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Collaborative filtering modification technology for recommendation systems in smart digital agribusiness marketplace

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Abstract

The rapid transformation in the agribusiness sector, driven by globalization and digitalization, necessitates the adoption of intelligent systems to enhance performance, market accessibility, and decision-making processes. Despite the growing use of personalized recommender systems in e-commerce, geographical context remains insufficiently integrated into recommendation processes. This lack of geolocation awareness diminishes recommendation relevance and accuracy by overlooking geographical factors that influence user preferences. To address this limitation, this work aims to enhance the performance of recommendation systems in agricultural e-commerce by incorporating geolocation context through the integration of the Geo-Mod Neuro Collaborative Filtering (GMNCF) model into an Android-based application for agricultural products. The GMNCF model improves collaborative filtering by incorporating geographical region data to capture spatial user preferences and reduce data sparsity. Using Graph Neural Networks (GNNs), the model captures complex relationships among users, items, and geographic regions to generate more accurate recommendations. Experimental results reveal that GMNCF consistently delivers substantial performance improvements over baseline models such as NGCF, GC-MC, ASMG, and GCZRec. Compared to the strongest baselines, GMNCF demonstrates relative gains of approximately 4.9% in Precision, 5.9% in Recall, 5.6% in F1-Score, and 5.7% in Hit Rate. These improvements underscore the model's effectiveness in capturing spatially influenced user preferences and strengthening the relevance of recommendations in the agribusiness e-commerce system. Furthermore, user testing with diverse respondents indicates high levels of satisfaction, particularly regarding location-based recommendation features and accessibility. These findings highlight the effectiveness of incorporating geographical region data into recommendation systems, which is particularly beneficial for geographically fragmented agribusiness markets.

1. Introduction

Globalization has driven various economic sectors, including agribusiness, to continuously adapt and evolve [1], [2]. This sector not only focuses on agricultural production but also encompasses processing and distribution, which are vital components in meeting societal needs while supporting economic growth [3]. In the context of an increasingly interconnected global market, agribusiness has developed into a dynamic network leveraging technology-based marketing strategies [4]. The shift toward digital platforms has become a strategic step in responding to the increasingly diverse consumer needs and the demand for efficiency [5].

This transformation has been further accelerated by the emergence of e-commerce, which has significantly revolutionized agribusiness [6], [7]. E-commerce not only expands market access but also reduces operational costs, enhances transparency, and promotes equitable distribution [8]. By connecting farmers directly to consumers, this platform creates a more efficient ecosystem. Mobile technology, particularly Android-based applications, strengthens the role of e-commerce in driving efficiency and accessibility in agribusiness [9], [10].

Android-based applications facilitate real-time interactions, provide easier access, and support rapid decision-making for agribusiness players [11]. This technology extends market reach and fulfills customer needs in a more personalized manner [12]. With user-friendly features and integration with various analytical tools, mobile applications have become a crucial element in addressing the continuously evolving market dynamics [13].

Over time, e-commerce has been supported by recommendation systems, which serve as a key element in increasing customer engagement [14], [15]. This technology provides personalized product suggestions based on user behavior analysis, thereby enhancing customer satisfaction and driving sales [16]. One of the primary approaches used in recommendation systems is collaborative filtering (CF), which analyzes the behavioral patterns of similar users to predict their preferences [17].

According to studies by Liu et al. [18] and Rendle et al. [19], Matrix Factorization (MF) has emerged as a widely adopted approach in Collaborative Filtering (CF), where the interaction matrix between users and products is decomposed to produce vector representations that estimate user preferences based on vector similarity. However, CF models have advanced by incorporating graph neural network (GNN) methodologies, allowing for a more sophisticated representation of user-product interactions [20]. One such advancement is the Graph Convolutional Matrix Completion (GC-MC) model proposed by van den Zhang et al. [21], which applies Graph Convolutional Networks (GCN) to learn latent representations of users and items. Unlike traditional MF-based approaches, GC-MC effectively captures higher-order connectivity within user-item graphs, leading to improved recommendation performance. Additionally, the Neural Graph Collaborative Filtering (NGCF) model further enhances recommendation accuracy by explicitly modeling user-item interactions through multi-layer message-passing mechanisms [22]. These models demonstrate the potential of GNN-based CF techniques in addressing challenges such as data sparsity and cold-start problems in recommendation systems.

Despite advancements in recommendation systems, many still overlook geographical factors that influence user preferences, especially in agribusiness markets characterized by regional diversity. This limitation reduces the contextual accuracy of recommendations and fails to support the location-based needs of users and producers. Addressing this limitation, this work proposes an Android-based agribusiness e-commerce application designed to enhance recommendation accuracy by incorporating geographical region data. The system leverages the Geo-Mod Neuro Collaborative Filtering (GMNCF) model to optimize the recommendation process.

The GMNCF algorithm integrates both geographical data and user preferences through a three-phase approach. Initially, it analyzes spatial relationships among users, items, and geographical regions. Following this, a graph neural network (GNN) is utilized to model regional influences, facilitating feature integration across nodes. In the final phase, the algorithm predicts user preferences by generating vector representations that encapsulate both geographical regions and item characteristics. The proposed approach is implemented and integrated into an Android-based digital marketplace, as illustrated in Figure 1.

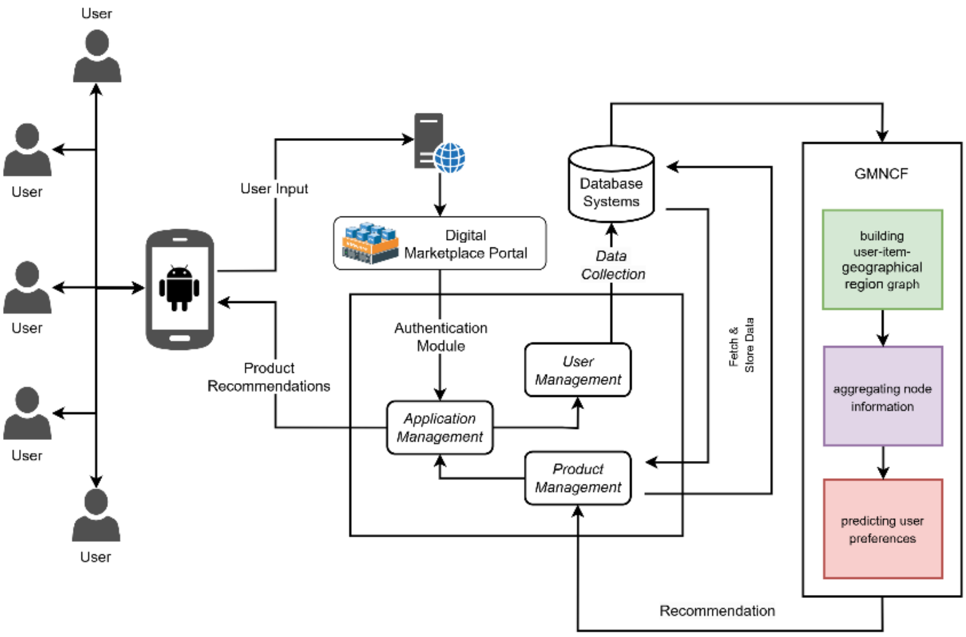

Figure 1. Digital Market System Framework with GMNCF

Unlike conventional Collaborative Filtering (CF) models, the Geo-Mod Neuro Collaborative Filtering (GMNCF) framework explicitly incorporates geographical context, which is highly relevant in agribusiness settings characterized by strong regional variations. By embedding spatial data into the recommendation process, GMNCF is particularly effective in enhancing recommendation accuracy within regionally dispersed agricultural markets. This capability provides a strategic advantage for digital platforms operating across diverse agricultural regions by supporting recommendations that reflect geographic relevance and regional characteristics.

2. Research Method

In this work, the hardware and software configurations were carefully selected to optimize the performance of GMNCF, as presented in Table 1.

Tabel 1. Specifications for Development Environment and System Configuration

Description	Specifications
Operating System	Windows 10
Processor	Intel Core i7-10700F
Graphic Card	NVIDIA RTX 3050
RAM	32GB DDR4
Library	Tensorflow, numpy, scipy, sklearn

2.1 Research Location

The work was conducted in Kopeng Village, located in Getasan District, Semarang Regency, Central Java. Kopeng Village was chosen as the primary research site due to its strategic position as a regional trade hub and its strong agricultural sector. The satellite imagery in Figure 2 illustrates the agricultural potential of Kopeng Village, which served as a crucial foundation for developing the recommendation model for agricultural products on the Android-based digital marketplace platform.

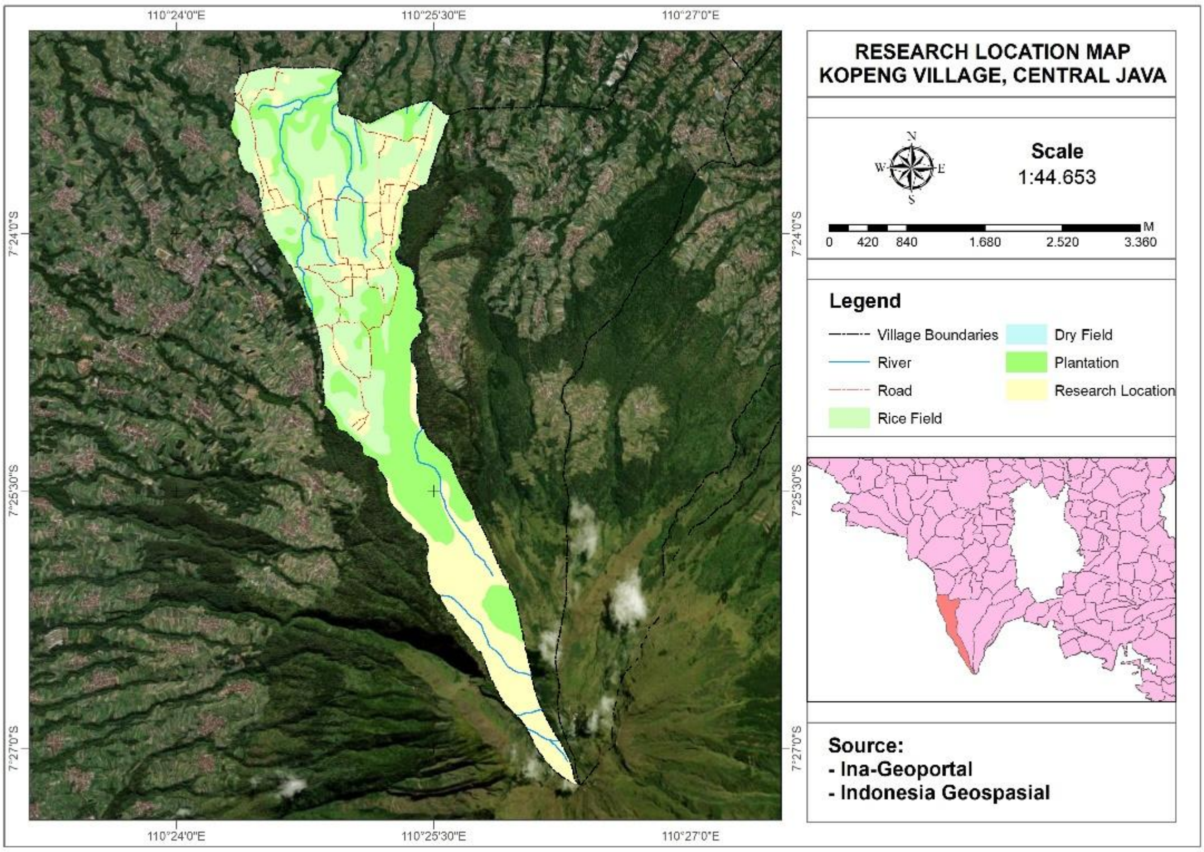

Figure 2. Satellite Imagery of the Data Collection Location in Kopeng

2.2 Geo-Mod Neuro Collaborative Filtering

This section describes how the Geo-Mod Neuro Collaborative Filtering (GMNCF) model worked by introducing geographical entities into the collaborative filtering-based recommendation system using Graph Neural Networks (GNN). This model considered the relationships between users, items, and geographical regions to improve the accuracy of user preference predictions, as depicted in Figure 3. The process was divided into three main stages, which included building a user-item-geographical region graph to represent spatial and behavioral interactions, aggregating information from neighboring nodes using GNN to capture higher-order relationships, and performing prediction and model optimization to generate personalized recommendations based on integrated representations.

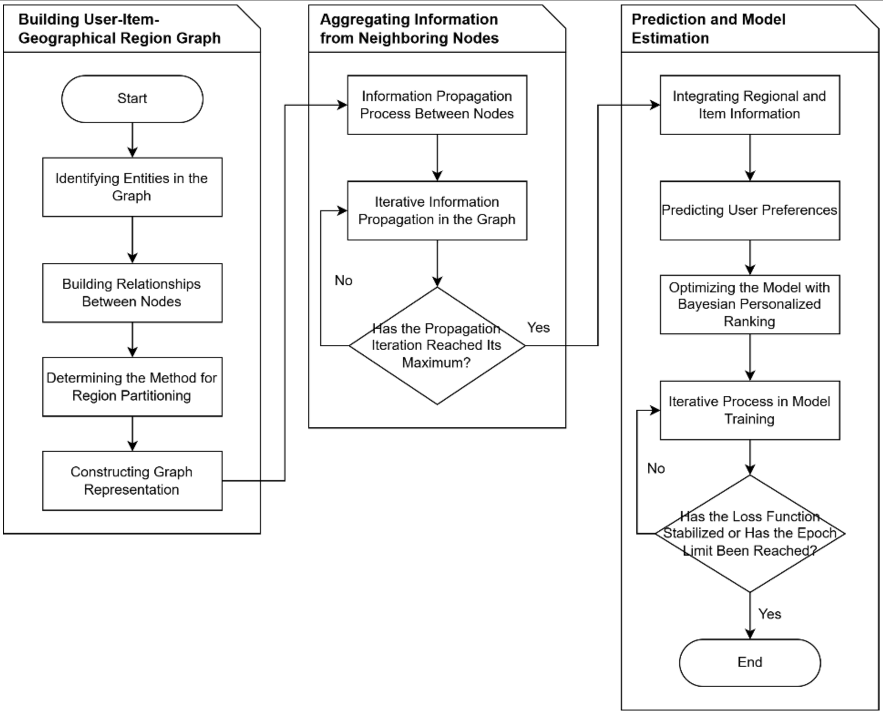

Figure 3. Agricultural Product Recommendation Process using GMNCF

2.2.1 Building User-Item-Geographical Region Graph

The first step in GMNCF involved constructing a graph representing the relationships between users, the items they accessed, and the geographical regions where the items were located. In conventional models, the relationships considered were only between users and the items they liked or visited. However, in GMNCF, each item was also associated with a specific geographical region, allowing spatial information to be incorporated into the recommendation system.

In this graph construction, each user was represented as a node, along with each item and each geographical region. There were two main types of relationships in this graph. The first was the relationship between users and the items they had accessed, which indicated direct interactions between users and items. The second was the relationship between items and their geographical regions, enabling the system to understand where an item was located and how geographical proximity could influence user preferences [23].

To build this structure, the system used user interaction records such as viewing history or purchases to connect users with items. Each item was then associated with its corresponding geographical region based on identifiers like postal codes. Through these connections, the graph captured both behavioral interactions and spatial associations. By integrating these spatial relationships into the graph, GMNCF was able to recognize patterns in user preferences that were influenced by location.

2.2.2 Aggregating Information from Neighbor Nodes

Once the graph was formed, the next step was propagating information among the connected nodes. At this stage, the role of GNN was crucial. In GMNCF, three types of aggregators were used to update the representation of each node: the item aggregator, the user aggregator, and the geographical region aggregator.

The item aggregator collected information from users and geographical regions associated with a particular item. This approach ensured that the vector representation of an item accounted for not only its direct interactions with users but also for the characteristics of the geographical region where the item was located. This was particularly useful in scenarios where certain items were more popular in specific geographical regions.

Meanwhile, the user aggregator updated the representation of users based on the items they had accessed. By propagating information from items to users, the system captured broader preference patterns, not only based on direct interactions but also by considering the characteristics of the geographical regions where the accessed items were located.

The geographical region aggregator gathered information from all items within a particular geographical region. This meant that each geographical region was understood not only as a geographical entity but also as a collection of items with specific characteristics reflecting user consumption patterns in that area. This approach enabled the system to recognize user behaviors within a given geographical region and adjust recommendations accordingly.

This aggregation process did not stop at a single step. Through multiple iterations, information continued to propagate to other nodes in the graph, allowing the model to capture more complex indirect relationships. For example, a user who had never accessed a particular item could still receive recommendations for it if the system detected that users with similar interaction patterns tended to like that item, especially if it was located in a frequently visited geographical region.

2.2.3 Prediction and Model Optimization

After all the information from users, items, and geographical regions had been combined and updated through the aggregation process, the final step was predicting user preferences. In conventional models, this prediction was typically performed by comparing the similarity between the user representation vector and the item representation vector. However, in GMNCF, geographical region information was also incorporated into this prediction process.

To improve recommendation accuracy, the model combined the geographical region vector with the item vector before making predictions. This allowed the system to recognize that user preferences might not only depend on an item's individual characteristics but also on its location. For instance, certain vegetables might be more popular in one geographical region than in another, and this factor needed to be considered in the recommendation system.

Predictions were made by comparing the user representation vector with the item representation vector, which had been integrated with regional information. The higher the similarity score between these vectors, the more likely the item was relevant to the user. To optimize recommendations, the model was trained using the Bayesian Personalized Ranking (BPR) approach [24]. This technique ensured that the system accurately determined which items were more relevant than others by continuously adjusting model parameters based on feedback from the training data.

Such predictions are enabled through the model’s structured propagation of information within its graph representation. Geographical regions are represented as dedicated nodes within the interaction graph, allowing the system to capture spatial characteristics that influence user preferences. As item vectors are updated through multiple layers of neighborhood aggregation, they gradually incorporate region-specific features. When combined with user vectors during the prediction phase, these enhanced item representations help the system provide recommendations that are more relevant to users’ locations and preferences. The overall approach also improves the system’s ability to perform well under conditions with limited data, which is especially valuable in agribusiness scenarios where user behavior is often shaped by geographical factors.

2.3 Development of the Agricultural Digital Marketplace Application

The application development process in this work followed several phases, as illustrated in Figure 4, beginning with planning, design, coding, and testing. The Planning and Design Phase started with the initial conceptualization, which included idea development and feasibility studies. During this phase, a more detailed concept was developed, focusing on system architecture design, data management strategies, and algorithm planning. This phase established a solid foundation that guided the subsequent development process.

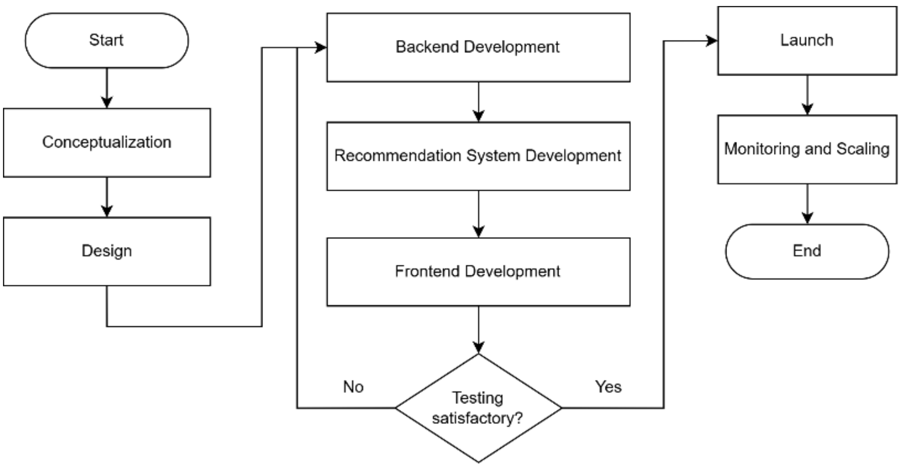

Figure 4. Development Process Workflow of the Application

During the Development and Integration Phase, the process began with front-end development, which included designing the user interface and gathering and processing data. The goal was to ensure an intuitive and seamless user experience. Once the front end was completed, the recommendation system was developed, covering model implementation, training and testing, and API integration. This step ensured that the system could optimally respond to user needs.

Subsequently, the back-end development was carried out, involving the setup of the required infrastructure and the integration of the entire system. The system was then evaluated through multiple rounds of testing. If any deficiencies were identified, the system was refined and retested until it met the established standards.

In the Deployment Phase, the system was launched for public use. After deployment, continuous monitoring was conducted to identify areas for improvement and adjustments. The system was also designed to be scalable to accommodate increasing user demand and ensure optimal performance over time. This phase marked the completion of the entire development process of the agricultural digital marketplace application.

3. Results and Discussion

3.1 Agricultural Digital Marketplace Application

The agricultural digital marketplace application incorporates several key features, as illustrated in Figures 5 and 6. The main features of the application include the home page and the product page. The home page functions as a central navigation area, while the product page displays detailed information about the items offered.

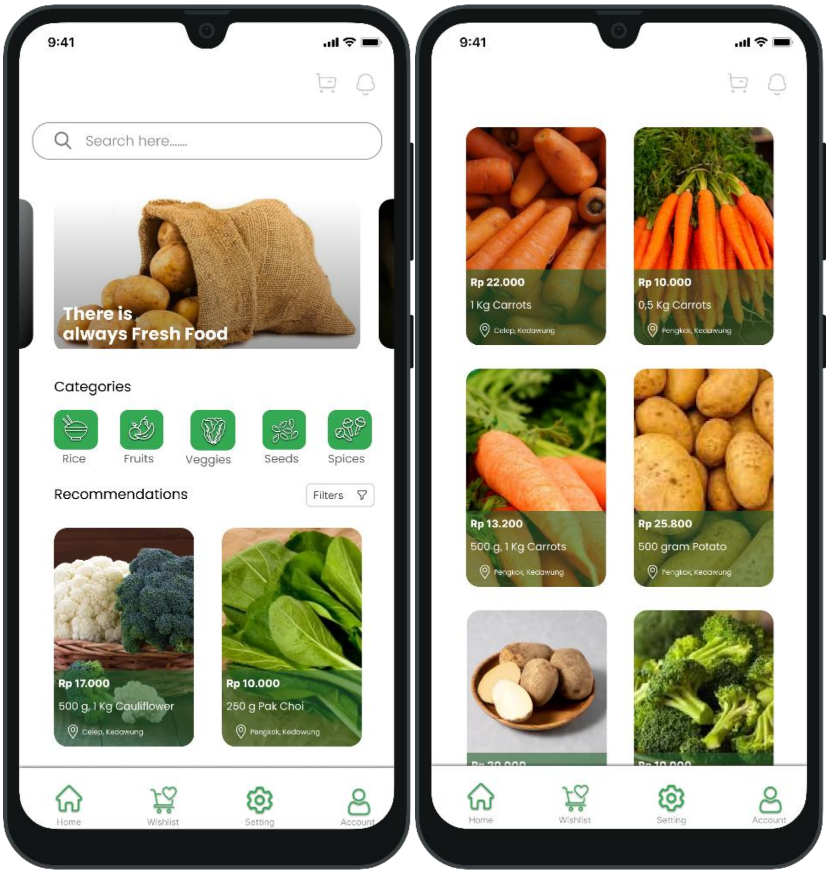

Figure 5. Interface of the Home Page

Figure 5 displays the Home Page, which contains various categories along with a recommendation section. Users have the flexibility to select products based on the available categories. The personalized recommendation feature tailors' suggestions according to user preferences while considering their geographical location. This design ensures that users receive choices that are not only relevant to their interests but also easily accessible based on their location.

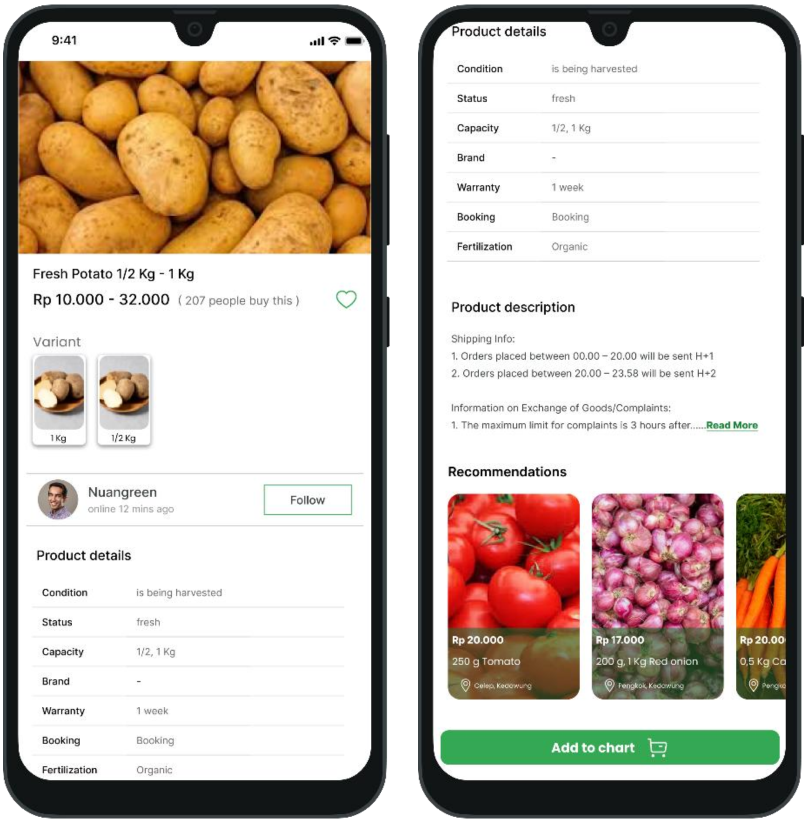

Figure 6. Interface of the Product Page

As illustrated in Figure 6, the Product Page offers a detailed presentation of each product, including specifications, descriptions, pricing, and other pertinent information. Users are provided with the capability to add selected items to their shopping cart for potential future purchases or proceed with an immediate transaction. This interface serves as a comprehensive platform, delivering users an extensive overview of product-related details.

Behind this interface, the recommendation system plays a key role in presenting relevant product suggestions to users. In practical implementation, integrating geographical region data enables digital agribusiness platforms to tailor recommendations based on spatial proximity. This approach facilitates market access for smallholder farmers by connecting them with nearby consumers, thereby potentially reducing logistical complexity and enhancing transaction efficiency. Such geographical personalization aligns well with the core objectives of GMNCF, emphasizing its applicability in real-world agricultural e-commerce settings.

3.2 Dataset

In this work, the dataset utilized for training and evaluating the recommendation system was collected from the research location, comprising 125,000 data points. The developed dataset focuses on agricultural products in Central Java, considering the relationships between users, items, and geographical regions. The dataset includes several key features, namely User Identity (User_ID), Agricultural Products (Item_ID), Product Location based on postal codes (Kode_Pos), Number of User-Product Interactions (Check-ins), Types of Agricultural Products (Categories), and User Reviews (Reviews), as shown in Table 2.

Table 2. Dataset

User_ID	Item_ID	Kode_Pos	Check-ins	Categories	Reviews
U000001	I101	50123	15	['Paddy', 'Rice']	High quality rice, abundant harvest.
U000002	I102	50241	22	['Corn', 'Grains']	Fresh corn, suitable for animal feed and consumption.
U000003	I103	50356	9	['Coffee', 'Spices']	Coffee with a distinctive aroma, suitable for export.
U000004	I104	50412	18	['Tea', 'Herbal Drink']	Organic tea with a typical mountain taste.

U000005	I105	50567	30	['Vegetable', 'Organic']	Fresh vegetables, pesticide free, very healthy.
…	…	…	…	…	…
U124996	I238	50123	12	['Paddy', 'Rice']	Rice with a fluffy texture, suitable for daily consumption.
U124997	I239	50241	25	['Corn', 'Grains']	High quality corn, consistent yields.
U124998	I240	50356	8	['Coffee', 'Spices']	Local coffee with a strong taste and distinctive aroma.
U124999	I241	50241	20	['Vegetable', 'Organic']	Fresh vegetables from local farmers, no chemicals.
U125000	I242	50567	28	['Fruit', 'Banana']	Bananas are sweet and fresh, perfect for snacks.

Before being used in the model, the dataset underwent a comprehensive preprocessing phase to enhance data quality for training and testing. The initial step involves normalization, ensuring that numerical values are scaled appropriately to prevent any single feature from exerting excessive influence on the model training process. Subsequently, an outlier removal process is performed to discard data points that deviate from the expected range, enhancing accuracy and reducing bias. This comprehensive preprocessing approach yields a high-quality dataset that effectively facilitates the training and validation of the GMNCF recommendation model, providing a solid framework for precise analysis and reliable predictions.

3.3 Data Sparsity Experiment

In this work, the evaluation metrics used include Precision, Recall, F1-Score, and Hit Rate to measure system performance. To assess system efficiency, the GMNCF model was compared with four other models: Graph Convolutional Matrix Completion (GC-MC), Neural Graph Collaborative Filtering (NGCF), Adaptive Sequential Model Generation (ASMG), and Generative Collaborative Zero-Shot Recommendation (GCZRec), as illustrated in Figure 7.

GC-MC is limited to first-level neighbor utilization and employs Graph Convolutional Networks (GCN) to derive representations of users and items [25]. In the relevant literature, a single-layer graph convolution and a hidden dimension are used, which are then adjusted to the required embedding size. On the other hand, NGCF applies Collaborative Filtering (CF) for ranking. NGCF leverages direct interactions between users and items within its interaction function, supporting the generation of more personalized and precise recommendations [26].

Meanwhile, ASMG improves incremental learning in recommender systems by utilizing a GRU-based meta-generator to retain long-term user preference patterns, mitigating catastrophic forgetting [27]. Additionally, GCZRec combines collaborative filtering with generative models, making it possible to recommend new items even without prior interaction [28]. These models demonstrate the potential of integrating sequential learning and generative approaches to improve recommendation performance, particularly in handling data sparsity and user preference shifts.

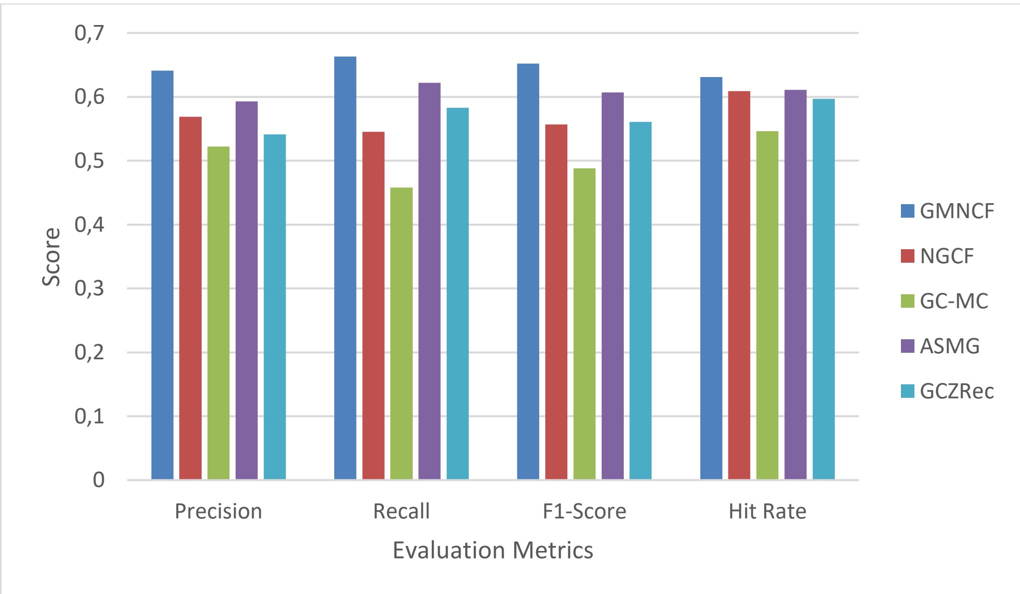

Figure 7. Evaluation Results

Based on the experimental results presented in Figure 7, GMNCF consistently outperforms the baseline models NGCF, GC-MC, ASMG, and GCZRec in all evaluation metrics. In terms of Precision, GMNCF achieved a score of 0.641, outperforming the other models and demonstrating its effectiveness in recommending relevant items. For Recall, GMNCF attained the highest value of 0.663, indicating its capability to comprehensively identify relevant items. Similarly, the F1-Score of 0.652 highlights GMNCF's balanced trade-off between precision and recall, outperforming the other four models. Furthermore, the Hit Rate of 0.631 reaffirms its reliability in delivering accurate recommendations. Overall, GMNCF proves to be more effective and optimal in capturing user preferences, making it a superior choice for location-based recommendation systems.

These findings demonstrate the effectiveness of the GMNCF model across various evaluation metrics while also validating its contextual relevance within agribusiness environments. In contrast to general-purpose recommender systems, GMNCF effectively captures region-specific preferences, which is an essential consideration given the geographical diversity present in agricultural markets. This capability enhances its usefulness in supporting decision-making in geographically diverse agribusiness applications. These insights are particularly meaningful for practical deployment in the agribusiness domain, where spatial variation often shapes user behavior.

The results are consistent with those reported by Li et al. [29], who demonstrated that incorporating regional information into graph-based recommendation models improves performance in environments where user preferences are influenced by geographical factors. Similarly, Wang et al. [30] emphasized that enriching graph neural networks with structured knowledge, including spatial context, can enhance recommendation quality by capturing more nuanced relationships between users and items. The outcomes of this work reinforce those findings by showing that GMNCF, through its integration of geographical data, performs effectively in agribusiness applications where location plays a key role in user-item interactions.

3.4 Evaluation of the Agricultural Digital Marketplace Application

The application testing involved 30 randomly selected respondents. The respondents had diverse backgrounds, with an age range of 20 to 45 years, a balanced gender distribution, and varying marital statuses. The random selection was conducted to prevent bias and ensure that respondents had no prior involvement in the application development. During the testing phase, respondents evaluated various key features of the application, including product search, purchasing process, and the recommendation system. The evaluation results of the agricultural digital marketplace application are presented in Figure 8.

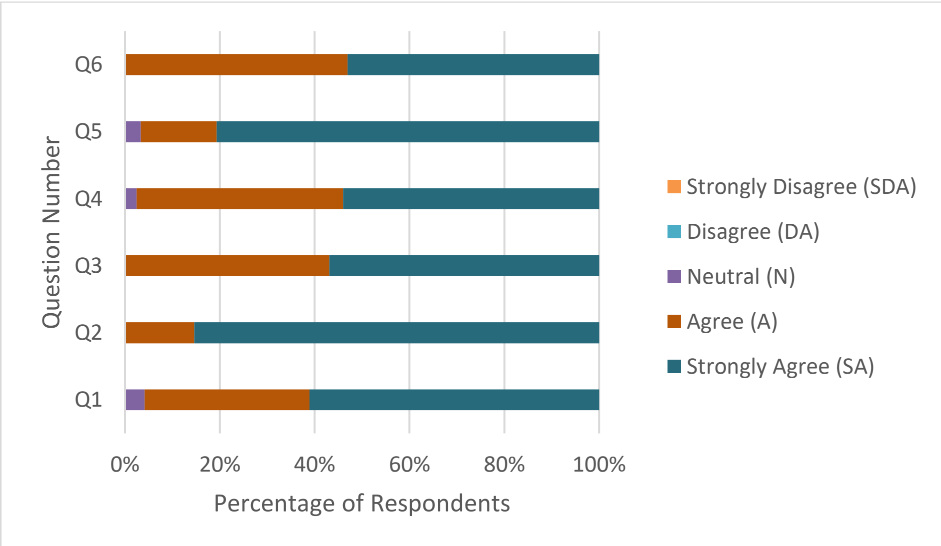

Figure 8. Evaluation Results of the Agricultural Digital Marketplace Application

As illustrated in Figure 8, the survey data analysis indicates that most users reported high satisfaction with system accessibility (Q2) and the usability of the recommendation feature (Q5). Specifically, more than 80% of respondents strongly agreed with these aspects, underscoring the system's effectiveness in enhancing user interaction and delivering personalized recommendations. These findings demonstrate a strong user appreciation for both features. Although there was slight variation in responses regarding satisfaction with the user interface (Q1), where 4.13% of respondents remained neutral, the majority still provided positive feedback, with 61.1% strongly agreeing and 34.77% agreeing. This reflects that the user interface was well-received, although there is some room for improvement for respondents who remained neutral.

The accuracy of product information (Q3) showed that 43.13% of respondents agreed and 56.87% strongly agreed, indicating a need for further improvements in providing more accurate information. Regarding operational ease (Q4), responses were also positive, with 54% of respondents strongly agreeing, 43.55% agreeing, and only 2.45% remaining neutral. The very low neutral percentage suggests that the majority of users found the system easy to operate. Additionally, the location-based recommendation feature (Q6) was well-received, with 53.08% of respondents strongly agreeing and 46.92% agreeing, demonstrating a high level of satisfaction with this feature overall.

These findings indicate not only user satisfaction but also demonstrate the system's readiness for deployment in real agribusiness environments, such as local markets or agricultural cooperatives. The relevance of the system is further underscored by its ability to support regional producers in reaching nearby consumers more effectively. This alignment between system functionality and challenges commonly encountered in agribusiness highlights its potential for wider implementation in agricultural digital platforms.

4. Conclusion

This work successfully developed and implemented the GMNCF model in an Android-based digital marketplace application for agribusiness. The model demonstrated superior performance in providing location-based recommendations with high accuracy, as evidenced by a comprehensive evaluation of Precision, Recall, F1-Score, and Hit Rate metrics. The resulting application offers a positive user experience, supported by relevant features and an intuitive interface.

These findings indicate that integrating geographical regions with GNN can significantly enhance recommendation quality in agricultural e-commerce systems. However, this work has several limitations. The dataset was limited to one geographical region, which may affect generalizability. Additionally, the current system assumes that user preferences remain constant over time, whereas, in practice, preferences in agribusiness can shift due to seasonal crop availability and planting cycles.

To overcome these challenges, future research can explore dynamic user modeling to capture evolving preferences, particularly those influenced by seasonal crop availability and agricultural cycles. Expanding the geographical scope of the dataset to include multi-regional data can also improve model generalizability. Moreover, integration with supply chain systems could further enhance operational efficiency for agribusiness stakeholders. Such advancements are expected to improve efficiency and competitiveness in the rapidly evolving digital agribusiness ecosystem.

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