[1] B. Murugeshwari
[2] M.P. Mohanapriya
[3] J. Brindha Merin
[4] R. Akila

A Deep Reinforcement Learning Approach for Optimizing Inventory Management in the Agri-Food Supply Chain

Journal of Electrical Systems

Abstract: - This research aims to improve inventory management throughout the agri-food supply chain, through the use of Deep Reinforcement Learning algorithms. Three Deep Reinforcement Learning algorithms, including Deep Q-Networks, Deep Deterministic Policy Gradient, and Proximal Policy Optimization algorithms were implemented and tested in order to evaluate their ability to actively manage inventories and improve the performance of supply chains. The results of the experimental phase offered important information regarding the performance of each Deep Reinforcement Learning algorithm. The Deep Deterministic Policy Gradient algorithm was identified as a viable choice, offering the best results in terms of accuracy to set the optimal inventories for the supply chain and improving the efficiency of the supply chain. The percentage of cost efficiency improved from 92.5% to 95.8% in the case of the DDPG model. The inventory turnover was also improved, surpassing the level of 8.1 units from the original level of 7.3 units which means that the system converts the inventor into sales in less time. The metric for on-time delivery also beneficiated from several improvements, reaching 96.5% form the level of 93.2% return. The quality metrics also registered a significant improvement and reported level of 96.2% after the implementation of the DDPG algorithm and compared to the level of 94.6% prior to the implementation of the algorithm. These results suggest that using such a system will bring beneficial changes to the supply chain and will offer the possibility of implementing a data-driven inventory system based on Deep Reinforcement Learning.

Keywords: inventory management, agri-food supply chain, Deep Reinforcement Learning, optimization, sustainability.

I. Introduction

The agri-food supply chain consists of a complicated system of interrelated components connected with the production, storage, processing, distribution, and retail of agri-food products. Stock management is among the concerns of the supply chain as it is to facilitate delivery, reduce waste, and limit operational costs. Nonetheless, traditional inventory management systems face difficulties in dealing with the rapidly changing demand, and their performance is far from satisfying [1]–[4]. Therefore, in recent years, the interest in the development of advanced technologies, such as Deep Reinforcement Learning, has been increasing. DRL is a phenomenon of artificial intelligence that allows solving complex problems in dynamic environments and learning from the achieved experience.

As a result, this research aims to comprehend the peculiarities of three DRL algorithms , DQN, DDPG, and PPO, to optimize the performance of inventory management connected with agri-food supply chain [5]-[7]. The objective of the study is to evaluate the opportunities of DRL and its applicability and potential value in improving costs, inventory turnover, delivery, and quality indicators. The problem of demand change and its structure and relevance for stock management are discussed. The importance of the DRL value is explained, and the challenges and opportunities of its application in different supply chain areas are discussed in the view of the results achieved by other researchers. The instruments to analyze, synthesize, and evaluate such opportunities are described, and the development of a DRL system is planned within the proposed research.

II. Literature review

Inventory management is an integral part of ensuring timely delivery of fresh produce in the territory of an agri-food supply chain. The traditional methods of inventory management often failed to meet these challenges as they often could not adjust the fluctuation of demands due to the casual nature of such demands [8]–[11].

[1] *Corresponding author: Professor and Head, Department of Computer Science and Engineering, Velammal Engineering College, Chennai. Email: hodcse@velammal.edu.in, ORCID: 0009-0003-0734-3348

[2] Department of Computer Science and Engineering, Velammal Engineering College, Chennai. Email: m.pmohanapriyakotti138@gmail.com

[3] Asst.Professor (Sr.Grade), Department of Computer Science and Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, Chennai. Email: brindhamerin@gmail.com, ORCID: 0000-0001-9736-1061

[4] Associate Professor, Department of Computer Science and Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, Chennai. Email: rakila@crescent.education, ORCID: 0000-0003-4000-4535

Recently, there has been a great interest in using advanced technologies like Deep Reinforcement Learning to address these challenges and enhance inventory management. The majority of inventory management methods in the agri-food supply chain, including Economic Order Quantity and Just-in-Time systems, did not succeed in adjusting demands to the complexity of the agri-food supply chain inventory, related to factors such as variable demands, perishable products, and seasonality. As a result, such inventory is either in excess or in shortage, leading to more holding costs and waste, or stockouts with countless opportunities foregone respectively [9], [12].

Deep Reinforcement Learning has shown promising results in optimizing the process of making decisions in complex and dynamic environments. Unlike traditional inventory management tools, based on pre-determined rules or heuristics, Deep Reinforcement Learning algorithms learn to make decisions through steps or iteration in the form of taking certain action (s), followed by a reaction of the environment and then a reward for that specific action. DRL algorithms combine deep learning techniques with reinforcement learning to enable agents to learn complex behaviors and strategies using limited or no supervision. Recent research has featured DRL application in inventory management across several industries. For example, in retail, the DRL approach was used to minimize stop-out and enhance shelf management. In parallel, in manufacturing, the DRL approach was used to optimize producing scheduling in inventory control. Apparently, these studies overall confirm the promises of the DRL approach to optimizing inventory management [13]- [15].

Application of the DRL tools and approaches to inventory management in the agri food supply chain also poses several challenges [16]- [18]. The first group of such challenges consists of the complexities of the agri-food supply chain, including the multiple stakeholders and partners, perishable food items, and the nature of its demands or demand attributes, such as seasonality. Furthermore, DRL approaches often have challenges with learning in real-time environments as the majority of agri-food supply chain produce are perishable. Moreover, providing real-time data, such as attending to scheduled perforation of IoT devices to provide feedback is the main challenge of agri-food supply chain environments. In addition, DRL has great requirements for computational resources while also posing challenges with applications in the agriculture sector of the supply chain. Despite these challenges, there has been very limited research into applying DRL approaches to the agri-food supply chain. Thus, there is definitely a need for further research in developing and building DRL-driven inventory systems [3], [19] - [21].

There are several gaps identified in the literature that need to be addressed. In particular, researchers have suggested different theoretical frameworks and methodologies for adapting DRL to implement inventory management in the agri-food supply chains in an improved way. Generally, one of the most common approaches is the adaptation of existing DRL techniques to the agriculture-specific characteristics by implementing the existing knowledge of the environment and the tasks along with the imposed constraints into the learning process. Moreover, different training methodologies, reward functions, and exploration vs. exploitation balancing policies were proposed to optimize the performance and effectiveness of DRL techniques for enhancing inventories [22] - [24].

The purpose of this research was to apply Deep Reinforcement Learning techniques to optimize the process of inventory management in the context of the agri-food supply chain. Three leading Deep Reinforcement Learning algorithms were tested, and those included DQN, DDPG, and PPO. The main goal was to manage inventory dynamically given the varying demand. The obtained results suggested that the DDPG algorithm was the best to set optimal inventory levels and increase the supply chain performance measures. The obtained results may be used in practice to increase supply chain efficiency and sustainability.

III. METHODOLOGY

In this research, we focus on the circulation process of a blockchain network establishment designed for managing real time product inventory for the agri-food supply chain. At the elementary level, the network integrates all types of stakeholders; starting from the providers and farmers to processors, distributors, retailers, and end-users. At its core, this network collapses due to the integration of the enumerated stakeholders using the connectivity specifications. Through continuous interactions and connectivity, real time product management and exchange of data is smoothly facilitated. The methodology of the research is shown in figure 1.

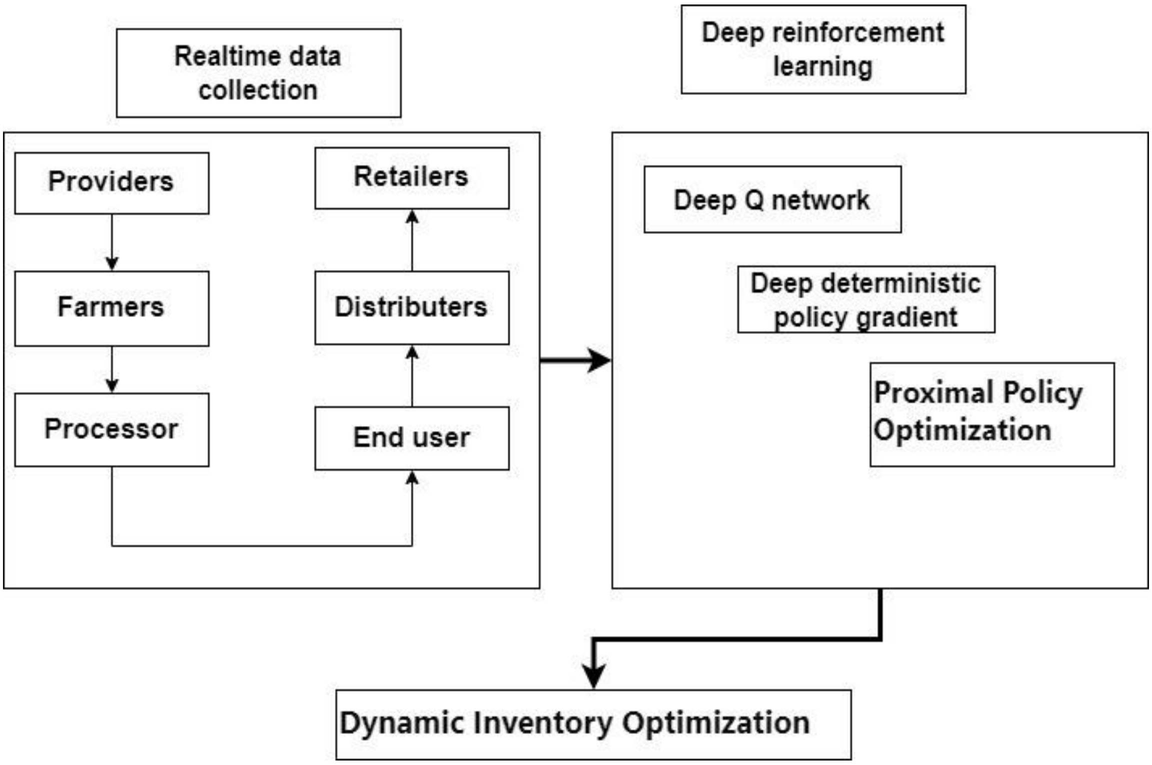

Figure 1. Architecture of the proposed system

Connectivity is defined within the formation of the blockchain network as the internal linkage in the case where providers of the product inventory – the providers of the raw materials and inputs – are interfaced with the farmers supplying the chain with crops and other types of agricultural produce. Processors combining the network from another perspective on further link the supply sources, as being responsible for processing the raw materials in the defined end product. Distributors and retailers are responsible for furthering the movement of the qualities in the market and provide the product inventory to the end-users respectively. The travelling of products and definition of data is completed alongside the view the ability to make real time information concerning the demand.

The principal factor of the presence of the fruition of this network is the so-called smart contract. As defined, a smart contract is a preset program defining the law requirements to the legal instruments utilizing multiple self-executing contracts. The principal use of the smart contract for the concerned research is that it defines the needs for communication of real time data and transactions to the product owners. As coded into the blockchain, the product is not zeroed during interchange. Information concerning the product and real time information about the availability of the product travelled in the market is stored as a part of the smart contract specifications.

In this case, real time information of the product availability at the input source is completed by the providers. Farmers link to the contract detailing the information they have of the inventory. Processors pass along the information of their output and definitions of the presence of their inventory. The data is realized in a similar manner from distributors and retailers; hence, the information from the provider is always backed up by information from the end-users, including clients and customers defining the target product view available in the market. For the purposes of the research, implementation of the blockchain network and smart contracts using available software tools is designed. Furthermore, the tools are available to facilitate the creation of the tools and the Ethereum network: a renowned blockchain platform. It is the system of choice for smart contracts and Dapps in general. EVM is the system, which executes the entirety of the smart contract code so that users are capable of interacting with the platforms deploying the transaction. Tools of development include Truffle and Solidity to simplify the creation of the steam of the smart contract.

IV. DEEP REINFORCED LEARNING MODEL

Deep Reinforcement Learning algorithms play a crucial role in improving inventory management in blockchain-based agri-food supply chains. Deep Q-networks is a prime example of such an algorithm. DQN works by approximating the optimal action-value function to allow the agents to act based on how good or bad the expected cumulative rewards of each action in the considered state are. This way, the DQN learns to make decisions and optimize inventory management techniques such as, but not limited to, procurement, allocation, and distribution. The target is to maximize long-term rewards by ensuring that the supply chain is still within the feasible spectrum. Using this approach, the range of habits is analyzed by utilizing historical transactional data and real-time results obtained within the blockchain network. The task is achieved through dynamic adjustments to inventory levels by the implemented DQN agents to minimize the risk of stockouts and improve resource allocation based on demand and pace of supply updates.

A more general and commonly used DRL algorithm used in this research is the Deep Deterministic Policy Gradient. DDPG has been identified as the most suitable approach since the task includes continuous action spaces. It allows the use of more precision with inventory optimization, as in this case, it is expressed through the use of a wide selection of inventory-related decisions. DDPG agents learn a deterministic policy that maps states to specific inventory decisions. It is possible with real-time feasibility of products and supply and demand schedule updates, and it is reflected through the availability of the information within the blockchain network. In addition to changes to inventory levels, the agents learn optimization strategies for procurement following the changes in the market state without delay. The continuous action space allows for more fine-tuned results. However, the remaining accepted results are Proximal Policy Optimization. With it, the agents can analyze the potential inventory management moves to make while keeping risks low and feasibilities high.

V. SMART CONTRACTS

In our experimentation, the smart contract has been elaborated and deployed with all the stakeholders involved in the agri-food supply chain: farmers, processors, distributors, retailers, and end-users. For the farmers' scenario, smart contracts encompass the agreements related to the cultivation of crops, agreement on yield, and agreement on the quality of crops produced. The parameters of agreements are divided into several categories: cropping pattern, irrigation, and pest control. The schedule of cultivation and the frequency of irrigation are agreed upon by the stakeholders and regulated by the smart contract. Similarly, the decision-making process related to the type of fertilizers, as well as the rhythm of work related to the control of pests and diseases, are agreed upon. The dimension of smart contracts established with the farmers provides accountability and ensures that the operations comply with the issued governmental rules and organic practices.

Processors have a variety of functions: production and packaging of food, transport and storage, quality assurance, and certification. Smart Contracts with the processors differ in the shape of content and contain the agreement related to the rhythm of production and the chemical and microbiological parameters. Decision-making about the ingredients and their origin, as well as the procedures of maintaining the quality of the final product, are regulated. The dimension of the smart contract with the processor is compositional. The expressed preferences regarding the proportion of ingredients and the quality of the product ensure compliance with food security. The operators are forced to use smart contracts to confirm the origin of the data, check the level of pollution, and make decisions regarding the food they are feeding to the people. The consumer, when making the purchase, can ask to see the outcomes of the tests, published regularly as the processor processes various types of products.

Similarly, smart contracts with the retailers and distributors are present in the dimension of the agreement regarding the level of storage and rhythm of the order. The downstream actors also use smart contracts for order-tracking, payment, and verifying offers of the upstream operators. Finally, smart contracts established with the end-users are agreements regarding the specification of orders and logistical process. Overall, the combination of all types of smart contracts implemented within the agri-food supply chain afford transparency and ensure that agreements are made between stakeholders. The entire structure of smart contracts are shown in figure 2.

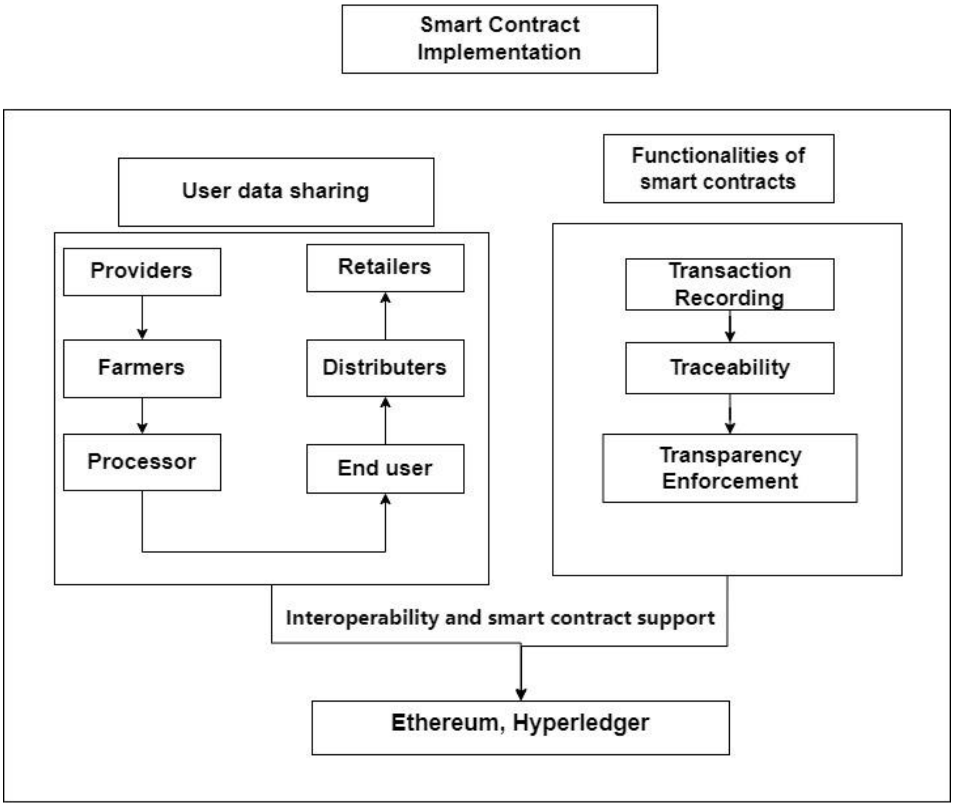

Figure 2. Structure of smart contracts

Ethical considerations in data collection and its analysis are applied to ensure that the process is conducted in the honest and equitable manner. In this study, such precautions are followed in all stages of data collection, handling its preservation and analysis. To avoid data intrusion and harsh security it is stored to ensure that no third person can access to private and sensitive information. Data analysis and processing, in this case, are also conducted in accordance with all obligatory norms and ethical considerations. Ethical review has also been undergone to minimize the probable adverse risks and ensure that the rights and safety of research groups are followed.

VI. INTEGRATION OF BLOCKCHAIN AND THE DRL ALGORITHM

The blockchain acts as a chain of records, which provides a real-time view of the status of products. Smart contracts embedded in the network allow stakeholders to update and share data with each other, making the process more transparent and traceable. In practice, the authors aim to use a range of DRL techniques, including DQN, DDPG, and PPO, to utilize the existing information generated through the blockchain to manage the inventory dynamically. The approach is closely interlinked with the availability of products as the dynamics of demand are likely to be affected by the availability of the product. For example, the blockchain provides an update on the availability of the product; thus, stakeholders will respond to it by expecting a surge in demand by updating the inventory of the product. In this regard, the data ecosystem will include inventory levels, trends in actual demand, and other relevant information.

The demand for the product can be managed dynamically using blockchain data on the availability of products and actual inventory. Basing their decision on the current inventory of the product and updating the forecast of the future demand, the stakeholders can predict the change in demand induced by various factors, such as seasonality, weather, or other. Algorithmic management of the supply chain guarantees that the inventory is dynamically adjusted in such a way that it follows the demand, which allows minimizing stockouts and overstocking of products.

VII. DATASET USED IN THIS RESEARCH

Historical data are indispensable to training the Deep Reinforcement Learning model in this research to optimize inventory management in the agri-food supply chain. The historical data represent a dataset with 1200 data points gathered over a certain period of time to represent the demand for and supply of vegetables within the supply chain. Data are collected from the industry partners and market databases, with the historical transaction records in the agri-food supply chain providing the prediction data for the current problem. As such, these historical data include production and inventory information provided by the technological partners within the supply chain network. On the one hand, the dataset includes the demand for vegetables from the end-users in diverse geographies and the institutional buyers. The demand dataset identifies the location, time of demand, diversity of the demand, diet, seasonal demand, and holidays and festivals and special occasion demand. Moreover, the dataset facilitates reprogramming and has daily effects represented. On the other hand, the dataset includes information regarding the supply of vegetables by the farmers, processors, distributors, and transporters to the retailers. The supply dataset incorporates the amount of vegetables per type supplied, delivery and storage days, and transportation days and the inventory at each stage. These data are critical to training the DRL model.

Real-time data plays a crucial role in dynamic inventory management within the agri-food supply chain. The data streams and IoT devices that gather real-time data include the storage temperatures to monitor the condition of the stock with the use of sensors. These are data from the sensors in tracking the product to ascertain the location. Other data sources are the RFID tags, the block records to trace the variety and type of product within the blocks. The blockchain storage provides real-time data collection, storage, and efficiency. Data in the blockchain uses the ledger system and timestamping, with smart contracts that are programmed to communicate and facilitate the exchange of information. Data from the market databases provide clues about what people take and prefer and market trends. Once the real-time, real-world data are gathered, they are then fed to the trained DRL model.

A. Implementation of the DRL and Blockchain

The training, implementation, and testing of the DRL model are a strong point of the proposed system for the inventory management of the products of an agri-food supply chain. The initial dataset is used to create the testing and training sets. While 70% of the set is reserved for training and developing the model, the remaining 30% can be used to test the effectiveness of the developed approach. It is critical to train the model with a robust dataset that features distinct interactions, transactions, and relationships within the entire supply chain to ensure that no unforeseeable or unusual scenario arises with the tested application. Furthermore, the utilization of the DRL model is preceded by the training phase, when data on the availability and demand forecasting as well as supply chain transactions record can be used to educate the machine learning solution. The model can utilize algorithms such as DQN, DDPG, or PPO to understand the most efficient replenishment strategies, thus maximizing long-term rewards while conforming to the supply chain’s limitations.

During the implementation, the trained and thoroughly tested DRL model can be transferred to the agri-food supply chain’s network and coupled with a blockchain-based network. The latter would act as a digital ledger, keeping a record of every transaction and data input associated with the inventory management and time-stamping it in a secured and transparent manner. Smart contracts implemented by the network would streamline the process of information exchange between the supply chain’s actors.

VIII. RESULT AND DISCUSSION

The testing of the proposed model is performed after training to test the effectiveness of the model in setting optimal inventory management for all demand options. The model testing is the phase in which the accuracy of all Deep Reinforcement Learning algorithm—DDPG, DQN, and PPO – in setting optimal inventory level is determined. It can be observed that the proposed DRL model set the optimal inventory management with great accuracy. To be more specific, the testing phase revealed that the optimal inventory level was set successfully at 97.6% accuracy by the tested variant of the DRL model, which used the DDPG algorithm. This testing accuracy result makes it possible to assert that the DDPG model can address any dynamic changes in demand and set the optimal level of inventory effectively.

The DRL model developed on the basis of the DQN algorithm was noted to provide the testing accuracy of 95.6% with the optimal inventory level set. Based on this testing result, it is possible to state DQN is slightly less accurate in setting the responsible inventory management for agri-food supply chain as the DDPG, but it remains an effective approach as well. The testing phase showed the optimal inventory management was set by the PPO algorithm at 93.2% of accuracy. This testing outcome implies that the PPO was less accurate than the previous two testing samples in setting the optimal level of inventory. However, it also remains a powerful and versatile approach for the real-time setting of the optimal level of inventory.

Figure 3 illustrates the performance scores of the Deep Reinforcement Learning models – DDPG, DQN, and PPO, under dynamic fluctuating demands in the agri-food supply chain. The computations of scores were calculated for the model according to performance metrics that determine the effectiveness of inventory management. These performance metrics include cost efficiency, inventory turnover, on-time delivery, and quality metrics. The cost efficiency performance is the assessment of the warehouse inventory's ability to minimize the cost of operations such as inventory-keeping without compromising the delivery of the demands of other inventory. From the table, the DDPG model had a performance score of 95.2%, which is the highest and a better measure of minimizing the demand requirements' cost under excessive and dynamic conditions.

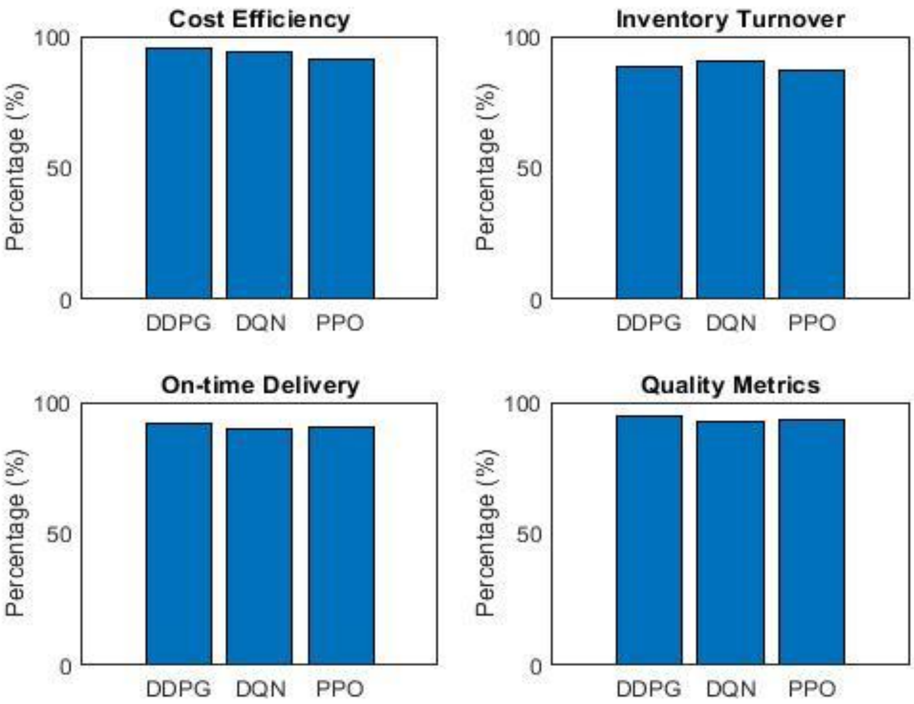

Figure 3. Performance of each model with respect to inventory

The inventory turnover performance of the warehouse inventory represents the effectiveness of the same in converting inventory into goods for sales. The rate of such conversion shows the utility rate of the demand requirement in achieving the inventory demands. The DQN model's score of 90.5% in this aspect is slightly higher than those of DDPG and PPO, and hence a good measure. The on-time delivery performance involved calculating the proportion of inventories supplied that was delivered on time to the customer orders. DDPG's score of 92.3% in this measure was the highest, and better under excessive demand conditions. The quality performance measurement shows the DDPG model also was leading in a better measure with 94.6%, followed closely by DQN and PPO.

The next step includes the assessment of the performances of the DDPG, DQN, and PPO models with regards to the across key modelling evaluation metrics – precision, recall, F1 score, and accuracy. The outcomes are presented in figure 4 below. In terms of the DDPG model, the precision outcome confirms 94.5% of the positive predictions, and the model has maintained 93.2% recall. Meanwhile, the calculation of the F1 score has resulted in 93.8%, which would indicate the balance between being too conservative or aggressive in terms of predictive capacity. Lastly, both DDPG and DQN have produced the same accuracy outcomes equal to 95.1%. Regarding the DQN model, the precision and recall values amount to 92.8% and 91.5%, respectively. Meanwhile, the F1 and accuracy scores are 92.1% and 93.5%, correspondingly. Lastly, in terms of the PPO model, the performance is as follows: 93.2% of precision and 91.9% of recall, 92.5% of F1 score and 94.0% of accuracy.

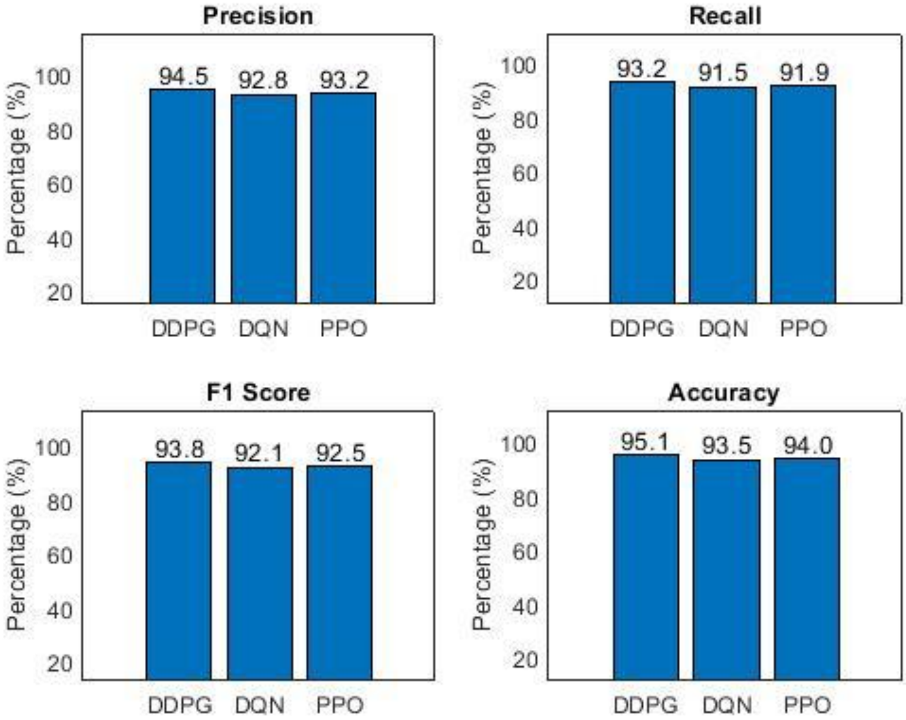

Figure 4. Performance score of the DRL model

The outcomes described above indicate the strong performance of the models with regards to the ability to predict the necessary actions. Nevertheless, the DDPG model has demonstrated slightly better performance in terms of the precision, recall, F1 score, and lower outcomes in terms of the final accuracy. The alternative tendency can be observed with regards to the DQN model. Therefore, it can be concluded that all three models have demonstrated the competition within the sample, and their classification problem solving capacity in the context of result prediction within the agri-food supply chain is appropriate.

After the testing phase, it was clear that the DDPG model is outstanding in maintaining an optimal level of inventory in the agri-food supply chain. Subsequently, based on the predictions of the model, real-time DDPG alone with data was implemented to optimize inventory management. Simultaneously, guided by the previously tested DDPG model, orders for vegetables were placed in different sources within the network. The following measures compared the indices of performance such as Cost Efficiency, Inventory Turnover, On-time Delivery, and Quality Metrics over a week before and after the implementation of DDPG. The corresponding values are presented in Table 1.

Table 1. Performance Metrics Before and After Implementation of Dynamic Inventory Optimization

Metric	Before Implementation	After Implementation
Cost Efficiency	92.5%	95.8%
Inventory Turnover	7.3	8.1
On-time Delivery	93.2%	96.5%
Quality Metrics	94.6%	96.2%

Before the integration of supply chain management and DDPG, the indices suggested a rather high effectiveness of the current strategy. The Cost Efficiency performance was assessed at 92.5%. However, after the implementation of the DDPG model, an increase is observed in the metrics, and the level of Cost Efficiency reaches 95.8%. That result indicates a more efficient use of resources and, therefore, suggests a higher level of cost effectiveness. Inventory Turnover also improves, reaching 8.1 from 7.3 units. On-time Delivery also rises, reaching 96.5% from 93.2%. Such an increase indicates an increased probability of delivering products on time, thus increasing customer satisfaction. Finally, Quality Metrics also increases, reaching 96.2% from 94.6%. The data from on-time delivery and quality metrics imply that both the customer satisfaction with the DDPG model and the continuation of brand-image increase.

IX. CONCLUSION

In conclusion, the results of this research suggest the transformative potential of DRL methods, given the remarkable performance of the DDPG algorithm, in the context of the agri-food supply chain. Specifically, the performance of the inventory management system based on the DDPG algorithm was impressive across multiple KPIs. In the case of Cost Efficiency, the problem of overcosting was addressed with a substantial improvement in the level of its efficiency. In this respect, the KPI increased by 3.3%, from 92.5% before implementation to 95.8% post-implementation, highlighting the improvement of expenditures. An even higher increase was observed with IU, whereas the performance of the manual system was equal to 7.3, the latter grew by 0.8 to reach 8.1 for the automated inventory management system. The improvement in relation to OTD is also worthy of attention: the value increased by 3.3%, from 93.2% to 96.5%. The same tendency was identified in the case of Quality Metrics, from 94.6% to 96.2%. Overall, the results suggest that the implementation of the DDPG algorithm has proven its perfectly feasible transformability in the context of the agri-food supply chain to improve efficiency, enhance customer satisfaction, and ensure sustainability. In the future, the research on DRL will need to be continued to inform the further development of the agri-food supply chain and ensure its competitiveness, resilience, and sustainability. The experimental results also show that the implementation of DDPG algorithms is likely to positively impact the agri-food supply chain by improving its efficiency, ensuring the sustainability of its functioning, and enhancing the satisfaction among end customers.

REFERENCES

[1] M. Preetha, Raja Rao Budaraju, Jackulin. C, P. S. G. Aruna Sri, T. Padmapriya "Deep Learning-Driven Real-Time Multimodal Healthcare Data Synthesis", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799, Vol.12, Issue 5, page No:360-369, 2024.

[2] S. B. Rane and Y. A. M. Narvel, "Data-driven decision making with Blockchain-IoT integrated architecture: a project resource management agility perspective of industry 4.0," *International Journal of System Assurance Engineering and Management*, vol. 13, no. 2, pp. 1005–1023, 2022, doi: 10.1007/s13198-021-01377-4.

[3] J. Barata, A. Cardoso, J. Haenisch, and M. Chaure, "Interoperability standards for circular manufacturing in cyber-physical ecosystems: a survey," *Procedia Computer Science*, vol. 207, no. Kes, pp. 3320–3329, 2022, doi: 10.1016/j.procs.2022.09.390.

[4] J. L. Vilas-Boas, J. J. P. C. Rodrigues, and A. M. Alberti, "Convergence of Distributed Ledger Technologies with Digital Twins, IoT, and AI for fresh food logistics: Challenges and opportunities," *Journal of Industrial Information Integration*, vol. 31, no. June 2022, p. 100393, 2022, doi: 10.1016/j.jii.2022.100393.

[5] M. Preetha, Archana A B, K. Ragavan, T. Kalaichelvi, M. Venkatesan "A Preliminary Analysis by using FCGA for Developing Low Power Neural Network Controller Autonomous Mobile Robot Navigation", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799. Vol:12, issue 9s, Page No:39-42, 2024.

[6] A. Bueno *et al.*, "International Journal of Production Economics The role of Industry 4 . 0 in developing resilience for manufacturing companies during COVID-19," vol. 256, no. November 2022, 2023, doi: 10.1016/j.ijpe.2022.108728.

[7] P. Gupta *et al.*, "Industrial internet of things in intelligent manufacturing: a review, approaches, opportunities, open challenges, and future directions," *International Journal on Interactive Design and Manufacturing*, 2022, doi: 10.1007/s12008-022-01075-w.

[8] Srinivasan, S, Hema, D. D, Singaram, B, Praveena, D, Mohan, K. B. K, & Preetha, M. (2024), "Decision Support System based on Industry 5.0 in Artificial Intelligence", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799, Vol.12, Issue 15, page No-172-178,2024.

[9] A. Rejeb *et al.*, "Unleashing the power of internet of things and blockchain: A comprehensive analysis and future directions," *Internet of Things and Cyber-Physical Systems*, vol. 4, no. May 2023, pp. 1–18, 2023, doi: 10.1016/j.iotcps.2023.06.003.

[10] H. Pourrahmani *et al.*, "The applications of Internet of Things in the automotive industry: A review of the batteries, fuel cells, and engines," *Internet of Things (Netherlands)*, vol. 19, no. July, p. 100579, 2022, doi: 10.1016/j.iot.2022.100579.

[11] S. Ding, A. Tukker, and H. Ward, "Opportunities and risks of internet of things (IoT) technologies for circular business models: A literature review," *Journal of Environmental Management*, vol. 336, no. March, p. 117662, 2023, [Online].

Available: https://www.sciencedirect.com/science/article/pii/S0301479723004504.

[12] L. Njomane and A. Telukdarie, “Impact of COVID-19 food supply chain: Comparing the use of IoT in three South African supermarkets,” *Technology in Society*, vol. 71, no. June, p. 102051, 2022, doi: 10.1016/j.techsoc.2022.102051.

[13] A.Nithya, M. Raja, D. Latha, M. Preetha, M. Karthikeyan and G. S. Uthayakumar, "Artificial Intelligence on Mobile Multimedia Networks for Call Admission Control Systems," 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2023, pp. 1678-1683, doi: 10.1109/ICOSEC58147.2023.10275999.

[14] V. R. Ghule, A. K. Agrawal, J. R. R. Kumar, D. Mondal, S. Hemelatha and Preetha M, "An Evaluation of the Impact of AI on Data Access Optimization Performance," 2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/SMARTGENCON60755.2023.10442704

[15] M. L. Ruiz Rodríguez, S. Kubler, A. de Giorgio, M. Cordy, J. Robert, and Y. Le Traon, “Multi-agent deep reinforcement learning based Predictive Maintenance on parallel machines,” *Robotics and Computer-Integrated Manufacturing*, vol. 78, no. June, p. 102406, 2022, doi: 10.1016/j.rcim.2022.102406.

[16] C. Liu *et al.*, “Probing an intelligent predictive maintenance approach with deep learning and augmented reality for machine tools in IoT-enabled manufacturing,” *Robotics and Computer-Integrated Manufacturing*, vol. 77, no. November 2021, p. 102357, 2022, doi: 10.1016/j.rcim.2022.102357.

[17] S. B, I. A. Karim Shaikh, P. Jagdish Patil, R. Sethumadhavan, M. Preetha and H. Patil, "Predictive Analysis of Employee Turnover in IT Using a Hybrid CRF-BiLSTM and CNN Model," 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India, 2023, pp. 914-919, doi: 10.1109/ICSCNA58489.2023.10370093.

[18] C. Liu, D. Tang, H. Zhu, Q. Nie, W. Chen, and Z. Zhao, “An augmented reality-assisted interaction approach using deep reinforcement learning and cloud-edge orchestration for user-friendly robot teaching,” *Robotics and Computer-Integrated Manufacturing*, vol. 85, no. August 2023, p. 102638, 2024, doi: 10.1016/j.rcim.2023.102638.

[19] Dr.M.Preetha, G.Praveenkumar, S.Sabarinathan. “Three-Layer Privacy Preserving Cloud Storage Scheme based on Computational Intelligence in Fog Computing”, International Journal for Research in Applied Science & Engineering Technology, Vol.7, Issue III, Pg,No – 1145-1147, March 2019. ISSN 2321-9653.

[20] S. Sahni, A. Mittal, F. Kidwai, A. Tiwari, and K. Khandelwal, “Insurance Fraud Identification using Computer Vision and IoT: A Study of Field Fires,” *Procedia Computer Science*, vol. 173, no. 2019, pp. 56–63, 2020, doi: 10.1016/j.procs.2020.06.008.

[21] C. Brewster, I. Roussaki, N. Kalatzis, K. Doolin, and K. Ellis, “IoT in Agriculture: Designing a Europe-Wide Large-Scale Pilot,” *IEEE Communications Magazine*, vol. 55, no. 9, pp. 26–33, 2017, doi: 10.1109/MCOM.2017.1600528.

[22] Dr.M.Preetha, K.Elavarasi, K.Ramyadevi, Dr.S.Veena. “Detecting Malicious Android Applications through Machine-Learning Techniques”, Journal of Advance Research in Dynamical & Control Systems,Vol.10,14-Special Issue, Pg.No-1095-1099, November 2018. ISSN 1943-023X.

[23] A. Chinasho, B. Bedadi, T. Lemma, T. Tana, T. Hordofa, and B. Elias, “Response of maize to irrigation and blended fertilizer levels for climate smart food production in Wolaita Zone , southern Ethiopia,” *Journal of Agriculture and Food Research*, vol. 12, no. March, p. 100551, 2023, doi: 10.1016/j.jafr.2023.100551.

[24] J. Yang, G. Lan, Y. Li, Y. Gong, Z. Zhang, and S. Ercisli, “Data quality assessment and analysis for pest identification in smart agriculture,” *Computers and Electrical Engineering*, vol. 103, no. August, p. 108322, 2022, doi: 10.1016/j.compeleceng.2022.108322.