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An Intelligent Business-to-Consumer Ecommerce Framework for Direct Agricultural Product Distribution

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***Abstract*—The rising demand for fresh, locally sourced agricultural products, along with the need for efficient distribution approaches, has prompted interest in direct-to-consumer ecommerce models within the agriculture industry. Existing agricultural distribution systems frequently incorporate intermediaries, resulting in inefficiencies, inflated costs and delays in the delivery of perishable goods. The development of advanced technologies, including artificial intelligence (AI), has facilitated the development of more efficient, transparent, and consumer-oriented agricultural distribution systems. This paper outlines the framework of an intelligent business-to-consumer ecommerce platform for the direct distribution of agricultural products using machine learning to improve shipments, transparency and user experience. The proposed framework analyzes key factors such as price, freshness, and shipping conditions to deliver customized product recommendations and improve shipment assignment. The intelligent product recommendation and shipment assignment ensures user preference as well as the freshness of perishable goods while reducing delays and transportation expenses. Also, the proposed framework comprises of overall conceptual framework including, data collection and preprocessing steps, feature extraction, the use of recurrent neural network and singular value decomposition to train data points and evaluation metrics such as RMSA, MAE, ranking quality and cold start testing to validate intelligent model efficiency. Also, it facilitates interaction between consumers and producers, promoting a transparent, efficient, and economical distribution process. The intelligent model continuously adjusts to customer preferences and market dynamics, improving efficiency in operation and user satisfaction.**

***Keywords*—Business-to-consumer ecommerce, Intelligent agriculture product distribution, Recurrent neural network, Agri-supply chain management, Intelligent shipment management.**

I. INTRODUCTION

Development in the ecommerce industry has emerged as a transforming agent in world trade which allows the seamless flow of products and services across digital platforms. However, due to lack of computational proficiency, limited infrastructure, and higher reliance on conventional supply chains, the agriculture industry lacks integration into this technological development [1]. Similarly, farmers in developing regions of the world have limited market access, which results in exploitation by intermediaries buying agriculture products at lower prices and reselling at substantially higher rates. While farmers battle lower profit margins, consumers are forced to pay higher prices for the same goods, this unequal income distribution affects both farmers and customers. A major issue in agriculture-based product distribution is the high perishability of fresh products, including fruits, vegetables, and meat respectively [2]. These products require efficient supply chain management to reach consumers at peak freshness.

However, due to market inefficiencies and logistical challenges across developing regions, farmers frequently suffer post-harvest losses when they are unable to sell their products in a timely manner [4]. This challenge is getting intensified in rural areas, where market access and adoption towards agricultural technology remains limited. Similarly, there are studies which highlight the potential of digital platforms to improve market connectivity for farmers.

According to Ali [3], a significant number of farmers in developing economies suffer financial losses due to unsold perishable crops, particularly tomatoes. Another study by [5] found that there are certain factors which influence consumer digital purchasing approach including consumer attitudes, digital literacy, and perceived behavioral control. The study suggested that a well-designed e-commerce platform could lead to a fair price mechanism allowing farmers to sell their products at good margins while ensuring consumers benefit from competitive pricing.

Additionally, a significant challenge to mitigate post-harvest loss (PHL) and higher product cost includes the moving of agriculture products through multiple interconnected intermediaries before reaching end consumers into the market, which leads to raising prices, compromised on freshness thus resulting in reduced profits for farmers and inflation with low quality product for consumers respectively. An efficient business-to-consumer ecommerce digital platform can replace this ineffective method by connecting farmers with consumers, which ensures mutual economic benefits for both parties. According to [6], a substantial markup of 10-40% is made on agricultural products as they transit via intermediaries for instance, a farm product originally priced at 1000 currency units could reach the consumer at 1500 or more after moving through interconnected intermediaries. Therefore, to enable direct selling, a business-to-consumer digital platform can ensure consumers pay only the price asked for by the farmers or producers, thus removing unnecessary inflated costs incurred by intermediaries. Moreover, farmers can gain better control over their selling behaviors, pricing strategies, market reach, and customer interactions, which encourages a more sustainable and equitable agricultural trade system. Considering these challenges, this study has proposed the framework for an intelligent business-to-consumer digital ecommerce platform which facilitates direct selling between farmers and consumers. The platform ensures reducing significant influence over intermediaries, and support farmers to receive fair market prices for their products directly while providing consumers with fresh agriculture products. Also, the study has proposed an optimized solution for effective supply chain to reduce PHL. The proposed solution improves farmers and consumers' buying and selling experience, to enable access to a well-structured, transparent and efficient marketplace.

II. LITERATURE REVIEW

Traditional agricultural supply chains are based on a multi-tiered distribution system where farmers sell their products to interconnected intermediaries such as wholesalers and retailers before reaching consumers. However, it often leads to inefficiencies, including high costs and significant PHL [7]. Similarly, farmers gained lower profits due to their high reliance on intermediaries, while consumers face inflated prices, lower quality and potential delays in accessing fresh products [8]. Additionally, the lack of real-time demand forecasting and supply chain transparency can contribute to shortages, which further has a negative impact on market stability. There are several studies which have highlighted the impact of direct business-to-consumer marketplace for agriculture markets which can help alleviate the inefficiencies of traditional distribution channels [9]. Also, numerous intermediaries typically add inflated costs to goods and increase delivery times. To enable farmers to sell directly to consumers, business-to-consumer platforms offers opportunities for farmers to retain a larger share of the retail price, while consumers benefit from reduced prices and improved access to locally grown, fresh produce [10]. Additionally, reducing the influence of intermediaries in agricultural distribution helps mitigate the impact of price volatility, which is a challenge for agricultural markets. Moreover, an ecommerce approach in agriculture serves as a transformation in fresh goods delivery by enabling direct selling between farmers and consumers through digital platforms. The study by [11] has figured out the negative aspects of downstream retailers such as supermarkets, hypermarkets, branded retailers etc. on the food distribution on farmers profitability. It has certain implications for such negative aspects including income inequality and overall farm production.

Similarly, mitigating the logistical challenges via emerging technologies such as blockchain for traceability, AI-driven logistics for optimized delivery routes, and data analytics for demand forecasting has gained its importance [12]. It supports reduces influence or dependence on intermediaries, improves efficiency, minimizes wastage, and improves price transparency. Also, developments in technology are essential to the advancement of business-to-consumer ecommerce platforms in agriculture. Artificial intelligence and machine learning are crucial in enhancing consumer experience, optimizing inventory management, and facilitating demand forecasting [13]. Furthermore, AI-driven recommendation systems have become integral components of ecommerce platforms, facilitating consumers in identifying products that align with their tastes. These algorithms examine historical purchasing data, seasonal trends, and local trends to forecast the things people are most likely to buy [14]. Another study by [15] has discussed the use of Internet of Things (IoT) to reduce the agri-waste due to ineffective supply chain and distribution for fresh agriculture products.

Additionally, AI is employed in agricultural supply chains to enhance harvest scheduling, facilitate efficient product distribution, and regulate inventory levels [16]. AI can forecast demand variations influenced by external factors including weather conditions, ensuring supply aligns with consumer requirements [17]. The combination of these systems enhances operational efficiency and reduces costs for both farmers and consumers, thus increasing the overall effectiveness of business-to-consumer agricultural platforms. Also, consumers can benefit from it for its convenience and access to local sources fresh products, while farmers gain fair price and an extended market reach. However, there are challenges associated with it, such as lack of digital infrastructure in rural areas, ineffective logistic structure, and the need for digital literacy among farmers needs to be addressed for a sustainable growth of ecommerce-based fresh agriculture product supply chain [18].

III. Methodology

The methodology to develop an intelligent business-to-consumer ecommerce framework for direct agricultural product distribution integrates emerging technologies, including machine learning, to improve efficiency, transparency, and consumer experience within the agricultural supply chain. The intelligent components of the system are designed to optimize various stages of product distribution, from order confirmation, shipment assignment to real-time tracking and product management. This section provides a detailed explanation of the architecture of the system, emphasizing the intelligent model that drives key decisions within the platform.

A. Conceptual Framework

The framework of the system comprises of interconnected components which work together to provide a seamless experience for both producers (farmers) and consumers (buyers). At the core of this system is an intelligent model that leverages multiple data inputs to make decisions regarding product recommendations and shipment assignment as shown in Fig. 1 which details on the overall architecture of the proposed framework while Fig. 2 elaborated on the flow of the proposed framework considering intelligent aspect of it. The model processes these parameters and adapts based on contextual data, consumer preferences, and shipment constraints. Also, it will facilitate product recommendations for consumers while optimizing shipment assignments for producers, ensuring efficient delivery of fresh, high-quality agricultural goods.

B. Intelligent Model for Product Recommendations

The intelligent model is designed to process several key parameters to generate product recommendations for consumers as shown in Fig. 3 which states the data collection and preprocessing steps, while also elaborating on both the content-based filtering and collaborative-based filtering to enable product-based recommendation. Similarly, the detailed process as shown in Fig. 4 explains the overall process for both the new and existing user(s). In case, if there is a new user then the recommendation will be based on content-based filtering since collaborative-based filtering considers user behavioral pattens to generate recommendations. On the contrary, the existing user will be provided with hybrid approach for recommendation in which both the content-based and collaborative-based filtering methods will be used respectively to generate recommendations. The content-based filtering considers existing content stored in the database for products while collaborative-based filtering considers behavioral data i.e. user clicks, views, purchases, dwell time etc. Additionally, the Fig. 3 and Fig. 4 connect directly to Fig. 2 which has highlighted the recommendation engine and shipment assignment parts as an overall aspect of it while the said diagram further details the insight of these proposed approaches.

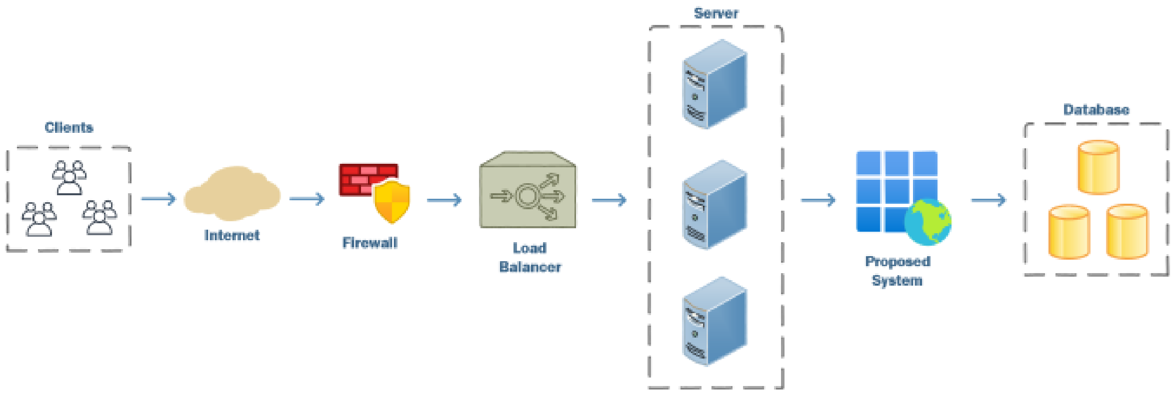

Fig. 1. Overall Conceptual Flow of the System

For the new user, the process starts with data gathering from existing metadata and (any) implicit feedback data i.e. clicks, view etc., then proceeds with preprocessing (checking for missing values, normalizing data and split into train/test sets) steps. The subsequent steps comprise of feature extraction such as TF-IDF (Term Frequency-Inverse Document Frequency) which is a statistical approach to evaluate the significance of a word towards a document in relation to a larger document collection. Also, word embedding will be applied to transform textual data into vector embedding to extract its meaning and relationship with other objects. The vector aggregation will be applied to determine the weighted average of the vector items by different categories i.e., ratings, confidence, recency etc. The similarity computation will then be applied using cosine similarity and inverted Euclidean distance to find the best matches based on common similarity measures. The model development will be followed by using singular value decomposition (SVD) [21] and recurrent neural networks (RNN) [22] to train data points. The SVD decomposes the vector matrix into subsequent matrices (three) to represent scaling singular values and other rotations, to determine the top n recommendations. The evaluation will be based on statistical validation metrics such as, RMSE, MAE; the quality of ranking using Precision@K, Recall@K, F-1 score, NDCG, MAP; the cold-start approach to see the initial outcomes of the recommendations to determine it working efficiency respectively.

For existing users, the process was similar with the data gathering and preprocessing step, however the flow begins from similar computation using cosine similarity to identify similarities among embedded vectors, then move on with model development using SVD and RNN to train data points. The model outcome brings top *n* generated predictions which will then be evaluated using statistical metrics such as RMSE and MAE; ranking quality and cold start testing respectively. In the real-world scenario, the process works in real-time to gather data from data sources such as databases or external resources, to continuously train the model for better prediction. This approach continuously improves the model efficiency and effectiveness to determine accurate recommendations of product to users based on their behavior and gathered data. It continuously learns from new data inputs and consumer interactions, allowing it to refine and optimize recommendations over time, improving the accuracy of the system's recommendation. Also, this real-time learning capability ensures that the platform evolves to meet changing market conditions and consumer preferences.

During model training the is a need to have certain parameters to train the model. The parameters considered to train models are as follows:

- **Price:** The intelligent model considers historical pricing data, market trends, and user purchasing behavior to recommend products which match the consumer's budget preferences. Similarly, dynamic pricing approaches adjust price based on factors such as weather seasons, demand fluctuations and available inventory.
- **Freshness:** As agricultural products are highly perishable, the intelligent model uses real-time data from data sources, to assess the freshness of products. Also, the system evaluates storage and transportation conditions to determine whether a product meets fresh standards before recommending it to consumers. This parameter ensures that only fresh products are suggested to buyers.
- **Shipment:** The model also considers shipment parameters such as expected delivery time, cost, and reliability of various shipping options. The ML model predicts the optimal shipping method for each order, considering factors such as quick delivery within the user's geographic location. This enables the model to recommend the best delivery option, balancing cost and speed while maintaining product quality.

C. Shipment Assignment and Optimization

On placing the order by the consumer, the intelligent model plays a crucial role in assigning the shipment to the appropriate courier partner. The intelligent shipment assigner is a key component of the system which uses recommendation engine to evaluate various shipment parameters as shown in Fig. 5 which includes the following:

- **Distance:** The system calculates the distance between the producer's location and the consumer's delivery address to optimize the shipment route.
- **Duration:** The model evaluates historical data on delivery times and considers current traffic patterns to predict how long it will take to deliver the product to the consumer.
- **Cost:** The model also assesses the cost of shipment options available in the shipping pool, considering the most cost-effective yet reliable method.

This data-driven approach ensures that the shipment is assigned to the most suitable courier partner from a pool that includes corporate partners, private riders, or the platform's in-house delivery service. Also, the intelligent model can dynamically adjust to real-time changing conditions such as route blockages or potential delays, providing alternative solutions when necessary. By optimizing the shipment assignment process, the intelligent model reduces delays and shipping costs, while maintaining the freshness and quality of the agricultural products.

D. Real-time Shipment Tracking

A significant aspect of the intelligent system is the real-time tracking of shipments. The tracking service integrates with the shipment assigner during transit, utilizing the collected data such as temperature, humidity, and location in real-time, by providing continuous updates on the condition of the products. Also, this data is fed into an intelligent model, which can predict the remaining time for delivery and provide alerts if there are any conditions, changes from the optimal range. Similarly, the consumers can access the tracking information via the platform, allowing them to monitor the status of their orders from farm to doorstep. The system uses machine learning models to predict any potential delays based on historical trends and current logistics data, alerting consumers ahead of time if an issue is detected. Additionally, producers and shipping partners can adjust shipment conditions dynamically, based on the real-time data, ensuring that the product maintains its desired freshness upon arrival.

E. AI-based Pricing and Market Analysis

The intelligent model is also responsible for dynamic pricing and market analytics. By continuously analyzing market trends, consumer preferences, and competitor pricing, the system can adjust product prices in real-time to maximize sales and profits. This dynamic pricing mechanism considers various factors, including seasonal changes in demand, competitor pricing strategies, and regional pricing preferences. Similarly, the machine learning models are utilized to detect patterns and predict future market shifts, allowing the platform to stay ahead of trends. For example, if a specific agricultural product is expected to see an increase in demand during a particular season, the system can adjust the pricing structure accordingly to capitalize on this demand. This level of price optimization ensures that producers remain competitive, while consumers continue to receive valuedriven offers. Additionally, market analytics play a significant role in helping producers understand consumer behavior and identify emerging trends in the agricultural sector. By accessing these insights, farmers and producers can tailor their product offerings to meet demand, improve both sales and customer satisfaction.

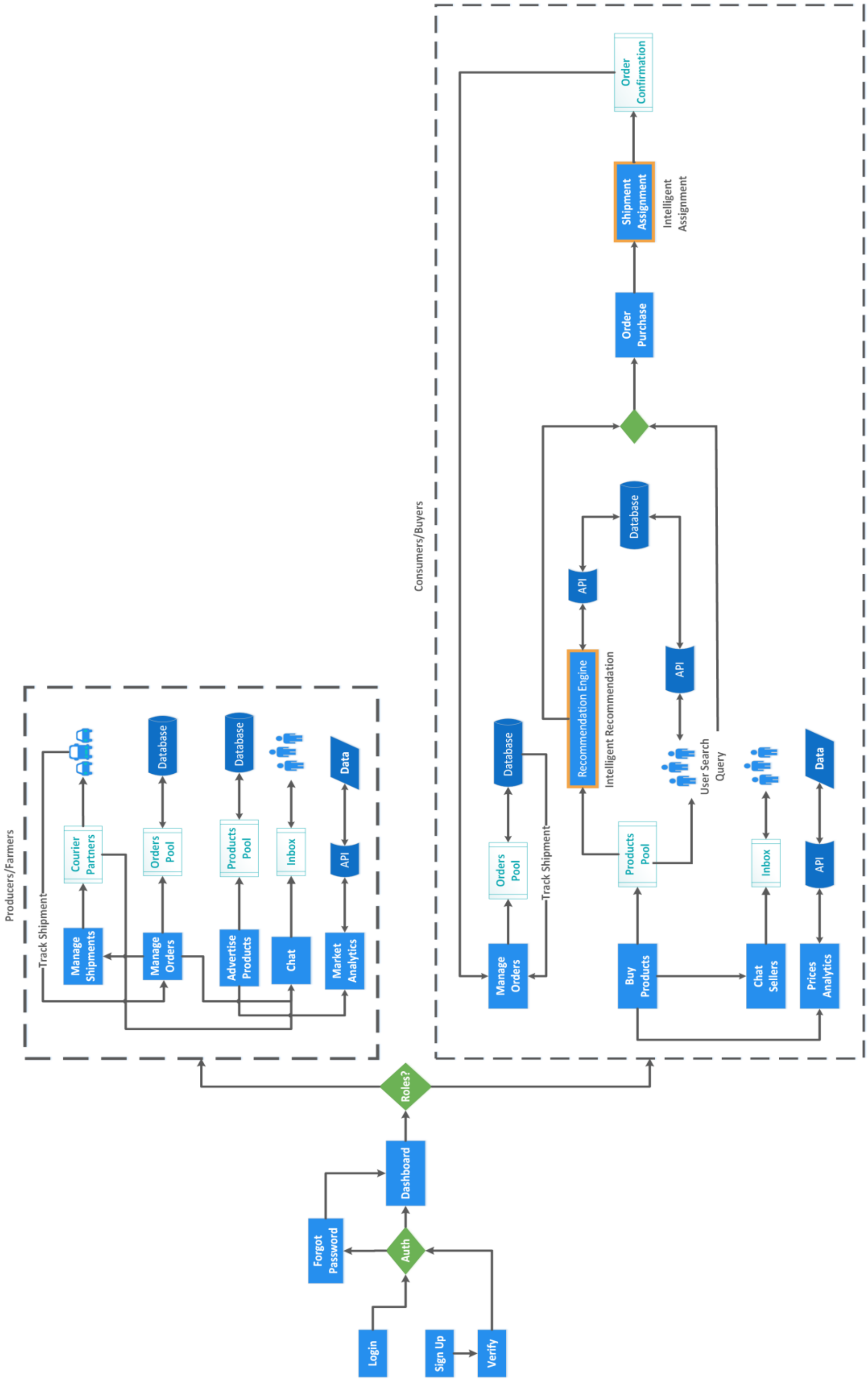

Fig. 2. Proposed Framework

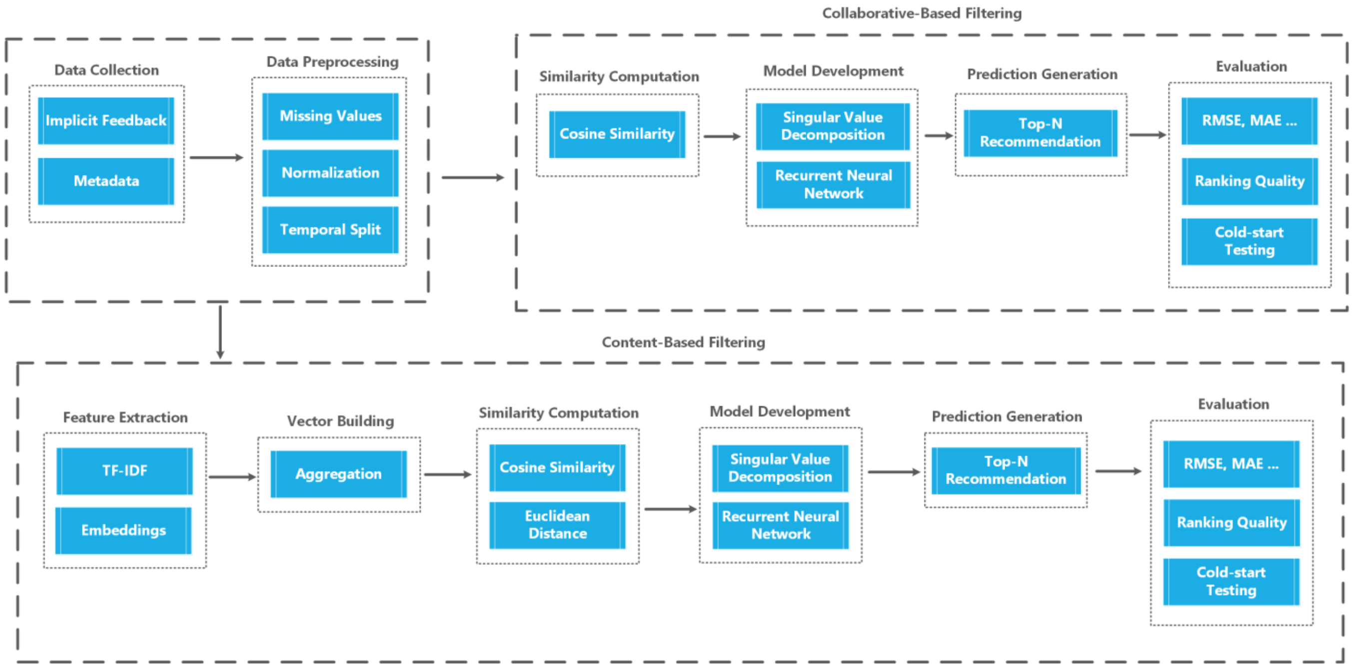

Fig. 3. Data preprocessing and recommendation engine process flow

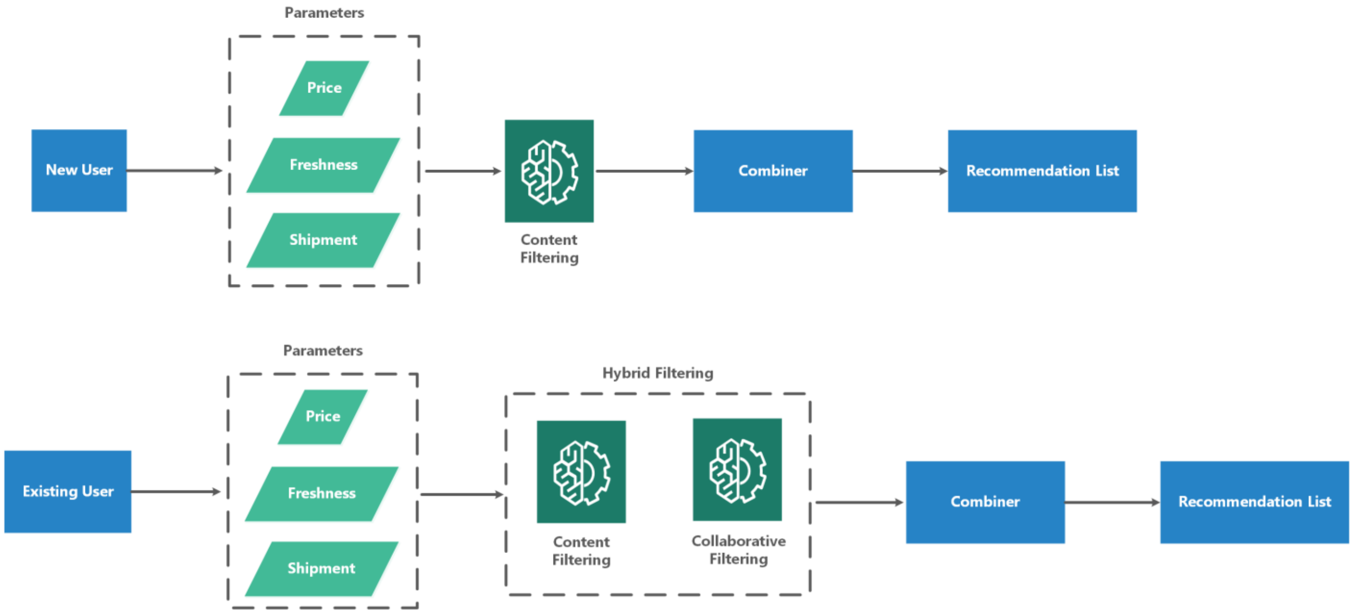

Fig. 4. Recommendation Process

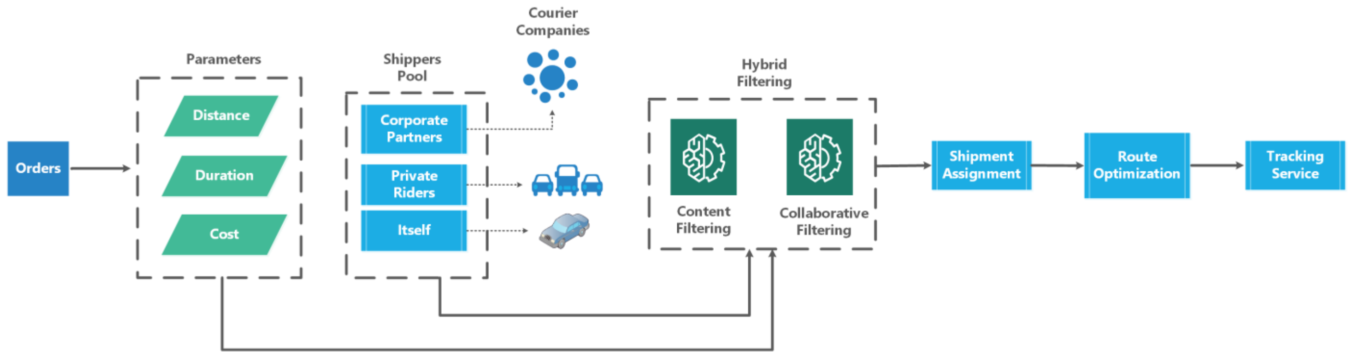

Fig. 5. Shipment assignment process flow

F. Consumer Interaction and Personalization

The intelligent model also plays a central role in personalizing the consumer's experience on the platform. The system tracks consumer behaviors via machine learning models such as browsing history, past purchases, and preferences, allowing it to tailor the user interface and product recommendations. For example, if a consumer consistently purchases organic products, the system will prioritize organic agricultural goods in the recommendations. Moreover, the intelligent model uses data about product demand and consumer preferences to optimize inventory management. If a product is popular among certain consumer groups, the system can predict its demand in the coming weeks and suggest re-stocking or promotional efforts to the producers. This demand forecasting helps to balance supply and demand, minimizing waste and ensuring that consumers can access the products they want. Also, the recommendation system becomes increasingly effective over time as the model learns from consumer interactions, leading to a more personalized shopping experience and higher satisfaction rates. Additionally, the system uses user ratings, feedback, and reviews to further enhance the recommendations by considering quality feedback alongside transactional data.

IV. DISSCUSSION

A. Intelligent Model Integration

The integration of an intelligent model that evaluates and processes multiple parameters such as price, freshness, shipment conditions, and logistical factors represent a critical feature of the system. The framework can optimize product recommendations utilizing machine learning-based on real-time data and consumer preferences. Also, this capability enables the system to cater to diverse consumer needs, providing them with personalized and relevant product options that improve their shopping experience. Furthermore, the ability of the model to assess shipment parameters, such as cost, distance, and duration, allows for more efficient use of resources and cost savings for both producers and consumers. This approach not only improves operational efficiency but also reduces the environmental impact by minimizing excessive resources on shipment.

B. Challenges in Product Freshness and Delivery Logistics

The key challenges in agricultural product distribution are maintaining product freshness during transit. Since agricultural goods are highly perishable, delays in shipment can lead to significant losses in quality and customer satisfaction [19]. The system design addressed this challenge by integrating real-time tracking features and shipment management tools which monitor certain parameters throughout the transportation process. Also, providing consumers with detailed information about the shipment's condition, the platform increases transparency and builds trust with users. Also, the use of machine learning to optimize delivery routes helps ensure timely and efficient shipments, improves further the possibility of enabling products to arrive in peak condition. Despite these advantages, shipment remains a major hurdle in the agricultural business-to-consumer ecommerce space. Last-mile delivery, particularly in rural areas, can be costly and inefficient [20]. The proposed framework addresses this issue by diversifying the available shipping partners, including private riders, corporate partners, and in-house shipping solutions. This flexibility allows the platform to adapt to various geographical regions and market conditions, ensuring that the delivery process remains cost-effective and efficient.

C. User Experience and Accessibility

User experience is crucial to the success of any ecommerce platform. The proposed system is designed with an emphasis on ease of use and accessibility for both producers and consumers. The inclusion of a simple yet functional interface that allows users to manage orders, track shipments, and communicate with sellers ensures a smooth experience for all stakeholders. Additionally, role-based authentication ensures that each user type has access to the specific features that meet their needs, further enhancing the system's usability. By offering a transparent and user-friendly platform, the system increases consumer confidence and develops long-term engagements.

D. Scalability and Security Considerations

Scalability is another important consideration in the design of the system. The platform is built to handle large volumes of traffic, with load balancers and multiple servers ensuring high availability and reliability. Additionally, the system architecture includes robust security features, such as firewalls and encrypted data storage, to protect sensitive user information and transaction details. This security framework is essential in building trust with consumers, who are increasingly concerned about the safety of their personal and financial data when shopping online. The proposed framework has the ability to scale and provide secure transactions ensures that it can accommodate future growth, whether in terms of user base or the geographic expansion on service areas.

E. Technological Innovations and Future Directions

The proposed framework comprises of cutting-edge technology, such as machine learning which contributes to its intelligent and efficient functionality. As these technologies continue to evolve, the framework can be improved with even more advanced features, such as predictive analytics, more personalized recommendations, and smarter inventory management systems. Future research could explore the integration of even more sophisticated technologies, such as autonomous vehicles or drones, to further streamline the delivery process. Additionally, expanding the platform's reach to global markets and enhancing the system's capabilities to accommodate different agricultural products and regional needs would be valuable areas for future development.

V. CONCLUSION

The intelligent B2C eCommerce system designed for direct agricultural product distribution, integrates a range of emerging technologies to optimize the agricultural supply chain. By utilizing machine learning, the system not only provides personalized recommendations and optimized pricing but also ensures the freshness of products through real-time tracking and dynamic shipment management. The intelligent model continuously learns and adapts based on real-time data, enhancing operational efficiency and improving consumer experience. Furthermore, the system's scalability and security ensure its ability to grow while maintaining high standards of data protection and performance. This intelligent approach to agricultural ecommerce offers significant improvements over traditional supply chain models, providing more efficient, transparent, and consumer-friendly distribution systems.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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