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Analysis of Deep Demographics for Advertisement Recommendation

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Abstract Advertisements are a popular marketing strategy that shapes consumer perception and brand image. Consumers engage in outdoor advertising messages and traditional media advertisements. Understanding consumer behavior and interest in advertisements is crucial for developing effective marketing strategies. One study used computer vision techniques to analyze customer demographics, clothing preferences, and facial attention cues to extract comprehensive features from individuals and assess their attention toward advertisement displays. The methodology uses object detection models, such as YOLO, to track individuals in a scene, followed by a fashion detection model to identify clothing styles. The MiVOLO model predicts age and gender and creates a dataset for demographic analysis. ReginaFace is used for face detection and head pose estimation to gauge viewer engagement. This system helps retailers and advertisers tailor marketing strategies based on real-time customer data, providing insights into consumer preferences and interests. This enhanced customer engagement and sales.

MSC: 65D18, 68T99, 68U10, 94A08

Keywords: Advertising; Deep learning; Demographics; Detection; Image processing

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1. Introduction

In the digital age, marketing has undergone significant changes because of the abundance of quantitative data generated by various online and offline platforms. Marketing is necessary for machine learning to be fully utilized in a range of corporate applications. Because it improves the efficiency of advertising communication, a critical component of strategic planning for companies dealing with goods or services, it is vital to corporate success. Beyond its impact on revenue generation, this vital role creates the foundation for other important business operations, such as customer service and sales strategy.

Although many small and medium-sized firms are still in the early phases of implementing this technology, larger corporations have incorporated machine learning into their marketing strategy. However, current trends suggest that machine learning applications in marketing are catching on quickly. Businesses are becoming more aware of how they may improve their decision-making, campaign optimization, and general productivity. The future of corporate operations in this field is expected to be shaped by the anticipated large growth in the application of machine learning in marketing [12].

In the past, mass advertising dominated the marketing industry and was typified by consistent messaging intended for a large audience. However, this one-size-fits-all strategy is no longer successful in today's hyper-connected and customer-focused world. A mass marketing strategy is less effective in satisfying the demands of modern customers, who demand more relevant and individualized interactions from firms.

Targeted advertisements are a strong substitute that gives companies the freedom to create campaigns that appeal to particular audience segments. Businesses can craft customized messages that connect with people at a more intimate level by utilizing information regarding client preferences, behaviors, and requirements. By concentrating resources on audiences most likely to convert, this strategy not only increases consumer satisfaction but also boosts the overall effectiveness of marketing initiatives that allow companies to better interact with their clients and adjust to the ever-changing needs of contemporary marketplaces [3, 4, 17, 22].

A key goal of marketing strategies is to gain a deep understanding of prospective customer's needs and preferences. This insight allows businesses to segment their target markets, focusing on individuals who are most likely to engage positively with advertising campaigns [6]. In addition, this information can be leveraged to refine the presentation of advertisements, ensuring that they are tailored to elicit a more favorable response. Numerous studies have been conducted to enhance the understanding of consumer behavior, adoption of new technologies, and brand performance across various contexts, including online shopping, electronic banking, and social media platforms [2, 13–15, 18, 24]. These findings provide valuable insights that inform marketing practices, enabling businesses to align their strategies better with evolving consumer expectations and preferences.

The important determinants of market segmentation are customer-specific psychological aspects. These elements include personality, way of life, and appearance are derived from a person's needs, wants, and preferences. Through targeted advertisements, marketers can use these characteristics to provide more individualized and successful communication [8]. When taken as a whole, these features are frequently called the psycho-cognitive spectrum or consumer psychological traits [20].

Research suggests that a variety of factors such as speech patterns, body language, and physical appearance can contribute to psychological qualities. The idea of "style" becomes especially pertinent when discussing physical attractiveness. The term "style" describes unique patterns in a person's external appearance that convey and reflect their behavioral, psychological, societal, economic, and occupational circumstances [11]. By matching their strategies with the distinctive characteristics of their target groups, marketers can better understand and interact with their audience thanks to the link between style and underlying features.

Although factors such as demographics are easily obtainable and can yield some information, their combined nature frequently leaves them unable to satisfy commercial needs. Psychological qualities, on the other hand, are more difficult to assess and acquire but provide insightful information. These qualities are usually disregarded in advertisement efforts because of the difficulty in obtaining them [5].

The concept of style holds significant importance in this study as it encapsulates psychological traits through the visible aspects of an individual's appearance [21]. By linking readily accessible elements such as photographs or videos, with the psychological traits essential for effective market segmentation, this approach paves the way for the development of a model that automates these processes. Such a model offers businesses practical tools to streamline marketing efforts and achieve their strategic objectives.

Personalized marketing has the potential to reinforce existing inequalities and biases, particularly when it relies on sensitive data such as race, gender, or other protected attributes. Marketers must remain mindful of these issues and adhere to ethical guidelines to ensure that their strategies promote inclusivity [19]. By recognizing and addressing biases thoughtfully and deliberately, marketers can design campaigns that are not only more impactful but also contribute to equitable and responsible marketing practices, ultimately enhancing their overall success [7].

By creating a system that can identify the styles of potential clients, this project tackles important issues in digital advertising and improves focused marketing campaigns. By analyzing full-body photography samples, this research discovers individual styles, which serve as essential segmentation characteristics for automatically generating individualized advertisements. Ultimately, this creative method bridges the gap between customer wants and marketing effectiveness by enabling firms to create more successful product sales tactics and assisting users in finding materials that suit their interests.

2. Methodology

This study was developed to solve problems and create business opportunities by analyzing the external characteristics of individuals. The internal subsystems were developed and optimized for efficient operation and were tested and used only within the university.

2.1. Developing a system to predict clothing, gender and age

The advertisement recommendation system consists of a computer processing various models such as clothing detection, age, and gender prediction models. The system uses two cameras, one installed near the display screen and another placed at a 45-degree angle on either side of the test area, ensuring that both cameras cover the test area. The data is processed through an application that receives the camera input and sends it to another system, as shown in Figure 1.

The clothing detection system uses video input to detect people and identify their location within a video [23]. Additionally, a fashion detection model analyzes an individual's clothing [23]. Moreover, age and gender prediction models determine a person's age range

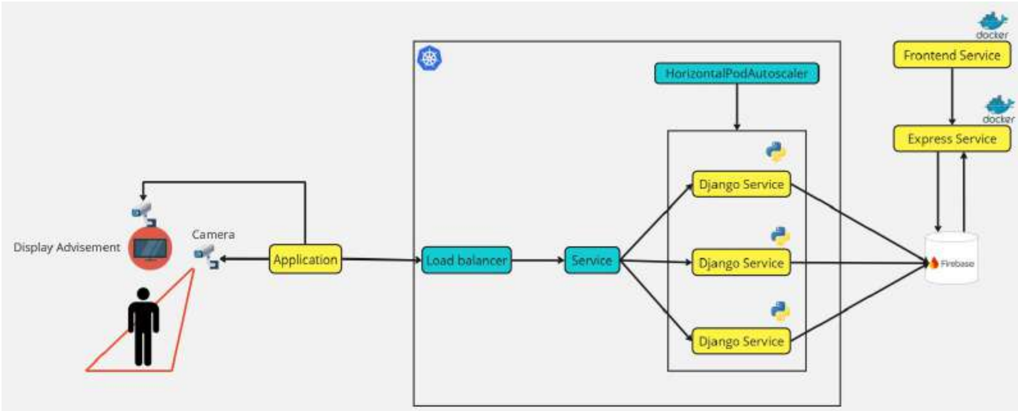


FIGURE 1. System Overview.

and gender [16]. Finally, the data was forwarded to a person tracking model using the StrongSORT model to track a person's movement [10].

The clothing detection system uses video frames of people walking as input and pre-trained models such as YOLOV8 Detection Official for detection, setting a minimum bounding box ratio of 1:1.5 and a maximum of 1:5.5 between width and height, with minimum dimensions of 50 pixels wide and 80 pixels long to capture individuals standing or walking [23]. The tracked person data is then passed on to fashion detection [10]. The input images were resized to 640x640 pixels to obtain the bounding box positions of the desired objects. The system collects all features, such as clothing, gender, and age, and stores them in a database. The stored data must include individuals facing the camera to capture their faces and must be able to identify both upper and lower clothing. See Figure 2.

2.2. Advertisement Viewing Detection System

The advertisement viewing detection system starts by receiving video input to a face detection model using RetinaFace to identify the position of the face [9]. The data was then forwarded to a face-tracking model using the BotSORT model to track facial movements [1]. It also includes a head pose estimation model and an age and gender prediction model.

The advertisement viewing detection system receives video frames of people watching the display screen as input using RetinaFace to detect each individual's face and determine the direction of the gaze [9]. BotSORT was used to track faces to avoid duplicate data collection [1]. All data was collected and stored in the database, with a minimum bounding box size of 80 $\times$ 80 pixels for the face and a pitch range of [-20, 20] and yaw range of [-30, 30] to identify faces looking at the screen. See Figure 3.

2.3. Advertisement Analysis System

The main function of the advertisement analysis system is to analyze and select suitable advertisements for the target audience. The process begins by displaying the first round of advertisements. After an advertisement ends, the system retrieves data from the database collected by the clothing detection and advertisement viewing detection systems during

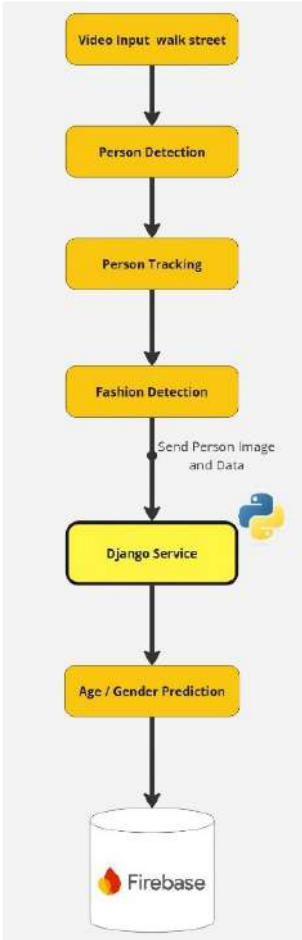


FIGURE 2. Clothing detection flow.

the last 30 seconds. These data were fed into a hierarchical clustering model to analyze and select the best advertisements for the target audience. The system then displays the most suitable advertisement based on the analysis results shown in Figure 4.

The system determines the presentation ratio using the advertising budget based on the following formula after identifying a target demographic and finding many advertisements that match the audience:

$$B = \sum_{i=1}^{n} C_i \text{ and } S_i = \frac{C_i}{B} \tag{2.1}$$

where C_i is the cost of advertisement i, S_i is the advertisement presentation ratio, and B is the total budget for all advertisements.

Each time an advertisement is shown, its cost is subtracted from the budget, changing the selection ratio and increasing the likelihood that additional commercials will be shown. Advertisements are shown randomly according to their ratios. In cases where the

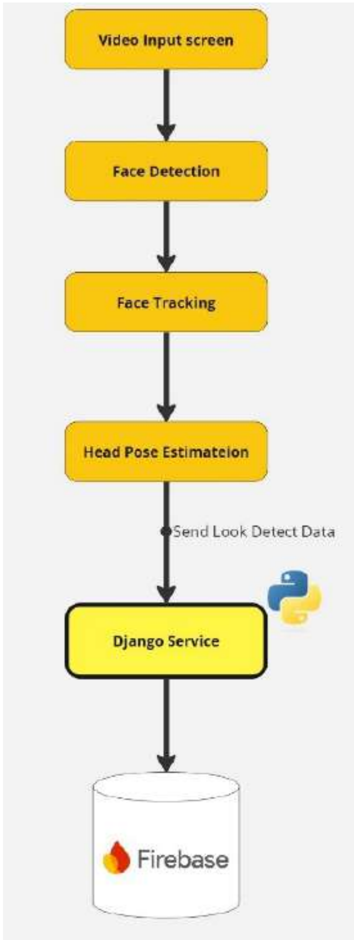


FIGURE 3. Advertisement viewing detection flow.

person viewing the advertisement is not the target group, the cost of the advertisement is subtracted at a lower rate in this instance.

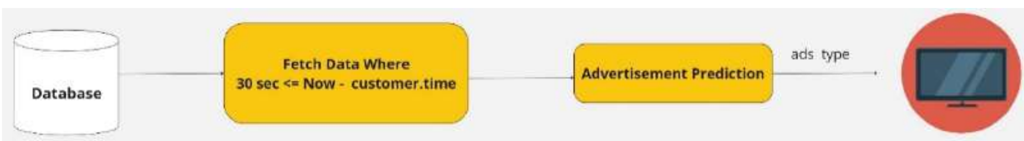


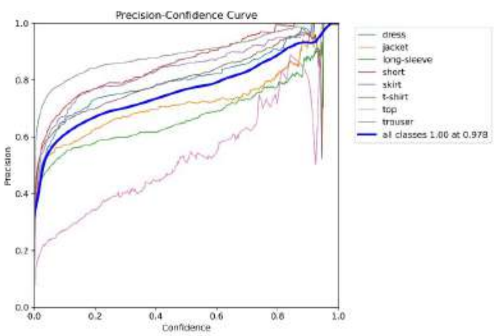
FIGURE 4. Advertisement analysis flow.

3. Experiment

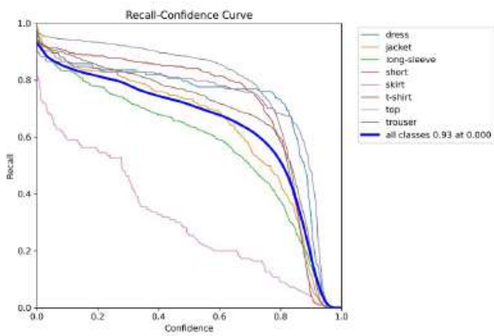
The results were divided into five parts: system performance of clothing detection, clothing detection results, advertisement gaze detection results, advertisement recommendation results, and real-world application testing.

3.1. system performance of clothing detection

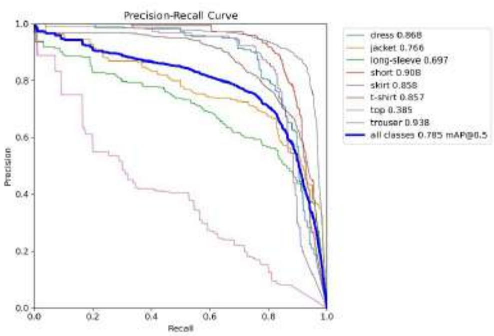
The average precision of the model was 97.8%, indicating a high accuracy. The precision increased as the confidence level increased, with lower-confidence predictions discarded, thereby improving overall accuracy, as shown in Figure 5a. The average recall rate of the model was 93%. As confidence levels increase, recall tends to decrease owing to an increase in false negatives, leading to lower accuracy, as shown in Figure 5b. The precision-recall curve shows that the model's average accuracy for classifying all types of clothing was 79.4%, indicating the model's high efficiency in detecting and categorizing clothing. The model performs better at classifying certain types, such as dresses and trousers, while some categories have lower accuracy owing to insufficient training data, as shown in Figure 5c. The average F1-score of the model is 74.0%. As the confidence level rises, the F1-score drops sharply because of the decline in the recall, affecting the overall F1-score calculation as shown in Figure 5d.



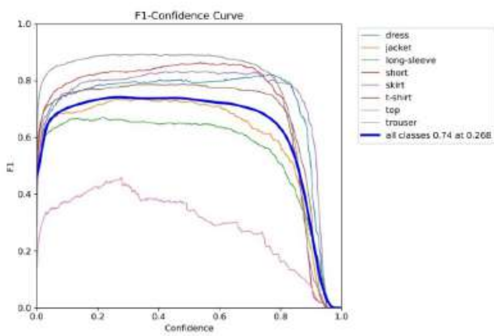
(a) Precision.



(b) Recall.

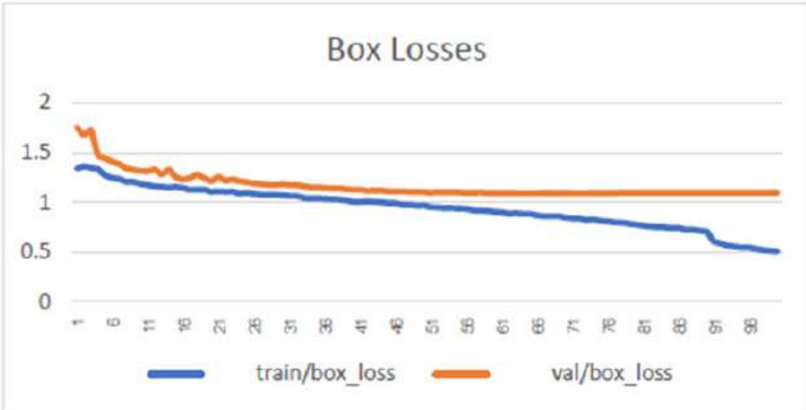


(c) Precision-Recall.

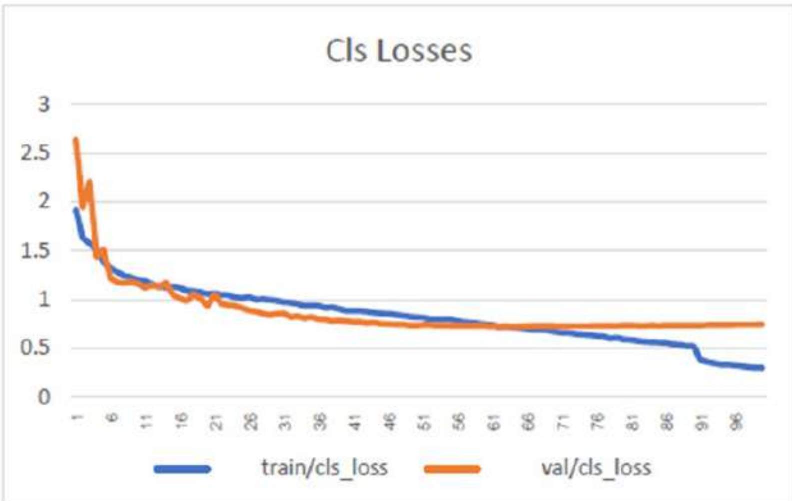


(d) F1-score

Figure 5. Performance of clothing detection



(A) Box losses.



(B) Class losses.

Figure 6. Losses.

Over 100 training rounds, error metrics such as box loss, classification loss, and detection-focused loss consistently decreased, reflecting an improvement in object detection accuracy as shown in Figure 6. However, errors for the test set remained higher, suggesting over-fitting. The model achieved its highest performance, with a mAP@50 score of 78.66%, precision at 70.56%, and recall at 77.41%. However, the test set's total box loss was still high at 1.078, indicating further refinement is needed.

3.2. Clothing detection results

The clothing detection system was tested with participants walking toward the camera to capture gender, age, and clothing information. The test included three video datasets as listed in Table 1.

Table 1. Results of accuracy testing for gender, age, and clothing detection.

Video Data	Gender	Age	Upper Clothing	Lower Clothing
Students walking toward [13 people]	84.82%	53.85%	100%	100%
Night street scene [31 people]	64.52%	90.32%	93.55%	87.88%
Random walking people [32 people]	90.91%	96.97%	93.94%	87.88%

3.3. Advertisement gaze detection results

The advertisement gaze detection system was tested using a video of students from King Mongkut's University of Technology Thonburi. Gaze detection was also evaluated by 11 assessors, comparing the system's results with the assessors' observations as shown in Table 2. From the results of these two groups, it was found that if the participants had a clear gaze direction and their faces were captured clearly by the system, the gaze detection system could accurately detect where they were looking. However, if the facial image was smaller or less clear, the system's gaze detection accuracy tended to decrease.

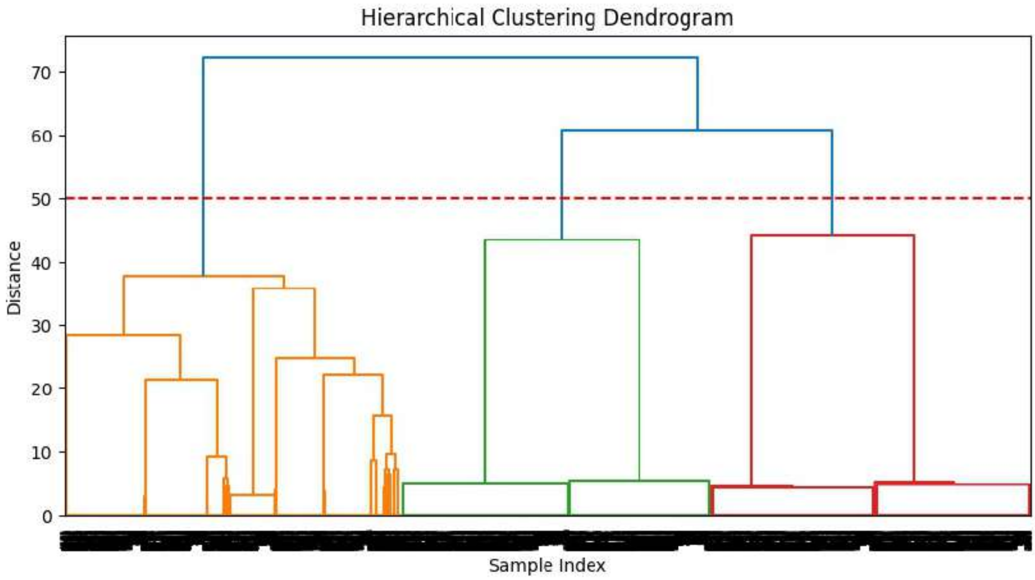
Table 2. Results of advertisement viewing test.

People	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Look	yes	no	yes	no	yes	no	yes	no	no	yes	no	yes	no	yes	no
Evaluator 1	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓
Evaluator 2	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓
Evaluator 3	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓
Evaluator 4	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓
Evaluator 5	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓
Evaluator 6	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓
Evaluator 7	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓
Evaluator 8	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✗	✓	✓
Evaluator 9	✓	✓	✓	✓	✗	✓	✓	✓	✗	✓	✗	✓	✓	✓	✓
Evaluator 10	✓	✓	✓	✓	✗	✓	✓	✓	✗	✓	✗	✓	✗	✗	✓
Evaluator 11	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓

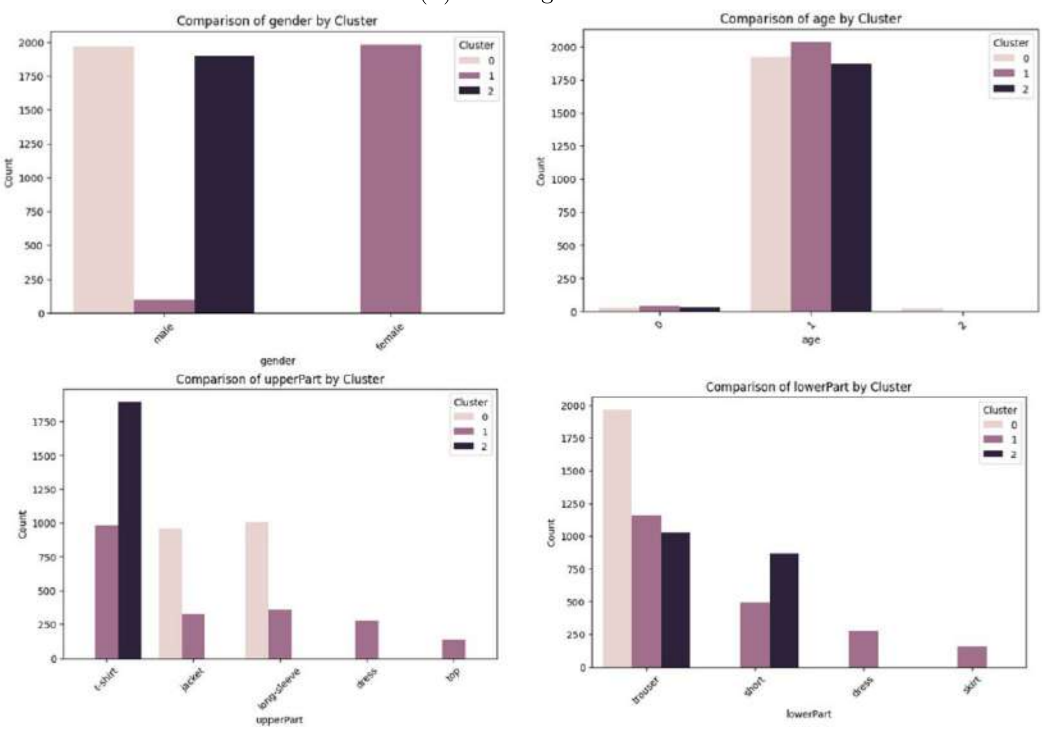
3.4. Advertisement recommendation results

The advertisement recommendation system was developed using hierarchical clustering owing to the high data variance and uncertainty of the ideal number of clusters. Based on this data, a linkage technique was applied to determine the optimal number of groups. The dendrogram graph indicates that the data should be divided into three groups, which is deemed the most appropriate segmentation, as shown in Figure 7a. After determining that three groups were the optimal number based on the dendrogram analysis, the developer created a model using hierarchical clustering with the agglomerative method. This method was used to group the data into three identified clusters, as shown in Figure 7b. Upon analyzing the clustering results, the following observations were made:

Group 0: Primarily men who wear long sleeves and trousers.
Group 1: Women with a wide variety of upper and lower clothing types.
Group 2: Predominantly women who wear T-shirts, shorts, and trousers.



(A) Dendrogram of the data.



(B) Comparison graph of each data group.

FIGURE 7. Advertisement clustering.

3.5. Real-world application testing

The system successfully logged the participant's data using clothing and gaze detection systems, as shown in Figure 8. However, there were delays in saving the participant data, causing issues with the advertisement recommendation system. This delay affected the systems ability to analyze and recommend advertisements in real-time owing to missing or incomplete data.

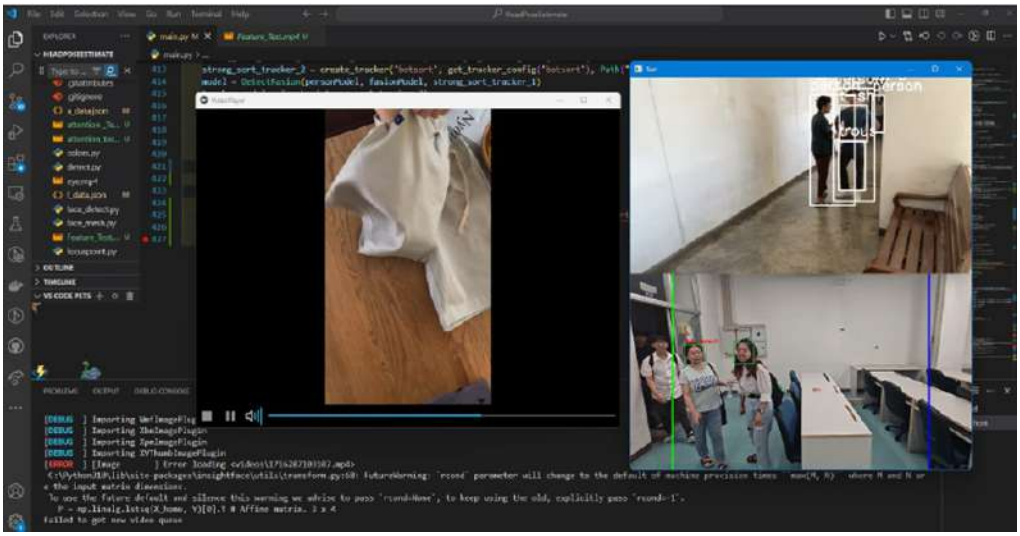


Figure 8. Images of actual application usage.

4. Conclusion

The project developers created a demographic-based recommendation system for advertisements, focusing on clothing detection and gender-age prediction. The clothing detection system categorizes clothing into eight types: dresses, jackets, long sleeves, short pants, skirts, t-shirts, tops, and trousers. It uses data from the Roboflow website and the YOLOV8m model for training. Additionally, the YOLOV8x model enhances the tracking and detection process before sending the detection person images to the clothing detection model. The system operates using a computer equipped with a camera for real-time clothing detection. The gender and age prediction system classifies data into two genders, male and female, and divides ages into three groups: 15-19, 20-59, and 60-99 years old. It uses the MiVOLO model, which is known for its flexibility and high accuracy, although it requires significant processing time. To optimize resource usage, the MiVOLO model runs on a server developed using Django, thereby reducing the burden on the camera-connected computer. All the data collected by the detection models are stored in a database, which is then displayed on a website and used to develop an advertising recommendation model. The data were obtained from CCTV footage and video recordings at King Mongkut's University of Technology Thonburi. The advertising recommendation system employs a hierarchical clustering model, an unsupervised learning technique, to group the data and recommend appropriate advertisements based on detected clothing, gender, and age.

Conflict of Interest

The authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

Author Contributions

Kantinan Meesuk: investigation; writing-original draft; software. Kittiphot Amnakkittikul: software. Nachanon Nuanphet:software. Warin Wattanapornprom: conceptualization; writing-review. Thittaporn Ganokratanaa: conceptualization; writing-review. Thidaporn Seangwattana: writing-review. Wachirapong Jirakitpuwapat: supervision; conceptualization; writing-review.

References

[1] N. Aharon, R. Orfaig, B.Z. Bobrovsky, Bot-sort: Robust associations multi-pedestrian tracking, ArXiv, abs/2206.14651, 2022.

[2] A.A. Alalwan, Y.K. Dwivedi, N.P. Rana, R. Algharabat, Examining factors influencing Jordanian customers intentions and adoption of internet banking: Extending UTAUT2 with risk, Journal of Retailing and Consumer Services 40(C) (2018) 125–138. Available from: https://doi.org/10.1016/j.jretconser.2017.08.026.

[3] A.M. Amiri, B. Kushwaha, R. Singh, Visualisation of global research trends and future research directions of digital marketing in small and medium enterprises using bibliometric analysis, Journal of Small Business and Enterprise Development, 2023.

[4] M. Andronie, G. Lăzăroiu, M. Iatagan, I. Hurloiu, I. Dijmărescu, Sustainable cyber-physical production systems in big data-driven smart urban economy: A systematic literature review, Sustainability 13(2) (2021). Available from: https://doi.org/10.3390/su13073824.

[5] M. Callow, L. Schiffman, Sociocultural meanings in visually standardized print ads, European Journal of Marketing - EUR J MARK 38(09) (2004) 1113–1128. Available from: https://doi.org/10.1108/03090560410548898.

[6] M.A. Camilleri, Understanding Customer Needs and Wants, pages 29–50, Springer International Publishing, Cham, 2018. Available from: https://doi.org/10.1007/978-3-319-49849-2_2.

[7] S. Cartwright, H. Liu, C. Raddats, Strategic use of social media within business-to-business (b2b) marketing: A systematic literature review, Industrial Marketing Management 97 (2021) 35–58. Available from: https://doi.org/10.1016/j.indmarman.2021.06.005.

[8] N. Dawar, P. Parker, Marketing universals: Consumers' use of brand name, price, physical appearance, and retailer reputation as signals of product quality, Journal of Marketing 58(2) (1994) 81–95. Available from: https://doi.org/10.1177/002224299405800207.

[9] J. Deng, J. Guo, E. Ververas, I. Kotsia, S. Zafeiriou, Retinaface: Single-shot multi-level face localisation in the wild. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 5202–5211, 2020.

[10] Y. Du, Z. Zhao, Y. Song, Y. Zhao, F. Su, T. Gong, H. Meng. Strongsort: Make deepsort great again, 2023.

[11] S.B. Gustafson, M.D. Mumford, Personal style and person-environment fit: A pattern approach, Journal of Vocational Behavior 46(2) (1995) 163–188. Available from: https://doi.org/10.1006/jvbe.1995.1011.

[12] K. Jin, Z. Zhong, E.Y. Zhao, Sustainable digital marketing under big data: an AI random forest model approach, LSE Research Online Documents on Economics 121402, London School of Economics and Political Science, LSE Library, January 2024.

[13] S. Kimiagari, N.S. Asadi Malafe, The role of cognitive and affective responses in the relationship between internal and external stimuli on online impulse buying behavior, Journal of Retailing and Consumer Services 61 (2021) 102567. Available from: https://doi.org/10.1016/j.jretconser.2021.102567.

[14] S. Kimiagari, F. Baei, Promoting e-banking actual usage: mix of technology acceptance model and technology-organisation-environment framework, Enterprise Information Systems 16(8-9) (2022) 1894356.

[15] S. Kimiagari, F. Baei, Extending intention to use electronic services based on the human-technology interaction approach and social cognition theory: Emerging market case, IEEE Transactions on Engineering Management 71 (2024) 1470–1489. Available from: https://doi.org/10.1109/TEM.2022.3147169.

[16] M. Kuprashevich, I. Tolstykh, Mivolo: Multi-input transformer for age and gender estimation. In D.I. Ignatov, M. Khachay, A. Kutuzov, H. Madoyan, I. Makarov, I. Nikishina, A. Panchenko, M. Panov, P.M. Pardalos, A.V. Savchenko, E. Tsymbalov, E. Tutubalina, and S. Zagoruyko, editors, Analysis of Images, Social Networks and Texts, pages 212–226, Cham, 2024. Springer Nature Switzerland. Available from: https://doi.org/10.1007/978-3-031-54534-4_15.

[17] J. Li, S. Pan, L. Huang, X. Zhu, A machine learning based method for customer behavior prediction, Tehnicki vjesnik-Technical Gazette, 2019.

[18] N. Malafe, S. Kimiagari, E. Balef, Investigating the Variables Affecting Brand Performance in the S-O-R Framework 06 (2022) 303–317.

[19] K.D. Martin, P.E. Murphy, The role of data privacy in marketing, Journal of the Academy of Marketing Science 45(2) (2017) 135–155. Available from: https://doi.org/10.1007/s11747-016-0495-4.

[20] B. Mittal, J. Baker, The services marketing system and customer psychology, Psychology & Marketing 15(8) (1998) 727–733. Available from: https://doi.org/10.1002/(SICI)1520-6793(199812)15:8<727::AID-MAR1>3.3.CO;2-Z.

[21] M.A. Moreno-Armendriz, H. Calvo, J. Faustinos, C.A. Duchanoy, Personalized advertising design based on automatic analysis of an individuals appearance, Applied Sciences 13(17) (2023).

[22] K.Y. Ngiam, I.W. Khor, Big data and machine learning algorithms for health-care delivery, The Lancet Oncology 20(5) (2019) e262–e273. Available from: https://doi.org/10.1016/S1470-2045(19)30149-4.

[23] M. Yaseen, What is yolov8: An in-depth exploration of the internal features of the next-generation object detector, 2024.

[24] Y. Zhang, Q. Weng, N. Zhu, The relationships between electronic banking adoption and its antecedents: A meta-analytic study of the role of national culture, International Journal of Information Management 40(C) (2018) 76–87. Available from: https://doi.org/10.1016/j.ijinfomgt.2018.01.015.