International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 2, April 2025, pp. 1968~1977
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i2.pp1968-1977

Android-based smart digital marketplace application on agricultural commodities using a new variant recommendation system

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Article Info

Article history:

Received Jun 7, 2024
Revised Nov 14, 2024
Accepted Nov 20, 2024

Keywords:

Agricultural products
Android application
Geolocation
Personalized recommendation system
Smart digital market

ABSTRACT

In the marketing of agricultural products, addressing the challenges associated with extensive distribution chains is essential, as these directly affect sellers. Additionally, the vast array of available product options often overwhelms customers, complicating their efforts to identify and purchase items that align with their preferences. This work aims to develop a smart e-commerce application for agribusiness, specifically designed for agricultural products on the Android platform. The application integrates a recommendation system that utilizes geolocation-aware neural graph collaborative filtering (GA-NGCF), which facilitates product marketing for farmers and streamlines the product search and selection process for users based on personalized preferences. The development process encompassed various stages, from planning to rigorous testing. The application’s recommendation system, which implements GA-NGCF, operates based on three primary elements: the creation of a geolocation graph of user-item data, the integration of information between neighboring nodes, and the prediction of user preferences. The resulting smart agribusiness e-commerce application, enhanced by GA-NGCF, demonstrated marked improvements in recommendation accuracy and overall application performance during testing. Empirical results indicated substantial enhancements in recommendation metrics, with GA-NGCF achieving a recall of 0.34, a precision of 0.36, and normalized discounted cumulative gain of 0.37, thereby outperforming existing models.

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1. INTRODUCTION

Agribusiness holds an increasingly vital role in the global economy, encompassing not only agricultural production but also the processing and distribution sectors that supply essential goods and drive economic development [1]–[3]. With the globalization of markets, this sector has transformed into a complex network that aligns with modern marketing strategies, transitioning from traditional approaches to digital platforms to better fulfill customer demands [4]–[6]. The advent of e-commerce has notably revolutionized the agribusiness sector by expanding market access, reducing operational costs, enhancing transparency, and promoting distribution equity through direct connections between farmers and customers [7], [8].

Advanced technologies, such as recommendation systems in e-commerce platforms, have further enhanced customer engagement by offering personalized product suggestions based on user behavior, thus increasing customer satisfaction and driving sales [9]–[12]. Mobile technologies, particularly Android-based applications, have also facilitated this transition by improving accessibility, enabling real-time interactions, and meeting the rapid decision-making needs in agribusiness [13], [14]. These technologies extend the market reach of agribusinesses and promote growth by effectively accommodating evolving customer preferences.

Recommendation systems in e-commerce applications enhance the online shopping experience by providing tailored recommendations, which improve customer satisfaction and drive sales. Research by Wang *et al.* [15] and Shokrzadeh *et al.* [16] emphasizes the use of collaborative filtering (CF) models, which operate on the premise that users with similar behavioral histories are likely to share similar preferences. These models function by learning vector representations of both users and items based on their previous interactions. One widely used approach is matrix factorization (MF), as described by Liu *et al.* [17] and Rendle *et al.* [18], which decomposes the interaction matrix between users and items to derive vector representations that predict user preferences through vector similarity. Recently, CF models have evolved to incorporate graph neural network (GNN) techniques, which enable more sophisticated modeling of user-item interactions, as demonstrated by Lyu *et al.* [19]. An example of this is the neural graph collaborative filtering (NGCF) model, which significantly enhances recommendation accuracy [20].

Despite the advancements provided by these approaches, traditional CF models often overlook the geographic factors that can influence user preferences, leading to recommendations that may not fully account for the geographic relevance of items. This limitation highlights an opportunity to enhance recommendation systems by integrating geolocation data, thereby providing customers with more contextually accurate product suggestions. Accordingly, this work aims to develop an Android-based agribusiness e-commerce application for agricultural products that incorporates the geolocation-aware neural graph collaborative filtering (GA-NGCF) algorithm to optimize the recommendation process. This algorithm, based on previous work by Li *et al.* [21], leverages geolocation data and user preferences in three distinct phases. First, the model examines spatial relationships among items, users, and geographic regions. Second, it employs a GNN sensitive to regional factors, facilitating feature integration between nodes. Finally, it predicts user preferences by combining vectors for regions and items. This algorithm is then applied within this work and integrated into an Android-based digital marketplace application, as illustrated in Figure 1.

The structure of the paper is organized as follows: The methodology section provides details of the GA-NGCF algorithm. The results and discussion section presents the application's final output display, describes the dataset, examines experiments on data sparsity, and includes the user acceptance test. Finally, the conclusion section offers a comprehensive summary and key conclusions drawn from the research.

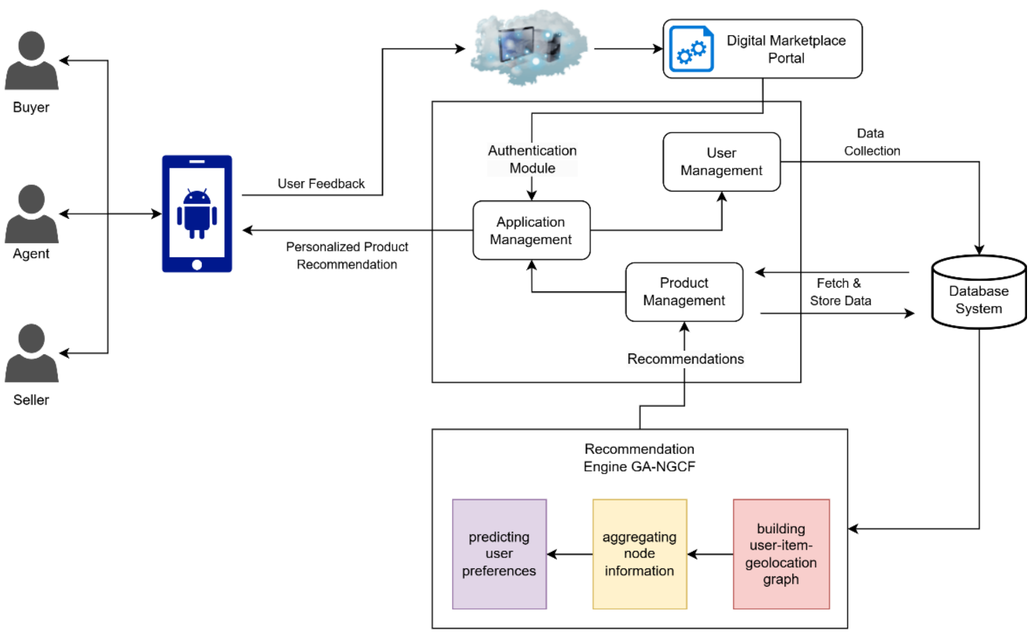


Figure 1. Framework for a digital marketplace system using a recommendation engine for personalized suggestions through an Android app

2. PROPOSED SMART DIGITAL MARKETPLACE RECOMMENDATION SYSTEM

2.1. Experimental design and system configuration

This study utilized a carefully chosen hardware and software configuration to optimize the performance of the GA-NGCF model. The hardware setup featured an Intel Core i7-10700F processor, 32 GB of DDR4 RAM, and an NVIDIA RTX 3050 graphics card, providing the computational power and graphical support needed for efficient model training and data processing. On the software side, essential libraries such as TensorFlow, NumPy, SciPy, and scikit-learn supported data processing and model learning tasks, while Android Studio facilitated the development of a user-friendly application interface on the Android platform, enabling smooth integration of the recommendation model for improved accessibility to end-users.

2.2. GA-NGCF model workflow

The GA-NGCF model is used in the proposed smart digital marketplace recommendation system. As illustrated in Figure 2, the workflow for the agricultural product recommendation process using the GA-NGCF model consists of several key stages. Initially, the process begins with loading a database of agricultural products, which includes essential user and product data required for the recommendation system. Once the database is loaded, the dataset is prepared for model training. At this stage, the GA-NGCF model is applied, incorporating three primary components.

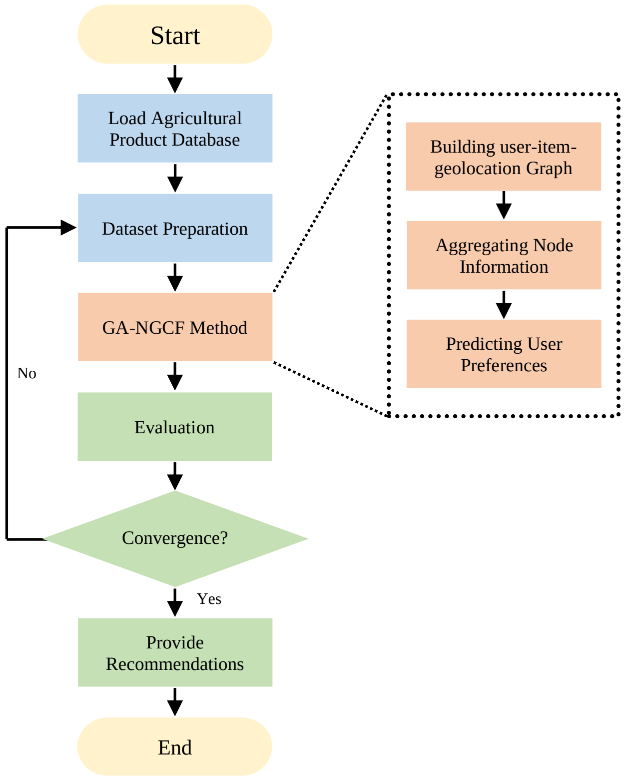


Figure 2. Agricultural product recommendation process using the GA-NGCF

2.2.1. Building the user-item-geolocation graph

The initial step in the GA-NGCF model involves the construction of the user-item-geolocation graph. This graph is essential for capturing relationships among users, items, and their geographic locations. Geographic locations can be defined using various methods, such as grid-based divisions or administrative boundaries (*e.g.*, zip codes). Grid-based divisions partition the area into uniform squares, which facilitates spatial analysis. However, administrative boundaries often offer a more precise reflection of social and economic interactions within a region. Once the geolocation for each item is determined, the relationships among users, items, and geolocations are mapped. In this work, these relationships are represented within a graph in which users, items, and geolocations appear as three distinct types of nodes, as shown in Figure 3 [21].

In the GA-NGCF model for agribusiness product recommendation systems, both control and status variables are vital for effective data processing and prediction. Control variables govern the model's training, including an embedding size of 64 for user and item representation, a learning rate of 0.001, and a batch size of 256, with training limited to 50 iterations. Regularization parameters are also used to reduce overfitting by penalizing complex models, with values adjusted based on preliminary experiments. Status variables enhance the model's functionality, capturing user preferences in user vectors based on past item interactions and refining these vectors by aggregating data from neighboring nodes, such as items and geolocations. Item vectors reflect item attributes derived from user interactions and geolocation data, while geolocation vectors describe geographic characteristics, incorporating both intrinsic attributes and influences from users' interactions with items in the area.

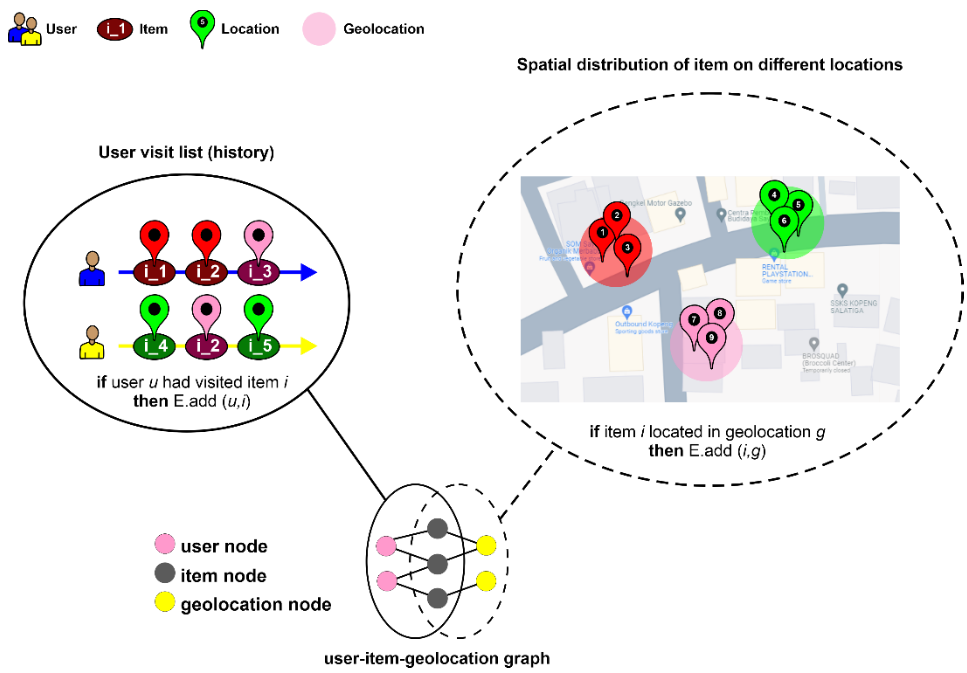


Figure 3. The user-item-geolocation graph illustrates creating edges between items and users on the left and edges between items and geolocations on the right

2.2.2. Aggregating node information

Aggregating information from neighboring nodes is essential for enhancing the feature representations of users, items, and geolocations within the graph. This process employs three aggregators: the item, user, and geolocation aggregators, each updating node vectors by integrating data from connected nodes. The item aggregator combines data from user and geolocation nodes, merging user preferences and geographic attributes into the item's feature vector, ensuring item features reflect both user behavior and spatial context. Similarly, the user aggregator enriches user vectors by incorporating features from neighboring item nodes, capturing a more detailed view of user interests and preferences. Lastly, the geolocation aggregator focuses on geographic attributes, gathering information from neighboring item nodes to ensure that geolocation vectors represent both intrinsic geographic characteristics and external influences from user interactions within the area [21].

2.2.3. Predicting user preferences

The final phase of the GA-NGCF model involves predicting user preferences and optimizing overall performance by integrating item vectors with corresponding geolocation vectors, creating enriched item representations that reflect both item-specific attributes and geographical context. User preferences are then predicted by calculating similarity scores between user vectors and combined item-geolocation vectors, which rank items based on relevance [21]. The model's effectiveness is evaluated through Recall, Precision, and normalized discounted cumulative gain (NDCG). If the model has not yet converged, it loops back to further GA-NGCF training. Upon convergence, the refined and validated recommendations are then made accessible to users.

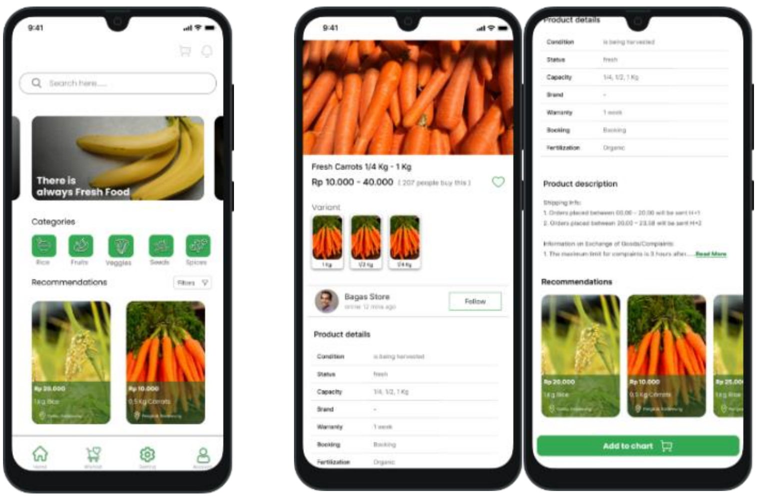
2.3. Interface testing and user acceptance evaluation

Following the implementation of the recommendation model, interface testing was conducted to ensure a smooth user experience. As illustrated in Figure 4, the interface features a homepage displaying product categories and personalized recommendations, along with a product page that provides detailed information on each item. User acceptance testing (UAT) was conducted over a two-week period with 17 participants. Participants were instructed to navigate the application, utilize the recommendation features, and provide feedback on overall usability. According to Otaduy and Diaz [22], UAT is a critical phase in software development, enabling end users to assess the application's functionality and usability to ensure it aligns with their expectations. Similarly, Mohd and Shahbodin [23] emphasize that UAT provides valuable insights into real-world usage scenarios, ensuring the application meets user needs and supports a seamless experience.

3. RESULTS AND DISCUSSION

3.1. Digital agricultural marketplace

The application features a user-friendly interface for both farmers and customers, making the buying and selling of agricultural products easier. As illustrated in Figure 4, the main components include: Figure 4(a) The homepage, which displays various categories and a recommendation section. Users can browse freely within these categories, while a personalized recommendation feature offers tailored suggestions based on user preferences and geographic location, ensuring options are relevant and easily accessible; and Figure 4(b) The product page, which provides detailed information for each product, including descriptions, specifications, prices, and user reviews. This page allows users to add items to their cart for later purchase or place orders directly for immediate processing, giving a comprehensive view of each product's specifics.



(a) (b)

Figure 4. Agricultural apps interface: (a) homepage and (b) product page

3.2. Dataset description

The dataset used to train and test the recommendation system was gathered from a survey site in Kopeng Village, Getasan District, Semarang Regency, Central Java, as illustrated in Figure 5. This dataset comprises 100,000 data points, each containing a unique user ID, the ID of the item visited, and the zip code of the item's location to provide geographic context. It also logs the visit time (date and time of each visit) and the visit duration, giving insights into user behavior, while user preferences collected through field surveys supply explicit preference data crucial for generating accurate recommendations. Before use in the model, the data undergoes a rigorous preprocessing phase. First, normalization scales numerical values uniformly to ensure no single feature disproportionately influences model training. Next, outlier removal excludes data points outside the normal range, enhancing accuracy and reducing bias. This comprehensive preprocessing process results in a high-quality dataset that optimally supports training and testing the GA-NGCF recommendation model, laying a strong foundation for precise analysis and results.

Figure 5. Satellite imagery data collection location for Kopeng area

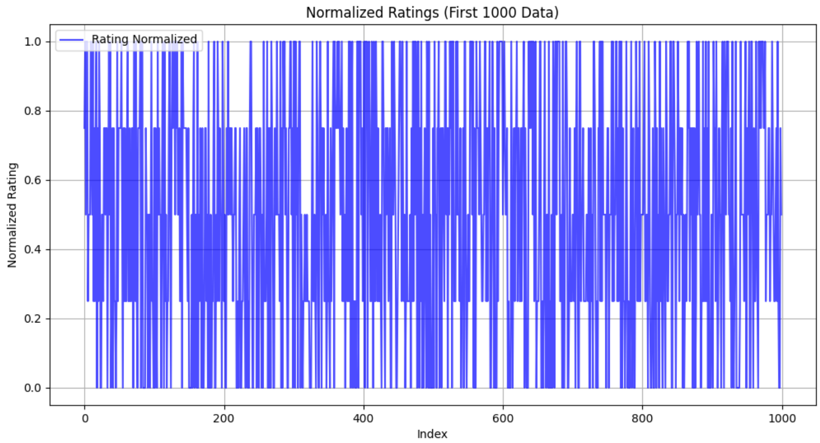
3.3. Model performance evaluation

This work evaluates the GA-NGCF model by comparing it to four other recommendation models: graph convolutional matrix completion (GC-MC), NGCF, CF, and neural causal graph collaborative filtering (NCGCF), using an 80/20 train-test dataset split. Model performance was assessed through the metrics recall, precision, and NDCG.

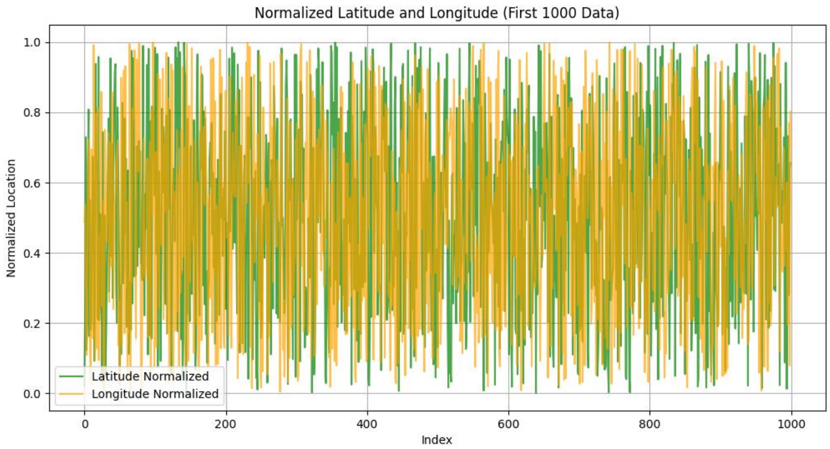
Each model offers unique approaches: the GC-MC model focuses on first-degree neighbors and uses graph convolutional networks (GCN) to generate user and item representations [24], [25], incorporating a single graph convolution layer aligned with the embedding size [26]. NGCF, a ranking algorithm based on collaborative filtering, leverages direct user-item interaction data to support more personalized and accurate recommendations [27]. Collaborative filtering (CF) serves as a widely adopted baseline model, utilizing historical user-item interactions to predict future preferences [28] and demonstrating simplicity and effectiveness in multiple recommendation tasks [29]. NCGCF, building upon NGCF, incorporates causal graph principles to capture causal relationships between users and items, offering improved ranking and recommendation accuracy, especially when causality is a significant factor [30].

Data preprocessing included min-max normalization (scaling data to a 0–1 range), with the first 1,000 entries from a 100,000-point dataset analyzed to ensure data accuracy, as shown in Figure 6. This process confirmed an even distribution of normalized rating values within the [0, 1] range, as illustrated in Figure 6(a). Additionally, normalized geographic coordinates around Kopeng, Central Java, displayed uniformity, as shown in Figure 6(b). After normalization, metrics showed values closer to 1, indicating improved ranking accuracy, with 1 representing an ideal score.

As shown in Figure 7, the GA-NGCF model demonstrates superior performance over the baseline NGCF model across key evaluation metrics: recall, precision, and NDCG, indicating significant gains in recommendation accuracy and relevance. GA-NGCF achieves a 5.54% increase in recall, underscoring its enhanced capability to retrieve relevant items, while NCGCF also outperforms NGCF with a moderate 4.31% improvement. In precision, GA-NGCF surpasses NGCF by 4.33%, though NCGCF attains the highest Precision score at 0.372, indicating strong recommendation accuracy. For NDCG, GA-NGCF leads with a 3.84% improvement over NGCF, while NCGCF exhibits a comparable performance. The GA-NGCF model’s enhanced performance can be attributed to its integration of geolocation data, which captures spatial relationships and provides a more comprehensive understanding of user preferences. This approach enables personalized, geographically contextualized recommendations, contributing to improved user satisfaction. However, the model’s computational complexity and challenges with processing large-scale geographic data are recognized limitations. Despite these constraints, GA-NGCF's utilization of geolocation data represents a significant advancement in recommendation systems for agricultural e-commerce, offering a distinct competitive edge over conventional models.



(a)



(b)

Figure 6. Min-max normalize: (a) rating data and (b) location data (latitude and longitude)

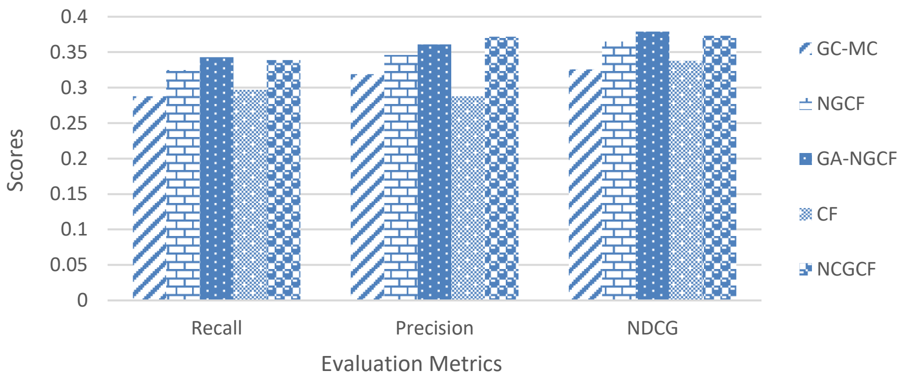


Figure 7. GA-NGCF algorithm testing result: recall, precision, and NDCG

3.4. User acceptance test

User acceptance testing (UAT) was conducted with a diverse sample of farmers and customers aged 25 to 45, with a balance in gender and marital status, selected randomly to prevent bias and ensure no prior involvement in app development. Participants evaluated various functionalities, including product search, purchase processes, and recommendation systems. As shown in Figure 8, survey results indicate that the majority of users were highly satisfied with the system's accessibility (Q2) and recommendation feature utility (Q5), with over 80% expressing strong agreement. Although there was some variability in responses regarding the accuracy of product information (Q3), where 11.77% of participants were neutral, the majority remained positive, with 52.94% strongly agreeing and 35.29% agreeing, suggesting a need for more precise details. Operational convenience (Q4) also received favorable feedback, as 52.94% strongly agreed and 47.06% agreed. Furthermore, the system's location-based recommendations (Q6) were well-received, with 58.82% of participants strongly agreeing and 41.18% agreeing, reflecting high overall satisfaction with this feature.

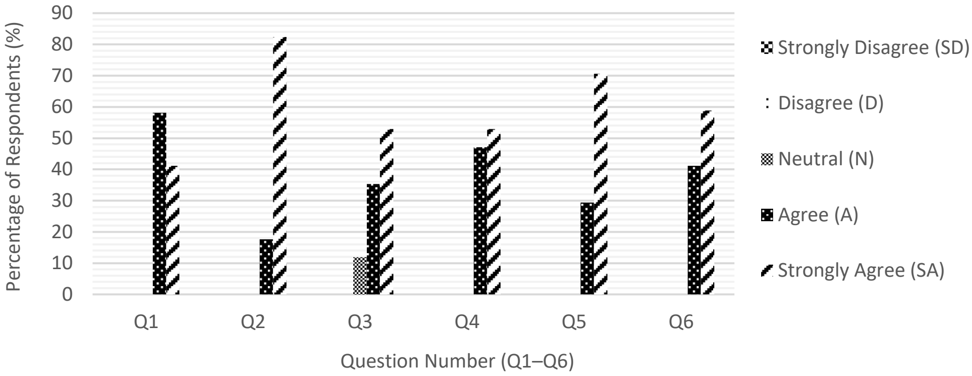


Figure 8. User acceptance test

4. CONCLUSION

This work demonstrates the transformative potential of e-commerce in agribusiness, particularly through advanced recommendation systems like the GA-NGCF model. Integrated into an Android-based digital marketplace, GA-NGCF offers users a personalized shopping experience that aligns with their preferences and geographical context, enhancing convenience for customers while expanding market access for farmers to create a more efficient and inclusive agribusiness ecosystem. The model's superior performance, measured by recall, precision, and NDCG, outperforms traditional models, highlighting the value of geolocation data in refining product suggestions. High satisfaction levels from UAT further validate its accessibility, recommendation accuracy, and ease of use. Overall, this work contributes to agribusiness digitalization by providing a scalable, user-centered platform that directly connects farmers with customers. Future directions could include enhancing computational efficiency and expanding geographic reach, strengthening the digital infrastructure of agribusiness, promoting sustainable growth, and improving market connectivity within the agricultural sector.

ACKNOWLEDGEMENTS

This work was supported by UNNES Electrical Engineering Students Research Group (UEESRG), Department of Electrical Engineering, Universitas Negeri Semarang, in facilitating this study. Additionally, funding for this research was sponsored by Institute of Research and Community Service in Universitas Negeri Semarang, under grant no. 227.12.4/UN37/PPK.10/2023.

REFERENCES

[1] H. A. Mahdiraji, M. Beheshti, S. H. R. Hajiagha, N. A. Kandi, and H. Boudlaie, "A process-based guide for international entrepreneurs while investing in the agrifood sector of an emerging economy: a multi-layer decision-making approach," *British Food Journal*, vol. 124, no. 7, pp. 1984–2011, 2022, doi: 10.1108/BFJ-08-2021-0876.

[2] A. B. L. Sabarre, A. N. S. Navidad, D. S. Torbela, and J. J. Adtoon, "Development of durian leaf disease detection on Android device," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 6, pp. 4962–4971, 2021, doi: 10.11591/ijece.v11i6.pp4962-4971.

[3] A. Mehmood, S. Ahmed, E. Viza, A. Bogush, and R. M. Ayyub, "Drivers and barriers towards circular economy in agri-food supply chain: a review," *Business Strategy and Development*, vol. 4, no. 4, pp. 465–481, 2021, doi: 10.1002/bsd2.171.

[4] S. A. Bhat, N. F. Huang, I. B. Sofi, and M. Sultan, "Agriculture-food supply chain management based on blockchain and IoT: a narrative on enterprise blockchain interoperability," *Agriculture (Switzerland)*, vol. 12, no. 1, 2022, doi: 10.3390/agriculture12010040.

[5] I. F. Gorlov, G. V. Fedotova, A. V. Glushchenko, M. I. Slozhenkina, and N. I. Mosolova, "Digital technologies in the development of the agro-industrial complex," *Lecture Notes in Networks and Systems*, vol. 87, pp. 220–229, 2020, doi: 10.1007/978-3-030-29586-8_26.

[6] S. Cook, E. L. Jackson, M. J. Fisher, D. Baker, and D. Diepeveen, "Embedding digital agriculture into sustainable Australian food systems: pathways and pitfalls to value creation," *International Journal of Agricultural Sustainability*, vol. 20, no. 3, pp. 346–367, 2022, doi: 10.1080/14735903.2021.1937881.

[7] X. Li and D. Huang, "Research on value integration mode of agricultural e-commerce industry chain based on internet of things and blockchain technology," *Wireless Communications and Mobile Computing*, vol. 2020, 2020, doi: 10.1155/2020/8889148.

[8] S. Karande, S. Patil, R. Gharat, A. Mhatre, and P. Sorte, "Application of intelligent recommendation for agricultural information-E-krishi," *International Journal for Research Trends and Innovation*, vol. 8, p. 693, 2023.

[9] P. M. Alamdari, N. J. Navimipour, M. Hosseinzadeh, A. A. Safaei, and A. Darwesh, "A systematic study on the recommender systems in the E-commerce," *IEEE Access*, vol. 8, pp. 115694–115716, 2020, doi: 10.1109/ACCESS.2020.3002803.

[10] B. Hssina, A. Grota, and M. Erritali, "Recommendation system using the k-nearest neighbors and singular value decomposition algorithms," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 6, pp. 5541–5548, 2021, doi: 10.11591/ijece.v11i6.pp5541-5548.

[11] R. V. Karthik and S. Ganapathy, "A fuzzy recommendation system for predicting the customers interests using sentiment analysis and ontology in e-commerce," *Applied Soft Computing*, vol. 108, 2021, doi: 10.1016/j.asoc.2021.107396.

[12] K. Wakil, F. Alyari, M. Ghasvari, Z. Lesani, and L. Rajabion, "A new model for assessing the role of customer behavior history, product classification, and prices on the success of the recommender systems in e-commerce," *Kybernetes*, vol. 49, no. 5, pp. 1325–1346, 2020, doi: 10.1108/K-03-2019-0199.

[13] G. Vich, O. Marquet, and C. Miralles-Guasch, "Green exposure of walking routes and residential areas using smartphone tracking data and GIS in a Mediterranean city," *Urban Forestry and Urban Greening*, vol. 40, pp. 275–285, 2019, doi: 10.1016/j.ufug.2018.08.008.

[14] D. Hindarto and A. Djajadi, "Android-manifest extraction and labeling method for malware compilation and dataset creation," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, pp. 6568–6577, 2023, doi: 10.11591/ijece.v13i6.pp6568-6577.

[15] R. Wang, Z. Wu, J. Lou, and Y. Jiang, "Attention-based dynamic user modeling and deep collaborative filtering recommendation," *Expert Systems with Applications*, vol. 188, 2022, doi: 10.1016/j.eswa.2021.116036.

[16] Z. Shokrzadeh, M. R. Feizi-Derakhshi, M. A. Balafar, and J. Bagherzadeh Mohasefi, "Knowledge graph-based recommendation system enhanced by neural collaborative filtering and knowledge graph embedding," *Ain Shams Engineering Journal*, vol. 15, no. 1, 2024, doi: 10.1016/j.asej.2023.102263.

[17] H. Liu *et al.*, "EDMF: efficient deep matrix factorization with review feature learning for industrial recommender system," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 7, pp. 4361–4371, 2022, doi: 10.1109/TII.2021.3128240.

[18] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian personalized ranking from implicit feedback," in *Proceedings of the 25th Conference on Uncertainty in Artificial Intelligence, UAI 2009*, 2009, pp. 452–461.

[19] Z. Lyu, Y. Wu, J. Lai, M. Yang, C. Li, and W. Zhou, "Knowledge enhanced graph neural networks for explainable recommendation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 5, pp. 4954–4968, 2023, doi: 10.1109/TKDE.2022.3142260.

[20] H. Tang, G. Zhao, X. Bu, and X. Qian, "Dynamic evolution of multi-graph based collaborative filtering for recommendation systems," *Knowledge-Based Systems*, vol. 228, 2021, doi: 10.1016/j.knosys.2021.107251.

[21] S. Li *et al.*, "Region-aware neural graph collaborative filtering for personalized recommendation," *International Journal of Digital Earth*, vol. 15, no. 1, pp. 1446–1462, 2022, doi: 10.1080/17538947.2022.2113463.

[22] I. Otaduy and O. Diaz, "User acceptance testing for Agile-developed web-based applications: empowering customers through wikis and mind maps," *Journal of Systems and Software*, vol. 133, pp. 212–229, 2017, doi: 10.1016/j.jss.2017.01.002.

[23] C. Mohd and F. Shahbodin, "Personalized learning environment: alpha testing, beta testing & user acceptance test," *Procedia - Social and Behavioral Sciences*, vol. 195, no. 837 – 843, 2015.

[24] Y. Zhang *et al.*, "BI-GCN: bilateral interactive graph convolutional network for recommendation," *International Conference on Information and Knowledge Management, Proceedings*, pp. 4410–4414, 2023, doi: 10.1145/3583780.3615232.

[25] W. Zhang, Z. Kang, L. Song, and K. Qu, "Graph attention interaction aggregation network for click-through rate prediction," *Sensors*, vol. 22, no. 24, 2022, doi: 10.3390/s22249691.

[26] R. van den Berg, T. N. Kipf, and M. Welling, "Graph convolutional matrix completion," *arXiv preprint arXiv:1706.02263*, 2017, [Online]. Available: http://arxiv.org/abs/1706.02263.

[27] X. Wang, X. He, M. Wang, F. Feng, and T. S. Chua, "Neural graph collaborative filtering," in *SIGIR 2019 - Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2019, pp. 165–174, doi: 10.1145/3331184.3331267.

[28] A. Shirali, R. Kazemi, and A. Amini, "Collaborative filtering with representation learning in the frequency domain," *Information Sciences*, vol. 681, 2024, doi: 10.1016/j.ins.2024.121240.

[29] L. Wu, X. He, X. Wang, K. Zhang, and M. Wang, "A survey on accuracy-oriented neural recommendation: from collaborative filtering to information-rich recommendation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 5, pp. 4425–4445, 2023, doi: 10.1109/TKDE.2022.3145690.

[30] X. Wang, Q. Li, D. Yu, W. Huang, Q. Li, and G. Xu, "Neural causal graph collaborative filtering," *Information Sciences*, vol. 677, 2024, doi: 10.1016/j.ins.2024.120872.

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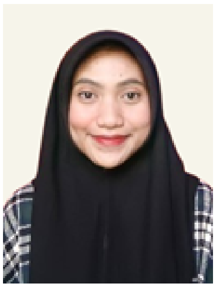

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