Enhancing Supply Chain Management Efficiency: A Data-Driven Approach using Predictive Analytics and Machine Learning Algorithms

Shamrao Parashram Ghodake[1], Vinod Ramchandra Malkar[2], Kathari Santosh[3],
Dr. L. Jabasheela[4], Shokhjakhon Abdufattokhov[5], Dr. Adapa Gopi[6]

Assistant Professor, Department of MBA, Sanjivani College of Engineering, Savitribai Phule Pune University, Pune, India[1]
Director, Sanjivani Institute of Management Studies, Savitribai Phule Pune University, Pune, India[2]
Assistant Professor, Department of MBA, CMR Institute of Technology, Bengaluru, Bengaluru, India[3]
Professor, Department of Computer Science and Engineering, Panimalar Engineering College, Chennai, India[4]
Automatic Control and Computer Engineering Department, Turin Polytechnic University in Tashkent, Tashkent, Uzbekistan[5]
Department of Information Technologies, Tashkent International University of Education, Tashkent, Uzbekistan[5]
Associate Professor, Dept. of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation,
Green Fields, Vaddeswaram, Guntur Dist, Andhra Pradesh, India[6]

***Abstract*—Contemporary firms rely heavily on the effectiveness of their supply chain management. Modern supply chains are complicated and unpredictable, and traditional methods frequently find it difficult to adjust to these factors. Increasing supply chain efficiency through improved supplier performance, demand prediction, inventory optimisation, and streamlined logistics processes may be achieved by utilising sophisticated data analytics and machine learning approaches. In order to improve supply chain management efficiency, this study suggests a unique data-driven strategy that makes use of Deep Q-Learning (DQL). The goal is to create optimisation frameworks and prediction models that can support well-informed decision-making and supply chain operational excellence. The deep Q learning technique is thoroughly integrated into supply chain management in this study, which makes it innovative. The suggested framework gives a comprehensive method for tackling the difficulties of contemporary supply chain management by integrating cutting-edge methodologies including demand forecasting, inventory optimisation, supplier performance prediction, and logistics optimisation. Predictive modelling, performance assessment, and data preparation are three of the proposed framework's essential elements. Cleansing and converting raw data to make it easier to analyse is known as data preparation. To create machine learning frameworks for applications like demand forecasting and logistics optimization, predictive modelling uses DQL. The method's efficacy in raising supply chain efficiency is evaluated through performance evaluation and acquired 98.9% accuracy while implementation. Findings show that the suggested DQL-based strategy is beneficial. Demand is precisely predicted using predictive models, which improves inventory control and lowers stockouts. Supply chain efficiencies brought about by DQL-based optimisation algorithms include lower costs and better service quality. Performance assessment measures show notable gains above baseline methods, highlighting the importance of DQL in supply chain management. This study demonstrates how Deep Q-Learning has the ability to completely change supply chain management procedures. In today's dynamic environment, organisations may gain competitive advantage and sustainable development through supply chain operations that are more efficient, agile, and resilient thanks to the incorporation of modern analytical methodologies and data-driven insights.**

Keywords*—Supply chain management; predictive analytics; demand forecasting; inventory management; exploratory data analysis

I. Introduction

Supply chain management plays a fundamental role in fostering economic growth by facilitating the seamless exchange of goods between businesses and consumers. The complex web of organizations participating in the supply chain process, each of which contributes to the smooth movement of goods from raw materials to end consumers, makes supply chain management effective [1]. Materials processors are essential because they convert basic materials from natural resources—like wood, rubber, and metal—into products that could be employed in subsequent processes. These resources are subsequently used by producers or manufacturers to make the wide range of things that are offered for sale, from tangible items to energy sources in industries such as the energy business [2]. After manufacturing, suppliers or sellers distribute goods to the next stops along the supply chain by acting as middlemen. Transportation businesses that are responsible for delivering goods to distribution centres or straight to retailers depend on warehouses as essential hubs for keeping products prior to their onward distribution [3]. Central facilities for dispersing goods to merchants, wholesalers, and occasionally direct customers are distribution centers, which are positioned strategically throughout different areas. Retailers are the final intermediary in the supply chain, providing goods to customers via a variety of channels such as physical storefronts and online platforms [4]. The supply chain affects and intersects with a number of business operations in addition to supply chain management. In order to create and engineer items that meet the demands of consumers, product development depends on the availability of resources and the creative abilities of humans [5]. In order to efficiently reach target audiences, marketing tactics, which include actions like price, product placement, and advertising, are essential in driving demand for goods [6]. The goal of operations management is to streamline internal procedures in order to increase output, save expenses, and guarantee the firm runs smoothly. Distribution is the process of making things available to end customers through direct or indirect distribution channels. It is frequently combined with marketing. Sales and finance work together to establish revenue targets, obtain funding, and distribute resources efficiently. Furthermore, customer service is crucial in forming consumer opinions and fostering customer loyalty. It includes actions intended to assist customers at every stage of the purchasing process, from pre-purchase consultations to post-purchase support and problem-solving. Supply chain management and these interrelated processes work together to propel corporate success and promote economic growth. Fig. 1 depicts the supply chain management architecture.

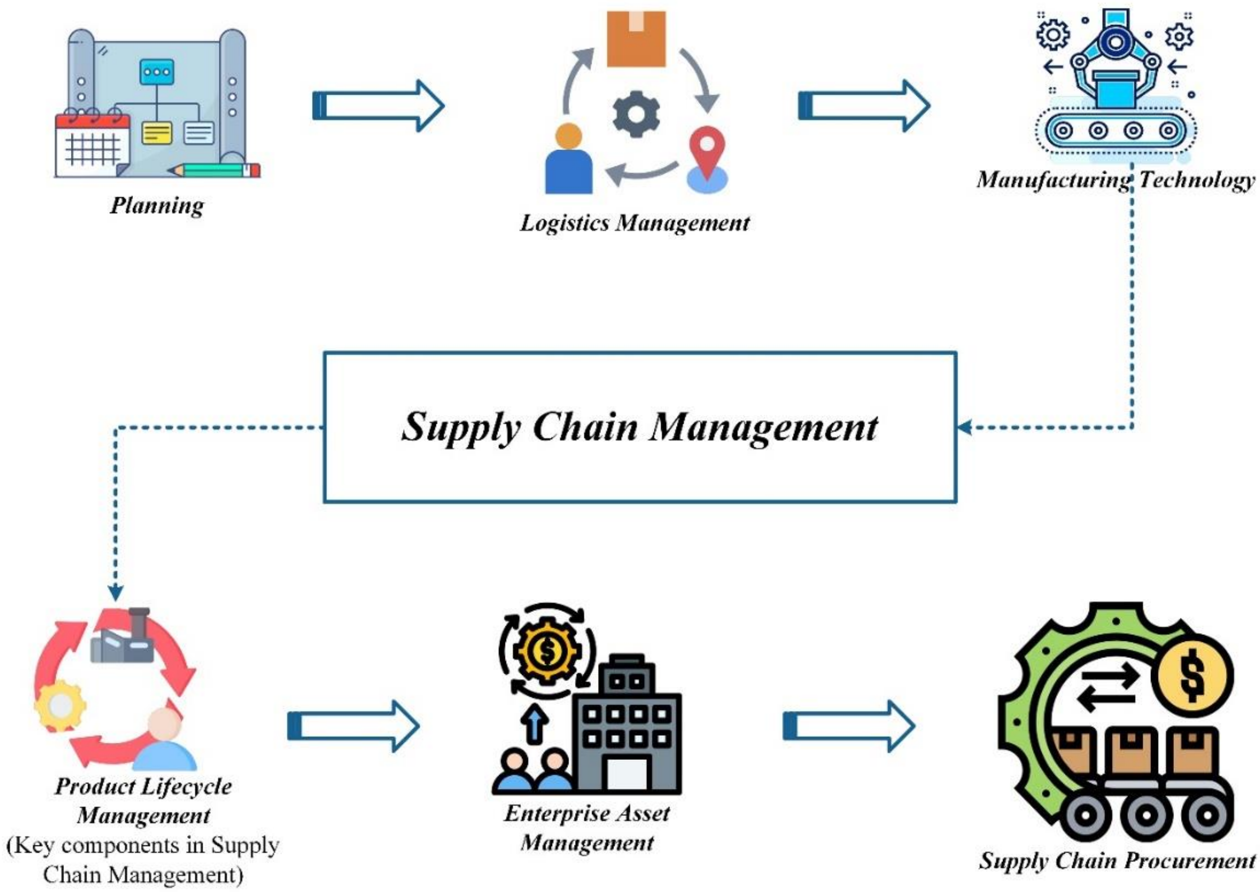

Fig. 1. Architecture of supply chain management.

The vulnerabilities of some of the most important global supply networks become apparent to the entire globe in 2020. Businesses rapidly realised that supply chain management procedures needed to be flexible without breaking and needed to be modernised. The most successful firms nowadays are examining their supply chain management (SCM) processes and the technology that power them with an unwavering gaze, asking themselves what steps they could take to improve their operations' efficiency, profitability, and resilience to change. The concepts and insights that drive global supply chain management are essential. Companies start by keeping an ear to market trends and asking their clients for input on the items they would like to see, as well as the best times and means of delivery. After that, businesses could utilize this data to streamline all aspects of their supply chain management, including procurement, production, research and development, last-mile transport, and final delivery. The proper execution of this immensely intricate task necessitates the integration of every collaborator, or "link," into a highly responsive and well-coordinated supply chain management system [7]. Seventy-five percent of American businesses reported supply chain disruptions early in the epidemic, according to Axios. The World Bank reports that a quarter of businesses saw a 50% decrease in revenue as a result of the epidemic. At the beginning of the pandemic, the National Association of Manufacturers estimated that 1.4 million manufacturing jobs in the United States were destroyed [8]. Global supply chain disruption was further compounded by geopolitical factors like the trade war between the United States and China. The supervision of the movement of products and services from raw materials to finished items is known as supply chain management. It covers every step of the process—including shipping—that goes into bringing goods to consumers. Demand and supply remain in conflict even as the world economy begins to improve [9]. Consider the more than eighty container ships, according to a Bloomberg story, that were awaiting offloading outside ports in California in mid-November 2021, just as the holiday shopping season got underway. A clear illustration of the significance of efficient supply chain management is given by this bottleneck. The seamless operation of supply and demand processes is ensured by supply chain management, allowing people to have access to products and services. A well-functioning supply chain is essential for preserving economic stability and a functional society, as it provides everything from food and shelter to the means of employment and entertainment.

Global supply networks have been irrevocably altered by the COVID-19 pandemic, which has also caused operational disruptions and widespread industry repercussions. This disruption has been most noticeable in Southeast Asian low-cost manufacturing regions like Vietnam, Indonesia, and Malaysia, where production slowdowns or plant closures have had a financial impact on multinational corporations [10]. Millions of Americans were forced into house confinement due to pandemic-related lockdowns, which resulted in a sharp increase in demand for supplies needed for remote work and learning environments. But the supply chain found it difficult to keep up, particularly for supplies that were mostly imported from Asian nations that were dealing with lethal variations and manufacturing limitations. Because there was a shortage of supply, the ensuing plant closures or decreased activity put further pressure on merchants, who were unable to keep up with the rising demand. Factories that were able to continue operating had to contend with issues such as reduced labour capacity, more restrictions on the supply of raw materials, and rising costs. The price of finished goods increased in tandem with the skyrocketing cost of raw materials, sometimes with abrupt surges. This phenomenon affected food costs in addition to consumer items. The U.S. Bureau of Labour Statistics reports that for the year ending in September 2021, prices for meat, poultry, fish, and eggs increased significantly by 10.5 percent. As global markets progressively recover, there continues to be a persistent mismatch between supply and demand because of the stark contrast between the recovery in demand and the still-restricted production capacity. According to the theory of scarcity, which holds that there are never enough resources to meet everyone's needs, this imbalance presents problems for companies, customers, and legislators [11].

The efficacy and efficiency of traditional supply chain management techniques are frequently hampered by a number of issues. These difficulties include having little insight throughout the supply chain, making decisions based mostly on historical data, having trouble correctly estimating demand, using ineffective inventory management techniques, and experiencing erratic disruptions in logistics and transportation [12]. These difficulties could outcome in higher expenses, longer order fulfilment times, surplus inventory, stockouts, and eventually, lower customer satisfaction. Utilising machine learning and predictive analytics methods in the supply chain industry is becoming more popular as a means of addressing these issues. The suggested conceptual framework for using Deep Q-Learning (DQL) algorithms to improve supply chain management efficiency provides a methodical way to combine cutting-edge machine learning techniques with conventional supply chain procedures. The framework initiates data gathering and preprocessing and moves on to predictive modelling with DQL algorithms for logistics optimization, demand forecasting, inventory optimization, and supplier performance prediction. Following that, supply chain activities are optimised using DQL-based algorithms. While iterative refinement enables adaptation to changing market conditions, continuous monitoring and assessment guarantee the achievement of performance objectives. Enterprises could acquire a competitive advantage in the current dynamic market by utilizing DQL-based predictive analytics and optimization to attain operational excellence, cost savings, and enhanced customer satisfaction. Organisations could boost satisfaction with consumers, save expenses, increase operational efficiency, and gain a competitive advantage in today's fast-paced business climate by using data-driven insights and sophisticated analytics approaches. The following list outlines how this study contributes in a way that goes beyond theoretical developments to provide useful insights and suggestions that help enhance processes for managing supply chains in the real-world context.

Contemporary firms recognize the pivotal role of supply chain management in fostering economic growth. However, modern supply chains face complexities and uncertainties that traditional methods struggle to address. The COVID-19 pandemic underscored the vulnerabilities of traditional supply chain practices, highlighting the need for innovative approaches. This study proposes a data-driven strategy leveraging Deep Q-Learning (DQL) to revolutionize supply chain management. By integrating sophisticated data analytics and machine learning, the goal is to develop optimization frameworks and prediction models for informed decision-making. Key elements include predictive modeling, performance assessment, and data preparation. DQL enables accurate demand forecasting, optimized inventory levels, and streamlined logistics. The motivation lies in addressing the shortcomings of traditional methods and adapting to dynamic market environments. By embracing innovation, organizations can enhance supply chain efficiency and achieve sustainable development. In summary, the integration of modern analytical methodologies has the potential to transform supply chain operations and drive long-term success.

- This research extends supply chain management technique by putting forth a fresh data-driven strategy that makes use of Deep Q-Learning (DQL). An established basis for supply chain optimization is provided by DQL, and it may be used for demand forecasting, inventory control, supplier performance predictions, and logistics optimization.

- Supply chain efficiency is enhanced by the application of DQL-based optimisation technique. Organisations could optimise their supply chain operations and make well-informed decisions by utilizing historical data and sophisticated analytics. This improves efficiency, lowers costs, and increases customer satisfaction.

- The practicalconsequences of the study's findings are significant for organisations functioning in the contemporary dynamic economy.

The rest of the section is as follow: Section II gives an overview of relevant studies. Section III covers the approach's research gap. The materials and methods are presented in Section IV, which describes Optimizing Supply Chain Management with Deep Q-Learning Framework. Section V goes over the findings and performance analysis. Finally, Section VI summarises the conclusion of research.

II. Literature Review

In the intricate healthcare supply chain, it is critical to prioritize efficiency in order to economize and streamline the process of acquiring medical supplies. This paper examines different types of machine learning programs like Naive Bayes, K-Nearest Neighbors, Random Forest, Support Vector Machine, and Linear Regression to improve how healthcare supplies are managed. The five categories analysed in this research are: 'Inspection Results', 'Defect Rate', 'Transportation Modes', 'Routes' and 'Cost'. Based on what I discovered, the Random Forest classifier showed 87% accuracy in classifying "Inspection Results" and "Transportation Modes," while the KNN classifier had an impressive 86% accuracy in classifying "Routes. The study demonstrates the essential role of machine learning methods across different categories. The various methods that classifiers operate within different categories indicate the importance of selecting the most suitable algorithm for the supply chain. This research demonstrates that ML classifiers are effective in improving the efficiency of healthcare supply chains. It also suggests that automation could be used in different parts of supply chain management. It assists in optimizing the performance of the healthcare supply chain. However, the Linear Regression and KNN Regression models showed poor performance as indicated by their higher MSE and lower R^2 values. It is crucial to consider these results thoughtfully when selecting models that can accurately predict and function effectively in various scenarios [13].

The coordination of information in a system is used in supply chain management to unify all elements of the supply chain. Implementing artificial intelligence within the supply chain can simplify visibility, automate processes, and enhance overall management efficiency. This can assist companies in reducing costs and improving their ability to meet customer demands, ultimately leading to greater overall efficiency. Choosing the right people to be a part of a team is important for making sure the supply chain runs smoothly. This study introduces a fresh approach for identifying the most qualified suppliers in a supply chain by employing the specialized computer program CGANs. It helps when there are a lot of options but not much data to make a decision. Classifying members on the chain can effectively streamline the classification process and reduce data complexity while maintaining accuracy. The application of machine learning involves examining and predicting purchasing and stock relationships within the supply chain. - The vehicle scheduling module is working on optimizing routes for improved operational efficiency. The completion of the SCM system was achieved through the use of the SSH framework. Still, there may be a disadvantage to depending just on large data and the robust Internet infrastructure for trade. It restricts the interchange to businesses that can access and use these technologies efficiently, which could exclude smaller or less tech-savvy supply chain partners [14].

The utilization of AI in supply chain management can improve operations and contribute to company prosperity. This summary discusses the ways in which AI can improve the supply chain, as well as the challenges and opportunities it presents. Companies can enhance their inventory management, forecast demand, coordinate transportation and deliveries, inspect product quality, and streamline their operations through the use of AI and machine learning.AI systems can look at a lot of information, find patterns, and give helpful advice so that people can make better decisions and react quickly to changes in the market. Furthermore, AI can improve the ability to see the supply chain, allowing for tracking, monitoring and evaluating risk in real time. This paper discusses the potential benefits of implementing artificial intelligence (AI) to improve the functioning of supply chains.AI can help make better predictions, manage stock, and improve the way things are moved in supply chains. The paper touches on the use of AI in supply chain management and provides instances of its successful implementation by companies. It is crucial to keep in mind, however, that the actual outcomes might differ based on the implementation's particulars and the environment, sector, organisational needs, quality of the data, and degree of AI acceptance [15].

The environment has been negatively impacted by companies' excessive use of natural resources, generation of excessive waste, and improper disposal of dangerous chemicals. The involvement of SMEs is significant in mitigating our influence on the environment globally. This has become an even more important part of our company's plan in the last twenty years. The industry is prepared for major shifts in supply chain management. Green Supply Chain Management means including environmental practices in the supply chain. Businesses can use Green Supply Chain Management to ensure that their procurement, production, distribution, consumption, and recycling practices are environmentally sustainable. The use of data analytics is increasing in operations management. In this area, new techniques involve the use of computer programs to examine organizational operations. The main objective of this study is to examine the utilization of machine learning in the management of supply chains and operations. Deeper learning offers a more accurate insight into customer preferences than MNL, but it's difficult to find solutions for challenges such as product selection and pricing in these models [16].

The global supply chain is facing significant challenges due to the combination of the COVID-19 pandemic and ongoing political and regional conflicts. Shipping items worldwide has become difficult and is resulting in delays in delivery. This is creating challenges in the shipment of goods globally and causing disruptions in the delivery schedule. It's becoming increasingly tough to ship items across the world, causing delays in the delivery process. One of the biggest concerns is the lack of information about the availability of products. This is important for companies to plan how to ship and deliver goods. Forecasting the timing of item availability is essential for the smooth and economical management of logistics. Different data sources are used to study the shipping availability of General Electric's gas and steam turbines. It evaluates a variety of models to measure their performance. Included in the list of models are Simple Regression, Lasso Regression, Ridge Regression, Elastic Net, Random Forest (RF), Gradient Boosting Machine (GBM), and Neural Network. The experiments show that tree-based algorithms like RF and GBM are better than other models at predicting real-world data. The prediction models are anticipated to offer assistance to companies in addressing supply chain issues and improving safety on a larger scale. Despite its benefits, there are some disadvantages to using time series analysis for predicting availability dates. It can make things more complicated and require more computer power. Furthermore, it can be difficult to utilize and refine advanced deep learning methods to achieve higher accuracy [17].

Precisely predicting customer demand is crucial for optimizing the pharmaceutical supply chain. Forecasters are still using advanced models despite the limited available information. These challenges arise regardless of the abundance of data, as outdated data becomes irrelevant in a fluctuating market. Meanwhile, there are other elements that can influence demand, but understanding their effects involves gathering a substantial amount of data and using more advanced models. The goal is to tackle these challenges by utilizing a fresh approach to anticipate demand. The analysis will involve using data from multiple products and applying advanced machine learning to uncover patterns. The improvement of cross-series model performance is achieved through the implementation of different "grouping" methods and the utilization of non-customer demand data, such as inventory and supply chain information. This novel framework was tested using various modeling options on two significant datasets from major pharmaceutical companies, demonstrating its superiority over other methods. This research shows that knowing how much inventory is available can help predict how much demand there will be for a product. Our process involves researching both before and after to confirm the viability of the forecasting method we aim to implement. Knowing the old inventory information, as anticipated, does not prove to be beneficial [18].

The literature study underscores the noteworthy contribution of artificial intelligence (AI) and machine learning (ML) methodologies in augmenting diverse facets of supply chain management (SCM) across diverse sectors, specifically in the domains of healthcare and environmental sustainability. Several machine learning classifiers, including Naïve Bayes, K-Nearest Neighbours, Random Forest, Support Vector Machine, and Linear Regression, have been investigated by researchers for use in optimising healthcare supply chains. The findings show promise in terms of classification accuracy for various aspects of the supply chain, including inspection results, defect rates, transportation modes, routes, and costs. Furthermore, SCM systems have benefited from the application of AI algorithms to create intelligent management, automation, and visualisation, which has decreased operational costs and increased responsiveness to market needs. Effectively lowering the dimensionality and complexity of the information, methods like conditional generative adversarial networks (CGANs) have been developed for dynamic supply chain member selection. In the supply chain, artificial intelligence has also been used for environmental operations integration, demand forecasting, transportation optimisation, and inventory management. Even with these developments, issues like scarce data availability, computational complexity, and technical accessibility still need to be taken into account for AI-powered SCM systems to be implemented and optimised effectively.

III. RESEARCH GAP

Effective supply chain management is crucial for businesses to fulfil consumer needs, cut costs, and increase profitability in the cutthroat business environment of today. However, plenty of businesses encounter difficulties when trying to efficiently optimize their supply chain processes. These difficulties could involve erroneous demand projections, inadequate inventory control, shaky supplier performance, and ineffective logistical procedures. Consequently, companies could encounter elevated expenses, setbacks, and discontent from clients, eventually impeding their ability to compete in the market. Thus, research is desperately needed to create workable solutions to these difficulties and improve supply chain performance, which could assist companies become more competitive and experience long-term growth. The present research puts forth a thorough framework that utilises deep Q-learning and sophisticated analytics to tackle the intricacies of supply chain management in the beauty product sector. The objective is to provide workable solutions for improving supply chain operations and increasing competitiveness by utilizing Deep Q-Learning to demand forecasting, inventory optimization, supplier performance prediction, and logistics optimization. This study's focus is on optimizing the supply chain for beauty products by applying Deep Q-Learning and predictive analytics approaches to demand forecasting, inventory control, supplier performance predictions, and logistics optimization. The goal is to increase the competitiveness and efficiency of supply chains for companies in the fashion and beauty sectors by offering them practical insights and ideas.

IV. RESEARCH FRAMEWORK

Deep Reinforcement Learning (DRL) is the approach that is suggested for the present research in order to enhance the supply chain for beauty products. The procedure commences with the formulation of the problem, which involves identifying the intricacies of supplier selection, price strategies, logistics optimization, and inventory management in the beauty product sector. Because it is data-driven and allows an agent to learn optimum policies through interaction with the supply chain environment, Deep Reinforcement Learning (DRL) is selected as an appropriate method. The process continues by defining the action space, reward function, and state representations. Factors including supplier performance indicators, demand projections, inventory levels, and transportation logistics status are all included in state representations. The agent's options for ordering quantities, choosing suppliers, modifying inventory levels, and establishing pricing strategies are all outlined in the action area. The purpose of the reward function is to penalise unwanted outcomes, like stockouts or excessive expenses, and to reward positive behaviours, such revenue creation, cost reduction, and customer pleasure. Following that, the Deep Q-Network (DQN) agent is implemented, which approximates the ideal action-value function using a neural network architecture. Utilising experience replay in a simulated setting that replicates the dynamics of the cosmetics product supply chain; the agent is taught. After a training process, experience replay enhances sample stability and efficiency by enabling the agent to learn from previous encounters. Through simulation assessments, the trained DQN agent's performance is evaluated in relation to a number of parameters, including cost savings, revenue creation, and service levels. In order to ensure the efficacy and resilience of the trained agent, parameters are adjusted and optimised depending on the findings of these examinations. Incorporating the DQN agent into the supply chain management system also makes it easier to make decisions in real time, which leads to increased productivity, lower costs, and happier customers. This research intends to drive improvements in supply chain management techniques by showcasing DRL's potential as a formidable tool for streamlining intricate supply chain procedures in the beauty product sector. Fig. 2 shows workflow of the suggested approach.

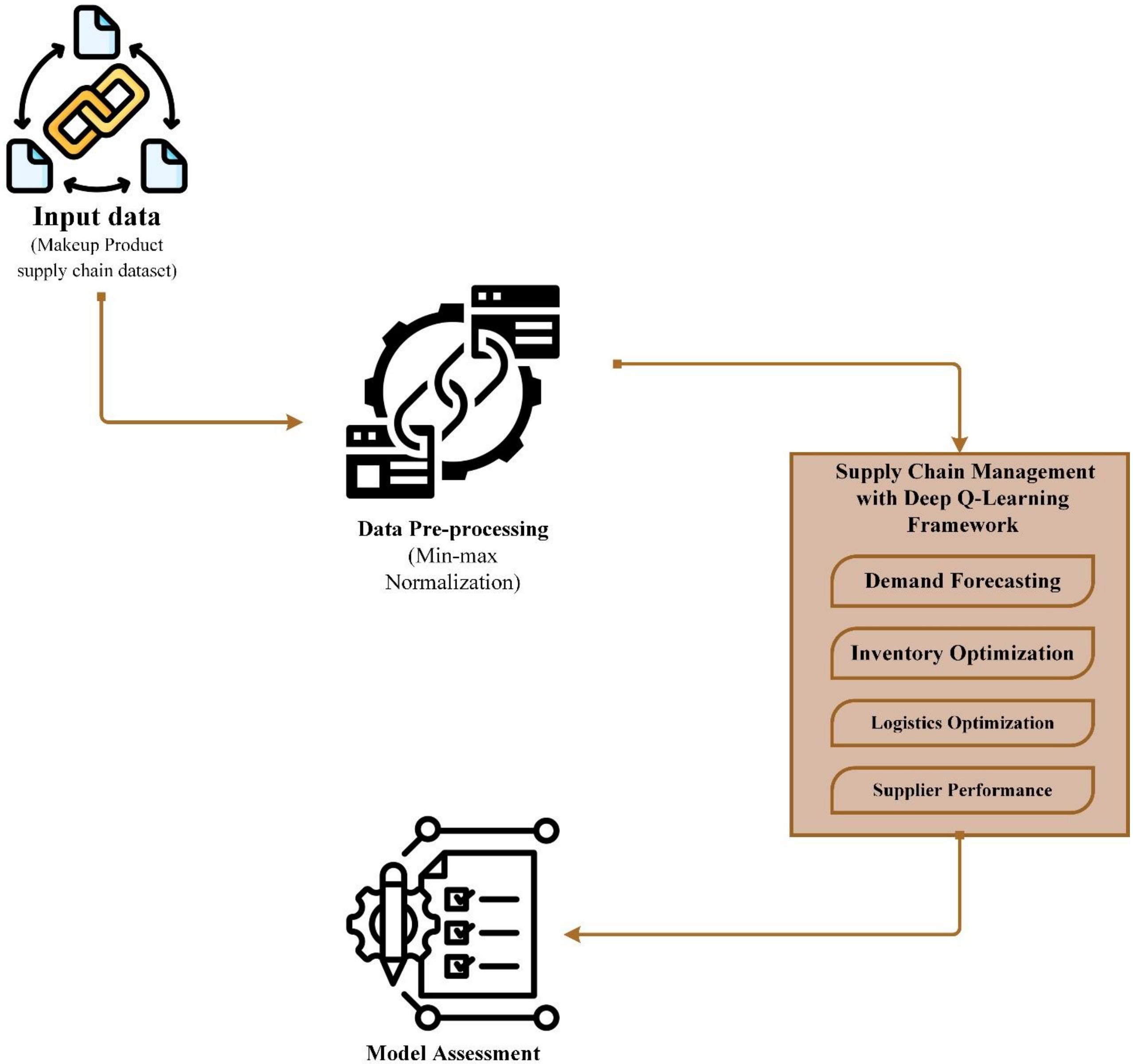

Fig. 2. Workflow of the suggested approach.

A. Data Acquisition

The present investigation employed a thorough dataset that was acquired from a reliable Kaggle database. The information set was specifically designed to address the supply chain activities of a fashion and beauty business that specializes in makeup items. The dataset contains a wide range of relevant characteristics that are essential for supply chain efficiency analysis and optimisation in this business. The proposed dataset for the supply chain activities of a fashion and beauty business specializing in makeup items encompasses a diverse array of attributes crucial for comprehensive analysis and optimization of supply chain efficiency. It includes product-specific details such as Product Type, SKU, Price, and Availability, offering insights into the beauty product portfolio and pricing strategies. Operational indicators such as the number of items sold, revenue earned, and stock levels provide valuable information for assessing sales success and inventory management. Additionally, logistical elements like lead times, order quantities, shipping durations, shipping carriers, and expenses shed light on transportation and delivery procedures within the supply chain. Supplier-related data reveals insights into supplier performance, production procedures, and quality control methods, covering aspects such as supplier name, location, lead time, production volumes, manufacturing prices, inspection results, and defect rates. Moreover, the dataset includes information on transportation modes, routes, and various costs associated with production, distribution, and procurement activities, facilitating a comprehensive examination of supply chain operations. This extensive dataset ensures the availability of essential information required for researching and enhancing the effectiveness of supply chain management specifically tailored to the makeup goods sector. [19].

1) Data pre-processing: In order to scale numerical characteristics to a particular range, usually [0, 1], min-max normalization is a fundamental linear transformation approach. A selection of features were made for normalisation from the makeup product supply chain dataset, including price, number of sold products, revenue generated, stock levels, lead times, order quantities, shipping times, shipping costs, lead time, production volumes, manufacturing lead time, manufacturing costs, defect rates, and costs. These elements reflect several facets of supply chain management, such as production procedures, inventory levels, and financial data. Each feature was subjected to a separate application of Min-max normalisation once the numerical columns were chosen. The following is the Eq. (1) for Min-max normalization:

$$V_{normalized} = \frac{V - V_{min}}{V_{max} - V_{min}} \quad (1)$$

Every feature was scaled to the range [0, 1] as a consequence of the normalization procedure, which comprised taking the least value of each feature and dividing by the range (maximum value minus minimum value).

where,

V: The variable or value that is being normalized.

V_{max}: The maximum possible value

V_{min}: The minimum possible value that

$V_{normalized}$: The normalized value of V after applying Eq. (1).

Larger-scale characteristics are kept from controlling the modelling process by means of this transformation, which guarantees that every feature contributes equally to the analysis. The original dataset structure was preserved by updating the dataset with the scaled values after normalization. In order to maximise supply chain management efficiency within the Makeup product business, preprocessing helps to prepare the data for further analysis and modelling.

B. Optimizing Supply Chain Management with Deep Q-Learning Framework

1) Deep Q-Learning mechanism: In 2013, DeepMind introduced the groundbreaking Deep Q-Network (DQN) reinforcement learning method [20], which revolutionized sequential decision-making in complex environments. The term "Q-Learning," which is represented by the letter Q in DQN, refers to an off-policy temporal differences technique that updates the value function for a particular State-Action pair while taking future rewards into account. Value-based approaches have the advantage of not requiring us to wait until the conclusion of the episode to learn the final reward and the discounted amount. Throughout the process go, update the value function of each action utilizing the Bellman equations [21]. Combining elements of Q-Learning with deep neural networks, DQN enabled agents to navigate intricate scenarios with sequential actions, showcasing remarkable capabilities, particularly in tasks like mastering video games. Central to DQN's architecture is the Q-network, a deep neural network that plays a pivotal role in decision-making processes. Given the current state as input, the Q-network outputs Q-values corresponding to each potential action, representing the expected cumulative reward associated with those actions in the current state. This design not only stabilizes the training process but also effectively handles high-dimensional state spaces, thanks to mechanisms like experience replay and target networks. The innovative design of DQN and its underlying Q-network marks a significant advancement in deep reinforcement learning, offering a powerful framework for addressing complex decision-making challenges in various domains. Deep Q-Learning (DQL) is a comprehensive reinforcement learning method that could potentially employed to optimize several aspects of supply chain management. This technique uses the ideas of reinforcement learning to learn the best decision-making techniques in dynamic, complicated contexts repeatedly. DQL is applied in several areas of supply chain management, such as demand forecasting, inventory optimisation, supplier performance prediction, and logistics optimisation.

Algorithm for DQL Framework for Supply Chanin Management

Step 1: Initialization: The algorithm establishes the replay memory buffer, initialises the Q-network and target network with random weights, and specifies hyperparameters like the exploration rate (ε) and discount factor (γ).
Step 2: Define Exploration Strategy: In this phase, the exploration strategy—like ε-greedy—is defined. It balances exploration with exploitation when choosing an action.
Step 3: Define Reward Function: Logistics objectives provide the basis of the incentive function, which allocates rewards for desired results such as shortened delivery times and cost savings.
Step 4: Training Loop: After choosing actions, carrying them out in the environment, and updating the Q-network with experiences kept in the replay memory buffer, the algorithm repeatedly cycles between episodes and time steps within each episode.
Step 5: Policy Deployment: The trained Q-network is employed for logistical optimisation when training is finished. Based on observable situations in the supply chain environment, it chooses the best course of action.
Step 6: Evaluation: To determine how well the deployed strategy performs in terms of streamlining logistics operations, important indicators like delivery times and cost savings are taken into consideration.

a) Accurate demand forecasting in supply chain management: In supply chain management, demand forecasting is essential because it helps companies estimate future client demand and adjust their operations accordingly. Within this framework, Deep Q-Learning (DQL) becomes a potent method for improving demand prediction accuracy through the implementation of reinforcement learning principles. Businesses can develop the best decision-making strategies using this method, which links the supply chain's present condition to activities that will optimize its future benefits—like income and satisfaction with clients. The interaction of the DQL agent with the supply chain environment is important to DQL-based demand forecasting. The agent looks at the condition of the supply chain as it stands right now, taking into account market trends, inventory levels, sales data from the past, and other pertinent information. The agent decides how to best maximise future benefits by using this knowledge to make decisions about order volumes and price. Environment-generated feedback—which takes the form of incentives or punishments depending on the results—is used to assess how successful these measures constitute. For instance, the agent may be rewarded if it effectively prevents stockouts by adjusting inventory levels in advance of expected increases in demand. On the other hand, the agency might be penalised if it overestimates demand and spends too much on inventory. The DQL agent improves its capacity to create precise demand estimates over time by iteratively enhancing its decision-making processes by learning from previous experiences. The agent adjusts its tactics to changing situations by absorbing patterns and trends in the supply chain environment. This results in more accurate forecasts and more informed decision-making. Additionally, DQL has the benefit of adaptability and flexibility, which enables companies to add new variables or change their forecasting tactics as necessary. To ensure that predictions are accurate and relevant, the DQL agent could modify its decision-making criteria in response to changes in market dynamics or the availability of new data sources. With deep Q-learning for supply chain management demand forecasting, companies may improve prediction accuracy and make better judgements. DQL enables companies to successfully predict future demand patterns and optimise their operations in response, resulting in increased efficiency and competitiveness. This is achieved by establishing decision-making policies via interaction with the supply chain environment.

b) Enhancing inventory optimization in supply chains: An essential part of supply chain management is inventory optimisation, which tries to find a careful balance between keeping costs as low as possible and guaranteeing product availability. To address this issue, Deep Q-Learning (DQL) presents a viable strategy by dynamically modifying inventory levels in response to a range of variables, such as variations in demand, lead times from suppliers, and operational limitations. The learning of a policy by the agent to traverse the intricate decision-making environment of inventory management is the fundamental component of DQL-based inventory optimisation. This policy links activities that determine inventory modifications to the present status of the supply chain, which includes elements like current inventory levels, demand predictions, supplier performance, and market circumstances. It is the responsibility of the DQL agent to optimise inventory levels in order to strike a balance between holding costs and stockout costs. Holding costs include all of the costs related to keeping inventory on hand, including obsolescence risks, storage fees, and capital invested in inventory. Conversely, stockout costs include the possible loss of income due to unfulfilled client demand in addition to the expenses associated with processing backorders and expediting orders. The DQL agent interacts with the supply chain environment to investigate various inventory management techniques and takes use of the best ones in order to maximise cumulative rewards over time. Through dynamically modifying inventory levels in reaction to evolving circumstances, the agent acquires the ability to predict demand trends, prevent stockouts, and reduce holding expenses. Feedback from the environment, which takes the form of incentives or punishments depending on the results, is employed to assess how effective the agent's activities were. For example, if stockouts are successfully avoided while holding costs are kept to a minimum, awards could be received; but, if stockouts occur frequently or at excessive inventory levels, penalties could be incurred. The flexibility and scalability of DQL also provide the agent the option to add more restrictions and variables as needed. To increase the resilience of inventory management techniques, the agent could, for instance, take seasonality, product lifecycles, and lead time variations into account while making decisions. Supply chain managers are empowered to make data-driven decisions that strike a compromise between cost effectiveness and service quality needs by utilising Deep Q-Learning for inventory optimisation. DQL helps organisations improve customer happiness, streamline operations, and gain a competitive edge in the market by dynamically altering inventory levels depending on demand projections, supplier performance, and operational restrictions.

c) Improving procurement decisions through supplier performance prediction: A crucial component of supply chain management is forecasting supplier performance, which is necessary to guarantee the dependability and calibre of providers. Providing a strong framework to assess supplier performance measures and forecast future behaviour, Deep Q-Learning (DQL) helps firms make well-informed procurement decisions. The relationship among DQL agent and previous supplier data is fundamental to DQL-based supplier performance prediction. In addition to lead times, defect rates, delivery dependability, and overall service quality, the agent gains experience evaluating a variety of supplier performance measures. The efficacy and dependability of the provider in fulfilling contractual obligations is shown by these criteria. The DQL agent learns patterns and trends in supplier behaviour by observing previous interactions and the results of such interactions. Through the examination of historical performance information, such as examples of timely delivery, high-quality products, and compliance with service level agreements, the agent has the capacity to identify markers of supplier efficacy and dependability. Using the information it has acquired, the DQL agent forecasts future supplier behaviour and foresees any problems or supply chain interruptions. Through an evaluation of variables including past performance patterns, current market dynamics, and outside influences, the agent could estimate the probability that suppliers will fulfil their commitments and provide products and services within the anticipated timeframe and quality requirements. Furthermore, the agent may dynamically modify its predictions and decision-making processes in response to changing circumstances and fresh data thanks to DQL. The agent regularly updates its models and improves its forecasts in response to changes in the supply chain environment and the availability of fresh data, guaranteeing relevance and accuracy in the evaluation of supplier performance. Ongoing review and input verify the efficacy of the DQL-based supplier performance prediction technique. Businesses may evaluate the precision and dependability of the DQL agent's forecasts by contrasting expected supplier performance with actual results, and they can make any necessary modifications to enhance performance. Through employing Deep Q-Learning to anticipate supplier performance, companies may improve their procurement procedures and arrive at better judgements. DQL enables organisations to choose the most dependable and efficient suppliers, maximise supply chain efficiency, and reduce operational risks by teaching them to evaluate supplier performance measures, forecast future behaviour, and foresee any hazards or interruptions.

d) Streamlining supply chain operations for logistics optimization: Supply chain management relies heavily on logistics optimisation, which aims to reduce costs and improve the effectiveness of distribution and transportation operations. To tackle this problem, Deep Q-Learning (DQL) provides a strong framework that learns to optimise decisions about scheduling, routing, and mode selection, which simplifies logistics processes and enhances supply chain performance overall. The learning of a policy by the agent to traverse the intricate decision-making environment of distribution and transportation is the fundamental component of DQL-based logistics optimisation. In order to create the best choices for moving goods from suppliers to warehouses and from warehouses to consumers, this strategy takes into account a number of variables, such as transportation prices, delivery times, vehicle capacities, and route restrictions. Through interaction and observation, the DQL agent observes the present status of the supply chain environment, which may include variables like available transportation alternatives, inventory levels, consumer demand, and market circumstances. The agent uses this data to make decisions on the best course of action for logistical operations, including delivery schedules, route selection, and mode selection. The agent constantly improves its decision-making rules over time by drawing lessons from its interactions with the environment and with its experiences. The agent aims to maximise cumulative rewards—such as lowering transportation costs, speeding up deliveries, and maximising resource utilization—by investigating and utilising various logistical solutions.

The Deep Q-Learning (DQL) procedure for supply chain management logistics optimisation is described in the presented algorithm. The Deep Q-Learning (DQL) method that is offered sets up basic parameters and selects actions based on exploration or exploitation as iteratively goes through episodes. It regularly modifies the target network settings and updates the Q-network using experiences kept in a replay memory buffer. The technique incorporates assessment and checkpointing processes and gradually reduces the exploration parameters. It offers a structure for discovering the best supply chain management logistics tactics.

Deep Q-Learning (DQL) algorithm for logistics optimization within supply chain management

Initialize the Parameters

- $Q - network\ parameters\ \theta$
- $Target\ network\ parameters\ \theta'$
- $Replay\ memory\ buffer\ D$
- $Exploration\ parameters\ \varepsilon$

$For\ episode\ = 1\ to\ max_{episodes}$:

$\boldsymbol{Initialize\ state\ s}$

$Set\ total_{reward}\ = 0$

$While\ not\ reached\ terminal\ state$

With probability ε

Select a random action a

Otherwise

Select action a $= arg_{max}\ (Q(s, a, \theta))$

Execute action a in the environment

Observe next state s', reward r, and whether next state is terminal

Store experience (s, a, r, s') in replay memory buffer D

#Sample a mini-batch of experiences (s_i, a_i, r_i, s'_i) from replay memory D
For each sample (s_i, a_i, r_i, s'_i) in the mini-batch
Compute target Q-value

If s'_i is terminal
$target = r\_i$

Else

$target = r\_i + \gamma * max(Q(s'\_i, a', \theta'))$
Compute current Q-value

$Q\_value = Q(s\_i, a\_i, \theta)$
Compute loss
$loss = (target - Q\_value)^\wedge 2$

Update Q-network parameters $\boldsymbol{\theta}$
Perform gradient descent on loss with respect to θ
Every C steps
Update target network parameters $\theta' = \theta$
Update state $\boldsymbol{s = s'}$
Accumulate $total_{reward} += r$
Decrease exploration parameter ε over time
$If\ episode$ % $evaluation\_interval == 0$:
Evaluate policy performance using test scenarios
$If\ episode$ % $checkpoint\_interval == 0$
Save Q-network parameters θ

Deep Q-Learning (DQL) is a powerful reinforcement learning technique that has gained significant attention in recent years due to its ability to handle complex decision-making tasks in various domains, including supply chain management. In the context of logistics optimization within the supply chain, DQL can be applied to address challenges such as route planning, fleet management, warehouse operations, and transportation scheduling. Key considerations in DQL-based logistics optimization are discussed below.

1) *Route planning:* DQL can be employed to optimize the routes taken by delivery vehicles or shipments within the supply chain network. By considering factors such as distance, traffic conditions, delivery time windows, and vehicle capacity, DQL algorithms can learn to generate optimal routes that minimize transportation costs and delivery times while maximizing efficiency.

2) *Fleet management:* DQL can assist in optimizing fleet management decisions, such as determining the appropriate number and types of vehicles needed to fulfill customer orders efficiently. By analyzing historical data on order volumes, delivery locations, and vehicle capacities, DQL algorithms can learn to allocate resources effectively, ensuring that the fleet operates at maximum capacity without incurring unnecessary costs or delays.

3) *Warehouse operations:* DQL can optimize warehouse operations by optimizing inventory placement, picking routes, and order fulfilment processes. By learning from historical data on order patterns, inventory levels, and warehouse layouts, DQL algorithms can identify the most efficient strategies for organizing and managing warehouse operations, minimizing storage costs and improving order fulfilment speed.

4) *Transportation scheduling:* DQL can be used to optimize transportation scheduling decisions, such as determining the best times to schedule shipments, allocating resources to different transportation modes, and coordinating logistics activities across multiple locations. By analysing historical data on transportation capacities, lead times, and delivery requirements, DQL algorithms can learn to generate optimal scheduling plans that minimize transportation costs and maximize delivery reliability.

Overall, DQL offers a flexible and scalable approach to logistics optimization within supply chain management. By leveraging advanced machine learning techniques, organizations can improve the efficiency, agility, and resilience of their supply chain operations, gaining a competitive advantage in today's dynamic business environment. Businesses could significantly boost the efficiency and performance of their logistics by learning how to optimize decisions about routing, scheduling, and mode selection with DQL. DQL enables companies to efficiently respond to shifting circumstances and shifting supply chain dynamics by continuously adapting and improving decision-making procedures. This eventually results in cost savings, improved customer satisfaction, and a competitive advantage in the marketplace.

V. Result and Discussion

Findings from the implementation of the study methodology in supply chain management are presented, demonstrating observable improvements in significant performance indicators such inventory turnover, delivery times, and cost reductions. The precision of demand projections, productivity enhancements in inventory management, and the capacity to recognise dependable vendors are emphasised. Moreover, improved resource and transportation efficiency are the results of well-run logistics operations. Comparative assessments show the value contributed by the framework, and visual aids facilitate understanding. Practical strategies for enhancing supply chain operations and boosting competitiveness are provided by the outcome's presentation.

A. Experimental Outcome

1) *Sales by Product Type:* Analysing sales by product type offers important insights into how revenue is distributed throughout a company's portfolio and shows how various product categories are performing. Through sales data analysis, companies may determine best-selling items, comprehend consumer inclinations, and customise their approaches to maximise income. In order to deploy resources effectively and capitalise on high-performing product segments, firms must do this research in order to plan their marketing strategies, inventory control, and general operations.

TABLE I. SALES PERCENTAGE BY PRODUCT TYPE

Product Type	Sales Percentage (%)
Skincare	45%
Cosmetics	25.5%
Haircare	29.5%

The distribution of sales percentages among the various product categories in the company's portfolio is shown in the above Table I. With skincare items making about 45% of the overall sales income, they are the biggest contributor to sales. Products for hair care come in second place with 29.5% of sales, after skincare with 25.5%. This distribution implies that skincare goods account for a sizable amount of the company's income. Furthermore, the greater sales percentage of skincare goods suggests that consumers find these products to be popular. Additionally, the relationship between the increased cost of skincare goods and the money made suggests that, in comparison to cosmetics and hair care products, skincare products could have better profit margins or more demand.

Fig. 3. Sales distribution by product type.

For strategic decision-making in areas like inventory management, marketing campaigns, and product development, it is important to comprehend the sales distribution by the kind of product. Through the identification of client preferences and sales patterns, organisations can customise their approaches to leverage profitable product categories and enhance their total income generating. The distribution of sales percentages among the various product categories in the company's portfolio is shown in Fig. 3. With skincare items making about 45% of overall sales income, they have the largest sales proportion. With a sales ratio of 29.5%, hair care goods trail closely behind cosmetics, which account for 25.5% of total sales. This graphic clearly illustrates the comparative sales performance of every product category and shows how skincare goods are the company's main source of income.

2) Total revenue by shipping carrier: Since shipping carrier income directly affects the profitability and effectiveness of logistics operations, it is a crucial component of supply chain management. This indicator shows how much revenue various carriers in the supply chain network make from providing transportation services. Organisations could assess each shipping carrier's financial contribution, identify top performers, and make well-informed judgments about carrier selection, shipping rate negotiations, and overall logistics optimization strategies by analysing revenue data. Comprehending the income generated by shipping carriers offers significant insights into the financial well-being of the supply chain and facilitates efficient resource allocation for organizations to optimize profitability and competitiveness.

The revenue produced by the various shipping companies in the supply chain is shown in the Table II. It offers a comparison summary of each carrier's revenue contributions, highlighting how well each performs in terms of generating money. With a total revenue of 250.0946k, Carrier B leads the revenue generation. Carrier C comes in second with 184.880k, while Carrier A comes in third with 142.63k.

TABLE II. SHIPPING CARRIERS DRIVE REVENUE GROWTH

Shipping Carrier	Revenue Generated
Carrier A	142.63k
Carrier B	250.0946k
Carrier C	184.880k

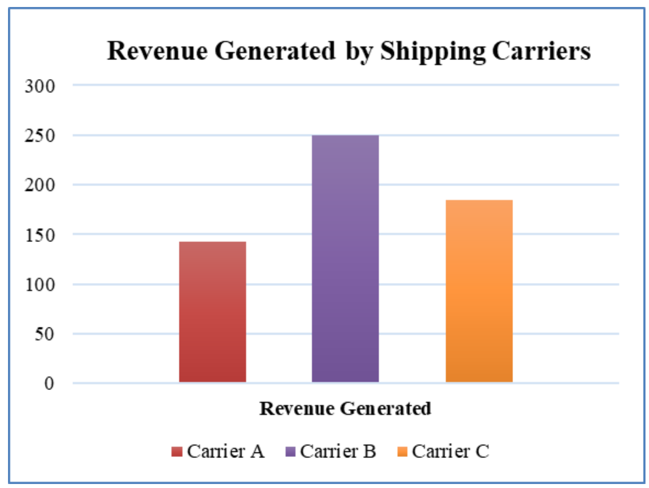

Fig. 4. Revenue generated by shipping carriers.

To facilitate simple comprehension and comparison of the revenue contributions, Fig. 4, which is an accompanying table, visually depicts the revenue earned by each shipping carrier through a bar chart. This graphical depiction makes the data easier to interpret and makes it easier to quickly identify the carriers that are performing at the top. In general, assessing the revenue that shipping carriers bring in from supply chain activities and choosing and managing them wisely depend on the analysis of their income.

3) Analysis of defect rates and costs across transportation modes and routes: This research explores the prices and defect rates related to different forms of transportation along distinct supply chain network routes. Through the analysis of these variables, enterprises may get significant understanding regarding the effectiveness, dependability, and efficiency of transportation processes. The defect rate (D) can be calculated using the Eq. (2):

$$D = \frac{Number\ of\ Defective\ items/\ Occurences}{Total\ Number\ of\ items/\ Occurences} * 100 \quad (2)$$

Once the defect rates are calculated for each route and transportation mode, they provide valuable insights into the reliability, quality, and performance of transportation operations within the supply chain network. Higher defect rates indicate a higher likelihood of issues or problems occurring during transportation, which may necessitate corrective actions or adjustments to improve supply chain efficiency and reduce risks. To maximise logistics tactics, reduce risks, and improve supply chain performance overall, it is crucial to comprehend the link between transportation options, route selections, defect rates, and prices. Supply chain managers could employ the practical findings from this research to guide their decision-making and promote ongoing advancements in transportation management techniques.

TABLE III. DEFECT AND COST RATE BY TRANSPORTATION MODE

Routes	Transportation modes	Costs	Defect rates
Route B	Road	187.752075	0.226410
Route B	Road	503.065579	4.854068
Route C	Air	141.920282	4.580593
Route A	Rail	254.776159	4.746649
Route A	Air	923.440632	3.145580

Table III offers comprehensive information on the prices and defect rates related to various types of transportation along distinct supply chain network routes. Supply chain managers need this information in order to evaluate the effectiveness and efficiency of transportation operations and to make well-informed choices about risk management tactics, carrier selection, and route optimisation. A path in the supply chain is represented by each item in the table, which also includes information on the mode of transportation employed, associated costs, and observed failure rates. Road transport, for example, is used most of the time on Route B; the following table shows two examples of this. With comparable defect rates of 0.226410 and 4.854068, respectively, the related costs for these road transfers are provided as 187.752075 and 503.065579. Similar to Route C, which has a failure rate of 4.580593, Route C mostly uses air transport and costs 141.920282. However, Route A combines rail and air transport, and its prices are 254.776159 and 923.440632, respectively. Its equivalent defect rates are 4.746649 and 3.145580.

The presence of two distinct entries for Route B with the transportation mode specified as Road in Table III signifies that there were multiple instances of transportation activities along this route utilizing road transport. This suggests that there were separate shipments or events that required transportation along Route B, each with its own associated costs and defect rates. The variations in costs and defect rates between these entries could be attributed to several factors. Firstly, different shipments may have varied in terms of their size, weight, destination, or urgency, leading to differences in transportation costs and quality control measures. Additionally, logistical factors such as the specific routes taken, the types of vehicles used, or the involvement of different transportation providers may have influenced the costs and defect rates associated with each transportation event. Furthermore, external factors like road conditions, traffic congestion, or weather conditions could have impacted the efficiency and reliability of transportation along Route B, contributing to the observed variations. By analyzing these differences, businesses can gain valuable insights into the performance of their supply chain logistics along Route B, identify potential areas for improvement, and implement strategies to optimize transportation operations, minimize costs, and enhance overall supply chain efficiency and reliability.

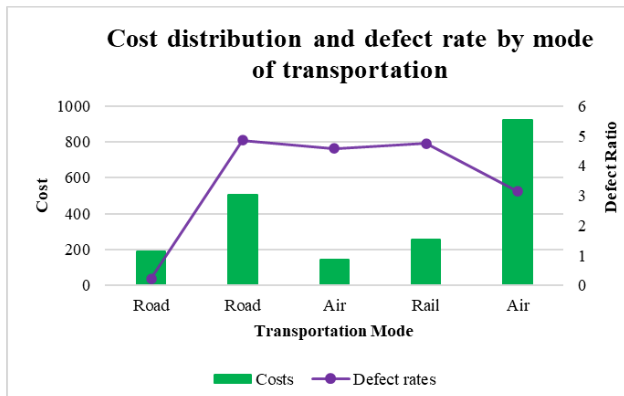

Fig. 5. Defect rates and costs across transportation modes.

The performance and dependability of various transport choices within the supply chain network are provided by this thorough analysis of defect rates and prices by transportation mode and route. Supply chain managers can find patterns, trends, and possible areas for improvement by examining this data. To reduce risks and guarantee product integrity during transportation, routes with high defect rates, for instance, could need more careful inspection and quality control procedures. Analysing the prices of various transportation options could additionally help to optimise logistics processes and reduce costs without sacrificing quality of service. Fig. 5 provides insights that enable supply chain managers to optimise transportation methods, improve operational efficiency, and make data-driven choices in order to efficiently fulfil company objectives.

4) Analysing defect rate by product: Within the supply chain network, examining the defect rate by product offers important information about the dependability and quality of each product class. Through a comprehensive analysis of product defect rates, enterprises may pinpoint opportunities for enhancement, execute focused quality control strategies, and augment the overall quality of their goods. In order to help businesses improve their quality management procedures, reduce the cost of errors, and uphold customer satisfaction levels, this research attempts to evaluate the defect rates seen across several product categories.

The fault rates seen for several product categories within the supply chain network are shown in the above Table IV. A distinct product category is represented by each row, along with the related failure rates. At 1.919287, cosmetics have the lowest fault rate of all the items. Conversely, haircare products had a somewhat higher failure rate of 2.48315. Skincare goods have a 2.334681 failure rate, which is in the middle. The quality and dependability of various product categories within the supply chain are usefully shown by this data. Through product-specific defect rate analysis, companies may pinpoint areas that could use improvement and put focused quality control tactics in place. Companies can minimise expenses related to returns and replacements, improve customer happiness, and keep a competitive advantage in the market by fixing faults and minimizing product inconsistencies.

TABLE IV. DEFECT RATE BY PRODUCT

Products	Defect Rates
Cosmetics	1.919287
Haircare	2.48315
Skincare	2.334681

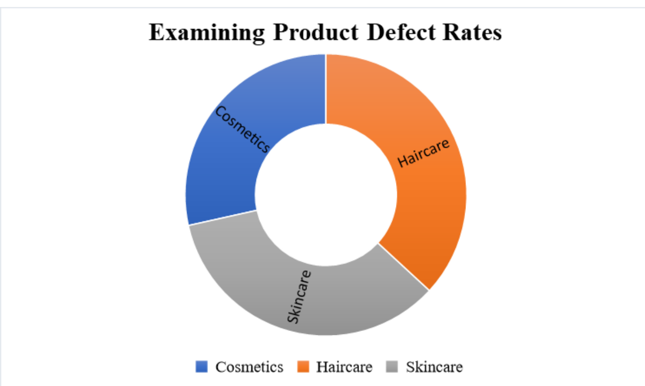

Fig. 6. Product-specific defect rates.

Stakeholders could frequently determine whether goods have greater or lower failure rates by referring to Fig. 6, which displays a graphical depiction that compares defect rates across several product categories. Understanding each product category's relative quality and dependability along the supply chain is made easier by the figure. Furthermore, it functions as a valuable instrument for decision-making, allowing organisations to arrange resources and prioritise efforts towards improving quality in order to reduce errors and raise the standard of their products.

B. Performance Assessment

To evaluate performance effectively, it is essential to take into account a variety of critical measures when comparing the outcomes of a proposed framework with baseline techniques or current solutions in the existing literature. When the suggested framework is compared to other well-established techniques, these metrics offer valuable information about its efficacy, productivity, and dependability.

1) Accuracy: When assessing the effectiveness of predictive models, such as those used in supply chain management, accuracy is a crucial parameter. The proportion of correctly categorised examples out of all examined instances is measured to determine the model's accuracy in making predictions. Accuracy is of the utmost significance in supply chain management since it has a direct impact on decisions made about inventory control, demand forecasting, and supplier selection. The aforementioned Eq. (3) represents accuracy as a percentage and shows how accurate the forecasts generated by the model.

$$Accuracy = \frac{No.of\ Correct\ Predictions}{Total\ No.of\ Predictions} \times 100\% \quad (3)$$

The performance of several techniques, including Support Vector Machine (SVM), Decision Tree (DT), Random Decision Tree (RDT), and the suggested Deep Q-learning methodology, is thoroughly compared in Table V. The accuracy measure is employed to assess the efficacy of every technique, with the outcomes displayed as proportions. The outcomes show that, with an astounding accuracy rate of 98.9%, the suggested Deep Q-learning methodology attains the best accuracy out of all approaches. This implies that the Deep Q-learning methodology has shown to be exceptionally effective in accurately categorising situations in the area of supply chain management. This approach's high accuracy suggests that it is good at identifying intricate patterns and correlations in the data, which could assist with prediction and decision-making.

TABLE V. PERFORMANCE COMPARISON OF THE SUGGESTED APPROACH

Methods	Accuracy (%)
SVM	94
DT	95
RDT	91
Proposed Deep Q	98.9

The Table V presents a comprehensive comparison of the accuracy percentages achieved by different methods employed for supply chain management optimization. Among the traditional machine learning algorithms assessed, Support Vector Machine (SVM) demonstrated a respectable accuracy of 94%, followed closely by Decision Tree (DT) at 95% and Random Decision Tree (RDT) at 91%. These methods, while effective, were surpassed by the proposed Deep Q-Learning (DQL) approach which increased by 3.8 % when compared to related accuracy, which showcased remarkable accuracy, standing at an impressive 98.9%. DQL, a reinforcement learning technique leveraging neural networks, showcased its superiority in addressing the complexities of supply chain management, offering unparalleled accuracy in predictive modeling and optimization tasks.

The results underscore the transformative potential of incorporating advanced methodologies like DQL into supply chain management practices. With its unmatched accuracy, the proposed DQL framework promises to revolutionize decision-making processes within supply chains, enabling organizations to navigate uncertainties, optimize resource allocation, and enhance operational efficiency. This study highlights the pivotal role of innovative techniques in driving the evolution of supply chain management towards greater agility, resilience, and competitiveness in today's dynamic business landscape.

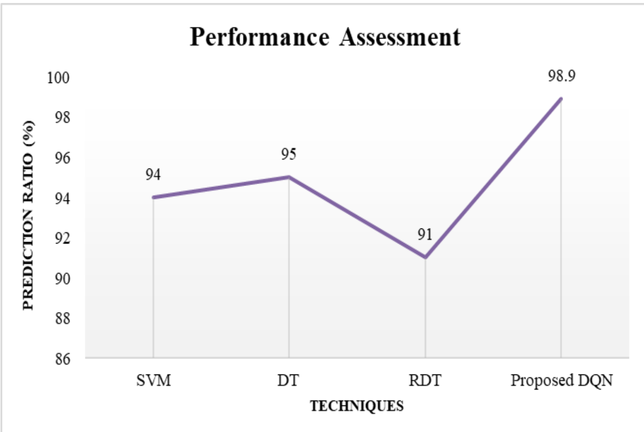

Fig. 7. Performance comparison of different methods in supply chain management.

The findings in Fig. 7 demonstrate the effectiveness of the suggested DQN method in relation to supply chain management. Enhancing forecast accuracy, streamlining processes, and eventually increasing value creation in the supply chain are all possible with this strategy.

VI. CONCLUSION AND FUTURE WORK

The present investigation delved into the efficacy of multiple supply chain management techniques, with a particular emphasis on the suggested Deep Q-Network (DQN) strategy. The research aimed to assess the predictive and optimization capabilities of various methods, including Support Vector Machine (SVM), Decision Tree (DT), Random Decision Tree (RDT), and DQN, within the realm of supply chain processes. Following a thorough examination, it became evident that the Deep Q-learning method outperformed conventional machine learning techniques, boasting an impressive accuracy rate of 98.9%. This superior performance underscores the capacity of deep reinforcement learning techniques to enhance forecasting accuracy and address complex challenges within supply chain management. The significance of this research lies in its potential to enhance both the efficiency and productivity of supply chains. By harnessing advanced AI techniques like Deep Q-learning, organizations stand to elevate customer satisfaction, streamline processes, and generate more precise forecasts. Moreover, the findings underscore the importance of leveraging innovative methodologies to navigate the dynamic obstacles inherent in supply chain management, particularly in light of increasing complexity and unpredictability.

This study contributes to the expanding body of research on machine learning applications in supply chain management. It not only showcases the substantial performance enhancement offered by DQN but also illustrates its effectiveness in optimizing supply chain operations. Future research avenues could focus on further refining the DQN approach, exploring its applicability across diverse supply chain scenarios, and investigating potential synergies with other cutting-edge technologies such as blockchain and the Internet of Things (IoT). These endeavors promise to pave the way for more comprehensive and robust supply chain optimization strategies.

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