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Leveraging AI in Embedded and Extended Warehouse Management for Enhanced Efficiency

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Abstract
Speed and accuracy of decision-making at the operational and tactical levels are critical in warehouse management. This paper conceptually presents decision support systems (DSS) powered by artificial intelligence (AI) at two levels – embedded warehouse management at the operational level and extended warehouse management at the tactical level. For enhanced efficiency, suggestions are categorized at the tactical level into system-front-end/back-end-heavy lifting, other back-end system suggestions, and system extensions. Several AI technologies such as expert system rule engines, machine learning models, and natural language understanding models can be applied at both levels. Efforts required for data preparation and model training are highlighted.
Warehouse management takes place in a dynamic environment. New inventory arrives, and orders for shipping out inventory are constantly issued. There is a large number of decisions to be made regularly to coordinate the flow of materials in and out of a warehouse. Speed and accuracy of operational and tactical decision-making are important in warehouse management. This paper begins by discussing decision support systems (DSS) enabled by artificial intelligence (AI) for efficient decision-making at both the operational and tactical levels. Subsequently, several AI technologies that can be applied to offer intelligence at both levels are discussed. Throughout the paper, suggestions are made about how to apply these technologies to enhance efficiency. Furthermore, the effort required in terms of data preparation and model training is discussed. The pathways presented are only feasible with a supporting, intelligent IT infrastructure. Intelligence needs to be built not only within the warehouse system but also extended out to the surrounding ecosystem. The paper wraps up by either highlighting or reiterating the suggestions and insights to help stakeholders make the most of the possibilities AI offers for decision-making in warehouse management. With the rapid growth of e-commerce, flexible, adaptable AI-driven DSS could be the solution needed to help warehouse management keep up with the ever-increasing pace and dynamism of the industry.

Keywords: Leveraging AI in Embedded and Extended Warehouse Management , Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM)

1. Introduction to Supply Chain Optimization

The acute shortage of labor in warehouses, aggravated by high turnover, has driven the implementation of multiple levels of automation to move to lights-out, 24/7 operations. Artificial intelligence (AI) can be used in both embedded and extended warehouse management systems to address the increasingly complex challenges that stem from operational, commercial, and social changes and upheavals. Examples are the uncertainty introduced by omni-channel logistics, the ever-increasing number, variety, and velocity of products that need to be handled, the variety of warehouses, including temporary ones (pop-up warehouses), and the variety of vehicles that transport the products. In addition to AI, the synergy between research, new technology such as blockchain, cloud and edge computing, IoT, etc., and standards (twin digital standards, digital supply chain framework data model, semantic web ontology, un/CEFACT core data model, etc.), contribute significantly to address the challenges. The ultimate goal is to optimize warehouse operations while ensuring that the right products at the right quantity and quality are delivered to the right destination at the right time, minimizing costs and still being socially responsible.

This paper presents some solutions. AI technologies, including machine learning, deep learning, and natural language processing, used in both embedded and extended warehouse management, are introduced. These AI technologies address specific warehouse problems to enhance efficiency. The advantages and disadvantages of using AI in warehouse management are also discussed. Furthermore, the use of standards and new technology, including blockchain, cloud and edge computing, the IoT, etc., in collaboration with AI, to address warehouse challenges, are also presented. Additionally, a case study involving the use of AI in a warehouse that handles health-related products is explored. The deployment of models—in the cloud, at the edge, or in the embedded

1.1Background and Significance

Warehouse management has grown from internal control and inventory oversight to logistics and supply chain management since its inception. WMS is a warehouse management system software that is widely used. This is a software application that is designed specifically to support the day-to-day operations and tasks in a warehouse. Tasks may include inventory receiving, put-away, picking, packing, and shipping. WMS uses a central database to provide highly configurable task logic for equipment such as conveyor systems, carousels, and other handling devices.

Warehouse management systems and embedded warehouse management systems are two types of warehouse management. The former is a specialized software package designed for control over most warehouse operations. A subsection of evolving ERP systems would include these applications. ERP systems, on the other hand, use warehouse functions, which are referred to as embedded warehouse management systems. Warehouse functions are available that allow the majority of warehouses with basic requirements to be managed.

Recent technological developments have increased the use of artificial intelligence techniques, especially machine learning, to enhance warehouse management system capabilities. Despite the rich literature on AI techniques for WMS enhancement, limited works use AI techniques for extending warehouse management functions and the combination of embedded and extended functions.

Embedded and extended warehouse management, providing sufficient intelligence in terms of capabilities, can enhance warehouse efficiency to the next level. AI techniques offer the advantage of self-learning over traditional optimization methods and can be utilized to address the problem of warehouse management across multiple areas. AI techniques not only provide opportunities for enhancement in areas of warehouse mismanagement but also boost the fusion of embedded and extended WMS functions through their appropriate design.

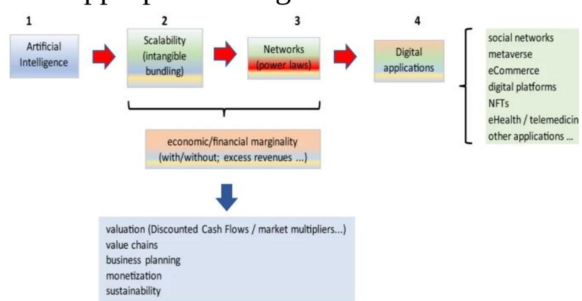

FIGURE 1: Networked scalability impact of AI.

1.2. Research Aim and Objectives

Given the promising potential of AI, this research aims to explore how AI can be exploited in both embedded and extended WM systems to enhance their performance. The primary objectives are as follows:

1. Investigate the current state of AI application in WM and identify the limitations of the existing WM systems concerning not fulfilling the tasks that AI can facilitate. 2. Develop AI-modified approaches or entirely new AI solutions that, when implemented in WM systems, can optimize warehouse operations.

In achieving these research objectives, this study first provides an overview of the tasks associated with WM at a macro level. We then explore the different AI technologies, methodologies, and components that can be applied within both the embedded and extended WM systems, elaborating on their specific tasks and subtasks the AI components can perform. Thereafter, we will highlight the WM system tasks that may not be currently achievable but have the potential to be performed with the help of AI. Next, the directions in which AI can utilize to contribute to WM system tasks are explored, and suitable guidelines will be presented for AI solution development.

2. AI Applications in Warehouse Management

Current, comprehensive inventories are pivotal for efficient warehouse management, and AI has remedied several warehouse-related problems. There are labeling and locating technologies for small and large-sized items. Automatic data capture technologies take over manual data entry tasks and increase the data's value. Sorting technology automates the time-consuming task of sorting items for shipment. Cranes, hoists, and forklifts help move large items and pallets. A warehouse's perpetual task is service rates and inventory turnover.

Warehouse management concentrates on ensuring that all functions performed in a material storage area contribute, to the utmost possible extent, to efficiency in serving the customer for minimum cost. Five functions are crucial in all warehouses: allocation, replenishment, aisle space assignment, order picking, and shipping. AI can optimize or assist in every one of these functions. Research work has been done with Expert, a rule-based system, simple office-like systems, neuron-like systems, and other systems as solving approach techniques for inventory allocation problems. The rapid development of AI technologies shows that much more sophisticated tools will soon be available for allocation problems. The warehouse can be seen as a complex dynamic system, which requires a more intelligent approach for its control. The potential use of AI technologies represents a step in this direction.

2.1.AI Techniques and Algorithms

This paper describes the application of several AI techniques and algorithms in embedded and extended warehouse management to enhance their efficiency. In particular, we describe our experience in solving real-world problems by developing commercial systems that support the automated and semi-automated handling of large sets of diverse orders in warehouses of different scales in several countries. We also describe some open research questions and our efforts to address them and present some evaluation results and lessons learned from our implementations. Finally, we offer some conclusions and outline our plans for future work.

Given the real-time requirements of embedded warehouse management for handling the movement and processing of goods, the applicability of traditional AI techniques and algorithms in this area is rather limited. The extended warehouse management system belongs to a higher level of control and utilizes several techniques and algorithms from AI to achieve greater efficiency. Typically, at the core of both types of systems is a knowledge-based system that utilizes a rule-based system represented with production rules. In embedded systems, the use of neural networks and genetic algorithms is also becoming increasingly popular. Furthermore, in extended systems, the use of multi-agent systems is emerging as a powerful approach. The increasing interest in using AI in both types of systems is also illustrated by the growing number of available implementations.

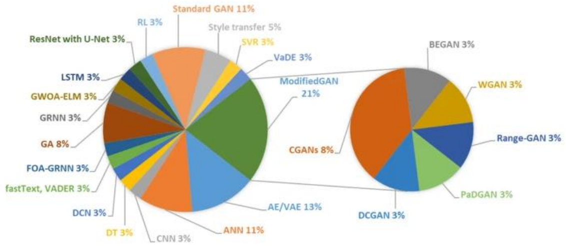

FIGURE 2:Product design phase

2.2.Use Cases and Benefits

Embarking on an AI-driven path for EWM or connecting an AI-powered EWX to an existing EWM offers varied operational benefits. Both the EWM domain and the adopters of embedded and extended types of these technologies have gained operational efficiency at scale as a common merit of an AI/ML intervention, as presented in Figure 2. Cross-industry use cases based on benefits along the warehousing stakeholder value chain are depicted in Figure 3 and are described in Table 1.

A. Supply Chain Director – Use Cases. Presented with global demand patterns which are often seasonal and based on leading economic indicators, the EWM AI/ML solution can receive prescient operational input. It can prepare the WMS in advance and stockpile a selection of necessary items based on the most probable demands. The EWM can recommend optimized inventory replenishment and allocation configurations for the DCs and store networks. It can also ensure the safety stock levels are adjusted perfectly, with the holding costs minimized. Moreover, the EWM solution can interact with the blockchain-based inventory system implemented at the EWX level, to ensure overly optimistic fraud-preventive reservations are detected and addressed, releasing blocked inventories for sale or redistribution to the other DCs.

3.Embedded vs Extended Warehouse Management

Artificial intelligence technologies in extended and embedded warehouse management solutions can be of great support in ensuring warehouse operations are efficient. Extended WMS focuses on the complete flow of goods, from the supplier's warehouse to the recipient's warehouse. It includes all the logistics business processes which begin from the receipt of goods in the warehouse to the issue of the goods from the warehouse, such as transport, stock accounting, picking, packing, inventory taking, and loading/unloading. Extended WMS operates with a large number of items, orders, and transports and is usually integrated with ERP systems, providing necessary data for the WMS operation.

Embedded WMS is focused on the optimization of internal warehouse processes - receiving, putaway, picking, packing, and dispatching - usually performed in the customer's or third-party warehouse. It is often implemented as a light version of the Extended WMS, typically including only a subset of its functions and working with a limited scope of items and orders - usually not exceeding the capacity of one warehouse or a few warehouse locations. Neuronimbus, a leading AI consulting and innovation company, deep dives into AI technologies used in embedded warehouse management solutions and the benefits derived thereof.

3.1.Definition and Characteristics

Leveraging AI in embedded and extended warehouse management for enhanced efficiency. Today's warehouse management scope has broadened from traditional in-and-out managing and storage of goods to sales support, light manufacturing support, reverse logistics support, etc. The extended warehouse management area focuses on the whole set of collaborative operations from the goods' origin (e.g., production sites, suppliers) to the customers and consumers, through the distribution networks. These scopes, along with the increasing dynamics and scale of operations in the respective areas, impose the development and deployment of intelligent tools for increased efficiency and reliability. The intelligence, AI in the presented cases, has to be embedded and extended, according to the two described above warehouse management sub-areas.

Embedded intelligence is characterized by the integration, closeness, and promptness of AI techniques to support daily operational warehouse management activities. The major characteristics of the AI techniques for use in that area are relatively low complexity, easy knowledge acquisition and representation, fast knowledge processing and feedback; easy knowledge reevaluation and readjustment; high real-time operation reliability, etc. Extended intelligence is characteristic of the use of AI techniques that permit high-efficiency knowledge processing and decision-making support, based on massive data/knowledge resources and repositories spread over distant warehouse management systems or related business systems. The major characteristics of the AI techniques for use in that area are high complexity to permit high-efficiency solutions; ability to acquire, represent, store, and process knowledge and get feedback distributed over several computing entities; ability to operate with dynamic knowledge distributed over several related operational or business systems; generally high global operation and decision-making reliability, etc.

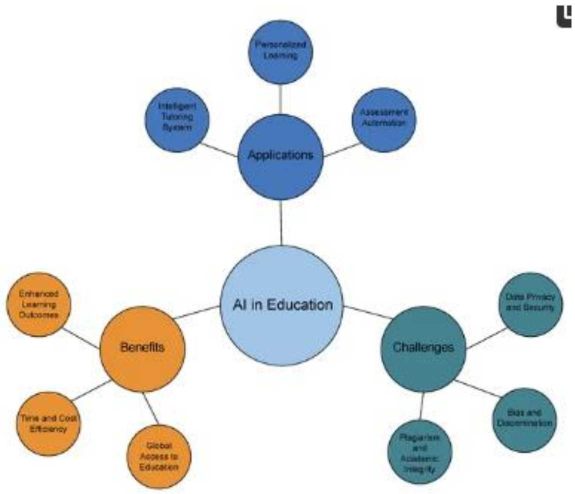

FIG 3:Multifaceted impact of AI in education.

3.2. Key Differences

This paper is inspired by the increasing relevance of both chapters 2.1 Artificial Intelligence in Warehouse Management and 2.2 The Extended Warehouse Management of the book, and the fact that the two technologies are typically addressed in isolation given the disparate technology platforms that currently support embedded warehouse management and extended WMS. Enterprise software platforms such as SAP and Oracle offer a discrete WMS module, either as part of their core ERP system or as an optional module tightly integrated with the ERP. These are commonly referred to as Extended WMS and typically require significant lead time, investment, and customization to implement.

Some key differences between these two types of WMS are worth noting. Embedded WMS typically runs on specialized technologies that enable real-time control of warehouse automation equipment (such as conveyor belts, sorters, robots, etc.) and mobile devices for inventory transactions. These technologies include programmable logic controllers, industrial PCs, inventory transaction processing engines, and wireless network infrastructure. In contrast, extended WMS runs on commercial, off-the-shelf computing architectures and leverages well-established enterprise transaction processing engines for inventory transaction processing and integration with the ERP. Furthermore, embedded WMS is designed to support high-throughput transaction processing scenarios, where a large number of inventory transactions need to be completed in the shortest time possible, such as goods movement inside a high-volume distribution center. As a result, the user interfaces for embedded WMS are typically minimalistic and optimized for execution speed.

4. Integration of AI in Embedded and Extended Warehouse Management

Warehouse management across the supply chain is evolving with a rapid increase in the development and deployment of extended warehouse management systems. These systems use service-oriented architecture both in embedded technology in the warehouse and at the enterprise level. When implemented with optimized AI and delivered through AI-based appliances, both the embedded and extended warehouse management service systems exhibit enhanced operational performance.

AI can easily be integrated into embedded warehouse technology when delivered through appliances. At the service-oriented enterprise level, AI should be delivered through an on-demand model with regular enhancements and updates. As services evolve and new services are developed, the AI infrastructure at the enterprise level needs to be scalable and manageable, with low total cost for service-oriented architecture. The governance of AI at the warehouse needs to be extended to an enterprise level, ensuring seamless integration of embedded technology through standards defined in consortia like ISA-95 and customization rules used at the warehouse for specific enterprise services. At both levels, the warehouse should leverage AI through learning and prediction optimization methods for enhanced operational performance.

4.1.Challenges and Solutions

Real-time embedded warehouse management and extended warehouse management have their challenges. For embedded warehouse management, it is required to support the real-time, on-the-fly, and just-in-time modes with inherently advanced simplified modes of operation that preclude user support. The real-time activities of the warehouse cannot tolerate lengthy switching between various AI subsystems or their modes of operation. The extended warehouse management faces the challenge of the inverse interface. While frequent AI-driven automatic formulation of rules, instructions, and task assignments for the warehouse staff can significantly enhance efficiency, the staff does not trust, and even resent, an offered intelligent system that implements micro-management. The more intelligence that is implemented by such a system, the fewer chances there are that the staff will accept and act upon it.

The solutions to the mentioned challenges imposed by the embedded real-time warehouse management include the creation of a very simple and shallow multi-tier architecture of AI subsystems, where at the top there is a light-touch type AIPS with occasional staff interactions, specifying most general policies and strategies. The warehousing process enacted by this top AI subsystem must evolve very slowly, with changes implemented in the on-the-fly and just-in-time AI modes being very infrequent. Rapidly evolving staff-tasking interactions are implemented by the underlying quicker-evolving AI subsystems that support execution and lower-level control, with their evolution mode being performed off-the-fly and off-the-time-slice.

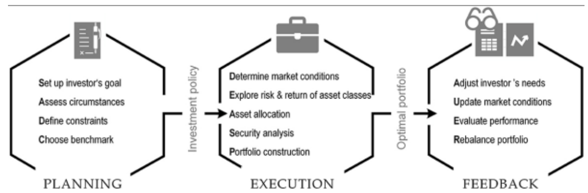

FIG 4: Portfolio management process.

5.Case Studies and Industry Examples

The section highlights case studies, industry examples, or real-world implementations that are relevant to the topic to help the reader better understand the practical and applied aspects of the concept.

Case Study 1: Picking Optimization in an AGV-based EWM System. In this case study, we combine a cloud-based extended warehouse management system (EWM) with multiple sets of automated guided vehicles (AGV). The commercial EWM system covers typical warehouse management functions from goods receiving to shipping. We program the AGV sets for part of the picking work and replenishment transports. A picking route optimization algorithm operates the AGV sets. AGV navigates through the warehouse based on a combination of natural features for localization and digital maps. The cloud logistics system controls the AGV: assigns order-based transport tasks, releases the transport system when ready, and tracks transport execution. The automatic data exchange of the cloud-based logistics system with the AGV sets includes order information, AGV availability, bin contents, and order totes transported by the AGV.

Case Study 2: Picking Optimization in a Swarm Robotics-based EWM System. In this work, we present a collaborative mobile robotics system for warehouse order processing. Instead of centralized coordination, we aim at loosely coordinating the activities of a heterogeneous set of entities: commercially available automated guided vehicles (AGVs) and proprietary small autonomous ground robots (AGRs) serving as a swarm. We introduce two types of functions assigned to the robots: picking goods to be shipped and replenishing goods to stock. For the picking function, we explore different strategies: dispatching independent robots to randomly selected goods and sending information-constrained robot groups to specific goods areas. The swarm AGRs are dynamically grouped based on the quality of information exchange between them. The collaborating robots are evaluated in terms of their performance and communication requirements. The demonstrated robotic warehouse system is modestly sized, but it scales appropriately; the presented configurations can easily be mapped to larger installations.

6. Conclusion

The evolution of eWM and the features that are embedded or extended to cater to quicker, efficient deliveries to service the superfast internet shopping order-delivery cycle are highlighted. An attempt is made to draw attention to the key inclusions that have the potential to bring about marked changes in the way warehouse operations are managed. The advancements in embedded AI models warrant periodic model refreshes to maximize operational efficiency through improved decision-making. AI is on a self-evolutionary track enabled by embedding into the operational process. The evolutionary extended models with feedback should ensure guaranteed convergence. The onus of the evolutionary process lies in the hands of the data custodian to preempt data drift and data shock, through data readiness for AI models, to initiate ground-breaking intelligence in warehouse operations.

The superfast changing world of internet shopping with overarching orders for same-day or one-day deliveries is putting immense pressure on fulfillment centers for efficient cycle-time operations. The warehouse management processes must keep pace with this accelerated demand for speedy deliveries. eWM with its embedded AI models is on a keel to revolutionize warehouse operations. Our readiness to leverage AI for intelligence infusion into warehouse operations will be an enabler for operational efficiency strides. We are at a point in time where AI is not just an enabler but is on the cusp of becoming a self-evolving intelligence with feedback mechanisms through extended models.

6.1 Future Trends

In the coming years, we anticipate several trends in the area of embedded and extended warehouse management that will result from the increasing proliferation of AI at different layers of warehouse software. Firstly, the traditional divide between embedded and extended WMS will blur as more functions from extended WMS will be augmented into embedded WMS, enabled by lighter and more specialized cloud-based extended WMS, and fast-evolving edge computing capabilities. As such, all warehousing companies, regardless of the scale of their operations, will be able to benefit from full-featured WMS. Secondly, the higher levels of embedding of AI will shift the focus of the enhanced efficiency derived from the advanced WMS from execution support to strategy optimization in the long run.

In the short term, due to the prohibitive costs of embedded AI or edge AI implementations, as well as the still-existing inflexibilities of embedded WMS, the focus of embedded AI WMS will be on the execution areas that require very quick, or even real-time, responses. Slotting optimization and real-time adaptive wave management are examples of such areas. As the costs of embedded AI implementations come down, and the capabilities of embedded WMS go up, it is set to become the primary area of growth in WMS-related AI enhancements, due to the focus on execution support for mid-scale and large-scale operations. Moreover, the fast response times of embedded AI

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