INTEGRATING MACHINE LEARNING TO OPTIMIZE STOCK FLOW AND GOODS REPLENISHMENT IN INTRALOGISTICS

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ABSTRACT

The intralogistics area has emerged and developed as a result of increasing the importance of Industry 4.0. Autonomously running intralogistics systems are gaining more and more attention as a result of digitalization. Intralogistics is a process of organization, control, execution, and optimization of internal material and information movement. It is a complex interplay of several logistical operations. The literature study highlighted how logistics inside the warehouse facility transformed with the major trends in the context of optimization, automation, system integration, and mathematical modeling techniques. Further, this study proves that numerous technologies can be altered and combined to improve intralogistics in terms of accuracy, quality, efficacy as well as sustainable aspects even in more complex settings in the discussion. In the paradigm shift of moving traditional internal logistics systems to autonomous advanced intralogistics systems, integrating various operations research applications with industry 4.0 concepts is vital. It will support to develop optimized, organized, and automated logistic systems within the warehouse. In this study, we have considered developing a storage and goods retrieval system amalgamating the intralogistics concept. In order to develop a demand-driven optimized storage plan for the warehouse, storage allocation was focused. The storage allocation was done by classification technique mainly considering the total consumption value of the items. The used classification mechanism was improved by integrating Machine learning (ML) approach. ML-based classification addresses the question that how a computerized system can automatically identify the correct storage segmentation for the items in the inventory including newly added items. Apart from the consumption value, cost of the item issued quantity of the item, and frequency of issuing were considered to develop the model. It is easy to retrieve the items from the warehouse as it is in the correct demarcated location to fulfill the orders received for the warehouse. The developed storage allocation will be used to perform a simulation model in order to identify how inventory segmentation utilizes and eases the internal logistics.

Keywords: intralogistics, storage and goods replenishment, inventory classification Machine Learning, Industry 4.0, optimization, simulation

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LIST OF ABBREVIATION

Abbreviation	*Description*
AGV	Automated Guided Vehicles
AI	Artificial Intelligence
AMR	Autonomous Mobile Robots
AR	Augmented Reality
AS/RS	Automated Storage and Retrieval Systems
BDA	Big Data Analytics
CPPS	Cyber Production Physical System
CPS	Cyber-Physical System
DL	Deep Learning
ICPS	Industrial Cyber-Physical System
IIoT	Industrial Internet of Things
IoT	Internet of Things
ML	Machine Learning
OPS	Order Picking System
SC	Supply Chain
SCM	Supply Chain Management
VR	Virtual Reality
WMS	Warehouse Management System

CHAPTER ONE: INTRODUCTION

1.1. Background of the Study

With the advent of Industry 4.0, turning warehouses into smart environments is becoming a trend within the supply chain (SC). Regulating and managing warehouse procedures through a centralized system is a key feature of the aforementioned trend. Intralogistics became a trending concept which manages internal warehouse operations. In other words, intralogistics is the study of integrating and automating materials and information flow within a warehouse or fulfillment center in order to maximize efficiency (Kartnig et al., 2012). It has been proven that intralogistics is emerging as a concept in research and development domains SC (Fernandes et al., 2019). Intralogistics refers to the management, automation, integration, and optimization of logistics within a fulfillment center or distribution center. Strong connectedness between physical processes and systems has been made possible through the interaction of technologies such as Cyber-Physical Systems (CPS) and Internet of Things (IoT) (Bechtsis et al., 2017). These combined technologies help to automate warehouse operations, increase productivity while reducing expenses (Ponis & Efthymiou, 2020). Logistics operations can be carried out using a variety of automated technologies and solutions, requiring less human involvement. These clever technologies help plan and manage workflow in the dynamic warehouse environment (Tang & Veelenturf, 2019).

The ability to monitor the movement of physical items in real-time and manage stock fluctuations to support goods replenishment is currently a major challenge in warehouses. (Shah & Khanzode, 2017). The primary goal of warehouse management systems is to regulate the flow of materials through the warehouse while taking inventory conditions and location assignments into account (Atieh et al., 2016). The functionality of handling sophisticated processes will improve by integrating warehouse systems with intralogistics approaches produced in the form of optimization and automation (Fragapane et al., 2020). Although intralogistics techniques for managing warehouse operations have been covered in previous literature adequately, information about stock-flow management and commodities replenishment is lacking. The influence of intralogistics solutions to enhance stock flow and goods replenishment is identified in this study.

The key strategy for managing complexity in warehouse operations requires a change from centralized organizational structures to autonomous systems which connected each node. Through collaboration and interaction with other systems and people, autonomous intralogistics systems make it possible for designing, controlling, and optimizing internal material and information flows in a self-sufficient, decentralized manner (Fottner et al., 2021). The optimization of warehouse operations would be aided by having a comprehensive grasp of directions of the products kept at various locations. Additionally, it will help minimize warehouse movements to facilitate energy- and cost-effective intralogistics (Perera & Perera, 2022).

A complicated interaction between numerous cooperating components defines warehouse logistic systems. It is difficult to determine a warehouse's characteristics based on its parts. To make precise predictions, reliable assumptions are needed especially when new components or operational methods are used (Verriet & Caarls, 2013). One of the important challenges in supply chain management is achieving optimal inventory control. By effectively regulating the inventory, the inventory control methodologies aim to lower the cost of SC. Among the number of inventory control mechanisms, inventory classification or segmentation can be known as a vital method. Through correct inventory segmentation, which is based on the demand and value of items, warehouse operations can be streamlined. The purpose of this study is to develop an optimized inventory system which employed ABC classification along with Machine Learning based inventory classification. Since the traditional ABC method will not be adequate to develop inventory classification which provides good control over the inventory, it should be improved through integrating advanced concepts. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) provide good implications for inventory systems to move forward with smart logistics. ML is considered as a sub-section of AI term which has the ability to identify significant patterns in datasets automatically.

Inventory allocation will be done according to the inventory segmentation. The identified various demand patterns for the items were used to develop a storage allocation plan. This study mainly shows that considering the different characteristics of inventory items will help to create an optimized plan for internal logistics. Also, when intralogistics amalgamates industry 4.0 concepts like AI and Machine Learning ML with the inventory control system, it will eventually increase the efficiency of overall warehouse operations.

Every customer should be entirely satisfied with their order and receive it promptly when a warehouse is performing at its best. All warehouse and logistical activities should also be done as quickly, inexpensively, and efficiently as feasible in a dynamic SC environment. (Kar, 2013). Therefore, this study targets to develop an inventory system which can support goods movements and highly productive replenishment processes.

1.2. Structure of the Thesis

This research dissertation's chapter breakdown is organized as follows. The background of the research is discussed in the first chapter, which is the introduction. Chapter 2 outlines research gaps, research issues, and research aim after discussing the relevant prior literature and theoretical concepts in the intralogistics field. The methodology is covered in Chapter 3. The methodology section consists of 3 sections; 1) identify the data and initial classification through the ABC classification, 2) Improved classification using ML, and 3) Simulation modeling to evaluate the warehouse system which uses inventory segmentation. Also, it offers a thorough overview of workable approaches and their applications in relevant subject areas. The design of the methodology, data collection methods, and data analysis methods were then described. This chapter's concluding section provides a summary of the entire study process. Data gathering and analysis are both included in Chapter 4. It offers a thorough examination of the research's conclusions and data from the inventory. The final chapter provides recommendations and future research directions that were identified through this analysis and summarizes the discussion and conclusion of this research.

CHAPTER TWO: LITERATURE REVIEW

2.1. Industry 4.0

The 4th industrial revolution, also known as Industry 4.0 or 4IR, is the notion of the rapid changes in technology, industries, and societal patterns and processes that have occurred in the 21st century as a result of growing interconnectedness and intelligent automation (Lerher et al., 2018). Through several trends that are interacting with one another, it is integrating the real, digital, and virtual worlds (Ponis & Efthymiou, 2020). Even though most businesses saw the physical movement of supply chain components as a separate task from the information flow and then struggled to synchronize and coordinate them, the fourth industrial revolution made clear that there will be no distinction between information flow and material flow (Fernandes et al., 2019). In comparison to earlier ideas of emerging alternative manufacturing systems (MS), the Scopus database has displayed more papers with the term "Industry 4.0." (Gunasekaran & Ngai, 2012, Monostori, 2014). This pattern in the literature on manufacturing suggests the need for a notion that offers a definitive method that is responding to the derived demands. Three distinct facets of Industry 4.0 can be identified: a paradigmatic aspect, a technological aspect, and a sustainability-related feature. Industry 4.0, from a paradigmatic perspective, satisfies the mass customization and paradigm of manufacturing (Deschamps et al., 2017), reconciling the scope and scale impacts of mass production with the impact of customized goods needs for flexibility and decentralization (Barman et al., 2015). Regarding technology, the increasing complexity is mostly addressed by new information technologies. Therefore, Industry 4.0 has something to do with the digital revolution. Industry 4.0's third component calls for sustainability through integrating future industrial systems with people and the environment (Deschamps et al., 2017).

Along with the need for new human-technology interactions, Kiehne & Olaru, (2017) initially highlighted the importance of tasks addressing the challenges while moving with resource-efficient manufacturing, as well as the importance of a supportive work environment to meet employees' demands for work-life balance, lifelong learning, and greater levels of autonomy due to changes in work characteristics. Consequently, concepts that are exclusive to a given technology lack abstraction. Industry 4.0 might be described as the idea of a fully integrated smart factory where individual products are produced sustainably in large quantities to meet consumer needs in a global market This definition combines the elements derived by Deschamps et al., (2017) and Hofmann & Rüsch, (2017).

CPS and IoT are the two primary technical pillars that are seen as crucial for the industry 4.0 vision (Hofmann & Rüsch, 2017). A high level of data transparency and stock-flow optimization will be possible due to the materials inextricably linked to their information. Industry 4.0 technologies like IoT, AI, Big Data, Blockchain, Drones, and CPS work together and have substantially made it possible for physical processes and systems to be connected robustly (Dalenogare & Benitez, 2018). Introduction of the IoT and CPS opens up new possibilities for improving intralogistics performance because such approaches build data process chains connected to intralogistics performance monitoring (Mörth et al., 2020). Industry 4.0 was labeled as an enabler of a high level of production efficiency through disruptive intelligent technologies. Therefore, it can dramatically influence economic, social, and environmental sustainability development (Bai et al., 2020). As Jafari & Azarian, (2022) illustrated, the nine key enabling technologies of Industry 4.0, which are regarded as the cornerstones of the fourth industrial revolution, are represented in Figure 1.

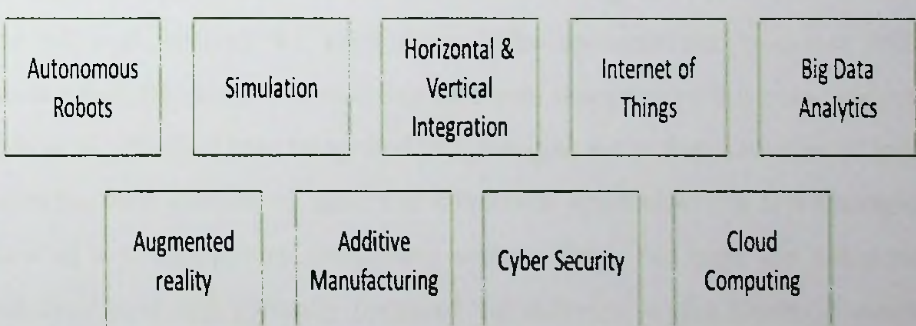

Figure 1: Key enabling technologies of Industry 4.0
Source: Jafari & Azarian, (2022)

Physical objects can generate and communicate information in the IoT, RFID. Consequently, the IoT can be considered as the foundation for many Industry 4.0

applications (Gunes et al., 2014). Through the IoT, billions of systems and devices were connected as of 2016, and billions of devices are anticipated to be connected by 2020. CPS is equipped with the ability to create and utilize information in the cyber sphere and use actuators to change the physical world. Cyber-physical production systems (CPPS) and cyber-physical production networks can be created in the manufacturing industry by many interconnected CPS (Mörth et al., 2020).

In addition, Big Data Analytics (BDA) is frequently employed as an essential tool of Industry 4.0 because of the enormous volume of data produced (Lu, 2017). For example, augmented reality (Hofmann & Rüsch, 2017) blockchain technologies (Kamble et al., 2018), and additive manufacturing which depends on 3D models, are technological drivers with a more focused scope. However, concentrating only on manufacturing is insufficient. Achieving the goal of supplying mass-customized, high-quality products sustainably requires effective logistics, particularly in global markets (Gunasekaran & Ngai, 2012, Hofmann & Rüsch, 2017). The opportunity for logistics systems to adapt to the new environment is a great advantage of Industry 4.0.

Even though logistics emerged as a social value creator during the first world war period, later various technologies assist to transform the logistics arm of companies into a competitive weapon. Industry 4.0 helps to gain safer and faster response, and improve accessibility, transparency, provenance, productivity, and mobility through drones, smart sensors, and embedded systems (Tang & Veelenturf, 2019). The logistics 4.0 and industry 4.0 revolutions offer opportunities to create industrial applications that are successful in today's fiercely competitive business environment (Bechtsis et al., 2017). These integrated technologies aid in the execution of logistical tasks with the least amount of human involvement while planning and managing the workflow in a contemporary warehouse setting. From the time the component is received until it is appropriately prepared for delivery to the client, it assists the factories and warehouses in a variety of processes.

Even though Industry 4.0 is not yet fully developed, many industry pioneers already have given their attention towards Industry 5.0 as well. Industry 4.0 is primarily focused on a shift in the industrial paradigm that is driven by technology; social and human factors have received less emphasis. The potential for job loss and job security with the rising deployment of autonomous systems is one worry associated with this industrial revolution (Jafari & Azarian, 2022). Therefore, it is crucial that the technological transition should be made in a sustainable manner and in line with the objectives of socioeconomic growth. The concerns of people and society throughout the industrial transition gave rise to Industry 5.0, which was introduced in 2015 to advance the idea of "Industrial Upcycling." In order to achieve the goal of giving authority to employees and using their thinking to control the technological tools, the industry 5.0 approach emphasizes the collaboration between people and new technology, such as industrial robots, 3D printers, etc. Studies are done to differentiate the objectives, goals, and techniques of Industry 5.0 as a newly updated phase of the industrial revolution because this idea is strongly related to the technical pillars now in use.

2.1.1. Logistics 4.0

Customers' growing expectations and the effects of global competition, which have radically changed today's industry, provide businesses with challenges. Industry 4.0 is currently the main idea for addressing these production challenges in light of this. However, logistics and industrial production meet client demands. Production paradigms alter as a result of those changes. To avoid rising costs and competitive disadvantages in international markets as a result of the present trend towards more individualized products, new production and logistics methods are required (Hofmann & Rüsch, 2017). As a result, Logistics 4.0 was developed to address these issues.

Different approaches, such as delay or modularization, have been developed to address the worldwide logistics networks of today's numerous product varieties (Costantino, Di, et al., 2014). It is doubtful whether the logistics systems of today will be able to manage even more complicated systems, such as one-off item manufacture (Windt et al., 2007), particularly without an increment in cost or a drop in quality. In this situation, the corporate environment necessitates a flexible and customer-focused response to changing needs, and novel approaches to achieving logistical objectives may be required. To be able to respond to rapid developments, real-time visibility into logistics becomes increasingly crucial (Kache et al., 2017). Because manufacturing systems fail if the connection between suppliers and consumers is weak. Whether it be B2B, B2C, or internal, it follows that Industry 4.0 enables mass customization. As a result, an appropriate Logistics 4.0 system is required.

The term "Logistics 4.0" was only used in a small number of studies in the literature. According to Strandhagen et al., (2017) characteristics of logistics 4.0 consist of time big data analytics (BDA) which can update in real-time, optimized routing, reduced storage needs due to advanced manufacturing concepts, autonomous logistics, and robotics with tracking and decision control systems to optimized inventory, transparency and visibility of information to avoid issues such as bullwhip effects, and less disruption of information due to smart concepts. In opposed to this, Barreto et al., (2017) discussed the integration of CPS's innovations and applications with the use of logistics. Furthermore, Logistics 4.0 was defined by (Timm, 2017) as the transition from hardware-oriented logistics to software-oriented logistics.

As can be observed, Logistics 4.0 has been more popular over the past few years, reflecting the growing significance of the methodologies under investigation. According to the study trend on Industry 4.0 technologies employed can be categorized into seven major groups: IoT-based systems, cyber-physical applications, robotics that operate autonomously, big data applications, cloud-enabled systems, Mobile-based systems, applications based on social media, and other technologically valued models. Since a considerable number of the articles discuss the different logistic-related directions of Industry 4.0, it can be argued that Logistics 4.0 has had a significant impact on intralogistics. However, publications from all areas of logistics were taken into consideration, highlighting the significance of task transformation in all directions of material flows.

Two points of view can be identified in terms of how humans are influencing Logistics 4.0 development. On the one hand, some papers discussed the innate influences of people, such as influences based on adoption intentions. On the other side, some studies center the research on the worker, such as when designing human-machine interfaces or exoskeleton support systems for material handling activities. When

Virtual Reality (VR) and Augmented Reality (AR) are used, for example, human work is frequently improved. This lends credence to the idea that technological systems will likely assist humans in their work rather than replace them.

The major findings of previous studies highlight the fact that systems like Lean Logistics are not replaced by Logistics 4.0, but rather are supplemented and improved upon when inefficiencies occur or managing gets overly difficult. Products, services, processes, technologies, networks, and even organizations can be supported by integrated products and tools throughout the entire lifecycle (Edirisuriya et al., 2019). Products and services could be better matched to client needs and quality could be raised. Employees should be encouraged to work more effectively, ergonomically, and with greater motivation, and a worker shortage could be avoided (Gasova et al., 2017). Contrarily, several obstacles might be found, such as the unpredictability of economic values and expenses and a lack of technical standards that impedes implementation. Additionally, the sample addressed regulatory concerns and infrastructure problems.

2.1.2. Industry 4.0 Applications in Warehouse Operations

The way we live and conduct business has undergone significant change as a result of digitization. Scholars have extensively studied the industry 4.0 and its impact on warehouse operations. Trends emerged with industry 4.0 such as IoT, BDA, Cloud Computing, Advanced Robotics, and Cyber Security has been received significant attention over the past years for the improvement of logistics operations (Winkelhaus & Grosse, 2020). Since the concept of industry 4.0 was initiated in 2010, industry 4.0 in logistics were discussed in scholarly works since 2014. However, the Scopus database suggests papers which are developed with the need for efficient warehousing and logistics operations using emerged concepts such as advanced information and communication technology and manufacturing systems even earlier than 2014 (Gunasekaran et al., 1999, Gunasekaran & Ngai, 2012). As a result of Industry 4.0's realization of mass customization, Logistics 4.0 is required (Costantino, Gravio, et al., 2014). Logistics 4.0 term has derived as e result of the state-of-the-art logistics research generated through the industry 4.0 concept (Strandhagen et al., 2017). Additionally, some studies noted the new set of logistical challenges promoted by the

Industrial Internet of Things (IIoT) might look for developments and advancements in technology, such as SC transparency, controllability, and visibility to track and trace whether the product has reached the final destination at the right time and place with required conditions. These changes also helped to establish Logistics 4.0 as a concept (Barreto et al., 2017b). As another application of industry 4.0, Big data analytics in warehouse management is emerging as a viable field for obtaining knowledge from massive data sets, improving outcomes, and lowering costs. BDA is the process of poring over vast amounts of unstructured data to find hidden patterns and correlations which can support to execute logistics operations efficiently (Ghaouta et al., 2018).

Novel manufacturing techniques, robotics with tracking and decision control systems lead to optimized inventory control, real-time information exchange. Also, papers on intralogistics area largely captured as intralogistics has emerged with industry 4.0. Later some authors used the term warehousing 4.0 when discussing industry 4.0 approaches specifically in storing and retrieving goods at warehouses. It also shows that implementing warehousing 4.0 would be possible when production and warehouse infrastructure, transport-warehouse technologies, and warehouse management systems are addressed simultaneously (Lerher et al., 2018). With the emergence of logistics 4.0, smart logistics, smart factories, and smart mobility concepts were discussed simultaneously. These smart structures are assisted by cloud technologies and industrial cyber-physical systems (ICPS) (Yue et al., 2015). Industry 4.0 concept and its technologies such as AI, ML, and Deep Learning (DL) are major enable for smart logistics and smart factory concepts (Korczak & Kijewska, 2019, Woschank et al., 2020). Therefore, this cluster covers a major proportion of the recent papers, and this cluster has wide scope including Industry 4.0, intralogistics, and smart logistics.

Further, paradigm shifts created by state-of-the-art technologies and less human involvement in industry 4.0 always raise the concern of sustainability. Discussion of sustainability in the context of industry 4.0 gives an insight into the challenges created through advanced technologies (Bechtsis et al., 2017). Some studies show the impact of less human intervention on the social sustainability. Therefore, studies show the importance of industry 5.0 which adopts the human-machine systems and human-robots collaborations.

2.2. Intralogistics

2.2.1. Evolution of Intralogistics

With the great influence of industry 4.0, intralogistics has emerged as a concept. However, the origin of intralogistics can be traced to the immediate postwar period, when manufacturing was the principal engine of economic and industrial growth (Kartnig et al., 2012). Initially, in-plant transportation was conducted using only basic tools like bag carts, other trolleys, and overhead cranes. Since block stacking had low visibility and accessibility, goods were kept at ground level. Early in the 1950s, under the influence of new transportation technologies created in the USA, this scenario started to alter. The US Army's enormous logistical demands throughout the two world wars and the Korean War were met thanks to the invention of pallets as universal loading devices and forklift trucks.

Strong economic growth during the 1960s led to explosive growth in manufacturing, distribution, and global trade. The economic boom was accompanied by rising labor and material cost inflation. At that time, management was already aware of the need to strive for efficiency across the board, not only in the manufacturing process but in all aspects of a company's operations. The storage space stood out for its potential for rationalization. Storage has to be transformed from a necessary evil to a valuable and effective buffer between the various production stages and between production and the market in order to fully realize this potential. It was already conceivable to incorporate the storage function into a company's work processes using technology that was available at the time. This led to lower warehousing costs, the use of space-saving storage systems, and higher throughput. The increased investment was unavoidably needed, and the resulting adjustments suggested a switch from labor-intensive to capital-intensive warehousing techniques.

In 1962, a 20-meter-high automated rack warehouse was constructed in Germany (Kartnig et al., 2012). A period of advancements in the creation of rack feeders, either suspended from rails or operating on ground level rails, began with the introduction of this sort of storage. Other developments included computerized storage management and the automation of transport and storage procedures. Because of the inability of the existing storage systems to keep up with changes in consumer behavior, businesses were compelled to reconsider how they approached production and distribution. A broader variety of product varieties and high-quality goods were now in high demand on the market. In addition, quick delivery times and high availability were now prerequisites. If businesses were to meet these demand patterns at an affordable cost, new approaches were required. New order picking, storage, and dispatching techniques, therefore, became increasingly important. Manufacturing and distribution businesses have invested heavily in automated high-rack warehouses and related material handling machinery in recent decades. Simple warehouses became distribution centers as a result of the expansion of order picking and distribution capabilities. Intralogistics plays a vital role in internal logistics systems in terms of operational costs and service quality. It manages all the warehouse functions properly as shown in Figure 2. The introduction of new technology, such as electric monorail systems, AGVs, Automated Storage and Retrieval Systems (AS/RS), and long products storage systems, at this time, had a significant impact on materials handling.

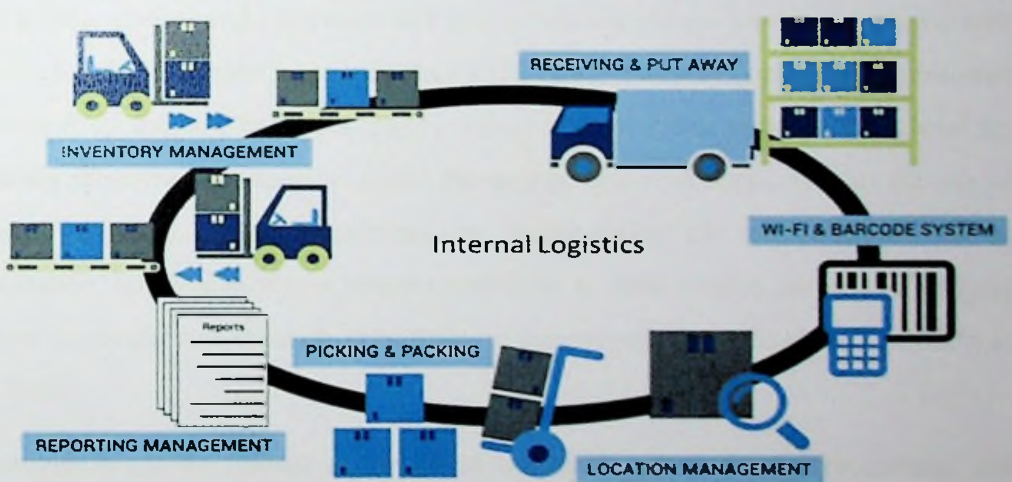

Figure 2: Managing internal logistics
Source: Vatumalae et.al. (2020)

Plant designers consequently started to consider production as a whole, which includes both internal and exterior processes. The so-called "just-in-time" and "lean production," which aimed to optimize the entire supply chain by attaining prompt delivery across it, was born out of this. The implementation of new IT systems and communication technologies was required for this reorganization of production processes. There have been new electronic data transfer systems implemented and information exchange standards established. It is now possible to meet the requirement for dependable coupling of product flows and information thanks to the complete maturity of barcode labels and scanners for industrial applications. The biggest intralogistics milestone of the 1980s can arguably be identified as the adoption of barcode systems.

Another great milestone of intralogistics is the dawn of the fourth industrial revolution. Industry 4.0 began to shape intralogistics with its's digital transformation drastically. All domains of logistics were considered in emphasizing the transformation of warehouse tasks in every direction. Since all the dimensions of industry 4.0 were triggered by technological developments, it directly impacted logistics operations as well (Winkelhaus & Grosse, 2020). Making warehouses smart environments has become popular along with industry 4.0 and increased usage of information and communication technologies (ICT). It offers efficient storage assignment and retrieval with greater control and execution, and end-to-end warehouse services at a lower cost (He et al., 2018). Currently, supply chains (SC) have more dynamic and complicated systems (Sugathadasa & Perera, 2021). As a result, logistics systems are crucial for ensuring effective coordination across the supply chain networks. Due to the rise of industry 4.0 and digital transformation, intralogistics has currently proven its importance. Intralogistics is a major contributor to both service and manufacturing sectors in several aspects such as utilization, throughput, and effectiveness (Mörth et al., 2020).

Intralogistics can be known as the art of automating, optimizing, integrating, and organizing the logistics flow within the walls of the warehouse or fulfillment center. Simply said, it is a procedure of moving materials within a facility while employing the most effective techniques. This term was particularly popular among German industries and then numerous scholarly works in this field were started to generate (Pawlewski et al., 2021). To accurately track the movement of physical commodities in real-time and manage stock replenishment in accordance with requests is a major issue for warehouses today. Systems for warehouse management make it easier to regulate material flow so that orders can be fulfilled correctly. Integrating warehouse systems with intralogistics solutions created in the form of optimization and automation will increase the functionality of internal material movements. (Fragapane et al., 2020). The state-of-the-art equipment is used in intralogistics to manage and handle material movements. In addition to the physical goods, computer systems and information technology (IT) tools are used to complete order fulfillment tasks more quickly. Because of the e-commerce industry's explosive growth, intralogistics now faces new difficulties. Growing inventory turnover rates with shorter storage periods, large numbers of orders in small quantities, and quick deliveries necessitate flexible intralogistics operations with increased throughput and productivity. The usage of intralogistics systems would be the best way to eliminate inefficiencies and improve the reliability and accuracy of warehouse operations (Furmans et al., 2019). However, it can be a challenge to foster intralogistics through expanding digital infrastructure and investing in specialized training to have a substantial impact on industries. Intralogistics is transitioning from huge rigid systems to modular, technology-driven solutions that are robot-supported and capable of self-optimization to achieve a smart warehouse environment with maximum flexibility and full automation. It is clear that cutting-edge design concepts like virtuality, interoperability, and real-time capabilities will influence how intralogistics develops in the future.

Even though Intralogistics has garnered considerable attention over the past few years, literature on the subject area is still limited. Few review articles could be identified which is related to intralogistics and emerging trends with industry 4.0 in logistics. Bigliardi et al., (2021) reviewed industry 4.0 in logistics through bibliometric analysis. They have highlighted the importance of industry 4.0 in the logistics field. Also, they claimed that was the first systematic review on logistics 4.0 best of the authors' knowledge. Winkelhaus & Grosse, (2020) did a systematic review on logistics 4.0 to develop a framework to identify future tactics and tech-oriented methodologies to fulfill certain logistics tasks combining outside factors, significant technical advancements, and the effects of human interactions. Considering current and future demand, logistics 4.0 solutions were summarized according to the technologies such as IoT, CPS, Big Data, cloud computing, and mobile-based systems. The scientific literature on artificial intelligence, machine learning, and deep learning is thoroughly examined by Woschank et al., (2020) in the context of smart logistics in various industries. Apart from that, there is a significant amount of review articles which has touched on the area of industry 4.0 in logistics. These papers are mainly focused on automated warehousing, smart logistics, supply chain analytics, and new trends (Kembro et al., 2018, Domanski, 2019, (Bag et al., 2020)Karakikes et al., 2019).

As for the intralogistics area, Kartnig et al., (2012) have reviewed the history of intralogistics as well as the trends that are most likely to influence its' future. This paper has discussed the changes in the logistics area and focus of intralogistics research due to globalization, urbanization, demographic shifts, and climate changes. There are other review articles which are focused on different trends and applications in the intralogistics area. Fragapane et al., (2021) have identified and classified research related to the planning and control of AMRs in intralogistics. The research implications related to digital twins technologies in the optimization of intralogistics processes have discussed by Pawlewski et al., (2021). Further, it demonstrates the connection between industry 4.0 and lean intralogistics in the context of digital twins. Another literature review was done related to the digital twin concept in internal transportation by Kosacka-Olejnik et al., (2021). The relationship between ideas like material handling, material flow, and intralogistics in the context of internal transportation networks and the Digital Twin has been examined by the authors.

2.2.2. Current & Future Trends in Intralogistics

"Digital twins" is a noticeable technology that simulates real-world systems, updates them in real-time, and aids decision-making. Digital twins and computer simulations are integrated in the optimization of intralogistics processes (Pawlewski et al., 2021). A Digital Twin System can be developed to collect real-time data from product-service systems in physical warehouses and then map it to a cyber model. For large-scale complex and automated warehouse systems, previous studies have presented revolutionary digital twin-driven joint optimization approaches. (Leng et al., 2021).

Industries constantly striving to reduce production and transportation costs and improve overall efficiency. In these considerations, internal logistics trying to shape with new trends. One recent alteration is shifting folk lift-based movements to milk-run delivery systems (Paszkowiak et al., 2021). Logistics trains can be considered as one of the intriguing intralogistics applications which are based on the "milk run" distribution system. When moving materials inside the warehouse, the train's trolleys used the double Ackermann steering system (Paszkowiak & Bartkowiak, 2020). The main consideration behind the logistics trains concept is the ability to identify whether the train can traverse the given path without colliding with other objects in the warehouse. The double Ackermann steering system's geometric layout and linkages are made to allow it to travel along the predetermined path without running into any nearby obstacles

2.2.3. Internal Logistics and Modern Warehouse Management

When thinking about the supply chain layers, logistics is a crucial component that connects the entire process. It entails the forward and reverses the flow of commodities such as planning, implementation, and management, as well as service-related information. Through the supply chain levels, logistics is a systematic procedure for managing and controlling the procurement, transportation, and storage of raw materials, semi-finished goods, and finished goods with the aim of maximizing profit using particular information (Gattorna, Day, & Hargreaves, (1991). Because logistics can organize, coordinate, and arrange the information and resources needed to transport goods smoothly, promptly, reliably, and affordably, logistics is regarded as the blueprint of the supply chain. As a result of rising demand around the world, logistics operations are becoming more and more necessary. Since supply chain integration is thought to be a means for businesses to obtain a competitive advantage, businesses are concentrating more on their logistics operations (Hertz & Alfredsson, 2003).

Warehouse services are important in supply chain and logistics. It deals with operations linking the various supply chain tiers, both incoming and outgoing. It merely accepts the goods, stores them under the necessary conditions, picks them, and consolidates them for shipments. Raw materials, semi-finished goods, and final goods must all be safely housed in the warehouse during product manufacturing. In addition to allowing continuous manufacture of goods and regular supply, warehousing enables timely delivery and distribution optimization. Today, the majority of businesses have outsourced their warehouse activities to third part logistic (3PL) providers (Hertz & Alfredsson, 2003). Manufacturing companies outsource warehousing and use experts to handle it, so they can concentrate more on their core duties. Using industry best practices and cutting-edge technologies, these 3PL companies can manage enormous storage spaces designated for various items.

Some operations need a lot of labor when it comes to warehouse operations. Picking is a crucial process in warehouse operations where Pickers locate and retrieve a variety of products to fulfill customer orders (Dallari et al., 2009). Picking is the most important and expensive warehouse operation, as mentioned by Marchet, Melacini, & Perotti, (2015) because poor performance could lead to unmet consumer demand and high expenses. As a result, it is seen as a crucial process that must be carried out precisely and at a high level of performance to ensure on-time delivery. Industry experts have noticed that picking caused more than half of warehousing costs and takes up the most time there. Therefore, the best strategy to reduce warehousing costs is to improve the picking process (Dekker, 2004). Due to emerging trends like globalization, e-commerce, rising customer expectations, and new laws, warehouses are competing to fill a lot of orders quickly. Because pickers must choose a large number of items in tiny amounts, order picking is more difficult at order fulfillment centers run by online retailers (Batt & Gallino, 2019). Therefore, the significance of improving the order picking system was highlighted more recently in the literature on warehouse architecture and planning (OPS).

In the recent past, barcode technology was used in warehouses for tasks like receiving, putting away, replenishing, picking, packing, and shipping as well as cycle counts, value-added tasks, and labor tracking. Radio Frequency Identification (RFID) technologies are currently used with wireless sensor networks to track stock movements due to the increased demands for mobility and transparency in most warehouses. Most of the conventional material handling methods have now been replaced by advanced technologies and trends (Furmans et al., 2019). Later, industries realized the importance of autonomous transport vehicles for handling internal logistics, especially for repetitive tasks (Kłosowski et al., 2018).

Further, Automated Guided Vehicles (AGVs) and the usage of mobile robots (AMR) in intralogistics operations are significantly increasing. In intralogistics fields such as manufacturing environments, warehouses, cross docks, fulfillment centers, and service fields like hospitals and port terminals (Furmans et al., 2019). These systems take charge of scheduling, routing, and dispatching in response to all the changes in these fields. called Automated Storage & Retrieval Systems (AR/RS) which is similar to AGVs applies their control mechanism to the replenishment of goods (Fernandes et al., 2019). By utilizing cellular transport systems, smart boxes, and multi-agent simulation, the factories and warehouses became more resource efficient. These systems ensure the constant and prompt interchange of information, which coordinates the autonomous design for material flow requirements (Furmans et al., 2019).

Warehouse automation has earned attention to maximize the warehouse throughput and optimize stock movements. The control and coordination of automatic material handling equipment were discussed in the early stage of this domain (Karlstrom, 1983). Technology has become an essential tool to manage warehouses in a competitive and complex market. Warehouses are equipped with various technological tools and warehouse management systems to execute dynamic storage allocation and functioning inventory tracking, order picking, order consolidation, and shipping. Therefore, studies are concerned about designing vehicle routing in an automated warehouse (Burkard et al., 1995).

Most of the studies published after 2000 have given their attention to automated OPS since order picking is the most labor-intensive task and it needs more attention (Dallari et al., 2009). Further, studies emphasized the usability of WMS with developed advanced computer and control technologies to manage OPS (Hompel & Schmidt, 2007). WMS is a necessary approach for the automated warehouse. Compared to a manually handled system, an automated warehousing system yields more reliable results with less work (Atieh et al., 2016). Even though barcodes and radio frequency technology were applied to warehouses in previous times, nowadays firms are trying to replace it with advanced automation and robotics to keep up with the latest requirements. Fulfillment centers (e-commerce warehouses) use robotics widely, as a large number of orders of small quantities require faster deliveries and necessitates flexibility with higher throughput and higher productivity (Azadeh et al., 2019).

The recent studies in warehouse automation and robotics, discussed automated systems such as conveyors, AS/RS and AGVs, and AMR to control warehouse operations easily (Fragapane et al., 2021). There was a significant number of studies on quantitative methods applied to warehouse automation. In the context of smart warehouse automation, mathematical methods such as probabilistic queuing theory, numerical analysis, and optimization techniques are used to identify customer order arrival patterns and assigned storage by AGVs (He et al., 2018). Intelligent systems are also considered as the main trend for warehouse systems in future (Jafari & Azarian, 2022). Therefore, integrating robotics technologies with artificial intelligence and machine learning is gained the attention of current studies. AI will leverage robotics automation through data-driven analytical approaches to maximize the efficiency of industrial systems (Fragapane et al., 2020).

2.2.4. Warehouse Optimization

Optimization and Operation research techniques have been widely discussed topics in logistics operations. The literature has extensively used OR methods, notably optimization and simulation techniques, to enhance Supply chain and logistics performance (Pourhejazy & Kwon, 2016). There can be seen an exponential increase in the number of papers published from 2005-2016 in SCN optimization and design (Farahani et al., 2014).

Despite the fact that supply chain optimization is a broad topic, it cannot be neglected when discussing on intralogistics as it is integrated with strategic inventory decisions in a logistics system which are vital to run the day-to-day operations of a company. In the view of uncertainty, the future behavior of market conditions and also inaccuracy of human decision-making highlight the need of improving the knowledge related to internal logistics using SC optimization and other analytical technologies (Agrebi & Abed, 2021). Decision-making models can evaluate the exact performance of drivers of the supply chain. It includes supplier selection, order quantity determination, production planning, capacity planning, and distribution planning (Le et al., 2021). SC network design has been a significant topic in operations research (OR) studies. The literature has extensively used OR methods, notably optimization and simulation techniques, to enhance SC performance (Pourhejazy & Kwon, 2016). There can be seen an exponential increase in the number of studies published from 2005-2016 in SCN optimization and design (Farahani et al., 2014).

In the intralogistics context, warehouse routing problems and inventory routing problems were discussed after analyzing the impact of routing cost and distance properly. Also, reliability and flexibility are vital in decision-making in SC (Kleywegt et al., 2004). Sustainability is attention-drawn topic in the domain of SC. Scholars have used various optimization techniques to achieving a balance between three dimensions (Economic, Social & Environmental) of Sustainability. Brandenburg et al., (2014) have discussed the quantitative methods used in Sustainable SCM including several optimization approaches. Various studies have clarified that mathematical and computational methods for optimal control, performance matrices, as well as qualitative methods, bridge industrial engineering terns and management terms (Dolgui et al., 2019). Warehouse management needs to put considerable effort into optimization to manage material flows efficiently. In order to fulfill customer demands precisely, on time, and with a minimum cost, order picking at the warehouse requires the execution of optimization strategies for OP routing, storage assignment, and order batching (Kovac & Djurdjevic, 2020). In past literature, many optimizations and simulation (SO) approaches have been applied to enhance SC performance. Because traditional approaches are no longer useful for designing and evaluating complex SC systems, SO approaches have gained popularity even today (Sahay & Ierapetritou, 2013). Simulation modeling can capture the dynamic behavior of systems more rigorously (Pourhejazy & Kwon, 2016). The simulation also can model automated warehouse systems and analyze the applicability of the used optimization mechanism. In intralogistics systems, optimized material movements are of growing importance. It has been demonstrated that there are a lot of potential to boost productivity when an automated system is integrated with optimization (Hafner & Lottersberger, 2016, Nicolas et al., 2017).

There are lot of OR methodologies used by various studies such as linear programming, non-linear programming, dynamic programming, fuzzy systems, vehicle routing problem, heuristics algorithms, and particle swarm optimization (Sadeghi et al., 2013). Different applications of vendor-managed inventory (VMI) have been proposed in the literature to reduce the bullwhip effect in SCM. The VMI problems and inventory allocation problems were presented in previous studies to find optimal solutions with improved heuristic algorithms (Sadeghi et al., 2013, Mousavi et al., 2016). Some studies have employed hybrid approaches as the methodology (Fan & Wang, 2017). The most recent studies in this cluster show trend towards the e-commerce and omni-channel logistics (Kembro et al., 2018, Risberg & Risberg, 2022)Warehouse routing challenges and inventory routing issues were studied in the context of intralogistics, and the effects of routing cost, dependability, and flexibility on decision-making were examined (Kleywegt et al., 2004).

2.3. Warehousing & Inventory Management

2.3.1. Inventory Optimization in SCM

Typically, production, distribution, marketing, and sourcing (procurement) have been operated independently. Unfortunately, although it is appearing to be working toward the same goal, these organizational functions have various goals. High customer service standards and high sales volumes are goals of marketing, however they contradict production and distribution functions. Production and distribution decisions frequently focus simply on increasing throughput while minimizing production (unit) costs without focusing on large inventory levels or lengthy lead times. Sourcing decisions typically depend solely on lowering the cost of goods. Supply chain management is the efficient blending and coordination of several enterprises with various goals toward a shared objective (Singh & Kumar, 2011). The challenge of inventory management is to keep enough of a given item on hand to satisfy a predicted pattern of demand while striking a balance between the expense of keeping the item(s) in stock and the penalty (loss of sales and goodwill) of running out. It is startling to discover that a very broad range of issues, each appearing to be distinct, can be mathematically defined as an inventory-control problem. Also, there are numerous distinct types of inventory system models (Radhakrishnan & Prasad, 2009). The costs of inventory management systems fall into three categories. Depending on the particular system, the relative importance will vary. The administrative cost of placing an order, also known as the set cost or reorder cost, the carrying cost of retaining inventory, which includes storage fees, interest, insurance, etc.; and the shortage cost, which is the loss of income, goodwill, etc. when stock runs out, are these costs. For effective supply chain management, all of the aforementioned should be optimized (Singh & Kumar, 2011).

Previous studies have given attention to inventory ordering costs, handling costs, and optimization criteria including ordering time and replacement time for inventory control. Optimization approaches considered several aspects of inventory including inventory policies, multi-echelon networks, and single-unit to multi-unit systems. When setting the objective functions, optimization approaches were frequently used to categorize the domains and inside information while addressing joint maintenance and inventory optimization. (Cattrysse et al., 2013). Warehouses use different mechanisms to optimize the goods replenishment while reducing the complexity.

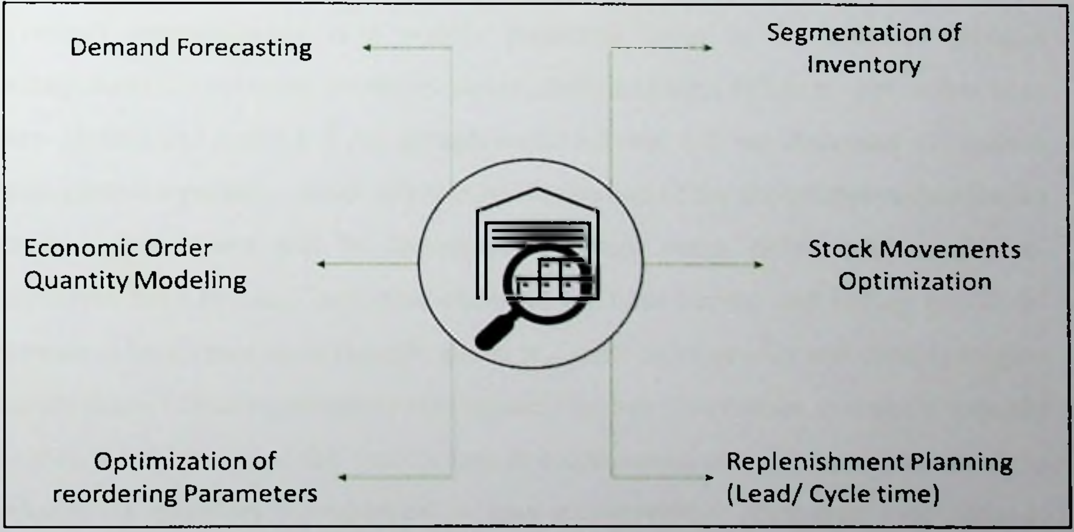

Figure 3: Inventory optimization techniques

2.3.2. Inventory Optimization using Machine Learning

To provide very precise control, warehouse optimization needs efforts from every link in the supply chain. In this context, ML and data driven algorithms are very useful. A number of useful machine learning (ML) applications for the supply chain have recently been unveiled (Mohamed-Iliasse et al., 2020). ML algorithms are used by e-commerce companies to keep track on their inventory levels based on the demand generated by their customers at different points in time. Therefore, warehouse management can offer their service while forecasting demand for the products and boost company's sales (Praveen et al., 2020). In addition to manage supply and demand, ML also offers a number of advantages, such as a better customer experience through the decrease of out-of-stock situations and cheaper costs due to better-planned stock. Therefore, ML will help to create intelligent warehouse stocking system. Warehouse decision support systems based on OR and ML can be used to assist strategic, tactical and operative decisions such as scheduling and location problems (Kahraman & Onar, 2015). Currently majority of the OR techniques embedded with intelligent systems powered by ML to solve variety of complex problems in warehouses.

2.3.3. Inventory Replenishment in Intralogistics

Inventory replenishment is a widely discussed topic in the area of logistics management. To optimize inventory replenishment models different approaches have been studied and applied. Even though under Section 2.4, we discussed automation optimization separately, under this section integration of the above approaches for the goods replenishment will be discussed. In recent years, online retailing and e-commerce have become important channels for both buying and selling goods. E-commerce businesses must provide goods to clients more swiftly and cheaply to gain market share. Effective inventory management in their distribution systems is required for this. Alibaba, one of the world's largest e-commerce companies, is attempting to enhance its inventory management to gain a competitive advantage over other e-commerce businesses (Dai et al., 2020).

Inventory replenishment problems are focused on inside the warehouse and outside the warehouse. When discussing about stock flows and goods replenishment, order picking is a non-negligible topic as both stocks flows and order picking systems directly contributes to replenishment

Inside the warehouse, most of the warehouse problems consider the stock flow inside the facility to deliver the goods with minimum lead time, cost, and movements. Storage assignment, order batching, and routing problems have all been addressed using a variety of ways. Warehouse management, storage systems, and decision-making in the stages of storage system designing, planning, and controlling are discussed in previous research. Many businesses are currently contending with fierce market competition. Having a reliable and adaptable supply chain and logistics is crucial. More cutting-edge approaches are employed to optimize inventory replenishment such as ML, big data, cloud computing, and coordination (Liu et al., 2017). Warehouses use different mechanisms to optimize the goods replenishment while reducing the complexity.

Making decisions is made much more difficult by the simultaneous intervention of complex relationships across the supply chain. In the area of inventory management, determining optimal replenishment model while responding to environmental changes is difficult. Therefore, scholars have taken efforts to apply ML to assist warehouse managers in comprehending these intricate situations and improving inventory flow (Priore et al., 2019).

2.4. Research Gaps

We systematically reviewed the literature published in intralogistics area. Even though intralogistics is still a trendy name in many industries, automation, optimization, and integration are not new concepts. Therefore, researchers have discussed warehouse efficiency in the context of automation, robotics, and optimization since 1970 up to now. Even before the fourth industrial revolution, considerable attention was given to improving logistics in both manufacturing and service industries. However, intralogistics term has emerged after launching the concepts such as industry 4.0 and logistics 4.0. It can be noted that 35% of the total published papers were published in 2019, 2020, and 2021.

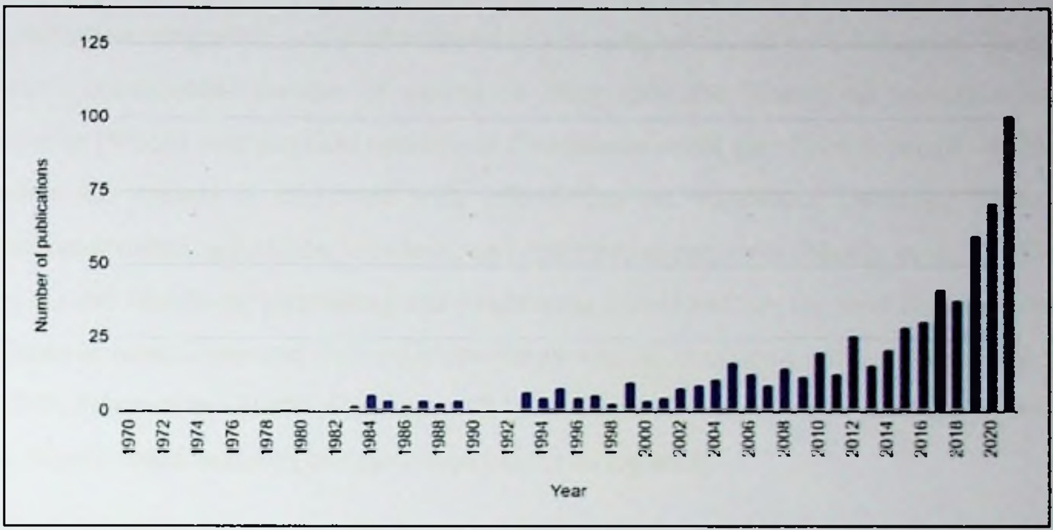

Figure 4: Number of publications in intralogistics domain

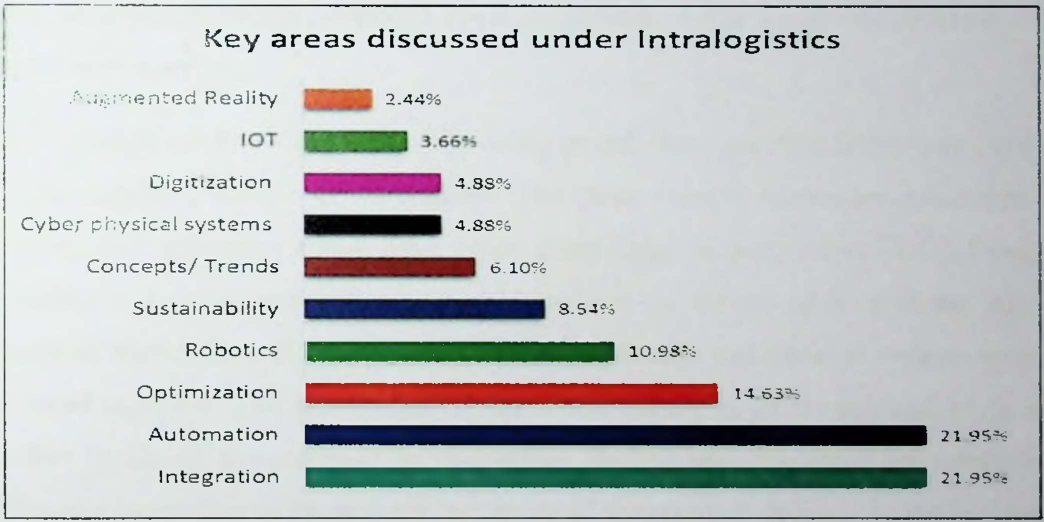

Figure 5: Key areas discussed under intralogistics

As shown in the Figure 5, various areas have been discussed in the intralogistics related papers. We searched the keyword "intralogistics" on the Scopus web and downloaded the CSV file which contains relevant information about published papers. Therefore, it gives a very broad view of studies carried out in this domain. Some of the domains are directly linked to the industry 4.0 applications while some domains represent the formation of intralogistics term (Optimization, automation, and integration). Among these key areas, integration in the form of system integrations and industry 4.0

application integration, and mathematical model integration had been discussed. There was a considerable number of studies on integrating the Warehouse Management System (WMS) with physical operations. Companies could get effective use of WMS when the system is integrated with information on warehouse inventory levels, customer ordering patterns, locations, and distribution networks (Mason et al., 2003). In several situations, forecasting and judgmental games such as the Beer Distribution Game is increasingly and frequently combined with SC decision-making (Perera et al., 2019, Perera et al., 2020). This area will be widespread even if we limited the papers in supply chain analytics and decision-making to logistics.

Since this study focuses on warehouse optimization and industry 4.0 to move forward with intralogistics concepts, various studies that used above mentioned approaches were given more focus. In the early part of the literature review section, we thoroughly explained the knowledge developed in various industry 4.0 in warehouse concepts and optimization concepts.

Even though goods are inactive while being stored, there are crucial decisions to be made regarding storage in warehouses. The three main concerns are assignment, zoning, and allocation which have given more focus in past years. Each of them contains a set of operationalized subproblems that can be solved by systems. Also, previous studies have discussed about automated storage and retrieval systems under a broad umbrella. The knowledge related to the execution of storage and retrieval orders inside of a warehouse or production facility was discussed considerably. However, according to the authors, too much of the research focuses on the analysis of AS/RS in static situations for granted as reality. The authors advise concentrating on more adaptable strategies instead. Thus, it is possible to satisfy volatile demand, shifting order behavior, and rising service level needs. Combining autonomous components with manual procedures may be necessary, depending on conditions (Fottner et al., 2021). There were studies on cost-based optimization models created to evaluate the suitability of automation. Other than that, optimized models and automated systems were studied separately in most cases.

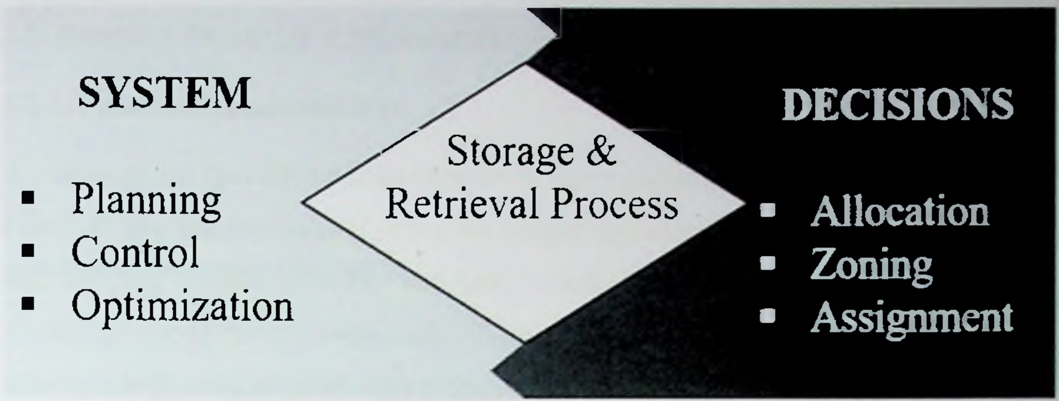

Figure 6: Main decision problems in intralogistics storage systems
Source: (Fottner et al., 2021)

There can be said various types of optimizations and OR-related work have been carried out in the warehouse logistics domain. Numerous studies have assessed the benefits of sharing demand information. Also by connecting ML approaches used in SC, studies have illustrated existing warehouse applications and potential research gaps (Mohamed-Iliasse et al., 2020). ML can be used to utilize past data to predict the demand pattern and goods retrieval in warehouses. However, there aren't many studies that focus on evaluating past demand patterns for classifying the inventory and allocating storage locations. In storage classifications, most studies have used conventional methodologies such as ABC, and XYZ. Also, few authors have given attention to improving classification through mathematical approaches such as fussy systems (Chu et al., 2008) and multiparametric dynamic models (Manzini et al., 2007). Even though ML is a very prominent method for data classification, applications in ML in inventory classification is limited.

Also, considering collaboration or information visibility of inventory issuing patterns and effects on supply chain performance at the local and global service levels (Costantino, Di, et al., 2014). By examining current technological trends and inventory related storage assignment related, it can be identified that this domain needs to be filled with lot of studies. This research study aims to close the gap by integrating advanced concepts in industry 4.0, optimization, and simulation in order to ensure a smooth flow of inventory inside the warehouse.

2.5. Research Problems & Research Objectives

2.5.1. Practical Considerations

Warehouses are operating a large number of items and stock keeping units (SKUs) for a day. All the basic processes of the warehouse including receiving, storing, picking, and shipping consist of many sub-tasks. Storage assignment, order batching and zoning are few of the main sub-tasks. These tasks should perform with competency to achieve a high level of productivity. Inside the warehouse, storage assignment is very crucial. It will directly affect the order picking task and then the retrieving process. Therefore, it should be required to identify the correct storage assignment for the items

2.5.2. Research Problems

RP1: How the material flow inside the facility is managed according to goods dispatch?

RP2: What are the improvements that can be done to enhance the stock flow movements using optimization techniques?

RP3: How intralogistics facilitates the stock flow movements considering segmentation of inventory integrating ML techniques

2.5.3. Research Objectives

RO: Identify the patterns of goods replenishment based on the orders received for the warehouse

RO: Develop an optimized storage plan based on inventory segmentation improved by the ML approach

RO: Investigate how intralogistics will facilitate replenishment of goods while improving the operational efficiency of the order fulfillment process

CHAPTER THREE: METHODOLOGY

The methodology is composed of 3 steps including understanding demand and data patterns through ABC analysis, Improved classification ML-based approach, and simulation. By identifying the logistics processes systematically, a demand-driven optimization plan is created integrating inventory segmentation. Then simulation model is used to execute and evaluate the developed optimization plan. The Simulation model focuses on storage allocation and moving the stored items through created logistics loops to execute the order fulfillment process efficiently (Pawlewski, 2019).

3.1. Identify the Demand for Goods and ABC Analysis

The inventory control issue is a particularly common one in operations research. To address inventory problems, an astonishing number of models were launched. There is a distinct set of assumptions for every model. Considering that businesses typically have many different types of items, raw materials, and assembling parts, it is easy to lose track of efficiently managing resources (Chu et al., 2008). It has long been recommended in operations management to prioritize topics for management attention. The topic is most frequently related to inventory management; however, it is far more general than that. The argument states that one can categorize the items in the inventory application into three groups: a small number of items that account for a sizable portion of the cost volume, an intermediate category of items with a moderate cost volume, and a sizable number of low cost and/or used items.

One of the methods that are most frequently applied in companies is ABC analysis. Using the ABC classification, a company can classify stock keeping units (SKUs) into three types: A stands for extremely important, B for important, and C for least important. The relative importance of each item should be taken into account when deciding how much time, effort, and money to devote to inventory control. The ABC analysis got its name since the categories were given the letters A, B, and C, respectively.

Although this may vary depending on the circumstances, it has been customary to employ these categories (Flores & Whybark, 1987). The notion is that focus should be placed on the "A category" items to maximize management performance when the analysis is completed, and the categories are established. This is a reasonable rule for distributing time for managing finite resources, according to empirical data.

The Italian economist Vilfredo Pareto conducted some of the earliest formal research. He postulated that the majority of a nation's output is produced by a small portion of its population. Although the numbers have changed, his legacy, the 80-20 rule, has persisted. Pareto believed that his findings of the 80-20 rule were generalizable, however, scholars have been discussing its applicability of it to various study environments. Inventory management is the area of operations where ABC analysis is most frequently used. The only criteria used to classify inventory items as A, B, or C, are cost or usage. In other words, if an inventory item has a high unit cost or high consumption, it is categorized as an A item.

Items have typically been categorized into A, B, and C groups using just one criterion. The annual monetary consumption of an item is frequently the criterion for inventory goods. Other factors, however, can represent additional vital managerial considerations. Examples of such issues are the need for a large order quantity, the rate of obsolescence, the rarity, the substitutability, and the lead time of supply. It is commonly known fact that the usual ABC analysis would not work to classify inventory items in reality as a result. (Chu et al., 2008). Since, previous studies claim that traditional ABC classification is not just adequate for inventory control systems, it is recommended to use joint classification techniques or matrices and multi-criteria classifications which have considered other factors such as lead time and safety stocks besides the annual consumption.

In business, classification has become a crucial tool for making decisions. The classification technique has applications in stock market prediction, credit scoring, classifying inventory goods, and event prediction including credit card usage. Previous studies have suggested a matrix-based approach and joint criteria matrix which is based on 2 criteria. Although this is a development in the multi-criteria ABC classification, it is challenging to employ when other factors need to be taken into account. Some studies have followed statistical clustering as a methodology for the foundation of an inventory classification model. It can support numerous combinations of features. However, this method uses a lot of data, factor analysis, and a clustering mechanism, which may make it unfeasible in normal stockroom settings. Some authors have employed the analytical hierarchy process (AHP) for ABC classification.

For multi-criteria ABC classification, complicated computational techniques or processes are typically required. Fuzzy theory is a subject that has gained a lot of attention recently and is frequently used to manage the fuzziness and ambiguity of data or information. In order to predict the value of a discrete or categorical dependent variable, fuzzy classification employs the information present in a set of independent attributes. This paper's goal is to suggest a novel inventory control method called ABC-fuzzy classification which can easily be applied and can consider the experience, and knowledge of managers, and their judgment when classifying goods (Chu et al., 2008).

As another technique for multi-criteria inventory classification, AI and its sub-section called ML techniques have been applied in more recent studies. The genetic algorithm was used by scholars to solve the inventory categorization problem. Another artificial intelligence-based method that can be used for categorization is the artificial neural network. An artificial neural network has been suggested to categorize SKUs in the pharmaceutical sector. The method employs two types of learning: back propagation and genetic algorithms. These methods are obviously heuristic and might not work well in all environments. Also, straightforward classification methods have been presented that are comparable to data envelopment analysis and used weighted linear optimization (DEA) (Ramanathan, 2006). Then, in order to meet the growing demand for ICT tools and I4 systems in the production and operations management sector, supervised classifiers in the ML research domain (like support vector machines and deep neural networks) are trained and used to categorize using the sample items solely based on the values they show on the features (Francesco et al., 2019). Francesco et al., (2019) have adopted ML based multi-criteria inventory classification approach for intermittent demand.

3.2. Improved Inventory Classification through Machine Learning

The significant contributions to the majority of the literature on inventory classification include an operational focus, straightforward implementation, and interpretability. Additionally, techniques based on AI and ML can be used to understand and imitate traditional ABC classifications (Lolli et al., 2017). A multi-dimensional inventory categorization scheme is essential for assigning SKUs to different locations while order fulfillment considers the demand distribution and inventory controlling policies (Lolli et al., 2017). Under a general service limitation, machine learning offers an extension of conventional classification. The methodological design is built on ML classifiers to develop decision trees that make classification judgments simple to understand and replicate. Unseen data can be categorized once trees have been created.

For this study, we used ML-based classification method to improvise the classification further. The initial data analysis and ABC classification was done by Excel. Then the excel data file was opened through Orange Data Mining software to continue with the machine learning classification. The proposed inventory classification approach is step-by-step defined. The goal is to assign each item to a certain considering certain demand variables of items. The initial classified inventory system is made by focusing on the total consumption value of each item under the ABC classification. Following that, the non-simulated things are classified in the best possible way.

3.2.1. Supervised classification through Machine learning

Supervised learning techniques are the most popular machine learning techniques (Jordan & Mitchell, 2015). The availability of annotated training data is what distinguishes supervised learning from unsupervised learning. The term derives the existence of a "supervisor" who gives the learning system instructions for the labels to attach to training samples (Cord & Delany, 2008). Identification of humans and objects through images, diagnosis systems for hospitals, and email spam classifiers are a few examples of supervised learning systems that exhibit the function of approximation problems. In these systems, the purpose is to generate a predicted dependent "y" in response to an independent "x". The training data are a collection of (target value-y & factors-x) pairs. Classical vectors or more sophisticated things like papers, photos, DNA sequences, or graphs could be used as inputs. A variety of output types have also been researched. Focusing on the straightforward binary classification problem, where y takes one of two values (for example in emails, "spam" or "not spam"), much progress has been made; however, there have also been a lot of studies done on issues like general structured prediction, ranking issues, and multiclass classification, in which y offers a partial order on a set of labels based on multilabel classification (If they satisfy the constraints, it can be given a label). This method is employed in this study.

Most of the time, supervised learning systems use a learnt mapping called f(x), which creates an output called y for each input called x. (or a probability distribution over y given x). The many mapping functions that exist include decision trees, decision forests, logistic regression, K-Nearest Neighbor (KNN), support vector machines, neural networks, kernel machines, and Bayesian classifiers, to name just a few. To estimate these various types of mappings, several learning algorithms have been suggested (Jordan & Mitchell, 2015). Additionally, there are generic techniques like multiple kernel learning that aggregate the results of many learning algorithms. Techniques for learning from data frequently draw inspiration from mathematical analysis or optimization theory, with a focus on machine learning challenges.

3.2.1.1.Decision tree

Each fold is used to train a decision tree, each node of which can binary split the items according to a single criterion. Following a pre-established dividing rule, the split is carried out. The test is conducted for both the fully developed tree and all of its pruned forms, and it involves testing each decision tree against the items not included in its training fold. In terms of the percentage of objects successfully identified in the test phase, a performance for each fold and trimming level is remembered (Lolli et al., 2017). The pruning level that produces the best performance for each pruning level is chosen after calculating its average performance across the folds. The final tree is trained using the components from every fold and is then pruned to the best pruning level.

3.2.1.2. *Logistics Regression*

Data can be classified using logistic regression, which is a statistical method that involves fitting the data to a logistic function. The foundation of logistic regression in machine learning algorithms is the intriguing link between generative and discriminative classifiers, which helps us comprehend probability. Modern categorization techniques are typically used by logistic regression (Gladence et al., 2015). The approach is enhanced by Orange with features including stepwise variable selection, handling of constant variables, and singularity handling.

3.2.1.3. *Random Forests*

The same folds can be processed using a Random Forest technique rather than a decision tree. Each fold is used to train a collection of Random Forests, which are then tested on things that don't belong to the current fold. By altering the number of trees in the forests and the number of randomly selected criteria for dividing the items at each node, a set of Random Forests is created. During the testing phase, each one generates a classification performance that allows the efficiency of the group of criteria and trees to be assessed in terms of the percentage of correctly categorized items. After determining the average performance across all folds for a particular combination, the combination yielding the best performance is selected. (Lolli et al., 2017). The items from all folds that had the best ratio of trees to criteria for dividing the items at each node were used to train a final Random Forest.

3.2.1.4. *KNN*

The k-Nearest-Neighbors (kNN), non-parametric classification approach is straightforward but frequently successful in many cases (Guo et al., 2003). In order to classify a data record of an object, its k nearest neighbors are obtained, creating a neighborhood for the object. A majority vote among the data records in the neighborhood, with or without taking into account distance-based weighting, is frequently used to determine the classification of t. However, choosing a suitable value for k is necessary before using kNN, and the results of the classification heavily depend on this number. The kNN approach is somewhat skewed by k. A case-based learning approach called kNN retains all of the training data for categorization. Due to its simplistic learning process, it won't work well in many applications, such as dynamic web mining for a large repository (Francesco et al., 2019). One method to improve its effectiveness is to select a small number of objects to represent the complete training dataset for classification or to build an inductive learning model from the training dataset and use this model (representatives) for classification.

3.2.2. Orange Data Mining Software for Classification

The inventory classification was carried out by Orange Data Mining Software usinga decision tree, random forest, and kNN-based classification methods in this study. The information used was primary data obtained from the industry. The first step is to enter the data file into the software. After importing the data, position the widgets so that the decision tree and other classifiers are installed on the Orange window. When Tree Viewer was added to the window it will display the generated results from the classifiers (Ishak et al., 2020). Orange can be known as user-friendly tool for ML-based classifications.

Data mining tools are arranged hierarchically in the orange library. The low-level operations at the bottom of the hierarchy, such as data filtering, probability assessment, and scoring the specific features, are merged into sophisticated algorithms like the classification tree method. This makes it simple for developers to integrate new features at any level into the existing code. The data management and pre-processing, classification and grouping, regression, assessment using cross-validation, and projections are the primary branches of the component hierarchy in Organe software (Demˇ & Moˇ, 2013).

3.3. Simulation Modeling

Simulation models are typically computerized replicas of commercial systems. A simulation can, in particular, imitate the behavior of a business system over time. Using simulation software, we can either create a simulation model that replicates the business system as it presently stands, or we can create a prototype of the future business system to forecast how it will function in the real world.

The goal of a simulation model is to assist us in developing a deeper understanding of the business system and working toward a comprehensive improvement of it. Once the simulation model is constructed, we should be able to experiment with various variables to better optimize the system. Additionally, it might evaluate how the company's system responds to changing circumstances using the simulation model.

Although simulation in the supply chain has been used in numerous studies, less attention has been paid to the operations of distribution centers or warehouses, which are crucial to the effectiveness of the supply chain (Gagliardi et al., 2007). These facilities' operations can be loosely divided into picking and storing. Receiving, sorting, and storing inbound products from external or internal manufacturers. On the other side, products are gathered at the shop by the pickers in accordance with customer demands before being carried to the transportation docks for distribution. The assignment of SKUs to the various storage locations is the fundamental focus of storage decisions.

Traditional storage techniques include class-based storage, which assigns products to specific zones or areas in the warehouse, dedicated storage, which assigns stock to demarcated locations, random floor or bin locations based on the amount of storage space available, and others. Combining these fundamental tactics can help you better meet particular needs. Due to the number of locations being typically limited, such decisions indirectly include determining the number of locations allotted to each product, which will have a significant impact on the warehouse's performance.

The order picking procedures specify how the items that need to be shipped are allocated into picking lists and assign one or more pickers to pick the items from locations. Order picking can be done in four ways: discrete, zone, batch, and wave. One individual picks one order, one line at a time, in discrete choosing. This tactic is frequently used since it is simple to use and always upholds order integrity. Zone picking involves dividing the warehouse into separate areas, with one picker assigned to each area. This implies that an order's elements are broken up into many selection lists. One individual may pick many orders simultaneously with batch picking. Orders are chosen in waves to meet the specified shipment timetable.

Choosing storage and selection strategies is just the beginning of running DCs or warehouses. In fact, even with a simple model such as dedicated storage, many choices should be made, including which equipment or tool should be used, such as racking, whether or not to use particular equipment, such as handling tools like conveyors, and which items should be sent to which bin locations. The outcomes of these choices are crucial to the operation of a supply chain because they enable storage systems to quickly respond to consumer needs. However, these difficult choices are exceedingly difficult to make, and as the literature review section will demonstrate, the analytically developed inventory models that are now available only address a portion of the issue.

Therefore, the main purpose of this analysis section is to present a simulation model focused on operations that could aid managers in evaluating the effectiveness of various storing and replenishment strategies. We specifically believe that streamlining the way storage locations are assigned to products could enhance operations. A simulation model was created as a design and deployment of a decision support system, incorporating several segmentations of inventory and replenishment strategies. Simulation can be frequently used to assess the effectiveness of a warehouse. It may take a long time to create a warehouse simulation. However, it is challenging to extrapolate the characteristics of a warehouse that is still being built from its parts. To develop precise projections, assumptions and reasoning are needed, especially when new parts or new operational procedures are involved (Verriet & Caarls, 2013). The current trends and recent advances in logistics lead to new, sophisticated, and partially conflicting scenarios on logistic planning and control systems.

3.3.1. Software Selection for Simulation

The planning of warehouse facilities can be done using a variety of simulation techniques and software. This study compared widely used simulation tools and the next section summarizes the specific features. Workstations and object options were considered when selecting simulation software that is suitable for the warehouse simulation model. yard locations, workstations, assembly, and disassembly stations, with humans, robots, manipulators, and AGVs, logistics trains as operators, are all included in the profile of objects. All material movement takes place inside the basic object. For this study, we evaluate a few simulation software. Table 1 summarizes the information about the considered software.

Table 1: Evaluation of Simulation software

Software	Pros	Cons
Tecnomatix	Comprehensive portfolio of digital manufacturing solutions	Difficult to customize for different industries
AnyLogic	Suitable for complex systems across a wide range of industries	Frequent bugs & run slow
AnyLogistics	Supply Chain Simulation Software	Manual calculations & planning are needed as some input features
FlexSim	Designed to make simulation modeling & analysis easier Various features for develop warehouse simulation	Difficult to identify errors in complex models

Considering various advanced features, FlexSim was selected as the simulation software for this study. FelxSim software is used to establish discrete event processes through its set of computer technologies for 3D image processing, simulation, artificial intelligence, and data processing. It is more useful software for the logistics sector. The software simultaneously offers the original input data fitting, modeling, virtual reality presentation, model simulation, optimization results, and other functions. It also generates 3D animation image files. FlexSim simulation software's primary purpose is to address issues with service, manufacturing, logistics, and the complex and uncertain discrete event systems that are present in real industrial environments (Huihui et al., 2016).

It can be observed the values that fluctuate in response to occurrences; flow items move fluidly through the processor, and the average content statistic is always changing. It would appear that this is contrary to the idea behind the event-based simulation. By associating important data with events, FlexSim simulates and considers all the kinds of variables for the warehouse model. For instance, the processor logs the arrival time when an item lands on it. It determines when the component will be completed and plans an event for that time. This implies that the processor can utilize the current time and the item's arrival time to position the box appropriately when it is drawn in the 3D display. The way the typical content operates is similar. FlexSim can save enough data during a content change to compute the value between events if that value is required.

3.3.2. Discrete Event Simulation

There are two types of simulation systems which can be used in the warehouse logistics model. These two approaches are agent-based and discrete event simulation systems. Both systems are created and appropriate for various autonomous logistic processes (Herzog et al., 2006).

Discrete event simulation (DES) - A popular method especially for simulating communication and transportation networks. Specific advancements in the last few years related to discrete events simulation include virtual reality, simulation optimization, visual interactive modeling, software integration, and simulation in the service sector (Robinson, 2005). Additionally, earlier research has shown how to simulate both communication and transportation networks while using object-oriented programming features like templates, access control, and design patterns. It has also shown how to simulate adaptive reactive routing protocols in transportation networks.

Agent-based Simulation - This is a cutting-edge method for implementing autonomous systems. A multiagent system (MAS) is a loose group or set of agents with clearly defined roles, duties, and functionalities. (Herzog et al., 2006). The smallest controlling entity in this technique is known as an agent, and a typical definition of an agent is something that can sense its environment through sensors and act upon it through actuators. A MAS, which is the system architecture under consideration, consists of several agents that communicate with the whole network.

For this study, we use the discrete event simulation approach as it will be useful for studying the event-based model and evaluation. The next section will provide more knowledge about the discrete event simulation approach and its applicability.

In discrete event simulation, the simulation is driven by the events that a model produces. The model will change as a result of an event at a particular time. On the event list, which chronologically arranges events, all events are listed. The simulation's clock ticks faster as it continues. The next event updates the model and is taken off the list when the clock time and the time of the subsequent event coincide. A discrete event simulation has three key components namely, a model, a clock, and an event list. In this simulation system, objects submit events to the scheduler that contain details about their intended destination, the time at which the event must be triggered, and occasionally any objects that are linked to the event. When the event's time comes, the scheduler passes it to its final location. The object receiving the event's event handling method carries out the object's operations in line with the event's contents. As a result, the logistic objects are modeled as event-handling object-oriented objects. The event handling approach incorporates the logistic objects' autonomy (Herzog et al., 2006). The ability to skip the interval between events is one of the key benefits of discrete event simulation. Due to this, even for complex models, the simulation clock can move much quicker than the actual time.

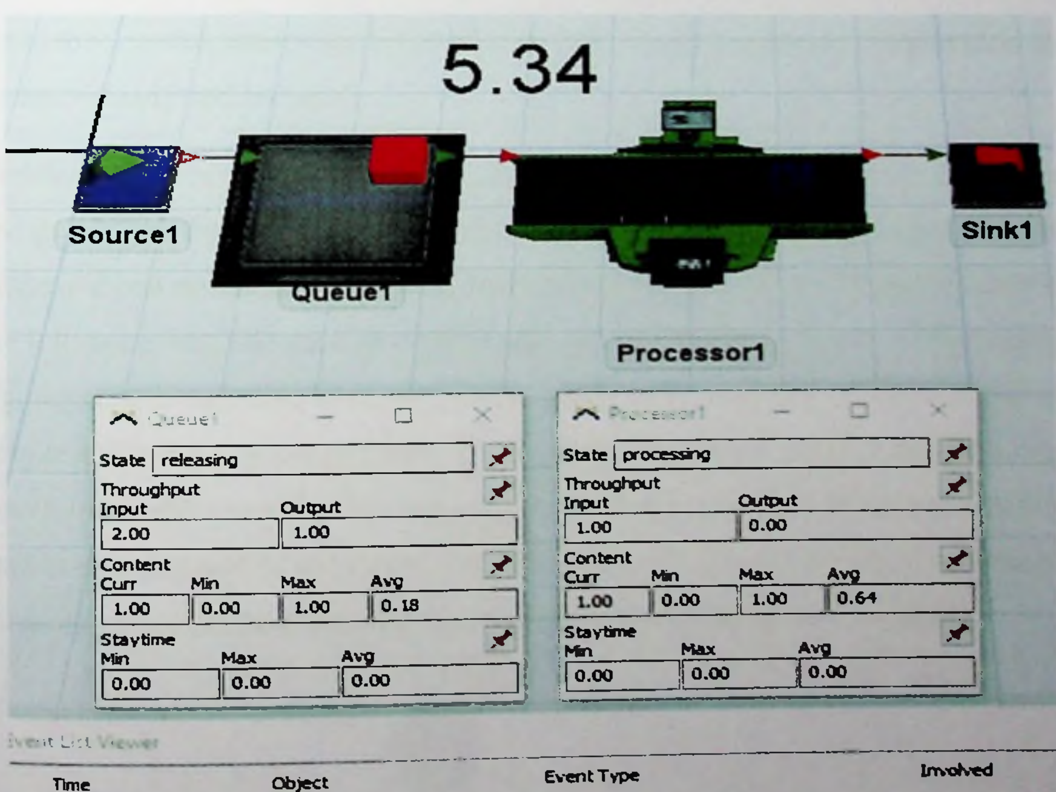

Figure 7: Discrete event simulation using FlexSim software

3.3.3. Simulation Optimization

Most of the simulation software programs come with some sort of optimization feature. The debate may center on how much the accessibility of optimization outcomes has altered simulation methodology. The issue is comparable to every other optimization issue in mathematics. Finding the best value for a few decision variables (simulation model inputs) within the constraints of an established objective function which is the outcome that we target and inputs which are in the constrained levels. Because there are no methods that ensure an optimal solution will be found, this approach differs from mathematical optimization. Scholars have long been interested in simulation optimization, and over time, numerous methods have been tested. The relationship between the inputs and outputs of the simulation model is represented, at least roughly, by one such technique that is based on response surface methodology, also known as metamodeling. Regression is one of the methods for demonstrating the relationship between inputs (independent variables) and outcomes (dependent variables). As a substitute, neural networks have also been used. A search of the response surface can be completed much more quickly with a metamodel than with a simulation model, improving the likelihood of finding the optimum. Metamodels can be run virtually and instantly.

Metaheuristic search techniques like simulated annealing, evolutionary algorithms, and the tabu method are alternate methods. The many optimizing engines run a number of simulations and based on the outcomes, choose which set of model inputs to use for the following run. The most straightforward strategy would be to use a hill-climbing algorithm, although this, of course, could result in the discovery of a local optimum despite achieving a global optimum. The metaheuristic algorithms do a more thorough search in an effort to solve this issue. The drawback is that these techniques are very time-consuming and do not ensure that an optimal solution will be found because the simulations need to be conducted for every possible combination of inputs.

3.4. Structure of the Methodology

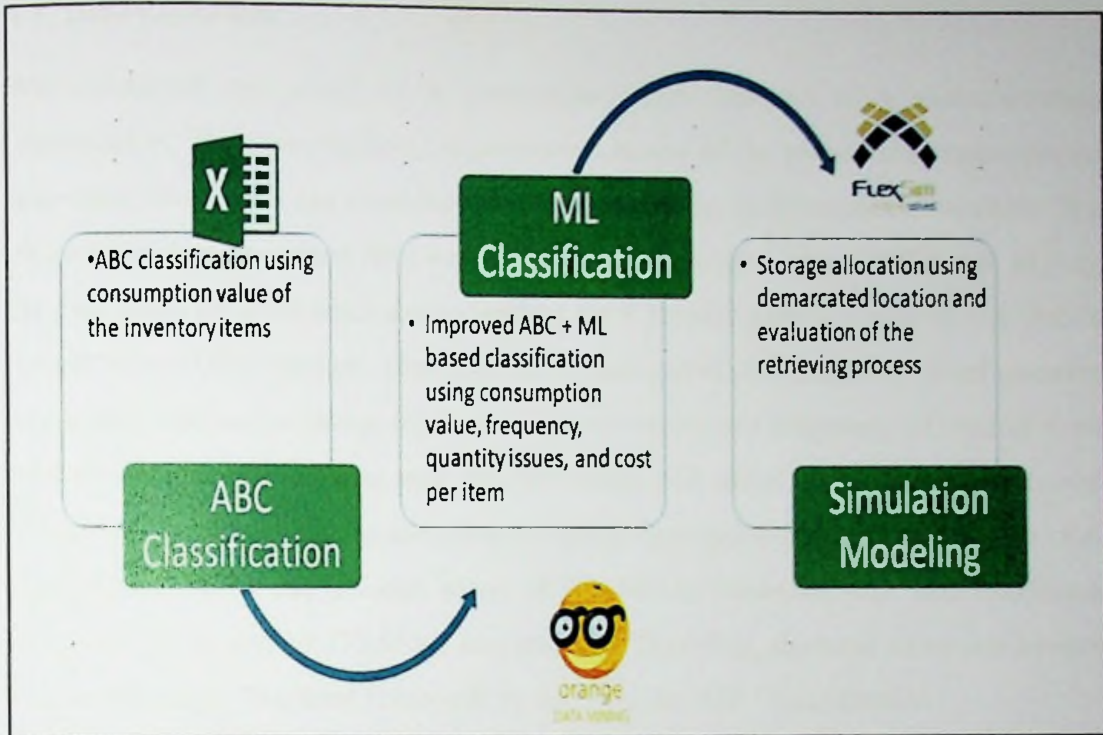

Figure 8: Overall design for the methodology

CHAPTER FOUR: DATA ANALYSIS

4.1. Data Collection

We conducted our study in a warehouse which belongs to a manufacturing organization. The manufacturing organization is one of the pioneering organizations renowned for Ceylon tea manufacturing and exporting to international markets. We obtained system generated data which includes information about 400 items. Mainly the data focus on good issuances extending for 8 months period. Based on the Goods Issued Notes (GIN) the item wise data have been stored. For each item, total quantity issues, the cost for the items, total consumption value, and frequency of issuing were recorded. This captured data was pre-processed, and initial ABC classification was conducted in Excel. When considering the initial descriptive statistics of data, the total consumption value has a mean value of 274,689.5. However, min and maximum values are 10.36 and 19,775,953.1 respectively. Therefore, the total value component has a wide range. The total value will be used for the ABC classification.

4.2. ABC Classification

All the items in the inventory do not have the same value. There will be certain products with greater value than others. Similar to this, some things are used more often than others, and some things have both a higher worth and greater use. A business can identify the items that are more significant and valuable and, thus, require more significant attention using ABC inventory analysis. The steps below can be used to determine which things fall into which category. We must first calculate the total consumption value of each item. This can be accomplished by multiplying the item's cost by its consumption volume over the period (8 months). The second step is to figure out the total consumption value for all the items in the inventory. The third step is to order the goods from highest to lowest consumption value. In the 4th step we should calculate each item's % inventory value using inventory value per item/ total inventory values. Fifth, assign the items to the proper category. For instance, the products that make up the top 80% of the inventory value go under Category A. Similarly, commodities making up the remaining 15% will fall under Category B. The remainder will fall under Category C.

Table 2: Inventory segmentation

Class	% Value	No. of items	% Items
A	80%	54	13.50%
B	80-95%	92	23.50%
C	>95%	254	63.50%

According to the findings, 13.5% of the goods' total worth account for 80% of the total consumption value. Simply, it indicates that 80% of a company's raw material costs are represented by 13.5% of the value of the products.

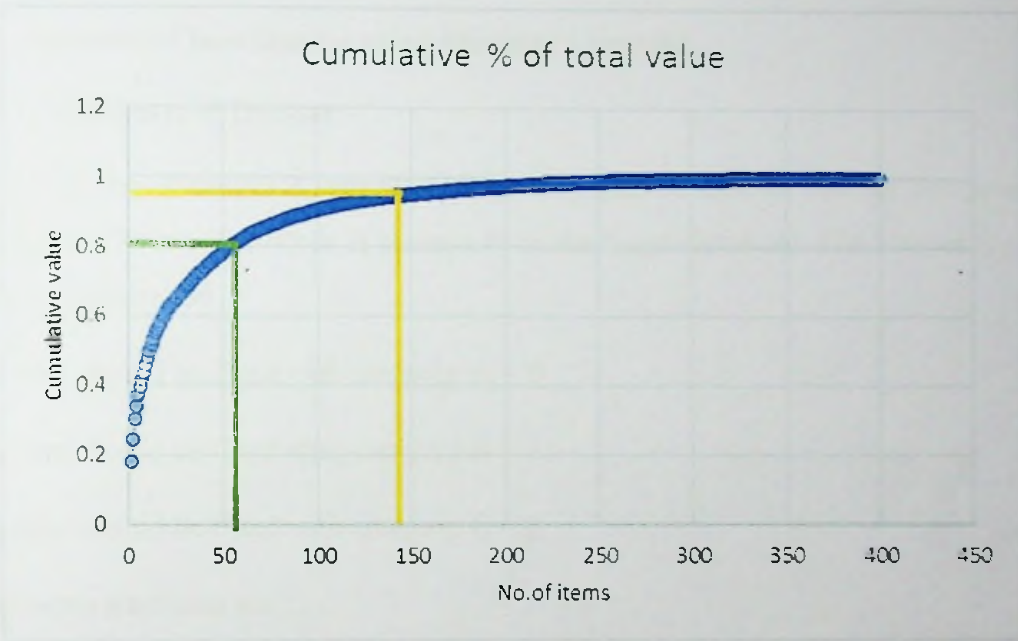

Figure 9: ABC Analysis

Different levels of management control are applied to the three different classifications of inventory. By categorizing the inventory, this strategy enables the management to spread its focus. As a result, group A (goods of high value to them) receives more attention while category B (goods of low value) receives less attention (under C-category).

However, when categorizing items based on total consumption value, there will be a few practical issues. As an example, there can be high-value items that should provide special management attention. Although it is high-value item that might not be captured under the A class if it has a low issuing volume. These situations are not considered under the ABC classification.

Another identified drawback of ABC classification method is we need the total items in a warehouse system which are issued for the period to classify for A, B, and C classes. It is required to get a percentage of the total value issued for each item to identify the category. When new items were added to the warehouse operation system, the consumption or the demand for that items also should be taken to the data list and the entire categorization should be carried out again.

4.3. Inventory Classification using Machine Learning

4.3.1. Attributes of Dataset

Knowing the attributes is essential since they play a crucial role in the process accuracy. The class attribute is created from the "type" attribute. The classes for the data set consists of:

An item should be fitted with category A = 0

An item should be fitted with category B = 1

An item should be fitted with category C = 2

And other attributes are

Cost of the item – nominal

Quantity issued – nominal

Frequency of issuing – nominal

Total value of issuing - nominal

4.3.2. Scatter Plots

A 2-dimensional scatter plot visualization is offered by the Orange Scatter Plot widget. Each point in the data display has a value for the x-axis attribute that determines its position on the horizontal axis and a value for the y-axis attribute determines its position on the vertical axis. On the left side of the widget, you can change the graph's color, point size and shape, axis names, and maximum point size.

The following scatter plots visualize the dissemination of issued quantities, cost, and frequency with ABC categorization. In other words, using the scatter plots it can be identified the characteristics of items in A, B, and C classes. When comparing the pair of variables at a time, it can be identified which pair displays the identifiable difference which can easily segregate A, B, and C.

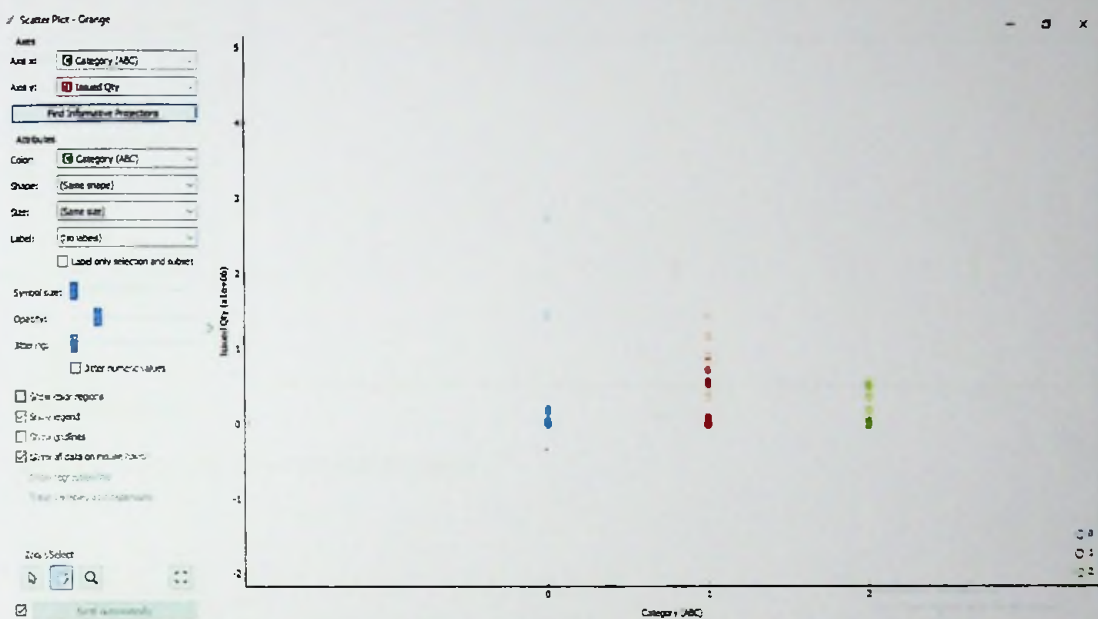

Figure 10: Scatter plot for category & issued quantity

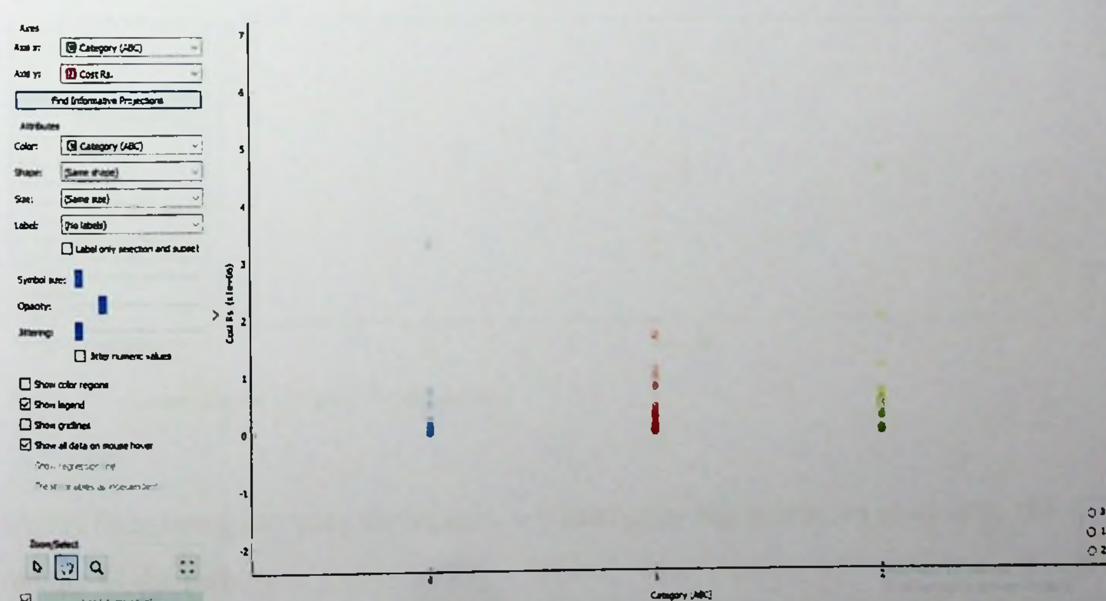

Figure 11: Scatter plot for category & cost

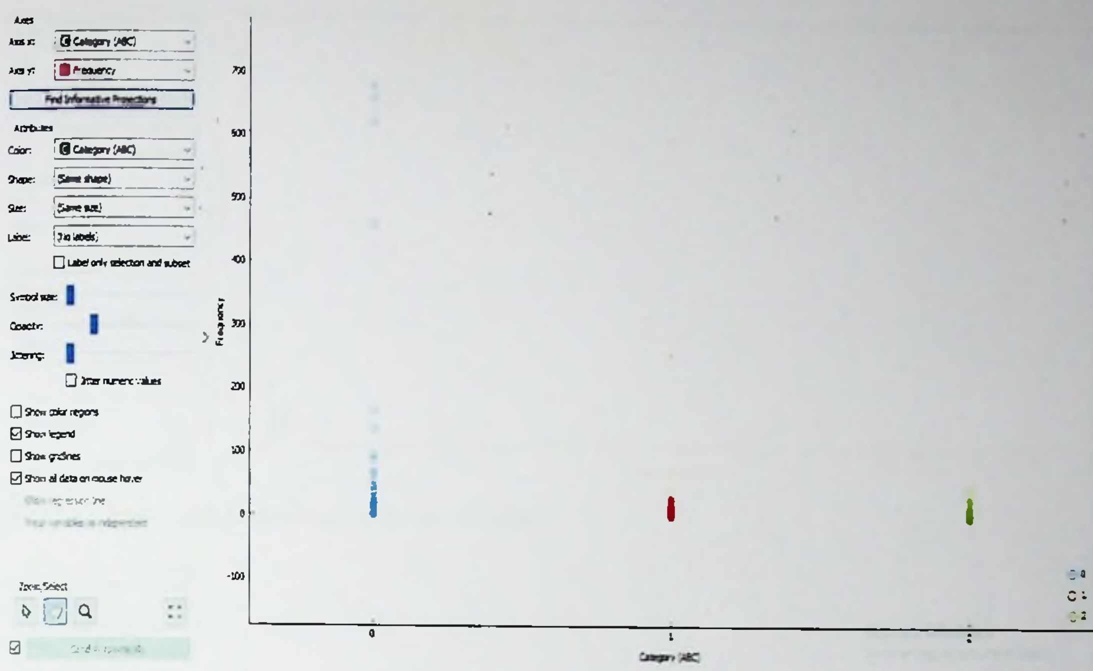

Figure 12: Scatter plot for category & frequency

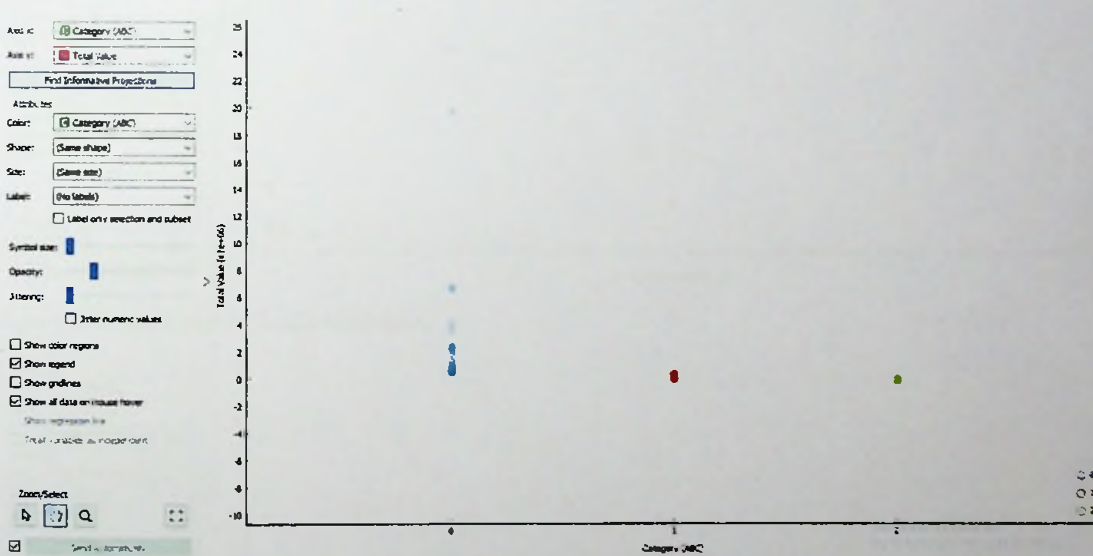

Figure 13: Scatter plot for category & total value

Apart from using category for an axis, we used pair-wise attributes to identify the nature of the data.

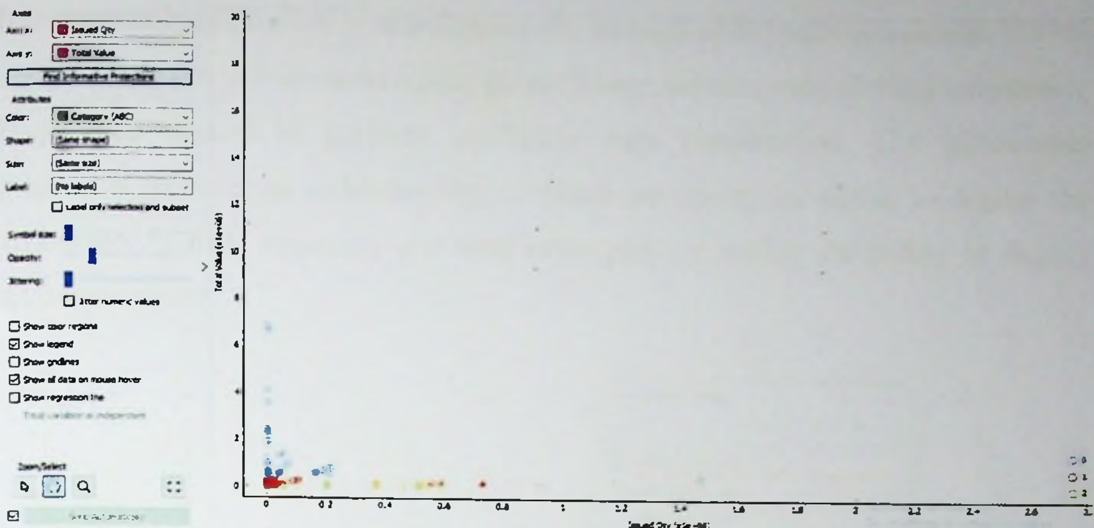

Figure 14: Scatter plot for issued quantity & total value

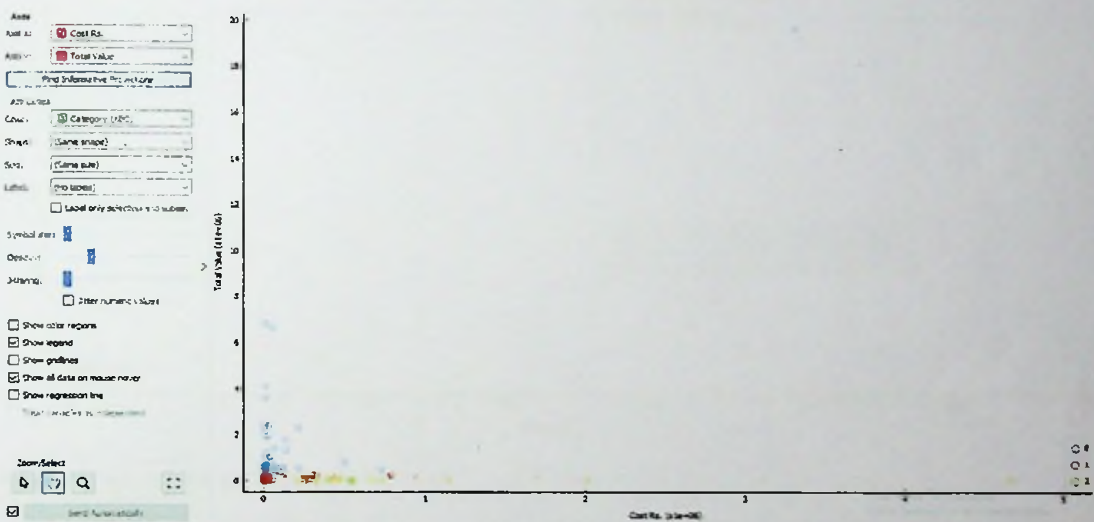

Figure 15: Scatter plot for cost & total value

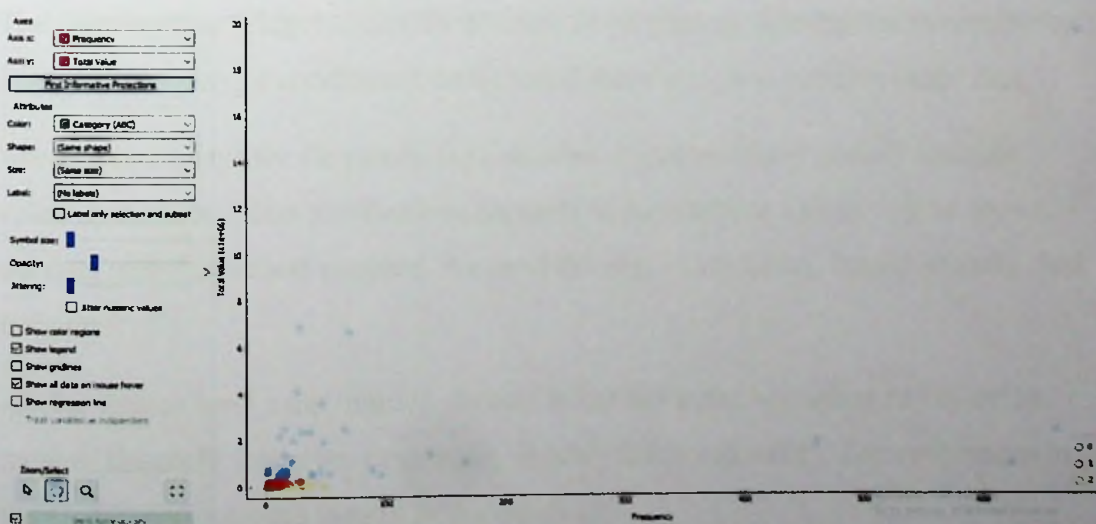

Figure 16: Scatter plot for frequency & total value

It is practically impossible to search manually through all the pairs in a dataset if it has several attributes to find useful scatter plots. Orange uses the widget's Find Informative Projections feature to perform intelligent data visualization. The informative projection provides an understanding of which are having the ability to display the difference. In that, frequency and total value pair are having the ability to display difference mostly.

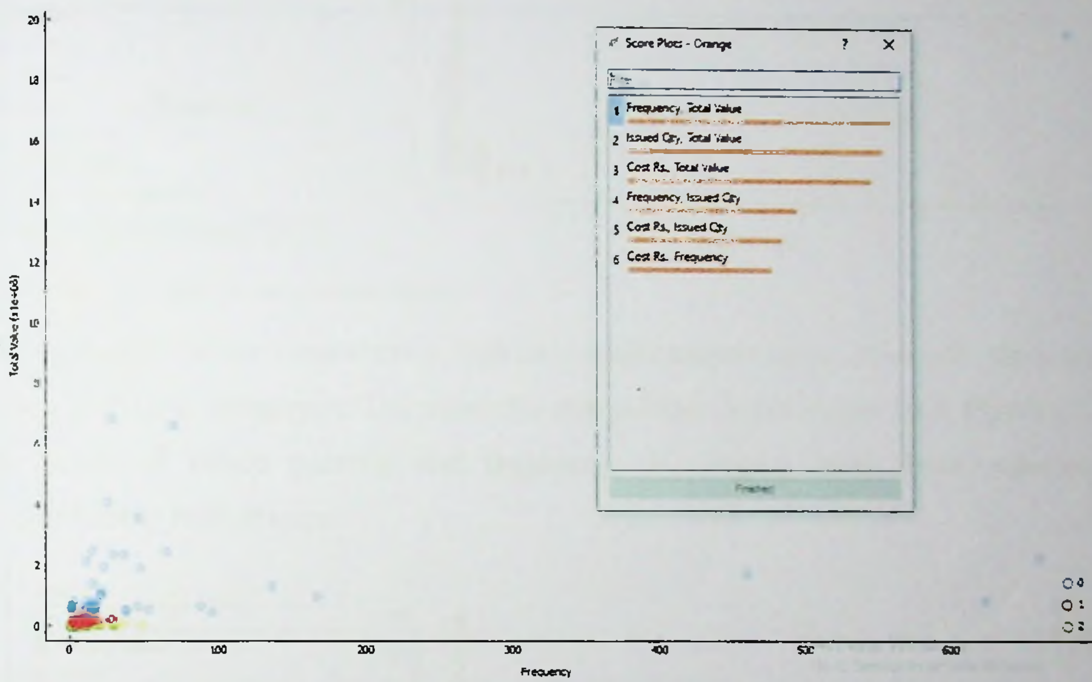

Figure 17: Informative projections

4.3.3. Distribution of Variables

The Distributions widget shows the discrete or continuous distribution for attributes. Distributions may be conditional on a class if there is a class variable in the data.

The graph displays the frequency (i.e., number of occurrences) of each attribute value in the data. Class distributions for each of the attribute values will be shown if the data includes a class variable. We used the cost of the items, Issued quantity, and frequency.

All the figures have a distribution skewed to the left side. According to Figure 18, most of the costly items are in category B (denoted in red color). The cost ranges in the C class are occurred mostly as per the chart.

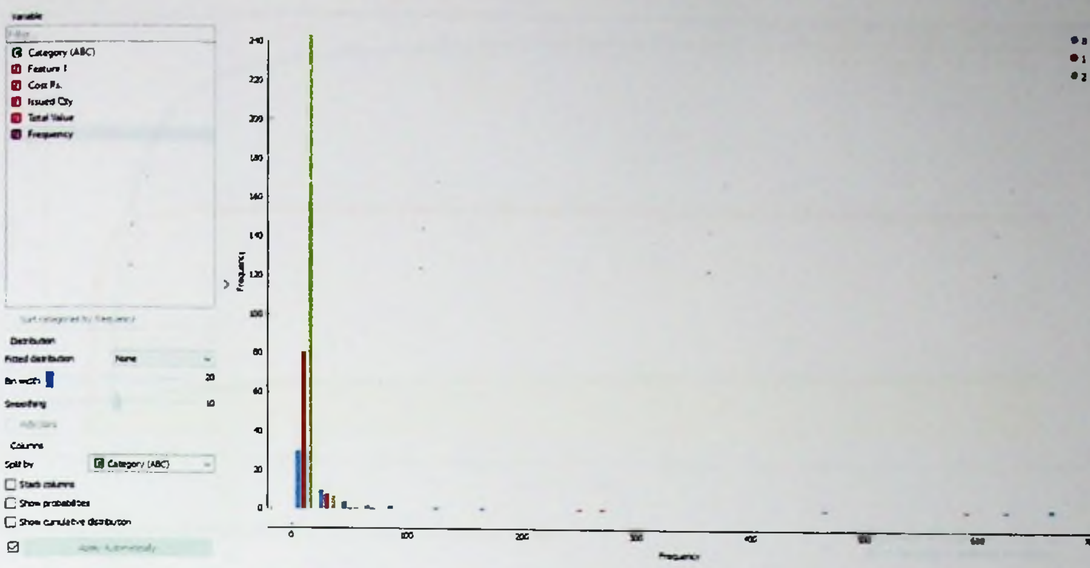

Figure 20: Distribution of data - frequency

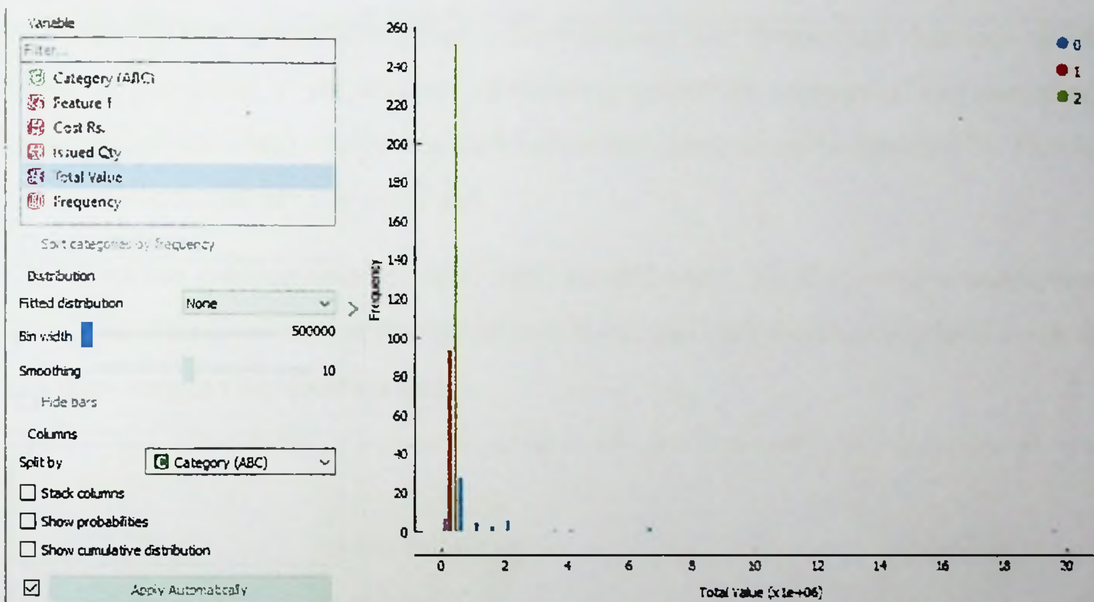

Figure 21: Distribution of data - total value

When pareto distribution is selected as fitted distribution, the curve for total value, all the 3 categories can be seen as below.

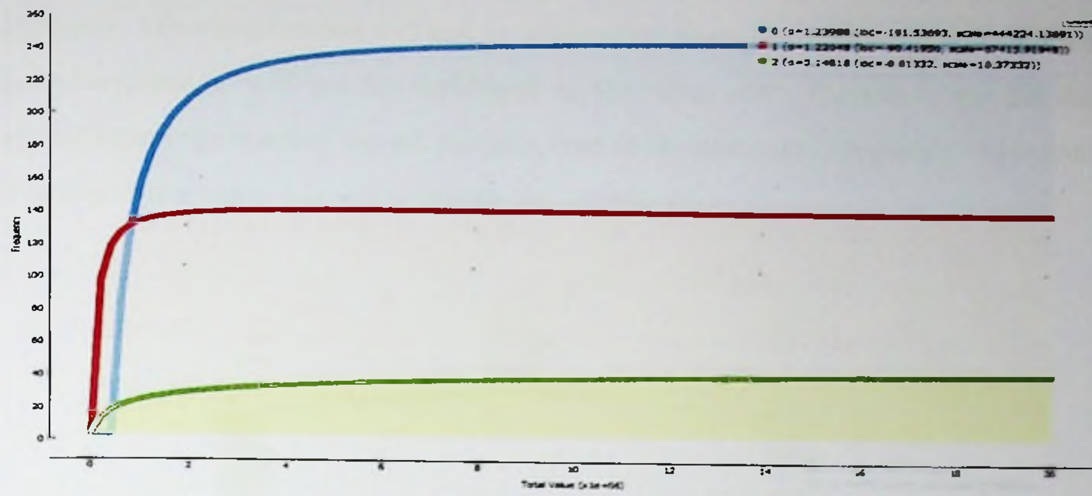

Figure 22: Pareto distribution for total consumption value

4.3.4. Classification Tree

A straightforward procedure called a classification tree divides the data into nodes based on the purity of the classes (information gained for categorical and numerical target variables). Both categorical and numerical datasets can be handled by Tree in Orange, which was created in-house.

The since the training data set used ABC classification based on total consumption value, the classification tree also developed the classification using only total value. It is a very simple classification tree.

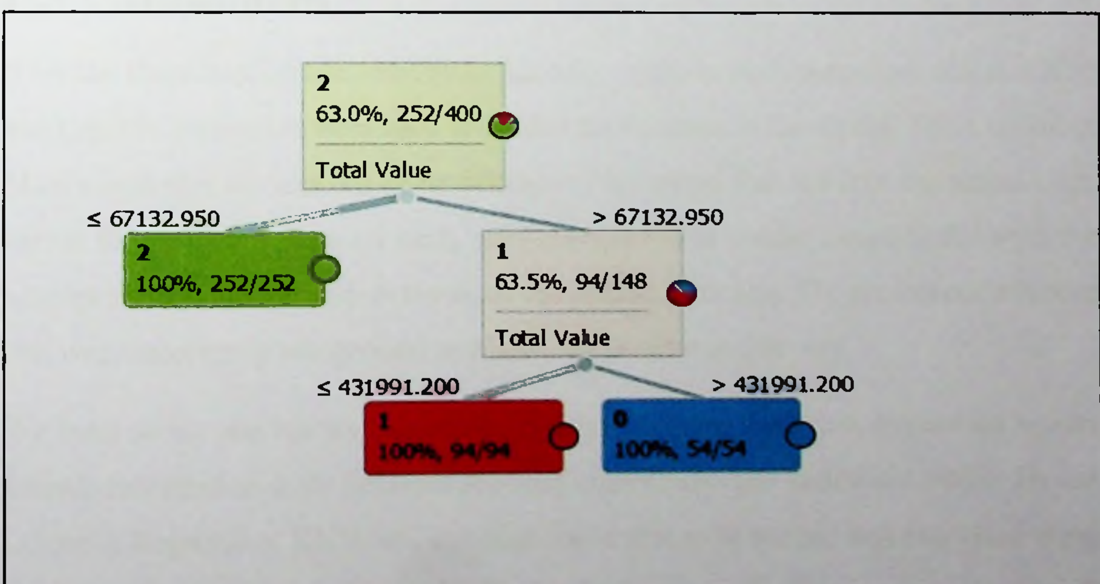

Figure 23: Classification tree with all attributes

However, this classification will not be appropriate when new items are added to the inventory, and it will not be replicated in the same way. Therefore, we did the classification again using, issued quantity, cost of the items, and frequency of issuing. The tree is limited to 5 levels to reduce the complexity.

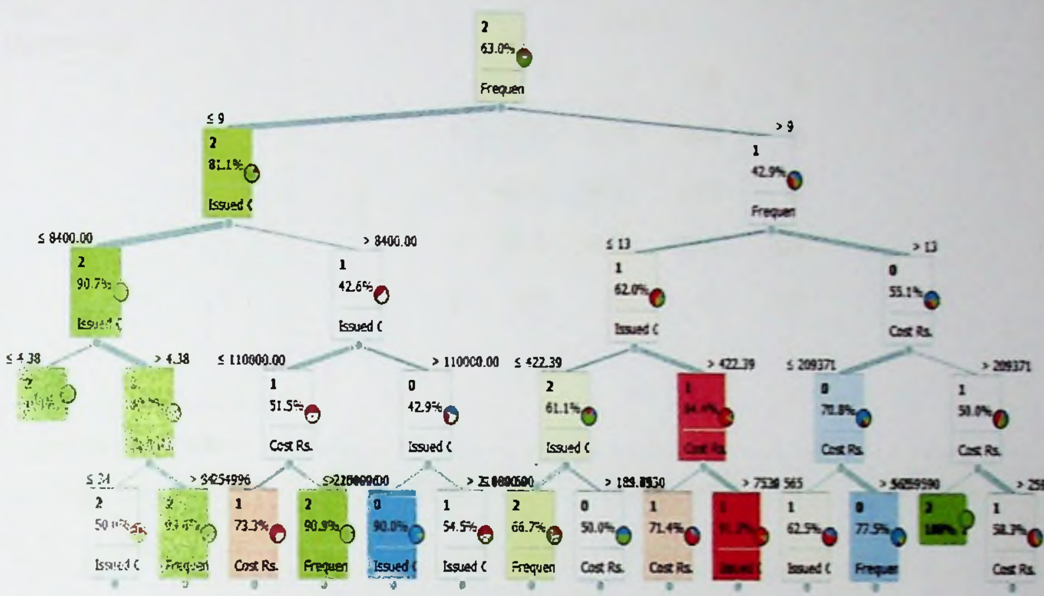

Figure 24: Classification tree removing total consumption value attribute

4.3.5. Confusion Matrix

After the classification tree, ensemble learning methods such as random forest, KNN, and Logistic regression were used to predict the features in the model. The Confusion Matrix indicates the amount or percentage of instances that fall into the actual class versus the predicted class for each used classifier. The output signal is fed with the appropriate instances based on the matrix's element selection. The precise occurrences that were incorrectly categorized and how can be seen in this way.

We must select one learning algorithm for the Learners box when evaluation results include information from different learning algorithms. The confusion matrix for the Logistics Regression, KNN, and Random forest that were trained and evaluated using the inventory is shown in Figure 25, Figure 26 & Figure 27. The Logistic Regression model's matrix is located on the right-hand side The columns correspond to the projected classes, and each row represents a correct class.

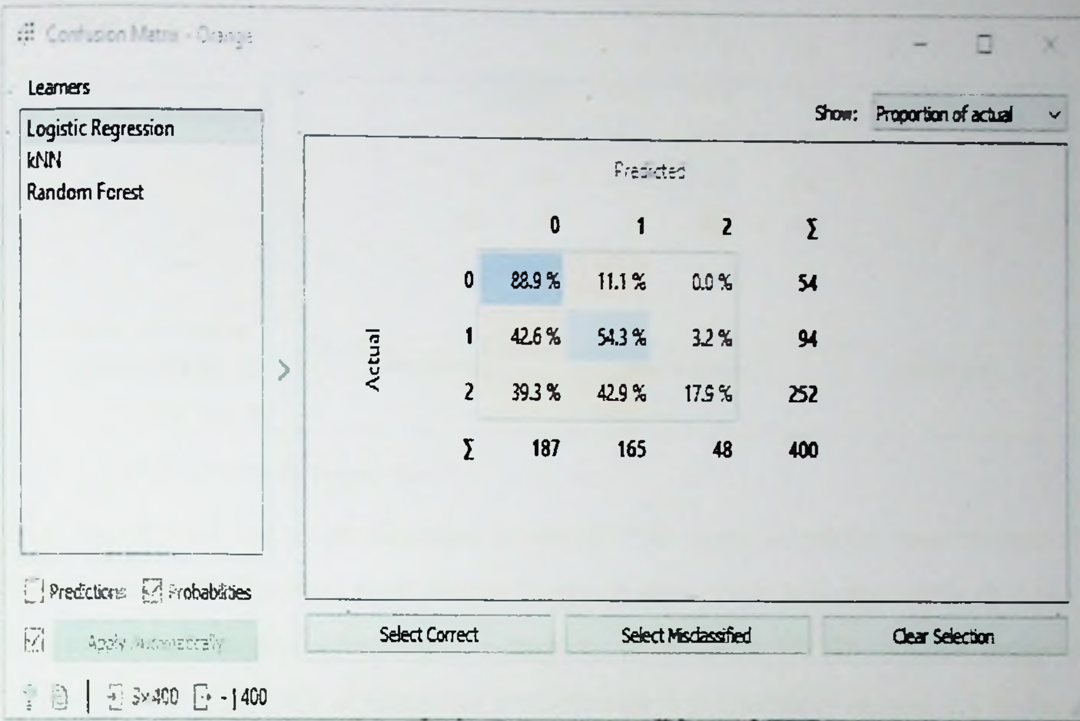

Figure 25: Confusion matrix for logistics regression

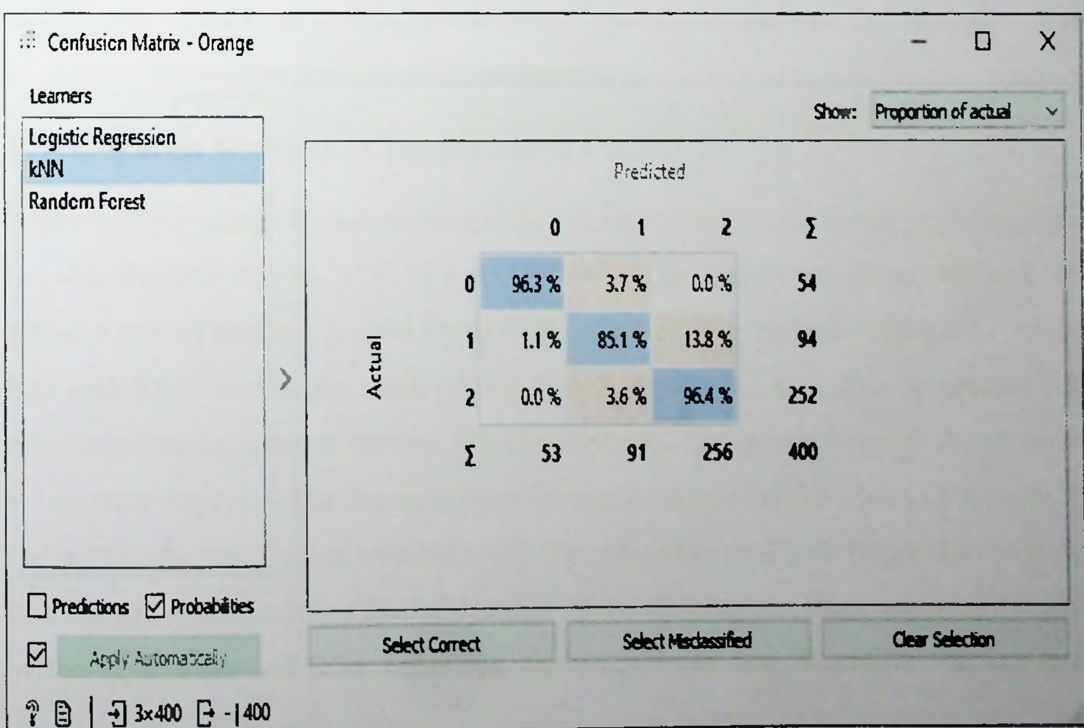

Figure 26: Confusion matrix for KNN

model's matrix is located on the right-hand side The columns correspond to the projected classes, and each row represents a correct class.

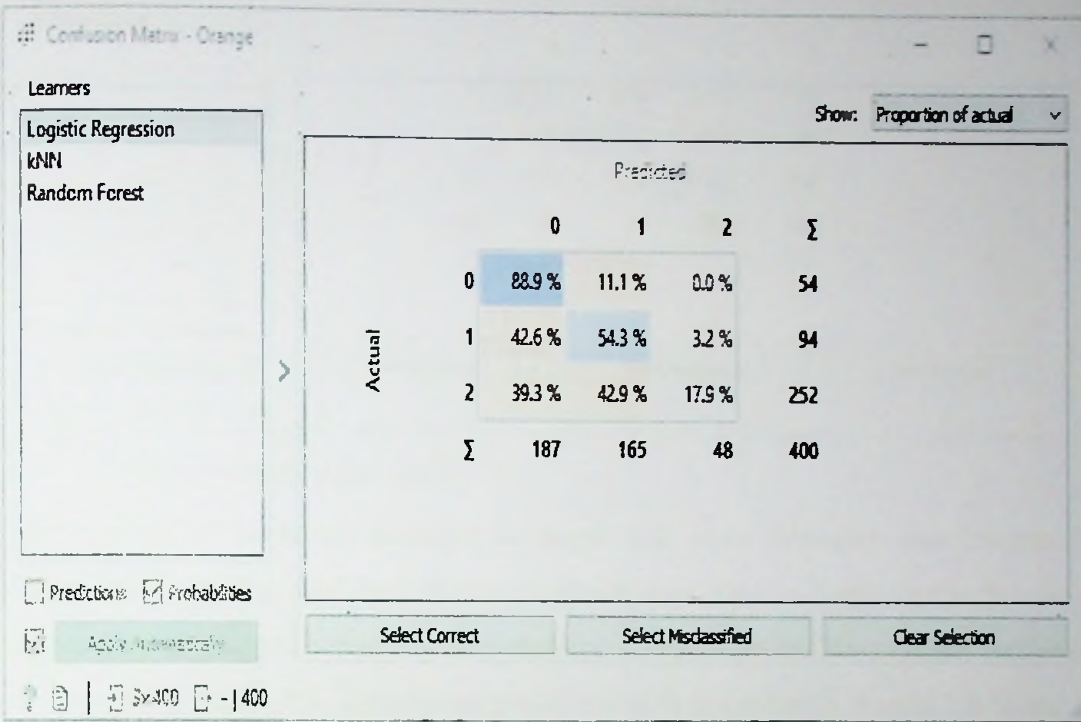

Figure 25: Confusion matrix for logistics regression

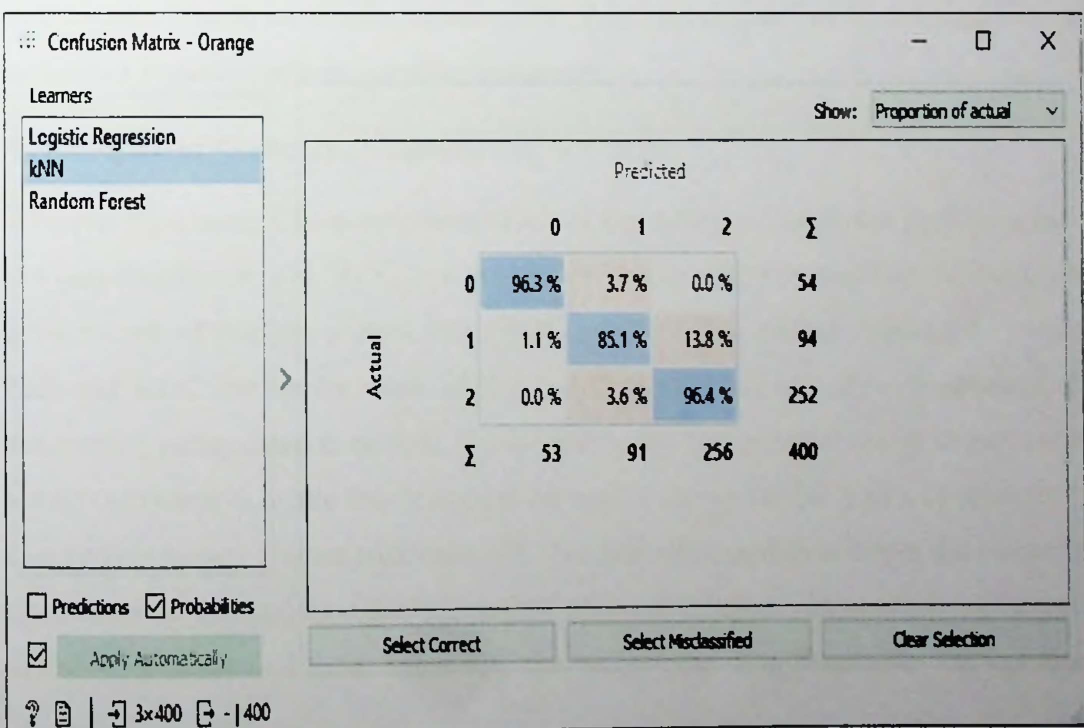

Figure 26: Confusion matrix for KNN

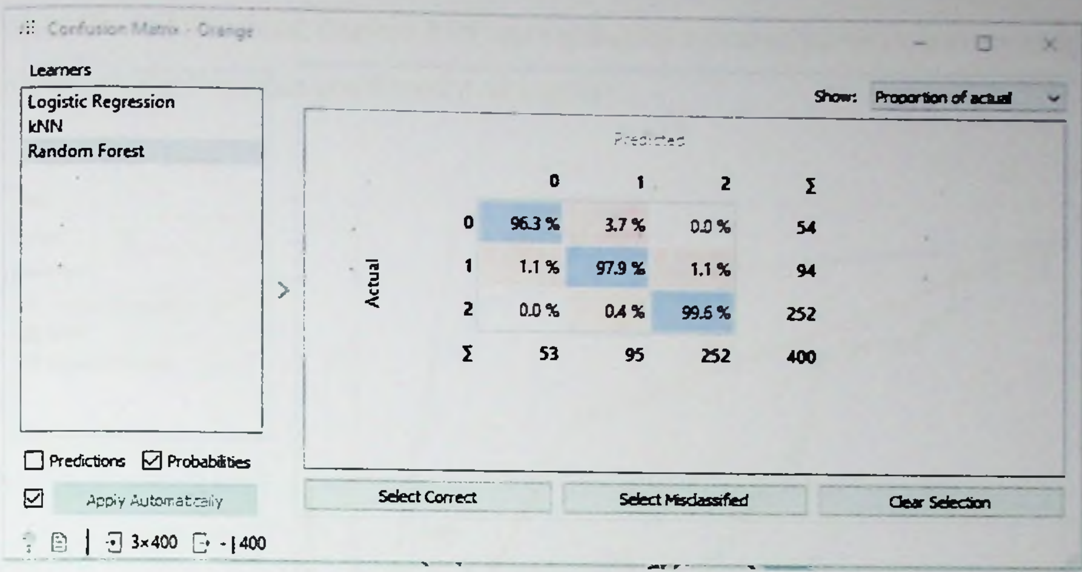

Figure 27: Confusion matrix for random forest

The number of instances displays incidents that were correctly and incorrectly categorized. As identified from the confusion matrix random forest methods have a higher accuracy in predicting items. According to the table, 96.3% of items predicted as A are truly A, 97.9% of instances predicted as B are actually B, and 1.1 % are A and C for each, 99.6% of the C category items are truly C. Proportions of predicted value show how many instances labeled as, for example, A items are in each true class. Actual data reveals the reverse relationship. Also, the output can be selected in terms of correct instances or misclassified instances.

4.3.6. Receiver Operating Characteristics Curve

Receiver Operating Characteristics (ROC) is important to check the performance of the classification model. ROC is a probability curve. The true positive rate and false positive rate of tests are plotted using ROC analysis. The widget displays the convex hull and ROC curves for each of the tested models. It acts as a benchmark for contrasting categorization models. On the graph, the true positive rate is shown on the y-axis (sensitivity), while the false positive rate is shown on the x-axis (1-specificity; chance that target=1 when true value=0). The classifier performs better the closer the curve is to the top and then the left borders of the ROC space. Depending on the costs of false positives and false negatives, the widget can also determine the optimum classifier and threshold. Convex ROC curves display a convex curve over every single classifier (the thin lines positioned over curves).

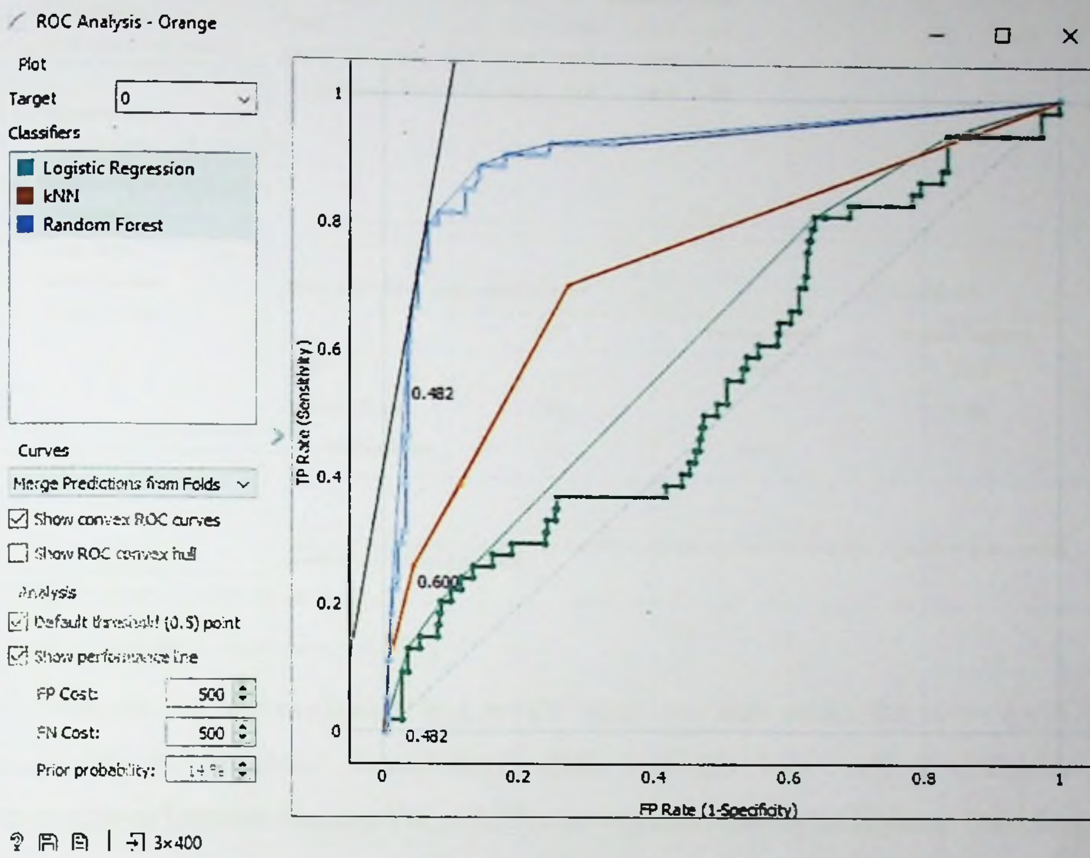

Figure 28: ROC curve for all classifiers

4.3.7. Test and Score

This widget evaluates different learning algorithms that were used for the study. There are different sampling techniques accessible, such as using distinct test data. The widget carries out two tasks. First, performance metrics such as percentage of prediction accuracy and area under the curve (AOC) of each classifier used for the classification, will be displayed. Second, it generates charts and tables of advanced findings such as ROC Analysis or Confusion Matrix to assess the effectiveness of classifiers more precisely.

4.4.1. Warehouse Simulation Model 1 – Without Storage Allocation Plan

In a traditional warehouse, when an item is received for the warehouse, WMS finds a bin location which has empty space and directs the items to that location from the putaway area. All the items are randomly allocated to the bins and item details will be noted with bin number and rack number. In some cases, the item is stored at the first empty space in the rack and then it will be input for the WMS. The following figure depicts a simulation of a warehouse which allocates items to the nearest empty space from the unloading/ putaway area.

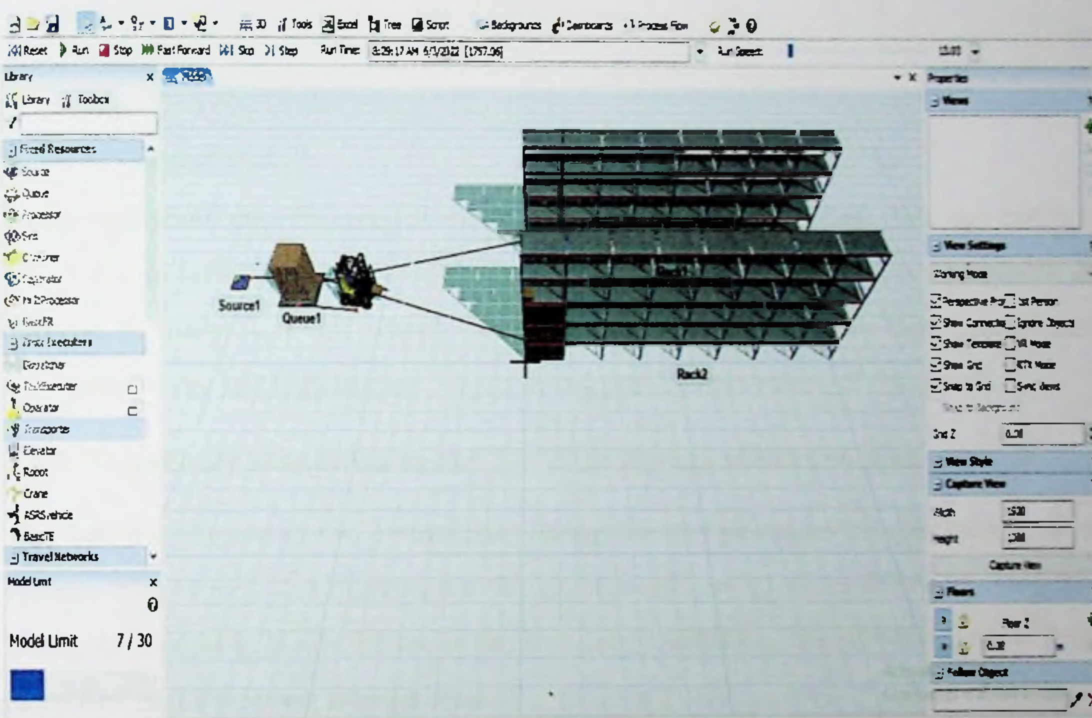

Figure 30: Storage allocation simulation model - loading to first empty space

To understand what's happening in a warehouse which has not given focus on the storage assignment and allocation, the charts developed through the FlexSim tools can be viewed.

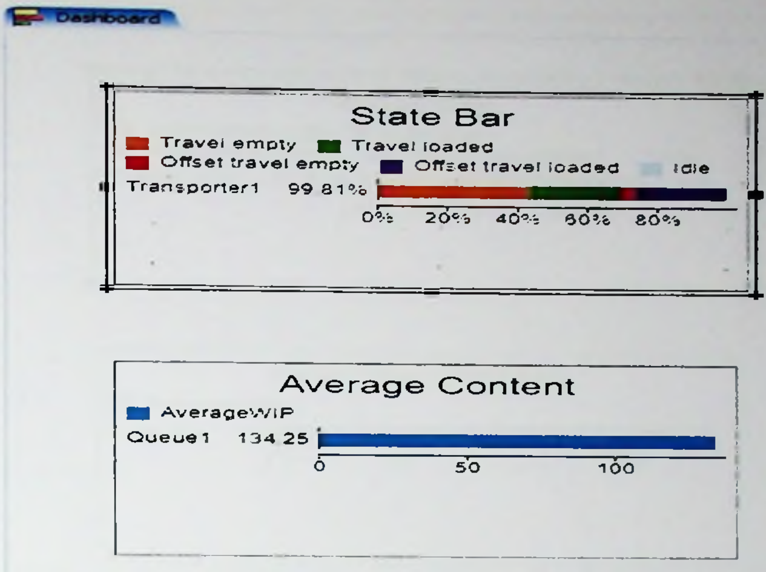

Figure 31: Status of model 1

Status bars show the efficiency in reference to the transporter. Then, Average content shows the movements in the warehouse pertaining to the putaway section which is denoted by queue 1. Even though the transporter has worked with high operational efficiency, there is a high queue. This will disrupt the movement of the goods.

4.4.2. Warehouse simulation model 2 – With storage allocation plan

The following figure shows a simulation model which uses an inventory classification system. The model also demarcated the storage area using color for each category. Using the matching labels feature in the simulation software, the relevant item will be classified in the relevant storage area.

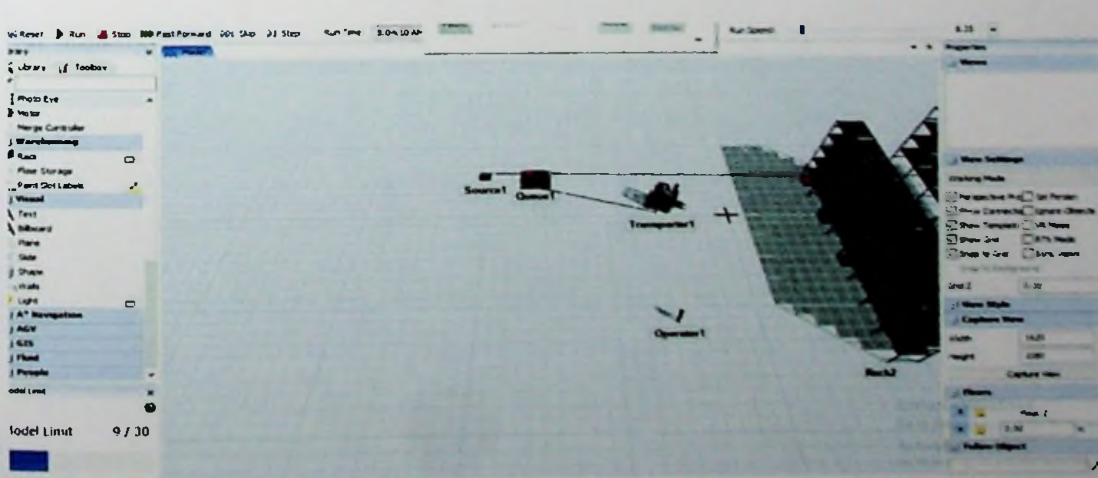

Figure 32:Storage allocation simulation model - loading to demarcated spaces

CHAPTER FIVE: CONCLUSION

5.1. Results & Discussion

In warehouse operations, inventory classification is crucial to operating order fulfillment efficiently. ABC classification method is a widely used classification method in most businesses. Even though it is required to classify items using demand volume, cost, frequency of issuing, and revenue, the ABC method only uses single criteria. Therefore, previous studies have taken efforts to develop multi-criteria classifications (Francesco et al., 2019). Also, few studies have recommended using ABC with advanced computational methodologies (Ramanathan, 2006). As previous studies generally highlighted, there will not be adequate contribution provided through the traditional ABC method (Chu et al., 2008).

Even though this study, we noted some practical issues related to the ABC method. As an example, when classifying products based on total consumption value, even though the item has a high value, if there is little demand for it, it will not be captured for class A. But that item will require managerial attention because of its high value of that item. Therefore, it neglects many important factors when classifying the items. We have to classify all items in the warehouse that were issued throughout the time to assign them to the A, B, and C classes, which is another highlighted downside of the ABC classification approach. The category must be determined by the proportion of the overall value instead of independent demand features.

The challenge of how computer systems automatically learn is addressed by ML. Due to the fusion of computer science and statistical approaches, as well as the foundation of AI and data science, it is currently one of the sophisticated methods with the fastest improvement rates. Recent advancements in ML can be attributed to the development of novel learning theories and algorithms, as well as the continuous growth in online data accessibility and low-cost procedures (Jordan & Mitchell, 2015). The use of data-intensive machine-learning techniques by science, technology, and business has enhanced the use of evidence-based judgment in a variety of industries, including marketing, manufacturing, health care, and financial modeling. ML can be regarded as the finest method for inventory classification among the numerous other methods that have evolved. For this study, all the learners can predict the class of the items with more than 90% accuracy. When the inventory is replenished with new items, it can be replicated by the suggested method.

As per the result of the simulation, it can be identified that, when the warehouse has improved storage classification supported by machine learning, it will increase the efficiency of retrieval processes. This will simultaneously create intelligent inventory management which can reduce the operational cost of storage/retrieval and order picking.

5.2. Future Research Directions

OR applications, mathematical modeling, simulation, and fuzzy sets for routing, scheduling, and sequencing can be identified as trending topics even before 2000, and warehouse automation also became more famous in this domain (Kar, 2013). After the 4th industrial evolution industrial robots, IoT, e-commerce, virtual reality, AGV, and AMR were discussed with more frequency. These technologies have appeared in supply chain and warehouse management areas proposing novel solutions (Tjahjono, 2017). Integrating different OR & mathematical approaches provide more assistance with the expansion of intralogistics. Computer-controlled systems such as AS/RS systems that can accurately, quickly, and precisely place and recover loads from chosen storage places (Hahn-woernle & Günthner, 2017). Additionally, a significant amount of user-generated data is now moving to the cloud, which is supporting the adoption of ASRS even more (Ponis & Efthymiou, 2020). A variety of industries, including automotive, food and beverage, e-Commerce, and pharmaceuticals use AS/RS systems. Therefore, the aforementioned elements suggest that using ASRS for intralogistics has enormous advantages. Likewise, different intralogistics concepts can be used and evaluate the applicability to improve storage systems and stock movements trough further studies.

The full potential of intralogistics solutions emerges in the field of e-commerce. The availability of intralogistics solutions aids e-Commerce businesses in ensuring quicker and more efficient product delivery. Since fulfillment warehouses maintain a wide variety of products in small quantities, inventory classification is further complicated.

Therefore, studies should focus on developing an advanced classification for support storage and retrieval system.

The development of storage allocation and stock movements can be improved through emerging concepts of intralogistics. The logistic train concept is a state-of-the-art technology that can be used to retrieve items which were stored according to a storage plan. Logistics trains will support moving the items without collisions. These areas should be developed with advanced technologies to react to market demands quickly and optimally.

5.3. Recommendations

To ensure a smooth flow of materials inside the warehouse despite the complex demand patterns and consumer behavior, well-organized intralogistics will be important. Also, there should be good coordination and synchronization of production and logistics processes to fulfill the demand timely while achieving better performance (Li & Huang, 2021).

Through this study, we believe all forms of intralogistics being achieved. The traditional warehouse classification system was improved through ML integration. That improved inventory classification is used as an inventory optimization mechanism to reduce the time taken to flow the materials and utilize the space inside the warehouse. After identifying the correct storage segmentation and flow of materials, the warehouse replenishment process was planned using simulation automation. The following findings were summarized as the recommendations for academic and industry-level practices.

- Each item in a warehouse has unique demand characteristics which directly affect for the internal logistics functions. Therefore, it is needed to have transparency and visibility over each item.
- AI and ML can be used to identify the demand patterns and at the same time, it can be used for storage assignment, zoning, and order batching.
- Since intralogistics is in the advanced interplay of internal logistics functions, it can coordinate warehouses even under a dynamic nature.

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