iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** VI **Month of publication:** June 2024

DOI: https://doi.org/10.22214/ijraset.2024.63463

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue VI June 2024- Available at www.ijraset.com

Advancements in Fashion: Exploring Machine Learning-Based Recommendation Systems

Dr. Sudhakar Baburao Jadhav
Assistant Professor at MKSSS's School of Fashion Technology, Pune, India
School Of Fashion Technology, Sr.13/1/2, Narhe Ambegaon, Pune – 411041, Maharashtra, India

Abstract: The fashion industry is experiencing a paradigm shift with the proliferation of online commerce platforms offering a vast array of choices to consumers. To effectively navigate this landscape, efficient methods for sorting, showcasing, and delivering products and information are essential. Online auction platforms have emerged as a prominent avenue for individuals to showcase and sell their creations, fostering inclusivity irrespective of demographic factors. Fashion Recommendation Systems (FRSs) leveraging image-based techniques are revolutionizing the shopping experience, drawing consumers to fast-fashion retailers.

However, despite the promising opportunities presented by advancements in technology, research in this domain remains limited, particularly regarding the design of FRSs and filtering methodologies. Addressing this gap, this study investigates novel approaches to FRS design and explores potential future directions for model implementation.

These abstract highlights the importance of leveraging machine learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), for image recognition in fashion recommendation systems. By providing insights into the fusion of artificial intelligence and fashion retail, this study aims to inform researchers, scholars, and practitioners interested in the intersection of technology and fashion.

Key Words: Machine Learning, Fashion Recommendation, CNN, RNN and Image recognition

I. INTRODUCTION

Clothing serves as a visual representation that communicates various aspects of individuals, including their choices, beliefs, attitudes, occupations, societal status, and behavioral patterns. It is a crucial component of human behavior, acting as a form of non-verbal communication. Recent technological advancements have empowered individuals to influence global fashion trends, shaping their preferences accordingly. The selection of clothing by consumers is influenced by a multitude of factors such as demographics, geography, personal preferences, social influences, age, gender, time, and culture. Research indicates that clothing styles vary significantly across regions, from rural to urban areas.

Understanding consumer preferences and tendencies is essential for designers and retailers, as it enables them to cater to the diverse needs of their target audience effectively. Given that clothing choices convey valuable information about individuals worldwide, both online and offline retailers leverage the internet to reach a vast customer base. Consequently, e-commerce has emerged as a dominant business channel, with recommendation systems playing a pivotal role in enhancing the shopping experience. Major e-commerce platforms and social networking sites utilize Fashion Recommendation Systems (FRSs) to provide personalized advice and prompt responses to customer preferences.

Platforms like Amazon, eBay, Shop style, and social media channels such as Pinterest, Snapchat, Instagram, Facebook, Chictopia, and Lookbook have become influential sources for fashion inspiration and recommendations. Effective recommendation systems not only enhance customer satisfaction but also contribute to increased sales volumes and reduced consumer costs. Despite the significance of recommendation systems in e-commerce, research in this area remains limited. While some studies have focused on fashion recommendation systems, comprehensive exploration of the topic is warranted to understand their full potential and impact on consumer behavior and online retailing.

II. REVIEW OF LITERATURE

The following literature survey provides insights into recent research contributions in the field of fashion recommendation systems and related technologies:

Chakraborty, S.; Hoke, S.M.A.; Kabir, S.M.F.: This study focuses on utilizing AI and prediction techniques to anticipate fashion trends. By analyzing images collected during the Fall-Winter 2019 New York Fashion Week, the study aims to forecast patterns and designs, thereby providing valuable insights for retailers and fashion designers.

Kang, W.- S .; Fang, S .; Van, Z .; McAuley, J: Recent research highlights the potential enhancement of visual applications, including clothing and art, through deep learning approaches. The study proposes leveraging deep neural networks to model visual images effectively, thereby improving the performance of recommendation systems.
Hu, Yu.; Maniconda, L.; Cambhampati: This study introduces the FIRN (Fashion Image Recognition Network) model, focusing on identifying clothing designs and textures from images. By employing techniques such as BiLSTM (Bidirectional Long Short-Term Memory), the study aims to personalize fashion recommendations based on individual user preferences.
Gao, G.; Liu, L.; Van, L.; Jean, Yu: Addressing challenges related to dynamic factors such as color and material in fashion recommendation systems, this study proposes a systematic approach combining FashionVC data and Siamese Networks with AutoEncoder. Experimental results demonstrate the effectiveness of the proposed method in enhancing fashion recommendation systems.
Sachdeva, H.; Pandey, S.: This study explores the development of systems capable of understanding and interpreting fashion images. By incorporating various factors such as physical attributes and visual cues, the study aims to enhance the accuracy of fashion recommendation systems, thus predicting future trends in the fashion industry.

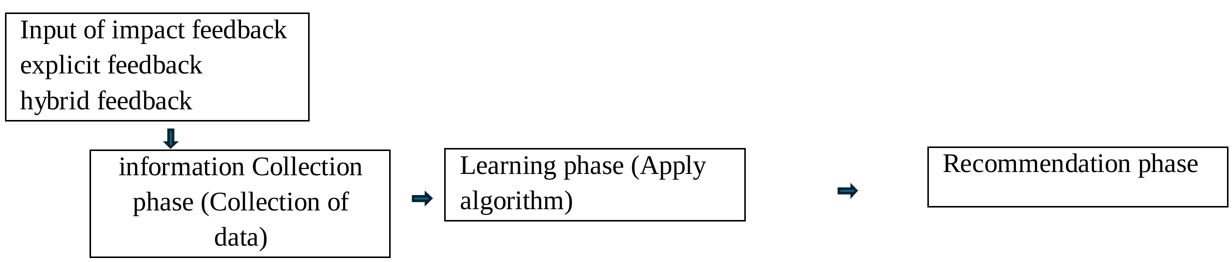
III. FUNCTIONAL REQUIREMENTS

1) *Information Collection Phase:* Collecting user behavior data to develop predictive models based on search engine queries and user interactions.
2) *Learning Phase:* Utilizing learning algorithms to filter and incorporate user preferences gathered during the information collection phase, thereby improving recommendation accuracy based on user history.

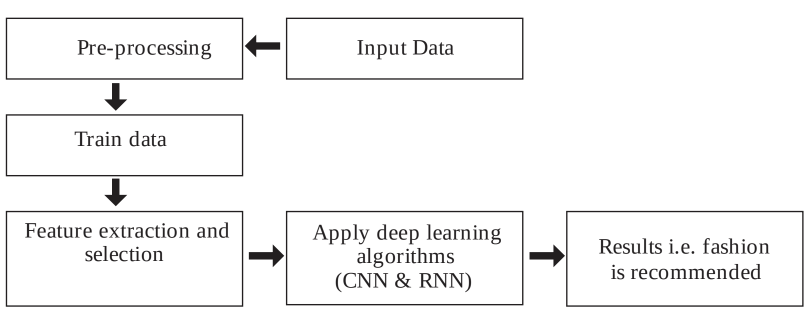
IV. NON-FUNCTIONAL REQUIREMENTS

1) *Performance and Scalability:* Ensuring the system performs efficiently and accurately, even as the user base grows.
2) *Usability:* Designing the system to be user-friendly, with features accessible through simple actions like taking a selfie.
3) *Compatibility:* Developing the system as an Android application to ensure compatibility across a wide range of devices.
4) *Maintainability:* Designing the system with flexibility to accommodate future improvements, such as replacing datasets for enhanced accuracy.

V. METHODOLOGY



Data flow Diagram



International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue VI June 2024- Available at www.ijraset.com

VI. MODULES

1) *Data Collection Module:* This module is responsible for gathering data from the Kaggle dataset, containing essential details required for the fashion recommendation process.
2) *Pre-processing Module:* Upon collecting data, this module processes it by removing missing values, eliminating redundancy, and handling duplicate entries, ensuring that the data is clean and ready for analysis.
3) *Feature Extraction and Selection Module:* In this module, relevant features are extracted from the pre-processed data. These features are carefully selected to facilitate the fashion recommendation process, enhancing the system's ability to understand user preferences and item attributes effectively.
4) *Recommendation Module:* After the data has been processed and relevant features have been extracted, this module applies machine learning algorithms such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN). By leveraging these algorithms, the system generates personalized recommendations for users based on their preferences and historical interactions. These recommendations encompass various types of fashion items that align with the user's interests and tastes, enhancing the overall shopping experience.

A. Proposed Algorithm

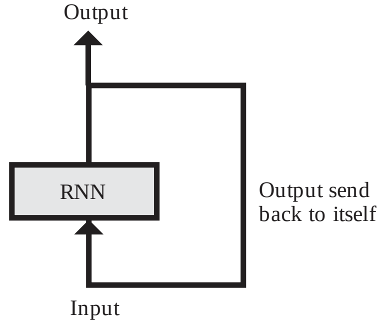
The Convolutional Neural Network (CNN) serves as a fundamental component in image organization and recognition tasks, particularly in fields such as object detection, facial recognition, and feature extraction. CNN processes images by categorizing them into distinct classes, such as dogs, cats, lions, and panthers. Each image is represented as a pixel array, with dimensions typically denoted as h * w * d, where h represents width and d denotes depth. For example, an RGB image would have dimensions of 6 * 6 * 3, while a grayscale image would have dimensions of 4 * 4 * 1.

Within a CNN architecture, input images traverse through a series of layers, including convolutional layers and pooling layers, also referred to as kernels. Convolutional layers apply filters to the input image, extracting features essential for classification, while pooling layers reduce the spatial dimensions of feature maps, retaining the most salient information.

Moreover, CNNs often utilize the softmax function to assign probabilities to each class, ensuring output values are constrained between 0 and 1, facilitating precise classification into predefined categories. Alongside CNNs, Recurrent Neural Networks (RNNs) play a crucial role, particularly in tasks related to natural language recognition and processing (NLP). RNNs excel in analyzing sequences of data and emulating the functioning of cells in the human brain. They are extensively utilized for tasks such as time-series prediction, language translation, and handwriting recognition.

RNNs are adept at deciphering sequential data, such as sensor readings, stock market trends, genetic sequences, handwritten notes, and governmental statistical data. While resembling the structure of the human brain, RNNs feature an expanded memory architecture, enabling them to effectively retain computational information.

In summary, CNNs excel in image processing tasks, while RNNs are highly effective in analyzing sequential data. Both networks contribute significantly to various applications, showcasing their versatility and efficiency in handling complex data structures and tasks.



B. Recurrent Neural Networks (RNNs) perform the Following Functions

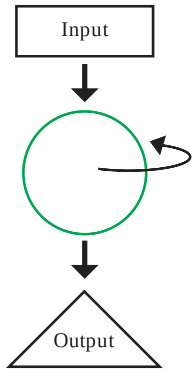
Temporal Dynamics Handling: RNNs excel at modeling sequential data by capturing temporal dependencies. They are adept at transforming independent actions into sequential patterns, thereby enabling the network to understand the context and relationships between consecutive inputs. This capability is crucial for tasks such as time-series prediction, natural language processing, and handwriting recognition.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue VI June 2024- Available at www.ijraset.com

Parameter Sharing: RNNs employ parameter sharing across time steps, allowing them to reuse the same set of weights and biases for each element in the sequence. This parameter sharing reduces the complexity of the RNN model and helps in conserving computational resources.

Memory Mechanism: RNNs possess a memory mechanism that enables them to retain information from previous time steps. This memory mechanism allows the network to maintain a state or context throughout the sequence, providing a consistent reference point for processing subsequent inputs. This is particularly useful for tasks where context plays a crucial role, such as language translation and sentiment analysis.

In essence, these components work together within an RNN to transform independent inputs into sequential patterns, maintain contextual information across time steps, and efficiently utilize shared parameters to reduce computational overhead. This makes RNNs well-suited for handling sequential data and performing tasks that involve understanding and processing temporal dynamics.



C. To Compute What Is Happening Within A Recurrent Neural Network (Rnn), The Following Steps Are Performed

1) The present status *ht* is computed based on the previous state $ht-1ht-1$ and the current input *Xt*.
2) Mathematically represented as: ht=tanh(Whhht−1 ($Whhht-1+WxhXt$)
3) Where:
   - *Whh* represents the weight of recurrent neurons.
   - *Wxh* represents the weight of input-bearing neurons.
   - tanh is the hyperbolic tangent activation function.

D. Output Estimation Technique

1) The output Yt is estimated based on the computed state ht.
2) Typically involves applying further transformations or computations depending on the specific task.
3) In the given example, it is represented as *Yt*=treat, indicating a hypothetical output.

E. Training through RNN

1) The training process involves iterating through the data sequence, typically following the same time steps as the input.
2) At each time step, the network computes the current state based on the previous state and input.
3) This process allows the network to capture temporal dependencies and contextual information.
4) After completing all steps for each input sequence, the final output is computed.

F. Error Calculation and Weight Adjustment

1) Once the output is computed, the error is calculated by comparing the predicted output with the actual output.
2) The error is then used to adjust the weights of the network, aiming to minimize the difference between the predicted and actual outputs.
3) This process is crucial for optimizing the network's performance and improving its accuracy over time.

VII. EXPECTED RESULTS

The overall architecture and the highest level of development of this project are illustrated in Figure 1. The primary objective is to facilitate the selection of clothing materials for businesses or consumers.

This implementation elevates the concept of outfit makeover recommendation systems and fashion network analysis to a new level by utilizing collected data in a direct, transparent, and integrated manner. The data collected from the program is intended to be utilized through popular opinion. With the gathered information readily available, the system processes the patterns to complete the cycle, ultimately showcasing the types of items available for selection by businesses or consumers.

A. Applications

When users are unsure about what to search for, the system can serve as a search filter or strategy.

In e-commerce, the system may prompt users or buyers to select the type of item they prefer.

Requirements can be based on user preferences or pre-defined criteria.

Users can register online to become members of the platform, and everyone can upload a digital copy of their wardrobe. They can then purchase their clothing items through auctions or at competitive prices. Each user can customize their preferences to easily access their favorite clothing items.

VIII. CONCLUSION AND FUTURE SCOPE

A voting system can uncover new opportunities to assist merchants in providing tailored recommendations to their customers based on data sourced from the internet. These systems aid customers in finding the most suitable products or services according to their preferences. Furthermore, a recommendation algorithm has been developed to offer products based on user and group associations. Consequently, research into the integration of virtual imagery in recommendation systems has become increasingly prevalent. This article presents an overview of modeling, algorithmic modeling, and filtering techniques based on theoretical concepts related to this subject. A comprehensive examination of the technical aspects, advantages, and disadvantages of filtering technology will help future researchers better understand recommendation systems. However, inadequate requirements can have a negative impact on users, so optimal results should be tested in commercial practice to ensure transparency and accessibility to the market. Furthermore, in order to discover the most effective method for providing recommendations, further research is needed, focusing on accurately categorizing product images by variation, apparel, and design differences. This approach will be followed by a targeted promotional campaign to offer users a more personalized and enhanced experience. Consequently, this study will be highly beneficial to researchers interested in developing a feedback system using additional, authentic material.

REFERENCES

[1] Chakraborty, S.; Hoque, M.S.; Surid, S.M. A comprehensive review on image-based style prediction and online fashion recommendation. J. Mod. Tech. Eng. 2020, 5, 212–233

[2] Hu, Y.; Manikonda, L.; Kambhampati, S. What We Instagram: A First Analysis of Instagram Photo Content and User Types. Available online: http://www.aaai.org (accessed on 1 May 2014)

[3] Gao, G.; Liu, L.; Wang, L.; Zhang, Y. Fashion clothes matching scheme based on Siamese Network and Auto Encoder. Multimed. Syst. 2019, 25, 593–602. [CrossRef]

[4] Liu, Y.; Gao, Y.; Feng, S.; Li, Z. Weather-to-garment: Weather-oriented clothing recommendation. In Proceedings of the 2017 IEEE International Conference on Multimedia and Expo. (ICME), Hong Kong, China, 31 August 2017; pp. 181–186. [CrossRef]

[5] Sun, G.-L.; Wu, X.; Peng, Q. Part-based clothing image annotation by visual neighbor retrieval. Neurocomputing 2016, 213, 115–124. [CrossRef]

[6] Zhang, Y.; Caverlee, J. Instagrammers, Fashionistas, and Me: Recurrent Fashion Recommendation with Implicit Visual Influence. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, Beijing, China, 3–7 November 2019; pp. 1583–1592. [CrossRef]

[7] Matzen, K.; Bala, K.; Snavely, N. StreetStyle: Exploring world-wide clothing styles from millions of photos. arXiv 2017, arXiv:1706.01869.

[8] Guan, C.; Qin, S.; Ling, W.; Ding, G. Apparel recommendation system evolution: An empirical review. Int. J. Cloth. Sci. Technol. 2016, 28, 854–879. [CrossRef]

[9] Sachdeva, H.; Pandey, S. Interactive Systems for Fashion Clothing Recommendation. In Emerging Technology in Modelling and Graphics; Mandal, J.K., Bhattacharya, D., Eds.; Springer: Singapore, 2020; Volume 937, pp. 287–294. [CrossRef]

[10] Kang, W.-C.; Fang, C.; Wang, Z.; McAuley, J. Visually-aware fashion recommendation and design with generative image models. In Proceedings of the 2017 IEEE International Conference on Data Mining (ICDM), New Orleans, LA, USA, 18–21 November 2017; pp. 207–216. [CrossRef]

[11] Garude, D.; Khopkar, A.; Dhake, M.; Laghane, S.; Maktum, T. Skin-tone and occasion oriented outfit recommendation system. SSRN Electron. J. 2019. [CrossRef]

[12] Karmaker Santu, S.K.; Sondhi, P.; Zhai, C. On application of learning to rank for e-commerce search. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, Shinjuku, Tokyo, Japan, 7–11 August 2017; pp. 475–484. [CrossRef]

[13] Chakraborty, S.; Hoque, S.M.A.; Kabir, S.M.F. Predicting fashion trend using runway images: Application of logistic regression in trend forecasting. Int. J. Fash. Des. Technol. Educ. 2020, 13, 376–386. [CrossRef]

[14] Barnard, M. Fashion as Communication, 2nd ed.; Routledge: London, UK, 2008.