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An Autonomous Self-Healing AI Architecture for Resilient Inventory Management Systems

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Abstract— The product should be made available to the customers at all times. However, the modern supply chains operate under uncertain circumstances because of fluctuating demand, supplier delays, transport delays, and operational interruptions. Traditional inventory management systems are largely dependent on some form of statistical forecasting and human intervention. This curtails their response to surprises. Self-healing artificial intelligence architectural framework that is autonomous and improves the resilience of an inventory system. The framework has an anomaly detection mechanism that employs the Isolation Forest technique. It then runs a decision engine that runs on reinforcement learning. Lastly, an automated recovery process is also done in this closed loop. The architecture constantly monitors inventory information, fetches anomalies, diagnoses disruption, and automatically takes corrective action. The experiment demonstrates that the suggested system can minimize stockouts, improve the recovery time, and increase the stability of the SC.

Keywords—Artificial Intelligence, Inventory Management, Self-Healing Systems, Supply Chain Resilience, Reinforcement Learning.

I. Introduction

Inventory management is a very important part of the supply chain operations since it influences the satisfaction of customers, service continuity and operating cost. Companies should make sure that they maintain adequate stocks to meet the demand without incurring unnecessary expenses that are related to keeping stocks. This balance is getting hard to keep in more complex global supply chains. This is because of unstable demands, uncertainty of suppliers, transport disturbances and breakdowns [1], [2], [4].

The key to traditional inventory systems is forecasting models, reorder rules and safety stock policies. Though these techniques have a fair performance in a stable condition, they are slow to respond to abrupt changes. In practice, the human manager should enquire into the matter, observe what might be the probable cause and proceed to take corrective action manually [1], [5].

With the evolution of the field of artificial intelligence, the chance of creating an inventory system remains to get better. We believe that a strong inventory system would be able to track the operations at any given time, identify abnormal behaviour and make corrective decisions on the fly. The huge amount of data in the supply chain can be filtered with models powered by AI to identify trends that remain hidden and responsive actions in unpredictable conditions [6], [7], [11].

Within huge chains of e-commerce and retail, the delays in delivery, cancellation of orders, and customer dissatisfaction can simply be the result of a minor mistake in what was listed and what was available. This has led to the need to have smart inventory systems to automatically identify and correct these anomalies. This study suggests a self-healing AI architecture to a resilient inventory management system.

II. Literature Review

Research has indicated that there is an increasing interest in the use of AI in supply chains and inventory management. Ivanov researched supply chain resilience and explained that a disruption in one area of the network can lead to a knock-on effect across the network [4]. Although this work is a strong resilience perspective, it does not have automated recovery.

Zhang et al. used AI-based demand prediction and demonstrated a better predictive capacity in retail environments [7]. Singh and Kumar use digital twins technology to model disruptions and study the behaviour of their supply chain despite external decisions being made by their framework [9]. Li and Zhao proposed how to align the various agents to enhance communication between the supply chain entities but the design did not incorporate anomaly handling and recovery as part of the design core [10].

Park and Lee noted that AI can enhance supply chain resilience, yet their framework does not take autonomous corrective actions [11]. The analysis of Zhao and Chen on the inventory system shows that AI can be used to detect abnormal patterns. Their model can only be used for detection and not recovery [12]. According to more recent

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studies on AI-enabled supply chains, deep learning for inventory optimization and logistics intelligence, there are robust improvements in predictive and operational efficiency, although the full self-healing capability is lacking [13]–[15].

According to this review, it is clear that there are four prominent gaps: (i) Anomaly detection is not integrated with decision making, (ii) Recovery is not automated, (iii) Not fully autonomous, and (iv) there is no closed-loop self-healing inventory system in general. Through the unification of detection, diagnosis, decision making, execution, and feedback learning, the proposed work fills these gaps.

Table I – Literature Comparison

Author	Method	Focus	Limitation
Ivanov [4]	Resilience Models	Disruption analysis	No automation
Zhang et al. [7]	AI Techniques	Demand prediction	No real-time action
Singh and Kumar [9]	Digital Twin	Simulation	No decision system
Li and Zhao [10]	Multi-agent Systems	Coordination	No anomaly handling
Park and Lee [11]	AI Framework	Supply chain resilience	No automatic correction
Zhao and Chen [12]	Anomaly Detection	Inventory monitoring	No recovery mechanism

III. Proposed System Architecture

The proposed architecture consists of a closed-loop system with monitoring, detection, diagnosis, decision-making, recovery, and feedback modules. They first collect and pre-process real-time inventory data such as stock levels, demand trends, supplier status, and warehouse activity. The analysis of these inputs is done through an Isolation Forest model to identify anomalies reflecting mismatched stock, demand spikes, or supply disturbances. [12]

After an anomaly is spotted, the diagnosis module assesses likely causes. A decision engine driven by reinforcement learning selects the best corrective actions, such as reordering, redistribution, or supplier switching. The action selected by a recovery module is executed while the feedback module updates the system state and improves future decision-making [3]. The figure illustrates the overall architecture. 1.

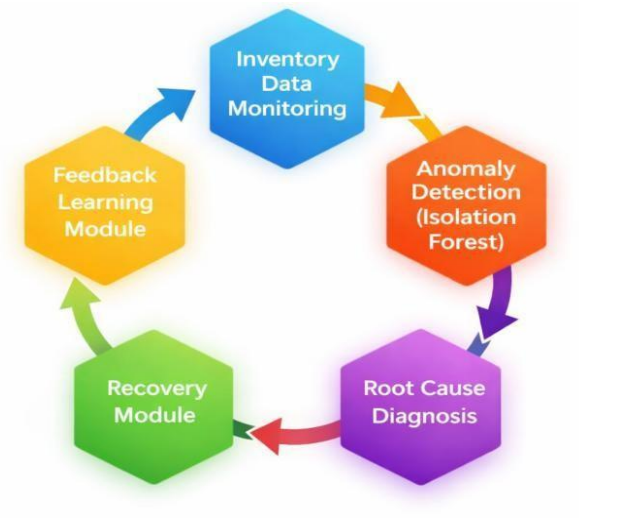

Fig. 1. Autonomous self-healing AI architecture for resilient inventory management.

IV. System Workflow

The operation workflow of the system starts with the inventory database, where the real-time information is updated continuously. The data stream is monitored. Accordingly, an observation is sent to the anomaly detection module. Once abnormal behaviour was detected, the diagnosis component analysed the disturbance and forwarded the interpreted status to the RL agent.

The decision engine selects the most advantageous recovery action and is informed by the system state, costs, and impact. The inventory database is updated, and the selected action is undertaken by the recovery execution module. Ultimately, performance feedback loops assess the outcome and refine future decisions, allowing the system to become more adaptive over time. As illustrated in the figure. 2.

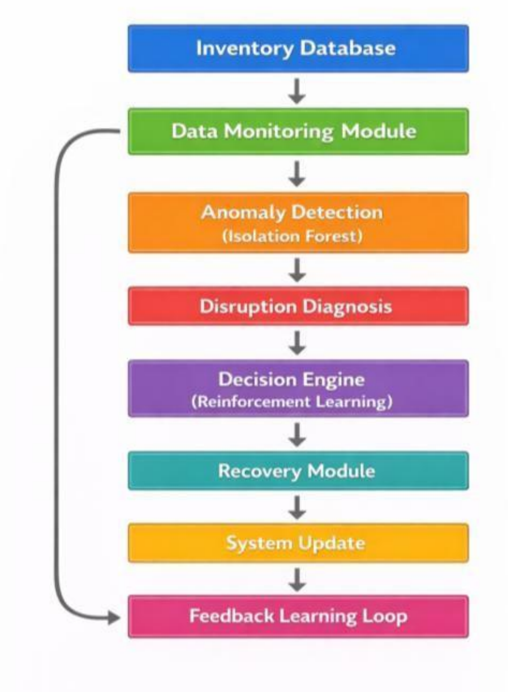

Fig. 2. Closed-loop workflow of the proposed inventory self-healing system.

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V. Algorithm Design

The model is based on two core AI techniques which are Isolation Forest for anomaly detection and reinforcement learning for actions. Isolation Forest separates observations through repeated random partitioning of datasets. Data points that get isolated through minimal steps are suspected to be anomalies since they deviate considerably from the normal behaviour [12].

The reinforcement learning agent tracks the existing inventory level, which is in the recovery stage, and takes some action out of a predefined set of possible actions, like reorder, redistribution, supplier adjustment, delay action. The reward function examines each action based on stock stability, continuity of service, speed of recovery and cost. Through repeated interaction with the environment, the agent learns a policy that builds operational resilience [3].

VI. Experimental Results

To evaluate the proposed framework, simulation-based experiments were conducted by contrasting an AI-based self-healing system with a traditional inventory management system. The things that were compared to are stockout control, speed of decision making, anomaly response, and adaptability under disruption conditions.

The suggested system enhances efficiency and effectiveness as compared to the previous systems. Through early detection of anomalies, it lowers stockout rate; via automatic decision making, it lowers recovery time; and via lessons learnt, it increases adaptability. The potential of anomaly detection and reinforcement learning can significantly fortify the ability for supply chain resilience, as seen in [11], [13], [14].

Table II. Comparison of Traditional and AI-Based Inventory Systems

Parameter	**Traditional System**	**Proposed System**
Decision Making	Manual	Automated
Stockout Control	Moderate	Improved
System Adaptability	Low	High
Supply Chain Resilience	Limited	Strong

Table III. Performance Improvement

Metric	**Traditional System**	**Proposed System**	**Improvement**
Stockout Rate	High	Low	Reduced
Recovery Time	Slow	Fast	Improved
Detection Accuracy	Medium	High	Increased
Decision Automation	Manual	Automatic	Fully automated

VII. Future Scope

Future studies might broaden the present system with use of IoT sensors from warehouses, transport fleets, and fulfilment centres so that the system can react to disturbances quickly and accurately. The framework is based on the use of information sharing backed by blockchain to enhance traceability, trust, and transparency among partners in a supply chain.

Future efforts could be directed towards large-scale industrial validation using real datasets as well as the integration of digital twin models with deep learning architectures for more effective prediction, scenario analysis, and adaptive decision-making [9] [14].

VIII. Limitations

Though the results reveal that the proposed architecture is effective, it has several limitations.

Each experiment is conducted in a virtual system with given parameters and disruption patterns are controlled. In the real world, supply chains are larger and consider the supplier relationships and contracts up to other levels. Deployment in the field is necessary to check its performance in real life conditions.

They need to be of high definition and with less latency in real-time all data and quality requirements. The integration of data between warehouse management and supplier systems in most organizations are either delayed or piecemeal to the ERP systems. Quality of data is key to the anomaly detection module and non-existent data or typographical errors can create false positives or cover up defects.

The Q-network itself has to be trained on representative past data offline before it can be implemented. Since an organization might not have information concerning previous disruptions, its performance at first can be low. Transfer learning on the products of similar categories can be used to overcome this limitation, but it needs additional validation.

The currently considered action set is based on the assumption that the system is authorized to take up measures like changing suppliers and fast ordering. As a matter of fact, these acts could either be approved or restricted by contracts. These architectures can be extended with the approval workflow but at the cost of autonomy.

Flexibility towards Multiple-Product Systems. The system in place is only one-product-based. Hierarchical RL or attention mechanisms control over thousands of SKUs (Stock Keeping Units) would be necessary, owing to

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computational complexity and interference of product policy.

IX. Conclusion

Through the autonomous self-healing AI architecture, the study was conducted. The framework can automatically perform repairing actions through reinforcement learning-based action selection to diagnose the fault, and analyze the disruption with anomaly detection based on Isolation Forest.

Results overall show that, compared to traditional inventory, architecture can increase operational efficiency, decrease stockouts and improve supply chain resiliency. Consequently, the framework offers an effective and scalable base for future inventory systems under dynamic and uncertain environments.

X. Future Work

Various future research directions are promising as a result of the work.

IoT Integration (Internet of Things) -Implementing Internet of Things (IoT) sensors in warehouses and at retail points would allow real-time inventory tracking and would allow physical events (e.g., temperature variations, damage to products) to be detected, which might impact product availability. The space of abnormality detection may also be enriched with IoT data.

Blockchain to Transparency — Smart contracts on blockchain networks have the potential to compute supplier selection and payment conditions when taking recovery measures, and would enhance trust and decrease settlement time. Indirectly, the self-healing architecture would invoke smart contracts in the event of supplier switching as a recovery measure.

Real-World Deployment -- In collaboration with industry partners, Collaborative pilots will be implemented to prove the architecture under live supply chain conditions. These pilots will also produce datasets to use in benchmarking and refining.

High Reinforcement Later Improvements — Deep Q-Networks (DQN) can mechanize sample efficiency and stability by adding a prioritized experience replay and dueling designs. Proximal Policy Optimization (PPO) could be better than Q-learning when dynamic pricing policies or quantity changes are added to the model.

Multi-Agent Self-Healing Systems - The generalization of the architecture to multi-echelon supply chains, where self-healing agents aren't unique to any single node, and coordination mechanisms are used to stop local behavior that is suboptimal, is an important research direction. Communication protocols based on Multi-agent RL might be able to provide system-scale resilience.

Explainable AI to Operator Trust Explanations to humans of anomaly detections and recovery actions suggested will be required to be adopted in safety- or high-value supply chains. SHAP (Shapley Additive exPlanations) values and natural language generation will be combined in future work to generate actionable insights.

Transfer Learning Across Products — Transfer learning techniques that would enable a policy trained on one product or supply chain to be reused on another one would offer high-speed training and faster training deployment.

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