4.

[19] Meshkini, K., Platos, J., & Ghassemain, H.: An analysis of convolutional neural network for fashion images classification (Fashion-MNIST), In Proceedings of the International Conference on Intelligent Information Technologies for Industry, 2019; pp. 85-95.

[20] Wazarkar, S., & Keshavamurthy, B. N.: Social image mining for fashion analysis and forecasting. Applied Soft Computing, 95, 106517, 2020.