10. Artificial intelligence and machine learning in supply chains

What is artificial intelligence (AI)? Is it really an "alive" creature capable of thinking and making its own decisions based on one its mind, past experiences, ethics, beliefs, etc? How is it connected to machine learning (ML)? Are AI and ML the same thing?

What tools are used in AI & ML? What roles do AI and ML play in the business context and how can it be used in everyday business operations and optimizations? Are there specific architectures and examples of applying AI and ML to supply chains?

On these and similar questions, we will try to provide answers in the following chapter, closing with a real case study example of the application of AI & ML algorithms in the distribution warehouse.

10.1 What is artificial intelligence?

The field of AI began in the 1950s with computer scientists asking, "Can computers think like humans"? Researchers at that time were enthusiastic about the possibility of teaching computers to perform complex tasks and accordingly developed a set of different algorithms for that purpose. The definition of the field could be stated as the effort to automate intellectual tasks normally performed by humans (Chollet, 2021). The most notable algorithms in the field of AI today are coming from ML and deep learning, which are subsets of AI. Besides ML and deep learning AI includes a lot of non-learning algorithms. Moreover, we can argue that these kinds of algorithms were more dominant in the early phase of AI development. Accordingly, this is part of AI known as Symbolic AI which is based on the idea that human level of performance and intelligence can be achieved by programming computers with a large set of explicit rules for solving the observed problem. This approach provided excellent results in a logical problem which were well defined, like a computer playing a chess game, but it proved to be complicated for more complex problems. The real world has proven to be much more complicated than all explicit programming rules could be inserted into the computer. This approach is centred around an idea for a given situation do this or that (if-then rules). This is an easily understandable approach, but on the other hand very time-consuming and sometimes very hard to determine all possible scenarios which need to be inserted into the program. As a funny example, but a good illustration of a given topic, please see Figure 10.1, which demonstrates several scenarios for determining the forecast based on the stone status.

Figure 10.1 If – Then programming rules (Gibbs, M. 2019).

The field of Symbolic AI has its biggest popularity in the 1980s with the emergence of expert systems (ES). ES represent a subset of decision support systems (DSS) (Turban, 1998), focused on delivering computerized decision-making abilities akin to those of a human specialist within a particular field. These systems are crafted to tackle intricate problems by employing a series of rules or algorithms that simulate human reasoning processes. Olson and Courtney describe expert systems (ES) as computer programs that simulate human thought processes to make decisions within a specific domain, incorporating a degree of artificial intelligence to match the conclusions a human expert would reach (Olson & Courtney, 1992). An ES component is particularly useful for supporting decision-makers in areas that require specialized knowledge (Turban et al., 2005). Essentially, an ES captures the expertise from a human expert (or another source) and transfers it to the computer. This technology can either aid decision-makers or fully substitute them, making it one of the most widely applied and commercially successful forms of artificial intelligence (Turban et al., 2005). One key reason for developing an ES is to distribute expert knowledge to a broader audience (Jackson, 1999). In the following subchapters, we will demonstrate the application of ES based on AI & ML algorithms, in the central warehouse as part of the overall DSS to managers.

Today, the field of AI consists of various approaches and algorithms, but the most used ones are described on Figure 10.2. It has diverged from the ES systems and the re-emergence of the field is mostly credited to the deep learning algorithms which had significant success in the last 12 years in the problems of image recognition, speech recognition, image segmentation, facial recognition, etc. Deep learning utilizes multiple layers of abstraction to identify complex patterns in high-dimensional data. This approach has achieved significant advancements in fields like speech and image recognition, drug discovery, and natural language processing. The deep learning's has ability to automatically discover relevant features and reduces the need for human intervention in feature design, making it highly efficient in leveraging large datasets and computational power (LeCun, Bengio, & Hinton, 2015).

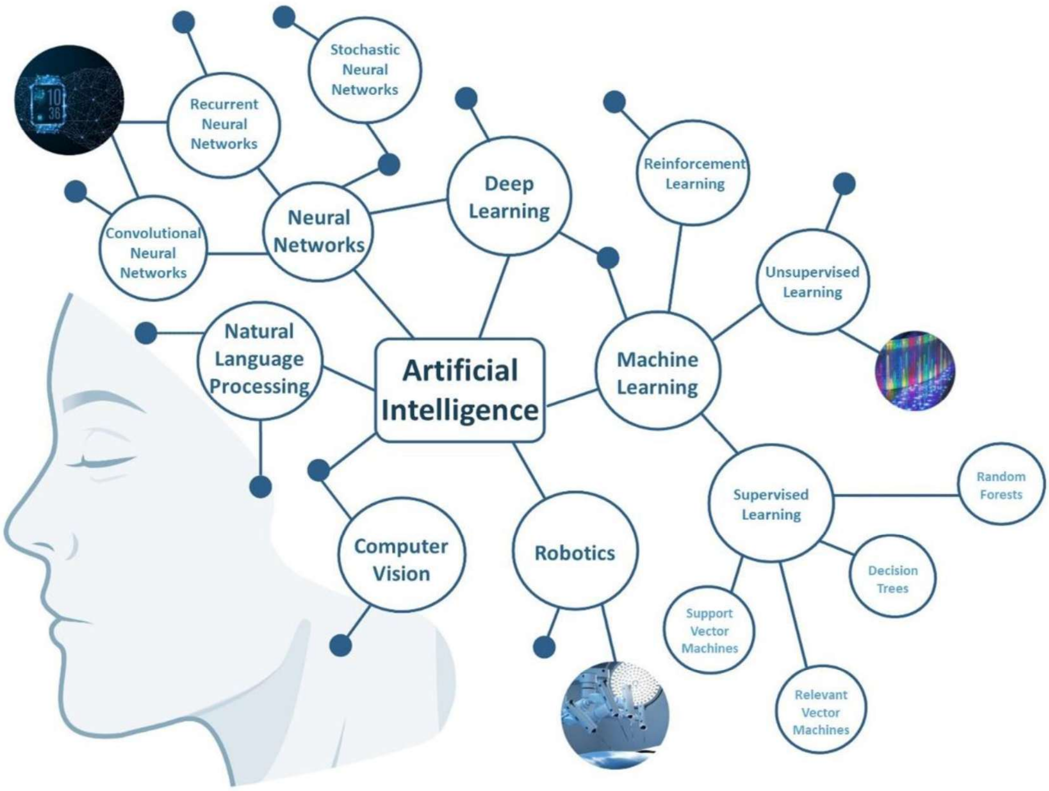

Figure 10.2 The main fields and subfields of AI (Athanasopoulou et al., 2022).

The big step towards today situation was research in the digit classification conducted by Hinton, Osindero, and Teh (2006), which manged to achieve more than 98% accuracy on classifying Modified National Institute of Standards and Technology (MNIST) data base. One way to think about how AI transitioned from Symbolic AI to ML, and what is the essence of the ML is to imagine ML algorithms as an amorphous mass that shapes itself according to the desired outcomes. The system of rules that takes input to output changes from problem to problem and adapts to the existing situation. It aims to find rules that will automate the task by seeking statistical patterns within the data. This kind of approach for solving different problems significantly reduced the time for system set up (compared to the if – then rules), and make it more universal approach for tackling various problems.

Bengio, Lecun, and Hinton (2021) emphasised that the future of the AI is in the deep learning and the revolutionary impact of soft attention and transformer architectures in AI. These innovations allow neural networks to dynamically focus on important inputs and store information in differentiable memories, significantly improving sequential processing.

10.2 What is the ecosystem of AI & ML?

The ecosystem of AI & ML algorithms consists of three key pillars:

- Input data;
- Output data;
- Cost function.

The input data represents data recordings of specific feature or features (depending on an observed problem). The accuracy of the input data is crucial for building accurate algorithms. This is often not the case in real applications and usually significant time and effort are devoted to data collecting, cleaning, wrangling, unifying, checking on false inputs, etc. Besides, accurate data, another important aspect of input data characteristics is its representation and encoding. Different ways of encoding the data can reveal different features of the data and significantly "help" ML models in revealing the hidden patterns in the data. Here we see the Achilles' heel of ML algorithms. Often, too much attention is given to creating the methods for extracting information and intelligence from the data (i.e., the algorithms themselves), while insufficient attention is paid to the input data and its relationship with the output data. It is generally taken for granted that the input data has a causal relationship with the output data, which is sometimes not the case at all. Therefore, the next big step in ML development should be finding better ways to collect, represent and encode the data.

Output data represent the measurements of the particular problem that we are trying to solve. In a classification problem, it would be the label of the classes. In regression, it will be a real number we are trying to predict. In a problem-specific context, for speech-recognition problems, the output data can be human-generated transcripts of the sound files. In an image recognition problem, the output can be image class labels, etc.

The cost function represents the way of measuring how the AI & ML is performing. Basically, we would ideally want answers from the algorithms to match the output data, for a given input data. The cost function is also a feedback signal to the set of parameters that guide the algorithm's work, i.e., it allows the optimization of overall algorithm performance via the process of learning (finding the optimal set of parameters). The learning process typically involves supervised learning, where a model is trained on labeled data to minimize prediction errors through techniques like stochastic gradient descent and backpropagation. This enables the model to adjust its internal parameters effectively, leading to improved performance on tasks such as object detection and classification (LeCun, Bengio, & Hinton, 2015).

10.3 What tools are used in ML?

Generally, ML algorithms can be classified into two main categories: supervised and unsupervised learning.

Supervised learning involves training algorithms on a labelled dataset, where each input data point is paired with the correct output. This clear "picture" of what the correct answer should be for a given input allows the algorithm to learn the mapping function from inputs to outputs. Accordingly, both the input and output data are known (Athanasopoulou et al., 2022). Common applications of supervised learning include classification tasks (e.g., determining whether an email is spam or not) and regression tasks (e.g., predicting house prices based on various features). Some of the most popular algorithms which have been proven by numerous applications are generalized additive models, random forests, boosting, classification and regression trees, support vector machines, extended linear regression, logistic regression, k-nearest neighbors, linear discriminant analysis, lasso, neural networks, adaptive neuro-fuzzy inference system, etc (Rostami-Tabar & Mircetic, 2023). Supervised learning is powerful because it leverages human-annotated data to achieve high accuracy in predictions. However, its effectiveness depends heavily on the quality and quantity of the labelled data.

In contrast, unsupervised learning deals with datasets that lack labelled responses. Accordingly, unsupervised machine learning algorithms use unlabelled datasets that include only inputs (Athanasopoulou et al., 2022). Here, the algorithm is provided only with the input data, and its goal is to find underlying patterns, structures, or relationships within the data. Common techniques in unsupervised learning include clustering (e.g., grouping customers by purchasing behaviour) and dimensionality reduction (e.g., reducing the number of variables in a dataset while retaining important information). Unsupervised learning is valuable for exploratory data analysis and discovering hidden structures in data. It is often used when labelled data is scarce or unavailable.

Another important category, although distinct from supervised and unsupervised learning, is reinforcement learning. Here, the algorithm learns by interacting with an environment and receiving feedback in the form of rewards or penalties. This trial-and-error approach helps the algorithm learn optimal actions to maximize cumulative rewards. Reinforcement learning is widely used in fields such as robotics, game playing, and autonomous systems.

One of the most popular and successful algorithms for ML comes from the branch of neural networks. Neural networks exist since the 1950s but gained their popularity in the 1980s and in recent 12 years. They are built on the approximation of biological neurons and the way they share pieces of information in the brain, but beyond that, there are no significant connections between these two. Today, the most commonly used form of neural networks are in the form of deep learning, which represents several stack hidden layers between the input and the output features, which perform several nonlinear transformations of the input features. Since this has been proven very successful deep learning is today one of the most prominent subfields of ML (Chollet, 2021).

10.4 Case study?

The findings of Wenzel, Smit, and Sardesai (2019) on ML in supply chain management indicate a growing integration of ML applications across various SC tasks. Accordingly, observed case study represents the application of AI & ML, performed in the central warehouse of the food factory (Mirčetić et al., 2016; Mircetic et al., 2014). In the factory complex, there are 30 forklifts. Forklifts are engaged in various operations inside the complex, which are crucial for logistics operations in production, warehousing and dispatching the products. The central warehouse has the capacity of 11 100 pallet places and the annual output from 300 000 to

350 000 pallets. Currently, the factory is supplying around 20 000 supermarkets via direct delivery.

The problem of forklift engagement is related to the fact over or under-engagement of the forklifts in the different factory processes leads to significant financial and market losses. Currently, the process of decision-making making where and what will each forklift do is based on the expert (managers) decisions. Expert decisions are based on their experience, without the help of any decision-support system (DSS). Ample empirical evidence suggests that human intuitive judgment and decision-making often fall short of optimal, particularly under conditions of complexity and stress (Druzdzel & Flynn, 2002). This underscores the importance of incorporating decision support systems (DSS) to assist experts in the decision-making process.

In this application, we have chosen several ML algorithms to assist in optimizing the loading warehouse operation. The ML algorithms are assembled in a unique decision-making framework which serves as DSS for managers and experts in a given company. Moreover, the entire decision-making DSS can be observed as an AI platform, since it constantly recalculates the suggestions from several ML models (how many forklifts to use and which ones) and automatically chooses the best ones, regarding the provided operators' inputs.

Problem description

The loading process is crucial for warehouse logistics, impacting market service levels. During shipments, the warehouse expert determines the number and selection of forklifts for loading, guided by three factors: (1) completing loading within the specified timeframe, (2) minimizing disruption to other forklift tasks, and (3) aligning forklift use with maintenance capabilities, which can handle two overhauls simultaneously. Each forklift undergoes four to five maintenance overhauls annually.

Forklifts are vital for loading operations, which must support the company's marketing strategy while ensuring the smooth operation of other activities. Misallocating forklifts can lead to resource underutilization or harm the company's reputation and service levels. Delays in loading incur penalties. The manager must coordinate forklift use across all activities to avoid simultaneous overhauls and manage varying maintenance needs. Though managers typically make accurate decisions, high-stress environments can lead to errors. Therefore, a DSS is needed to enhance decision-making confidence and reliability.

AI & ML as DSS for central warehouse

The first step for generating the AI & ML systems is to acquire a stable and correct source of knowledge (database) and to shed light on the business roles it needs to support. Therefore, Figure 10.3 presents a methodology for building the AI & ML DSS system.

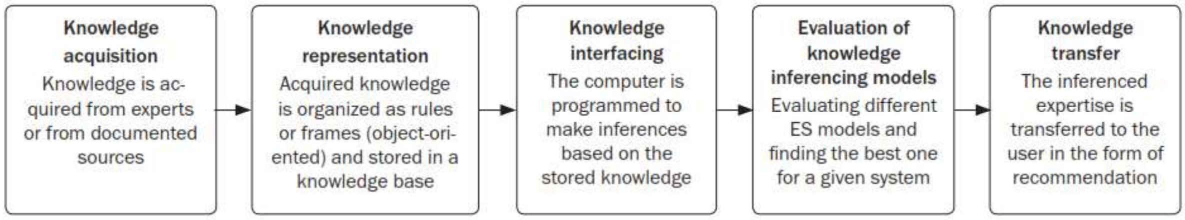

Figure 10.3 Methodology steps for building the AI & ML DSS system (Rainer & Turban, 2008; Turban, Aronson, & Liang, 2005).

Knowledge acquisition was achieved through manager interviews, observing their decision-making processes, and reviewing warehouse records. To develop the DSS for the given problem, two knowledge bases were established. The first knowledge base includes decisions on the number of forklifts deployed in the loading zone (434 expert decisions), while the second covers which forklifts were used (368 expert decisions) in various operational scenarios. During the knowledge inference stage, several ML algorithms were applied using Matlab software: Adaptive neuro-fuzzy inference system (ANFIS), generalized additive models (GAM), Random forests, Boosting, classification and regression trees (CART), Extended Linear Regression, Logistic Regression, k-Nearest Neighbors (KNN) and Linear Discriminant Analysis (LDA). Various ML models were evaluated, and those with the best performance were identified. ANFIS and CART demonstrated superior results and were selected as the final DSSs for practical application in the company. Knowledge transfer was facilitated through the user interface of the final DSS models. The structure and logic of the DSS is illustrated in Figure 10.4.

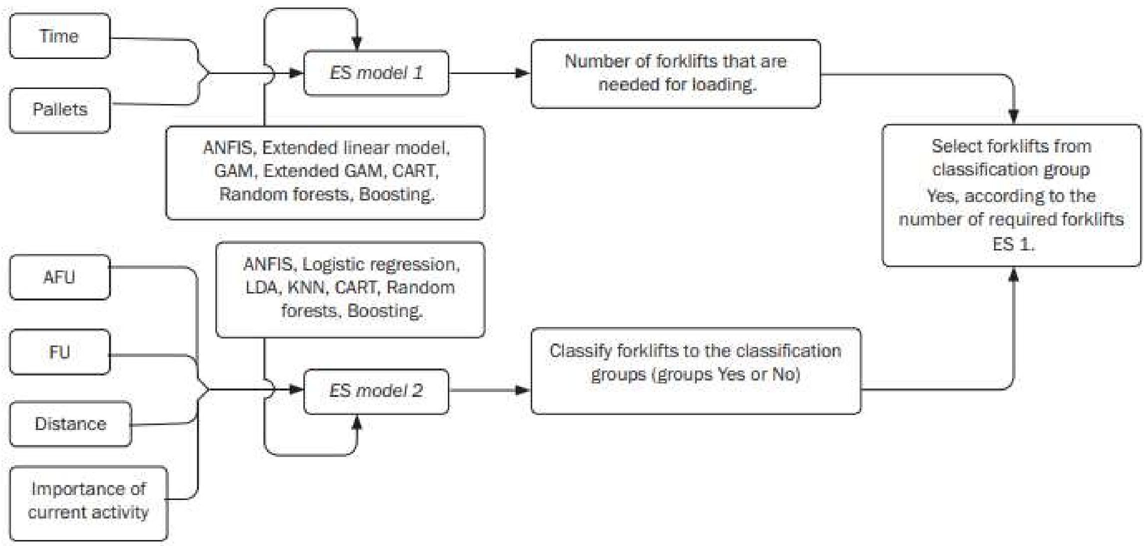

Figure 10.4 Building structure of warehouse DSS based on the AI & ML algorithms.

The DSS framework consists of an input layer, consisting of several key factors which influence forklift engagement. The ML layer has ML models that are recalculating the suggestion on how many and which forklifts to use in a given input scenario. The best-performing models are chosen as expert system models (ES models) since the knowledge base on which the ML models are created is extracted from the experts. The first model focuses on determining the number of forklifts required in a loading zone (ES model 1). The second model addresses the problem of selecting which specific forklifts should be engaged (ES model 2). Both models are developed using supervised machine learning techniques. According to Turban, Aronson, and Liang (2005), machine learning has demonstrated excellent results in designing intelligent decision support systems (DSS). The ES models send signals (ML suggestions and proposals) further to the sorting operation, where each forklift that is classified in the sorting group "Yes", can be engaged in a given loading operation.

The factors influencing the manager's decisions were identified through consultations. For determining the number of forklifts to deploy in the loading zone, the key factors are the specified loading time (15 to 135 minutes) and the amount of cargo (15 to 225 pallets). When choosing which forklifts to engage, the manager considers the importance of the current activity (rated 1 to 9 by company policy), the forklift's utilization rate, its distance from the loading dock, and the average utilization rate of all forklifts. Each forklift has a set number of working hours before an overhaul is needed, and its usage is restricted beyond this limit.

Forklift Utilization (FU) is the percentage of working hours used by an individual forklift, while Average Forklift Utilization (AFU) is the average working hours used by all forklifts. A higher AFU suggests that most forklifts will soon need an overhaul.

The user interface of DSS

In the majority of input situations, the best performance was demonstrated via ANFIS and CART. Accordingly, they were chosen as the engines of the given DSS and its ESs. The ES model 1 user interface is presented in Figure 10.5, and it allows operators to make decisions quickly and easily about the number of forklifts to deploy by simply moving a vertical line through the domain of input variables, based on the specified loading time and cargo amount.

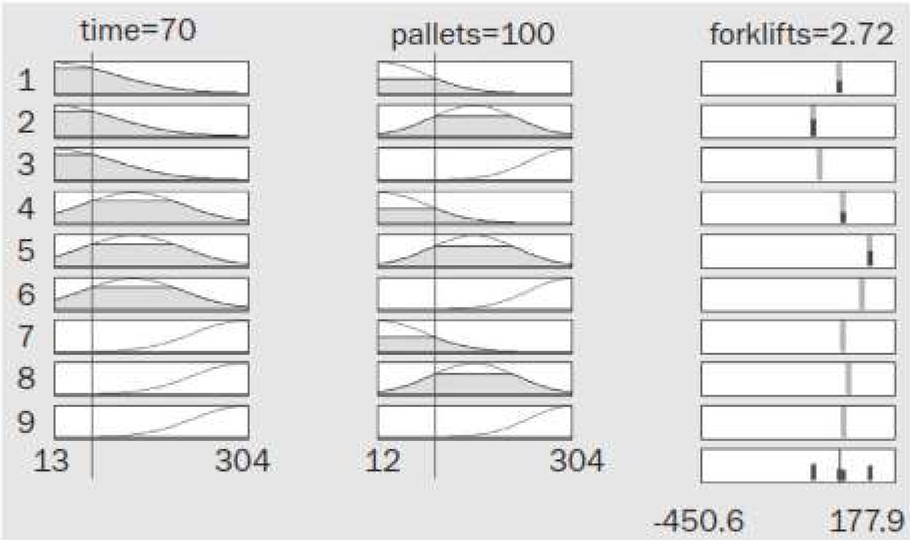

Figure 10.5 Fuzzy Inference System of ES model 1.

ES Model 2 serves as a supplementary tool to ES Model 1, enhancing decision-making by providing information on whether a specific forklift should be deployed in the loading zone (Figure 10.6). By considering the position of a forklift (distance from the loading zone), its current activity (importance of activity), its utilization of working hours (FU), and the average utilization of all forklifts (AFU), users can easily determine if a particular forklift is suitable for loading or if another should be selected. The CART decision tree is straightforward to interpret, eliminating the need to input values into software. Instead, the tree from Figure 10.6 can be printed and displayed prominently in the warehouse for quick reference.

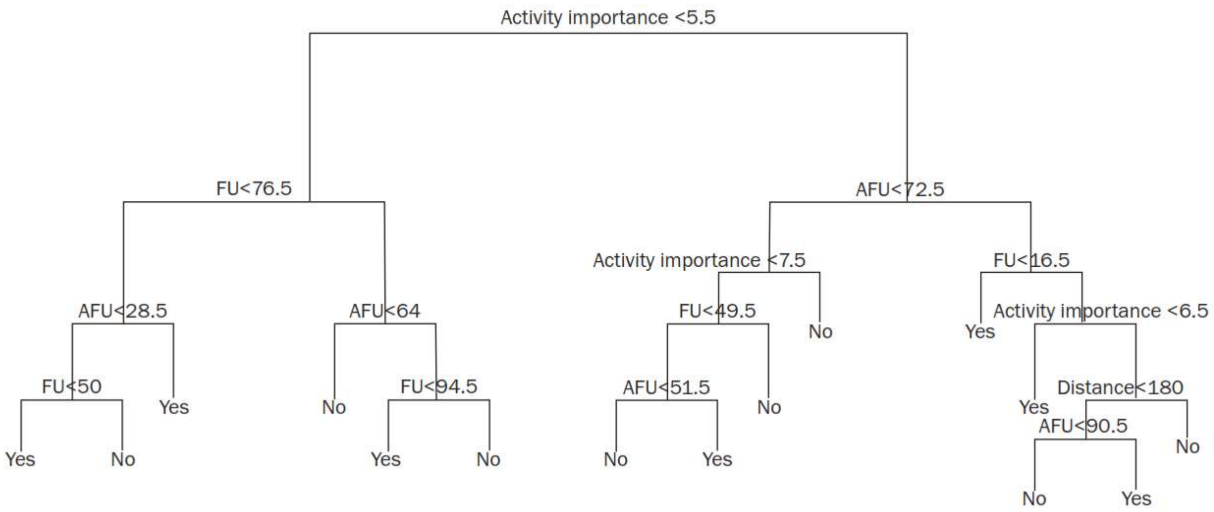

Figure 10.6 ES model 2 decision tree regarding the forklift engagement.

Managers can utilize the presented DSS daily, aiding in achieving higher supply chain responsiveness to customer demands and ensuring a high probability of on-time delivery. The proposed AI & ML DSS has demonstrated successful results in acquiring the expert's "know-how" knowledge and capturing their "inference logic." By using this method, managers' expertise can be extracted and applied to other warehouse operations. This is particularly valuable for practitioners since hiring warehouse experts is often expensive. Additionally, DSS can also serve as a training tool for novice managers, helping them gain experience and improve their decision-making skills over time. Therefore, AI and ML systems that can simulate a manager's decisions are essential tools, offering significant cost savings and increased efficiency in warehouse operations.

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