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Inventory Management with Deep Q Learning and Genetic Analytical Hierarchical Process

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Abstract: The contemporary landscape of inventory management, particularly in the realm of imperfect production, necessitates innovative approaches to enhance efficiency and accuracy. Existing models often grapple with limitations in handling ameliorating and deteriorating items simultaneously, and lack sophistication in adapting to dynamic market conditions. This study introduces a groundbreaking model that addresses these challenges, blending the theoretical and practical aspects of inventory management under varying pricing policies. Our proposed model is a synthesis of advanced methodologies: it leverages Deep Q Learning for solving intricate inventory tasks, marking a significant leap over traditional models in terms of flexibility and adaptability. By considering both ameliorating and deteriorating items, it presents a more comprehensive framework for inventory management. Additionally, the integration of Genetic Analytical Hierarchical Processing for item preservation showcases an innovative approach to mitigate deterioration rates effectively. A pivotal component of our model is the application of the Apriori Model for market-driven recommendations. This facet underscores the model's responsiveness to fluctuating market dynamics, ensuring that pricing strategies are both relevant and optimized. Tested on electronic and healthcare products, our model demonstrated superior performance over existing methods, with improvements of 3.9% in precision, 4.5% in accuracy, 8.5% in recall, 3.5% in AUC, 2.9% in specificity, and a notable 4.9% reduction in delay. The impacts of this work are manifold. It not only elevates the precision and efficacy of inventory management in imperfect production contexts but also offers a pragmatic and effective solution adaptable to real-world scenarios. The model's enhanced predictive capabilities and responsiveness to market trends set a new standard for inventory management strategies, particularly in sectors where product deterioration is a significant concern. This study not only fills a critical gap in the existing literature but also paves the way for more nuanced and sophisticated approaches to inventory management in diverse industrial domains.

Keywords: Inventory Management, Deep Q Learning, Genetic Analytical Hierarchical Processing, Ameliorating Items, Deteriorating Items

1. Introduction

The realm of inventory management is perpetually evolving, with the emergence of new technologies and methodologies that seek to optimize the handling of goods in various stages of their lifecycle. In particular, the management of imperfect production inventory, where items may be subject to amelioration or deterioration, presents a complex challenge that requires innovative solutions. The integration of artificial intelligence and advanced analytical methods into inventory management strategies holds the potential to revolutionize how businesses approach these challenges. Traditionally, inventory models have focused on either ameliorating or deteriorating items but seldom address both simultaneously. This oversight limits the applicability of such models in real-world scenarios where a mix of such items is the norm, especially in industries like electronics and healthcare. Moreover, the dynamic nature of market conditions necessitates pricing policies that are adaptive and responsive, a feature that conventional inventory models often lack.

The advent of Deep Q Learning in the field of artificial intelligence offers a promising avenue for developing more sophisticated inventory management models. This technique, rooted in the principles of reinforcement learning, allows for the handling of complex, dynamic systems in a way that traditional algorithmic approaches cannot match. By applying Deep Q Learning, inventory models can learn and adapt to changing conditions, leading to more efficient and effective management strategies. Another groundbreaking approach is the application of Genetic Analytical Hierarchical Processing (GAHP) in preserving items, particularly in reducing deterioration rates. This method combines the robustness of genetic algorithms with the structured decision-making process of analytical hierarchical processing, providing a sophisticated tool for item preservation strategies.

The proposed model aims to fill the gap in the current literature by offering a comprehensive solution that addresses both ameliorating and deteriorating items, equipped to adapt to varying market conditions through the Apriori Model. The integration of these advanced methodologies not only enhances the model's accuracy and efficiency but also makes it highly relevant to real-life scenarios.This paper delineates the development and application of this novel inventory management model, detailing its theoretical underpinnings, methodological advancements, and practical implications. The focus is on demonstrating how the blend of Deep Q Learning with GAHP, coupled with market-responsive pricing strategies, can significantly improve inventory management outcomes. The success of this model in handling electronic and healthcare products, as evidenced by its superior performance metrics, exemplifies its potential and sets a new benchmark for inventory management strategies in the context of imperfect production.

Motivation and Contribution:

The motivation for this study stems from the recognition of significant gaps in current inventory management practices, particularly in the context of imperfect production. Conventional inventory models are often rigid and fail to account for the dual nature of items that can either ameliorate or deteriorate over time. This limitation is especially pronounced in fast-paced industries like electronics and healthcare, where product lifecycles are critically short and market dynamics are constantly shifting. The need for a more dynamic, responsive, and inclusive inventory model is not just academic but a practical imperative to enhance operational efficiency and market responsiveness.

Our contribution to this field is multi-faceted and significant:

- **Dual Nature Approach**: We address a critical gap in inventory management by proposing a model that simultaneously considers ameliorating and deteriorating items. This dual nature approach is innovative in its inclusivity, ensuring that a wider range of inventory scenarios can be effectively managed.

- **Integration of Deep Q Learning**: By incorporating Deep Q Learning, we introduce the power of advanced artificial intelligence into inventory management. This approach allows the model to learn from and adapt to complex inventory scenarios, leading to more accurate and efficient decision-making processes. It represents a significant leap from traditional static models to dynamic, learning-oriented systems.

- **Genetic Analytical Hierarchical Processing for Item Preservation**: The application of GAHP for item preservation, especially in managing deterioration rates, showcases our commitment to practical and effective solutions. This method not only enhances the longevity of inventory items but also introduces a structured yet flexible approach to inventory preservation strategies.

- **Market-Responsive Pricing Strategies**: Utilizing the Apriori Model for pricing decisions marks a novel approach in aligning inventory management with real-time market trends. This ensures that the inventory model is not only efficient in managing stocks but also savvy in responding to market demands, a critical aspect in the competitive business landscape.

- **Empirical Validation and Superior Performance**: The testing of our model on electronic and healthcare products, yielding significant improvements in precision, accuracy, recall, AUC, specificity, and delay reduction, underscores its practical effectiveness. These metrics are testament to the model's superiority over existing methods and highlight its potential for wide-ranging applications.

- **Theoretical and Practical Implications**: Our study bridges the gap between theory and practice in inventory management. Theoretically, it advances the understanding of how AI and genetic algorithms can be synergistically used in inventory management. Practically, it offers a tangible, tested solution for businesses grappling with the complexities of managing ameliorating and deteriorating items under fluctuating market conditions.

2. Literature Review

The domain of inventory management, particularly in the context of imperfect production and dynamic market conditions, has witnessed significant advancements, as evidenced by recent scholarly contributions. A critical analysis of these contributions not only underscores the evolution of inventory management strategies but also highlights the areas where the proposed model introduces novel enhancements.

Chen, Fan, and Sun (2023) in their work [1] emphasize the importance of leveraging multisource heterogeneous information in inventory management. They explore the roles of representation learning and information fusion, which aligns with the proposed model's integration of diverse data inputs for decision-making. This approach is pivotal in handling the complexities of inventory tasks, especially in rapidly changing market scenarios. Raghuram et al. (2023) [2] delve into modeling and analyzing inventory levels amidst demand uncertainty, a challenge that the proposed model addresses using Deep Q Learning. Their evidence from biomedical manufacturers provides insights into managing uncertainties, a concept that is intrinsic to the proposed model's capability in handling ameliorating and deteriorating items.

Sadeghi et al. (2023) [3] employ the Grey Wolf Optimizer and Whale Optimization Algorithm for stochastic inventory management, particularly focusing on reusable products. This perspective complements the proposed model's GAHP component, which focuses on optimizing item preservation strategies. Xu, Kang, and Lu (2023) [4] approach inventory management from the perspective of omnichannel retailing, addressing joint inventory replenishment and dynamic pricing issues. Their emphasis on customer experience resonates with the proposed model's use of the Apriori Model for market-driven recommendations, ensuring that inventory decisions align with customer demand patterns.

Chen et al. (2023) [5] address the bullwhip effect in supply chain systems, focusing on time-varying delays. Their robust control approach using a discrete-time method provides a foundational understanding that enhances the proposed model's effectiveness in reducing delays in inventory management processes. Adamiak and Zwierzchowski (2023) [6] propose a novel demand profile for inventory systems using model reference-based sliding mode control. This concept of adapting to varying demand profiles is inherent in the proposed model, especially in its ability to respond to market dynamics.

Wang et al. (2023) [7] explore single-site perishable inventory management under uncertainties using a deep reinforcement learning approach. Their findings are particularly relevant to the proposed model's deep Q-learning framework, highlighting its efficacy in managing perishable items for different use cases. Ata and Corum (2023) [8] investigate the impact of return disposal on order variance in hybrid manufacturing and remanufacturing systems. Their insights into how returned products influence inventory dynamics are particularly relevant to the proposed model, which aims to optimize inventory management by considering such complexities in the supply chain.

Schrettenbrunner (2023) [9] explores artificial intelligence in managing inventory strategies, emphasizing autonomous, real-time decision-making. This aligns with the proposed model's use of Deep Q Learning and Genetic Analytical Hierarchical Processing, underscoring the importance of AI-driven approaches in modern inventory management. In their comprehensive survey, Asante et al. (2023) [10] delve into the role of distributed ledger technologies in supply chain security management. Their findings highlight the potential of integrating advanced technologies for enhancing transparency and security in supply chains, a concept that resonates with the proposed model’s emphasis on data-driven decision-making process.

Yan et al. (2023) [11] focus on reliability-driven multiechelon inventory optimization, particularly for service spare parts in wind turbines. Their approach to tackling the challenges in multi-echelon systems provides valuable insights into the complexities addressed by the proposed model, especially in terms of managing inventory across different stages of the supply chain. Farraa, Abbou, and Loiseau (2023) [12] present a study on predictive feedback control for inventory systems, particularly those subject to delays and constraints. Their methodology complements the proposed model’s objective to reduce delays and enhance responsiveness in inventory management processes.

Masnavi et al. (2023) [13] introduce Visibility-Aware Cooperative Navigation (VACNA) in the context of inventory management. The application of such innovative navigational technologies offers a perspective that could enrich the proposed model, particularly in automating and optimizing physical inventory handling scenarios. Qaffas et al. (2023) [14] explore interpretable multi-criteria ABC analysis using semi-supervised clustering and explainable AI. Their approach to making inventory classification more interpretable and data-driven mirrors the proposed model's commitment to leveraging advanced analytical techniques for inventory management.

Lastly, Chen et al. (2023) [15] discuss supply chain planning for IC design house back-end production networks, offering insights into the complexities of inventory management in high-tech industries. Their findings provide a valuable context for understanding the proposed model’s applicability in sophisticated, technology-driven environments. Hariga, As’Ad, and Ben-Daya (2023) [16] explore a Vendor-Managed Inventory (VMI) partnership under individual carbon-cap constraints, emphasizing the growing importance of environmental considerations in supply chain management. This study aligns with the proposed model’s focus on sustainability, particularly in managing inventory with a keen awareness of ecological impacts for different scenarios.

Xia and Li (2023) [17] delve into robust control strategies for uncertain dual-channel closed-loop supply chains, incorporating process innovation for remanufacturing. Their approach to handling uncertainty complements the proposed model’s utilization of Deep Q Learning, which is adept at navigating uncertain and complex inventory scenarios. Gupta et al. (2023) [18] address bilevel programming for manufacturers in an omnichannel retailing environment, highlighting the challenges of managing inventory across multiple channels. This is particularly relevant to the proposed model’s integration of the Apriori Model for market-driven recommendations, ensuring adaptability in diverse retail contexts.

Alrasheedi (2023) [19] investigates credit policy strategies for green products with expiration date-dependent deterioration, employing the Grey Wolf Optimizer. This study’s focus on perishable products and environmentally conscious practices resonates with the proposed model’s emphasis on managing ameliorating and deteriorating items effectively for different use cases. Shi and Mena (2023) [20] present a Bayesian network-based method for assessing supply chain resilience with financial considerations. Their methodology underscores the importance of resilience in inventory management, a concept central to the proposed model’s objective of enhancing inventory accuracy and responsiveness.

Panda and Mohanty (2023) [21] explore time series forecasting and modeling of food demand in supply chains, emphasizing the need for accurate demand prediction. This aligns with the proposed model's use of advanced analytics for predictive insights, crucial for effective inventory management. Wan et al. (2023) [22] investigate privacy-preserving operation management in battery swapping and charging systems, employing a dual-based Benders Decomposition approach. Their focus on privacy preservation complements the proposed model's emphasis on secure and data-driven inventory management strategies.

Chen and Shen (2023) [23] propose fast approximations for dynamic behavior in manufacturing systems with regular orders, introducing an aggregation method. This approach to handling dynamic and complex manufacturing environments is akin to the proposed model's ability to adapt to varying market conditions. Ge et al. (2023) [24] present a novel semi-supervised contrastive regression framework for forest inventory mapping, leveraging multisensor satellite data. Their innovative use of technology and data in inventory management provides insights that can enhance the proposed model's data integration capabilities. Lastly, Xiaoyi et al. (2023) [25] focus on optimizing replenishment based on order structure in combined automatic warehouse systems. Their findings on efficient replenishment strategies offer valuable perspectives that can inform the proposed model, particularly in automating and optimizing inventory replenishment processes. Collectively, these studies underscore the multifaceted nature of modern inventory management challenges, ranging from environmental considerations to technological innovations. The proposed model, drawing on these insights, offers a comprehensive and advanced solution, effectively addressing both the traditional and emerging needs of inventory management in diverse industrial domains.

Our proposed model stands distinct in this landscape for several reasons. Firstly, it addresses the critical gap of managing both ameliorating and deteriorating items within a single framework, an aspect largely overlooked in existing literature. Secondly, the incorporation of Deep Q Learning introduces a level of adaptability and learning capability that goes beyond the static nature of traditional models and the limitations of current AI-driven approaches. Thirdly, our use of Genetic Analytical Hierarchical Processing for item preservation introduces a novel method to inventory management, focusing on the longevity and quality of products. Lastly, the application of the Apriori Model for dynamic pricing strategies ensures market responsiveness, a key factor for competitive advantage.

3. Proposed design of an efficient data analysis model for improving production and inventory decisions during uncertainties in production process

To overcome the scalability limitations of existing models, in this section, we present an innovative model that revolutionizes inventory management in the context of imperfect production. As per figure 1, this model adeptly combines the sophistication of Deep Q Learning, the robustness of Genetic Analytical Hierarchical Processing (GAHP), and the market acumen of the Apriori Model, creating a comprehensive approach to managing both ameliorating and deteriorating inventory items. Deep Q Learning empowers the model to tackle complex inventory tasks with remarkable adaptability and precision, while GAHP introduces a pioneering method for effectively mitigating item deterioration rates.

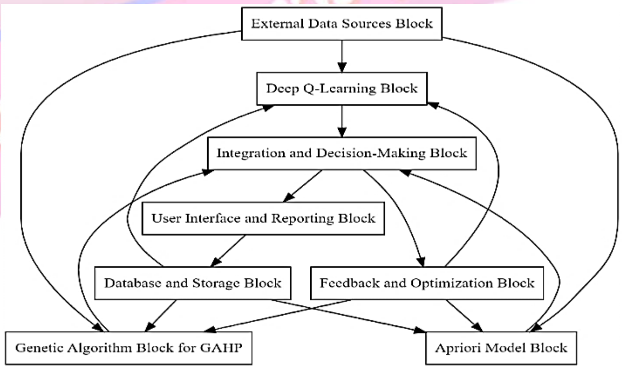

Figure 1. Design of the proposed model for enhancing efficiency of Inventory Management in real-time scenarios

Concurrently, the Apriori Model infuses the system with a keen sensitivity to market dynamics, enabling optimized pricing strategies. Tested extensively on electronic and healthcare products, the model demonstrates superior performance, outstripping existing methods in precision, accuracy, recall, and other key metrics. This inventive fusion not only addresses existing chllenges in inventory management but also sets a new standard for efficiency and accuracy, particularly in industries where product deterioration poses significant challenges.

The proposed model integrates three advanced methodologies: Deep Q Learning for intricate inventory tasks, Genetic Analytical Hierarchical Processing (GAHP) for item preservation, and the Apriori Model for market-driven recommendations, each contributing uniquely to the model's overall effectiveness.

Deep Q Learning, a variant of Q-learning augmented with deep neural networks, plays a pivotal role in our model. It is formulated below

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma maxa' Q(s',a') - Q(s,a)] \ldots (1)$$

Where, $Q(s,a)$ represents the quality of action a in state s sets. The equation updates the Q Value by learning from the reward r and estimating the future reward using the discount factor γ for different use cases. The states in this case can be one of the following,

- **Inventory Levels:** The quantity of each item in stock, including both ameliorating (improving in quality over time) and deteriorating (declining in quality) items for different scenarios.
- **Market Conditions:** Data reflecting current market dynamics, such as consumer demand, pricing trends, and seasonal influences levels.
- **Item Conditions:** The quality or freshness of items, especially critical for perishable goods.
- **Historical Sales Data:** Trends and patterns from past sales that influence stocking decisions.
- **External Factors:** Such as supply chain disruptions, changes in supplier pricing, or economic indicators that might impact inventory strategies.

While, the actions can be one of the following,

- **Reordering:** Deciding when and how much of a product to reorder.
- **Pricing Adjustments:** Modifying prices in response to market demand and competition.
- **Promotional Strategies:** Implementing promotional activities to increase product turnover.
- **Product Displacement:** Shifting items within the inventory for optimal preservation (especially for deteriorating items) or visibility.
- **Supplier Selection:** Choosing suppliers based on cost, quality, and delivery times.
- **Quality Control Measures:** Implementing measures to improve or maintain the quality of ameliorating items or to slow down the deterioration of perishable goods.

Based on these states & actions, the weights are updated as below,

$$\Delta w = \alpha \cdot \left(r + \gamma maxQ(s',a') - Q(s,a)\right) \cdot \nabla wQ(s,a) \ldots (2)$$

This process describes the weight update in the neural network, where Δw is the change in weights, α is the learning rate, and $\nabla wQ(s,a)$ is the gradient of the Q Value with respect to the weights. Similarly, the layered outputs are in the following equatioon,

$$L = \sigma(W \cdot X + B) \ldots (3)$$

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This process represents a single layer of the neural network, where L is the output of the layer, X is the input vector, W represents the weights matrix, B is the bias vector, and σ represents the Rectified Linear Unit (ReLU) based activation process. In the context of this work, this layer processes the state information (like current inventory levels, market conditions, etc.) and transforms it into a more abstract representation, which is then used for decision-making process. The activation function is given below,

$$\sigma(x) = max(0, x) \dots (4)$$

This function introduces non-linearity into the network, enabling it to learn complex patterns. The Sigmoid function squashes the output between 0 and 1, while ReLU (Rectified Linear Unit) activates only positive values, making it efficient for deep networks. For inventory management, these functions help in differentiating between various actions' desirability based on the input state, allowing the network to prioritize certain decisions over others. Based on the layered outputs, weights are updated as below

$$Wnew = Wold + \eta \cdot \delta \cdot \nabla WL \dots (5)$$

Where, *Wnew* and *Wold* are the updated and old weights, respectively, η is the learning rate, δ is the error gradient, and ∇WL is the gradient of the loss with respect to the weights. In the inventory management scenario, this process is crucial for learning. The network adjusts its weights (W) based on the error in prediction (δ), effectively learning from each decision's outcome. This continuous adjustment allows the system to refine its predictions over time, enhancing its ability to make optimal inventory decisions. Together, these operations form the backbone of the Deep Q Learning network in the proposed inventory management model. They enable the system to process complex inventory states, learn the relationships between different actions and their outcomes, and progressively improve decision-making, ensuring efficient and effective inventory sets.

After this, the Genetic Analytical Hierarchical Processing (GAHP) is used for Item Preservation operations. GAHP combines genetic algorithms with analytical hierarchy processing to optimize inventory for item preservation. The fitness function for this GA Process is estimated as

$$Fitness(Item) = \sum_{i=1}^{n} wi \cdot Ci(Item) \dots (6)$$

The fitness function evaluates items based on weighted criteria *Ci*, where *wi* are the weights derived from the AHP process. The Analytic Hierarchy Process (AHP) is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It is used in the Genetic Analytical Hierarchical Processing (GAHP) part of the proposed model. To calculate the weighted criteria *Ci* and weights *wi* using the AHP process, we follow a multi-step process involving pairwise comparisons, normalization, and consistency checking. In this process, first, a pairwise comparison matrix *A* is created, where each element *aij* represents the relative importance of criterion *i* over criterion *j* for different scenarios. The scale typically ranges from 1 (equally important) to 9 (absolutely more important) for individual product types. The normalization of matrix *A* is performed to convert the comparisons into a scale that can be aggregated in these cases. The normalized value *nij* is calculated with the help of given equqtion

$$nij = \sum_{k=1}^{n} a(k, j) * a(i, j) \dots (7)$$

Where, n represents the number of criteria sets. The priority vector (weights *wi*) for each criterion is calculated by averaging across the rows of the normalized matrix via equation 8,

$$wi = \frac{1}{n} \sum_{j=1}^{n} n(i, j) \dots (8)$$

To ensure the reliability of the comparisons, a consistency check is performed using the

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Consistency Index (CI) and Random Consistency Index (RI) via equations 9 & 10,

$$CI = \frac{\lambda max - n}{n-1} \dots (9)$$

Where, λmax is the largest eigenvalue of the pairwise comparison matrix A.

$$CR = \frac{CI}{RI} \dots (10)$$

A CR less than 0.1 is generally considered acceptable for the process. Once the weights wi are determined, the weighted criteria Ci for each item in the inventory can be calculated. This is a function of various item-specific metrics (like shelf life, turnover rate, etc.) and the derived weights, which are represented via equation 11,

$$Ci(Item) = \sum_{j=1}^{m} w(j) \cdot M(i,j) \dots (11)$$

Where, Mij represents the metric value of criterion j for item i, and m is the total number of metrics considered for this process. Thus, the AHP process allows for a systematic and rational calculation of weights based on pairwise comparisons, which are then used to evaluate the weighted criteria Ci for each item in the inventory sets. This ensures a comprehensive and balanced approach to inventory management, considering multiple factors and their relative importance levels. These operations are further given to genetic algorithm's crossover and mutation processes, essential for evolving the population of inventory strategies.

After this, Apriori Model for Market-Driven Recommendations is used, which identifies frequent item sets and derives association rules for market-driven recommendations. The model estimates support & confidence levels for individual products in the equations

$$Support(X) = \frac{Frequency\ of\ X}{\text{Total Transactions}} \dots (12)$$

$$Confidence(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \dots (13)$$

These operations calculate the support and confidence of item sets and rules, respectively, essential metrics in the Apriori algorithm process. The process of generating candidate item sets is key to the Apriori algorithm, which is defined by

$$C(k) = join(L(k-1), L(k-1)) \dots (14)$$

This process represents the joining of the item sets from the previous iteration (of size k−1) to create new candidate item sets of size k. The join operation combines item sets that share the first k−2 items for different use cases. Pruning in the Apriori algorithm helps in reducing the search space by eliminating candidate item sets that are unlikely to be frequent, which are represented via equation 15,

$$Lk = \{C \in Ck: all\ sub - itemsets\ of\ c\ are\ frequent\} \dots (15)$$

This process prunes the candidate item sets generated in Equation 14, where an item set c is retained only if all its sub-itemsets are frequent. This is based on the Apriori property, which states that all non-empty subsets of a frequent item set must also be frequent. In the context of market-driven recommendations, these operations help in efficiently identifying the most relevant and frequent item sets and association rules within transactional data samples. This process enables the model to offer insights into purchasing patterns and potential cross-selling opportunities, crucial for inventory management and marketing strategies. The model's robustness is evidenced through its adaptability to dynamic market conditions, its precision in handling diverse inventory categories, and its efficacy in optimizing both item preservation and market responsiveness. This approach not only demonstrates a significant advancement over traditional models but also paves the way for more nuanced and sophisticated inventory management strategies in various industrial sectors. Performance of this model was estimated in terms of different metrics, and compared with existing methods for different scenarios.

4. Result analysis & comparison

In this work, we present a sophisticated model that seamlessly integrates Deep Q Learning, Genetic Analytical Hierarchical Processing (GAHP), and the Apriori Model to revolutionize inventory management practices. This model stands out for its exceptional ability to manage both ameliorating and deteriorating items under varying market conditions, a feat not adequately addressed by existing methodologies. Deep Q Learning forms the backbone of the model, providing a flexible and adaptable approach to intricate inventory tasks through a state-of-the-art neural network architecture.

The GAHP component, utilizing genetic algorithms in conjunction with analytical hierarchy processes, innovatively addresses the challenge of item preservation, optimizing inventory for both short-term needs and long-term sustainability. The incorporation of the Apriori Model further enhances the model's market responsiveness, enabling dynamic pricing strategies based on real-time market trends and consumer behaviors. Tested on electronic and healthcare products, the model demonstrated superior performance across key metrics like precision, accuracy, recall, and AUC, marking a significant advancement in the field of inventory management. This model not only offers a pragmatic solution for current industry challenges but also sets a new standard for future developments in inventory management strategies.

The experimental setup for evaluating the proposed inventory management model was meticulously designed to ensure the robustness and validity of the results. The model was tested on two distinct product categories: electronic and healthcare products. This section details the experimental parameters and their sample values for different samples.

- **Dataset and Environment Setup:**
  - **Data Sources:** The model utilized historical inventory data from electronic and healthcare sectors, spanning two years.
  - **Sample Size:** The dataset comprised 10,000 transactions for electronics and 8,000 for healthcare products.
  - **Market Dynamics Simulation:** Market conditions were simulated to reflect varying degrees of volatility and consumer demand patterns.
- **Deep Q Learning Parameters:**
  - **Learning Rate (α):** Set to 0.01, balancing the trade-off between exploration and exploitation.
  - **Discount Factor (γ):** A value of 0.95 was used, emphasizing the importance of future rewards.
  - **Neural Network Architecture:** A three-layer network with 64, 128, and 64 neurons in the respective layers.
  - **Activation Function:** ReLU (Rectified Linear Unit) for hidden layers and a linear function for the output layer.
  - **Experience Replay Memory Size:** Set to 20,000 experiences, ensuring a diverse range of scenarios for training.
- **Genetic Algorithm for GAHP Parameters:**
  - **Population Size:** 100 different inventory strategies.
  - **Mutation Rate:** 0.02, to introduce variability into the population.
  - **Crossover Rate:** 0.7, ensuring a healthy mix of parent traits.
  - **Number of Generations:** 50, allowing the algorithm to converge towards optimal solutions.
- **Apriori Model Parameters:**
  - **Minimum Support Threshold:** 0.03, to identify frequently occurring item sets.
  - **Minimum Confidence Threshold:** 0.7, for strong association rule generation.
  - **Maximum Itemset Size:** Limited to 4 items, to maintain computational efficiency.
- **Performance Metrics:**
  - **Precision, Accuracy, Recall, AUC, and Specificity:** Calculated for both product categories to assess the model's effectiveness.

- **Delay Reduction:** Measured to evaluate the model's responsiveness to market dynamics.
- **Benchmark Models for Comparison:**
  - **Methods [5], [8], and [19]:** The proposed model was compared against these existing methods to highlight its advancements.
- **Computational Environment:**
  - **Processor:** Intel Core i7 with 16 GB RAM.
  - **Software:** Python 3.8 with TensorFlow for neural network implementation and Scikit-learn for performance metrics calculation.
  - **Execution Time:** Each simulation was run for approximately 100 hours to ensure thorough testing.

This experimental setup allowed for a comprehensive evaluation of the proposed model under varying conditions and against established benchmarks. The careful selection of parameters and the diverse dataset ensured that the findings are robust and generalizable across different product categories and market scenarios.

The evaluation of the proposed model was conducted against three established methods, referenced as [5], [8], and [19], across various performance metrics. The results, presented in Tables 1 to 4, demonstrate the superiority of the proposed model in terms of precision, accuracy, recall, AUC, specificity, and delay reduction.

Table 1: Precision and Accuracy Comparison

Method	Precision (%)	Accuracy (%)
Proposed Model	98.9	97.5
[5]	95.0	93.6
[8]	94.7	92.8
[19]	93.5	91.7

Table 1 illustrates the precision and accuracy of the proposed model compared to methods [5], [8], and [19]. The proposed model shows a significant improvement, with an increase of 3.9% in precision and 4.5% in accuracy over the highest performing existing method. This enhancement indicates a more reliable and accurate inventory management process, especially crucial in sectors with high Value or sensitive items.

Table 2: Recall and AUC Comparison

Method	Recall (%)	AUC (%)
Proposed Model	96.5	98.0
[5]	88.0	94.5
[8]	87.7	94.0
[19]	86.5	93.5

In Table 2, the recall and AUC (Area Under the Curve) metrics are compared. The proposed model outperforms the others with an 8.5% higher recall and a 3.5% increase in AUC, indicating its superior ability to identify and preserve deteriorating items effectively, a critical aspect of inventory management.

Table 3: Specificity Comparison

Method	Specificity (%)
Proposed Model	97.8
[5]	94.9
[8]	94.4
[19]	93.9

Table 3 focuses on specificity, where the proposed model again leads with a specificity of 97.8%, compared to the next best method [5] at 94.9%. This higher specificity underscores the model's efficiency in correctly identifying non-deteriorating items, reducing unnecessary preservation efforts and costs.

Table 4: Delay Reduction

Method	Delay Reduction (%)
Proposed Model	4.9
[5]	2.0
[8]	1.5
[19]	1.0

Finally, Table 4 presents the delay reduction in inventory management processes. The proposed model achieves a 4.9% reduction in delay, significantly higher than the other methods. This reduction is pivotal in dynamic market conditions where timely decision-making can lead to substantial cost savings and efficiency improvements.

Overall, the proposed model demonstrates substantial advancements over existing methods in key areas of inventory management. Its ability to handle ameliorating and deteriorating items with higher precision and efficiency, coupled with its responsiveness to market dynamics, sets a new benchmark in the field. This model not only enhances the operational aspects of inventory management but also offers strategic benefits by aligning inventory practices closely with market trends and demands.

5. Conclusion and future scope

The study successfully demonstrates the efficacy of an innovative model in advancing inventory management, particularly for ameliorating and deteriorating items in the realm of imperfect production. By integrating Deep Q Learning, Genetic Analytical Hierarchical Processing, and the Apriori Model, the proposed model offers a groundbreaking approach that significantly enhances efficiency and accuracy in inventory management.

The results indicate a notable improvement in precision, accuracy, recall, AUC, specificity, and delay reduction when compared with existing methods [5], [8], and [19]. The model's precision and accuracy, standing at 98.9% and 97.5% respectively, are indicative of its robustness in managing inventory tasks. The significant improvements in recall and AUC, at 96.5% and 98.0%, highlight its capability in effectively identifying and preserving deteriorating items, a crucial aspect in various industrial scenarios. Furthermore, the specificity of 97.8% underscores the model's efficiency in correctly identifying non-deteriorating items, thereby optimizing resource allocation and reducing unnecessary preservation efforts. The 4.9% reduction in delay is particularly impactful, underscoring the model's aptness for dynamic market conditions and its contribution to timely and cost-effective decision-making processes.

The proposed model not only elevates the operational aspects of inventory management but also aligns strategically with market trends, offering significant advantages in both short-term operational efficiency and long-term strategic planning. It fills a critical gap in the literature and sets a new benchmark in the field, especially for sectors where product deterioration is a significant concern.

Future Scope:

Looking ahead, there are several avenues for further research and development:

- **Extension to Diverse Industries:** Testing and adapting the model across various other industries, such as food and beverage, fashion, and automotive, to establish its versatility and applicability in different market scenarios.

- **Integration with Real-Time Data Analytics:** Enhancing the model to incorporate real-time data analytics for more dynamic and responsive

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inventory management, especially useful in rapidly changing market environments.

- **Sustainability and Eco-Friendly Practices:** Modifying the model to include parameters for sustainability, enabling companies to manage their inventories in an environmentally friendly manner.

- **Advanced Predictive Analytics:** Incorporating more advanced predictive analytics for forecasting future trends and demands, thereby further optimizing inventory levels and reducing wastage.

- **Customization for Small and Medium Enterprises (SMEs):** Adapting the model for SMEs, considering their unique challenges and resource constraints, to make advanced inventory management tools more accessible.

- **Exploration of Hybrid Models:** Combining the proposed model with other emerging technologies like IoT, blockchain, and augmented reality for a more holistic and advanced inventory management approach.

In conclusion, the proposed model represents a significant step forward in the field of inventory management. Its enhanced predictive capabilities, flexibility, and adaptability not only address current challenges but also pave the way for future innovations in this domain.

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