Machine Learning Applications for Enhancing the Supply Chain Productivity- A Review

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Abstract

The movement of products, commodities, and information from manufacturers to consumers is part of the supply chain, which is a dynamic and complicated process. Recent technological developments, notably in the area of machine learning (ML), have created new possibilities for raising supply chain productivity. It is possible for devices to study from information and generate predictions or judgements using machine learning (ML), a subset of artificial intelligence (AI), without having to be explicitly programmed. Demand forecasting, inventory management, transportation planning, and supply chain risk management are just a few of the supply chain-related tasks that may be handled by ML algorithms. In addition, ML can be used to optimize transportation routes and schedules, which can help reduce transportation costs and improve delivery times. Overall, by enabling businesses to make better decisions, streamline their operations, and lower risks, ML has the possibility of significantly improving the efficiency of the supply chain.

Keywords
Supply chain Management (SCM), Artificial intelligence (AI), Machine Learning (ML).

1. Introduction
Supply chain management may be completely transformed by machine learning (ML), a fast-expanding subject. ML is able to evaluate vast volumes of data, make predictions and conclusions that were previously impractical, and do statistical analysis using sophisticated algorithms. As a result, the supply chain may become significantly more productive, which includes greater predicting and demand planning, quicker and even more accurate decision-making, and more supply chain visibility.

There are several key ML applications that can be used to enhance supply chain productivity, including:

1. Predictive analytics: By analysing historical data, ML algorithms can make predictions about future trends and patterns. This can be used to optimize supply chain operations, such as demand forecasting and inventory management.
2. Optimization: ML can be used to optimize complex supply chain processes, such as logistics and distribution, by identifying the most efficient routes and schedules.
3. Intelligent automation: ML can be used to automate repetitive and time-consuming tasks, such as data entry and analysis, which can lead to significant productivity gains.
4. Robotics: ML can be used to develop intelligent robotic systems that can automate tasks such as warehouse management and material handling.

Overall, by boosting productivity, cutting expenses, and enhancing response to market changes, the implementation of ML in supply chain management may provide businesses a competitive edge. It will be more crucial than ever for businesses to use ML to remain ahead of the curve as technology develops.

2. Some common Algorithms of machine learning

1. Decision Tree (DT): DTs depict various implications with distinct graphs. Each node in the graphs provides to one unique characteristic. DTs are generally used for differential categories and multiple regression. While

DTs are straightforward to detect and have little bias, they are simple to be over-fitting. That's where the RF steps in.

2. Random Forest (RF): RF employs various DTs built with various data sources and picks the random feature subsets that are used to create projections by availing use of the average scores of all the distinct prediction outputs. DT and RF are the two possible procedures which reflect the develop a suitable in SCM by outlining the advantages of each option and their likelihood of fulfilment. These two choice approaches then produce an overall presentation by conducting lead-scoring for SC management to allocate resources.
3. K-means: It is an unsupervised clustering approach. This strategy is possible to partition the data into k groups that would lower the square errors within each cluster. K-means is cost-efficient with its limited computation complexity, but the K has to be presented in advance, which demands the prior information of the data sets. What's more concerning is that it is susceptible to just being impacted by anomalies and noise.
4. Logistic Regression (LR): This widely used Linear Regression Model variant. In contrast to a linear regression model, a non-linear model may be used to replace a linear fitting model in order to fit every independent variable and dependent variable. Nevertheless, this method still has poor fitness and is highly reliant on the fitting model that is selected. As LR is good at anticipating continuous data, SCM uses it for sales forecasting.
5. The Naive Bayes Classifier (NBC) is a powerful tool for small-scale data sets since it is centred on the Bayesian Theorem. NBC has the ability to be used in SCM for identifying a stakeholder's credit, notifying whether he or she would violate contract rules, and subsequently giving a heads-up to other stakeholders.
6. Neural Networks (NN): NN were initially deployed in 1988 and were built in the 1980s. It was developed to simulate how the human mind adapts to complete assignments. In order for SCM to employ NN to warn about possible rivals, it needs to be able to discern sophisticated nonlinear input/output linkages. To SCM, each of these variants apply. Consider CNN as an illustration. CNN is an important factor of deep learning and is commonly used for image processing. It is applied in SCM to achieve lead-time scheduling and personalise along with visual and audio analysis of client and salesperson interactions. Sadly, NNs have a constructed constraint, that means that they are unwilling describe their thinking process since the numerical solutions are formed by continuous programming in a "black box".
7. Support Vector Machine (SVM): Since SVMs have features of simple structure and replace experiential optimal with optimal solution, they may compensate for the weakness NNs have. SVMs have strong mathematical know how to adapt and generalisation capabilities. Moreover, SVMs are suited for high-dimensional challenges, giving new options for cross-selling and slightly higher compared for SCM. SVMs, however, largely depend on their kernels, that also involve previous grasp of the essential data sets.

3. Literature Review

3.1 Demand/sales estimation

Sales and demand estimation is an important aspect of supply chain management. Accurate sales and demand estimation helps organizations to make informed decisions regarding inventory management, production planning, and logistics. Machine learning techniques can be used to develop predictive models for sales and demand estimation. These models can analyse historical sales data and identify patterns and trends that can help in forecasting future demand.

As ML algorithms do not heavily depend on the accuracy of historical data, they have been touted as potential options for planning and demand in SCM. This is in contrast to earlier approaches like moving average, simple exponential, time-series methods, and Box-Jenkins methods.

For example, (Ning et al. 2009) created the shortest description length optimum NNs that could forecast store preferences to alter the restocking strategy with variable time delays, which is impossible for existing models to do. Several forecasting techniques that (Thomassey 2010) gave generated more accurate sales projections than did normal techniques. These models, which were created applying cutting-edge methodologies like NNs, fuzzy logic, and data mining, worked well when dealing with obstacles like strong seasonality in sales, depends on the availability, a lack of previous data backgrounds, or a vast variety of commodities with short lifespans. In contrast to standard techniques, algorithms that use machine learning are better capable of eliminating the imperfections in the data sets and produce non-linear algorithms that more closely fit the demand/sales curve.

Several researchers have explored the use of machine learning techniques for sales and demand estimation in supply chain management. In a study conducted by Arshad et al. (2020), machine learning algorithms were used to develop a predictive model for demand estimation in a supply chain. The study used historical sales data and weather data to develop a model that could accurately forecast demand.

Similarly, Chen et al. (2018) developed a machine learning-based approach for sales forecasting in supply chain management. The approach used a combination of time series analysis and machine learning algorithms to forecast sales based on historical data.

In another study, Lee et al. (2019) proposed a machine learning-based approach for demand forecasting in a food supply chain. The approach used a combination of historical sales data, external data sources, and machine learning algorithms to develop a predictive model for demand forecasting.

In a study conducted by Kourentzes et al. (2020), machine learning techniques were used to develop a demand forecasting model for a large retail chain. The study used a combination of time series analysis and machine learning algorithms to forecast demand for different products in the retail chain.

3.2 Production

Production processes involve complex procedures that require detailed analyses for optimal output. The use of ML has enabled researchers and companies to develop models that can automate, optimize, and predict different aspects of production. Some of the critical areas that ML can be applied include production scheduling, quality control, and predictive maintenance.

For enhancing the quality of production and also for reducing to production time, predictive maintenance plays a very key role where the defect in any part of the machine can be predicted before its failure and there after we can significantly reduce the production time and cost.

ML algorithms will improve industrial planning efficiency and production scheduling by accounting for different restrictions. Moreover, Machine learning algorithms will enable manufacturers that depend on build-to-order and begin producing manufacturing processes to balance the limits more successfully than they could in the past. Manufacturers may remove SC delay for elements and components used in their most substantially changed products by using ML. For instance, (Chen et al.) proposed a method using NNs to combine identical customization requests in response to the varied customisation demands and manufacturing constraints of each nation.

As compared to human judgement, this significantly reduced the cost during the SC. They then used the existing stock information to select the elements for production managers. Similar to this, (Juez et al. (2010)) used SVMs to take into account a variety of factors to set boost production lead-time prior manufacturing in the aircraft industry. As a consequence, the ML algorithms may provide the production lead-time estimate with a quicker reaction time.

Several studies have explored the use of ML in production processes in the supply chain. Li and Li (2019) developed an intelligent maintenance system that uses deep learning to identify and predict equipment faults. The system enabled timely maintenance that helped avoid unexpected downtimes, improve production efficiency, and reduce costs.

In another study, Garcia-Sanchez et al. (2020) developed a predictive model using ML techniques to optimize production planning. The study proposed a hybrid model that integrated simulation optimization, ML, and a genetic algorithm. The hybrid model produced better results compared to traditional models by reducing manufacturing lead times, inventory, and costs.

Zhang et al. (2020) proposed a machine learning-based approach to optimize production scheduling. The study used a decision-making model that integrated production scheduling, quality control, and inventory management. The approach enabled efficient production processes, reduced inventory, and improved on-time delivery.

In a study conducted by Chaudhary et al. (2018), a deep learning model was used for quality control in the production of steel sheets. The model identified surface defects that were not detected by traditional methods, resulting in improved quality and reduced waste.

3.3 Inventory and storage

ML has been applied in different areas of storage and inventory management, including demand forecasting, stock replenishment, and warehouse optimization. ML models can analyse large datasets, identify patterns, and predict future demand, which enables efficient inventory management.

Costs associated with storage and supply chain inventory management (SCIM) are high. (Timme and Williams-Timme), for example, calculate that the annual cost of storage is equal to 15% to 35% of the total enterprise value. SCIM aims to increase product variety, improve customer experience, and save costs. Yet, since they heavily rely on the knowledge and experience of inventory managers themselves, it may be challenging to effectively estimate, anticipate, and gather information for all of these purposes. Due to the unexpected nature of inventory entry into warehouses, a solution is required to help people navigate this uncertainty.

ML systems are capable of quickly searching for similar patterns in warehouse data sets. NNs and neuro-fuzzy desire were used to do lead-time prediction in a multi-echelon SC. The results showed that their recommended technique successfully increased the level of inventory management. Moreover, internal delivery or hazard identification at logistics hubs has shown to be an effective use of machine learning (ML). Findings from two minor SC scenarios where (Wan et al.2012) used SVM and NBC shown that their approach may increase inventory safety. The ML algorithms may discover previously unknown hidden inventory patterns, which can result in total cost savings.

Several studies have explored the use of ML in storage and inventory management in the supply chain. In a study conducted by Kuo et al. (2019), a demand forecasting model was developed using an ML algorithm. The model used historical sales data and external factors such as economic indicators and weather conditions to predict future demand. The model enabled efficient inventory management and reduced the risk of overstocking or stockouts.

In another study, Zhao et al. (2020) proposed an ML-based approach for stock replenishment in a warehouse. The approach used a combination of data mining and ML algorithms to optimize the stock replenishment process. The approach resulted in improved stock replenishment accuracy, reduced stockout rates, and better inventory control.

In a study conducted by Jia et al. (2019), an ML-based optimization model was developed for warehouse layout design. The model used data analytics and optimization techniques to determine the optimal layout design that minimized the warehouse's operational costs. The approach resulted in reduced operational costs and improved warehouse efficiency.

In another study, Shen et al. (2018) proposed an ML-based approach for inventory optimization in a distribution center. The approach used a combination of supervised and unsupervised learning algorithms to predict future demand and optimize inventory management. The approach resulted in improved inventory accuracy, reduced inventory costs, and improved customer satisfaction.

3.4 Transportation and distribution

ML has been applied in different areas of transportation and distribution, including route optimization, carrier selection, and shipment tracking. ML models can analyse large datasets, identify patterns, and predict future demand, which enables efficient transportation and distribution management.

One of the most popular SCM applications involves using ML to solve truck routing problems. SC must choose the best routes from a range of options in order to deliver a product to the required clientele. The ability of the human brain to determine the best pathways is often limited. ML algorithms and the apps that use them are skilled at evaluating enormous, diverse data sets with high demand forecasting accuracy. A model for light delivery truck routing among providers of logistics services was created by (Cirovic et al.2018) To address the routing issues in the model, an adaptive NN was built using a simulated annealing technique to test the effectiveness of the distribution network routes.

The Hamburg Harbor Car Gateway, a logistics facility with around 46,500 car-routing options, served as the basis for an actual simulation used by (Becker et al.2020). According to simulation findings provided by Becker et al., the neural-net model performed 48% higher than the average heuristic routes examined in prior studies. As a consequence, ML algorithms may generate better distribution networks by quickly and objectively analysing trends in infrastructure, vehicle, transit, and consumer behaviour.

In a study conducted by Li et al. (2020), an ML-based approach was proposed for shipment tracking. The approach used a combination of deep learning and natural language processing techniques to extract information from shipping documents and track shipments in real-time. The approach resulted in improved shipment visibility, reduced transportation costs, and improved customer satisfaction.

In another study, Chen et al. (2019) proposed an ML-based approach for demand forecasting in transportation. The approach used historical data and external factors such as weather and economic indicators to predict future demand. The approach resulted in improved capacity planning, reduced transportation costs, and improved customer satisfaction.

Several studies have explored the use of ML in transportation and distribution in the supply chain. In a study conducted by Tan et al. (2019), an ML-based approach was proposed for carrier selection. The approach used a combination of supervised and unsupervised learning algorithms to predict carrier performance and select the best carrier for a particular shipment. The approach resulted in improved shipment delivery times and reduced transportation costs.

In another study, Lee et al. (2018) proposed an ML-based approach for route optimization. The approach used a combination of genetic algorithms and neural networks to optimize transportation routes based on real-time traffic data. The approach resulted in improved route efficiency, reduced transportation costs, and improved delivery times (Table 1).

Table 1. Transportation and distribution

Sr. No.	Author	Date	ML Algorithms	Key Findings	Conclusions
1.	Alvarez Quiñones, L.I., Lozano-Moncada, C.A. and Bravo Montenegro,	7 March 2023	Supervised learning (claasification) SVM	The suggested model is a useful tool for making decisions and offers the best answer to the scheduling issues for distribution transformer preventative maintenance.	By applying the SVM model 13% effectiveness was observed in the expenses for 2020.
2.	Kalliopi Tsolaki, Thanasis Vafeiadis, Alexandros Nizamis, Dimosthenis Ioannidis, Dimitrios Tzovaras	3 February 2022	ANNs, SVM, LR, reinforcement learning	Utilization of machine learning techniques and hybrid approaches on problems regarding freight transportation, supply chain and logistics operations Management	focusing more on ANNs and ensembles learning methods, which have been shown to have better performance than simpler machine learning methods like SVM or LR.
3.	Abidi, M.H.; Mohammed, M.K.; Alkhalefah,	14 March 2022	Recurrent Neural Network (J-SLnO algorithm), KNN, SVM	The RNN model was deployed on two database that is an aircraft engine database and a Li-ion battery.	According to the study, the J-SLnO-RNN method was 95.3% more developed than the NN, 95.1% more progressed than the KNN, 96.9% more evolved than the RNN, and 61.8% more modern than the SVM-RNN in terms of its RMSE.
4.	D Singha, Dr Chetan Panse	18 April 2022	MLP, CNN, LSTM	The MLP technique performs a little better than other applied methods in estimating more accuracy	LSTM and CNN models tend to work better in the case of long sequence data as it stores the previous sequences in their memory
5.	Lin, H., Lin, J. and Wang, F.,	10 Oct 2022	CGAN(conditional generative adversal network)	In order to analyse and forecast the purchase and inventory relationships in the supply chain, machine learning is applied. The route is sensibly developed for the vehicle routing module to increase operating performance. The SSH framework is used to complete the integrated execution of the SCM system.	A flexible supply chain member selection technique based on CGAN was presented to address the issue of more decision characteristics and fewer data samples for decision analysis.

6.	Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T. and Ivanov, D.,	13 Oct 2022	Reinforcement learning, Q-learning	The major outcome of the study was a hierarchic classification framework that applies RL applications to supply chain.	According to their view Qlearning is the most popular and inventory management is the most common application of RL in SC.
7.	Hardik Meisheri, Nazneen N. Sultana, Mayank Baranwal, Vinita Baniwal, Somjit Nath, Satyam Verma, Balaraman Ravindran, Harshad Khadilkar	15 May 2021	Deep reinforcement learning	A special approach in the inventory problem of dynamical system control was formulated against the theoretical optimum achieved by linear programming under the assumptions that demands are determininstic.	High-quality solutions can be produced by the parallelized decision-making framework at low online computing costs, and it can also learn to abide by the aggregated system capacity restrictions.
8.	Javad Feizabadi	26 July 2020	ARIMAX(Autoregressive Integrated Moving Average with Explanatory Variable), NN	The devised technique takes time series and explanatory variables into account. In the context of a functional product and a steel producer, the procedure was used and assessed.	Both operational and financial indicators might be improved by using ML-based forecasting techniques (ARIMAX and NN). Lowering inventory results in cheaper transportation, storage, and facility costs without lowering the quality of service.
9.	Amihai, I., Gitzel, R., Kotriwala, A.M., Pareschi, D., Subbiah, S. and Sosale, G	02 September 2018	Random Forest Algorithm	2.5 years old data was collected from 30 industrial pumps and metrics was observed from vibration data for the prediction	The prediction of Key Control Iindicators a number of days ahead serves as a stepping stone towards predicting asset failures before they occur.

4. Conclusions

Machine learning techniques have been used successfully in supply chain management for sales and demand estimation. The studies reviewed in this literature review demonstrate that machine learning algorithms can be used to develop accurate predictive models for sales and demand forecasting. The use of machine learning in supply chain management can help organizations to improve their inventory management, production planning, and logistics, and ultimately improve their bottom line. Mechanical engineering students can benefit from exploring these studies and applying machine learning techniques in supply chain management for their future projects.

Machine learning has been applied in various aspects of supply chain management to improve production processes. The studies reviewed in this literature review demonstrate that ML can be used for predictive maintenance, production planning, scheduling, and quality control. The use of ML in production processes has enabled companies to optimize production, reduce downtime, and improve quality, leading to better profits. Mechanical engineering students can learn from these studies and apply machine learning techniques in supply chain management for their future projects in production.

Machine learning has been applied in different aspects of storage and inventory management in supply chain management. The studies reviewed in this literature review demonstrate that ML can be used for demand forecasting, stock replenishment, warehouse layout design, and inventory optimization. The use of ML in storage and inventory management has enabled companies to reduce costs, improve customer satisfaction, and meet customer demands. Mechanical engineering students can learn from these studies and apply ML techniques in supply chain management for their future projects in storage and inventory management.

Machine learning has been applied in different aspects of transportation and distribution in supply chain management. The studies reviewed in this literature review demonstrate that ML can be used for carrier selection, route optimization, shipment tracking, and demand forecasting. The use of ML in transportation and distribution has enabled companies to reduce costs, improve delivery times, and meet customer demands. Mechanical engineering students can learn from these studies and apply ML techniques in supply chain management for their future projects in transportation and distribution.

Finally, machine learning has demonstrated to be a potent tool for increasing supply chain productivity across a range of sectors. Machine learning models may simplify operations, anticipate demand, and improve procedures by utilising massive volumes of data and cutting-edge algorithms. Machine learning technologies are being created and put into use to increase productivity and cut costs in areas like inventory management and logistics planning. It is crucial to remember that a successful adoption of ML algorithms with in supply chain demands a thorough comprehension of the business operations as well as data availability and quality. In order to support these activities, businesses that engage in machine learning technology must also invest in the infrastructure and labour that are required. Nonetheless, the potential benefits of machine learning for supply chain productivity make it a promising area for continued research and innovation.

By enhancing efficiency, cutting costs, and raising customer happiness, machine learning has the potential to completely transform supply chain management. Despite the fact that machine learning has numerous uses in SCM, it is crucial to remember that the field is still in its infancy. As a result, there are still a lot of difficulties to be solved, including issues with model interpretability, data quality, and ethical issues. Yet as technology develops, we may anticipate seeing even more avant-garde uses of machine learning in supply chain management.

5. Future Scope

The future scope for ML in supply chain management is vast, and it will continue to transform the way businesses operate. The future of ML in sales and demand forecasting lies in the integration of big data, artificial intelligence (AI), and ML. The use of real-time data streams and advanced algorithms will allow businesses to respond to demand fluctuations rapidly. As ML algorithms improve, they will be able to predict and detect patterns in demand data with greater accuracy and precision. ML in production will involve the development of smart factories, where ML algorithms will be used to optimize production processes, reduce downtime, and improve product quality. The integration of the Internet of Things (IoT) and ML will enable the collection of real-time data from machines and equipment, allowing for more proactive maintenance. In predictive maintenance will involve the use of ML algorithms to analyse real-time data from sensors and equipment to predict maintenance needs. The use of ML in predictive maintenance will reduce equipment downtime and improve productivity. The growth for storage and inventory management lies in the integration of big data, AI, and ML. The use of real-time data streams and advanced algorithms will allow businesses to optimize inventory levels, reduce waste, and improve customer satisfaction. Transportation and distribution will involve the use of advanced algorithms to optimize delivery routes, reduce transportation costs, and improve delivery times. The integration of the IoT and ML will enable the collection of real-time data from vehicles and transportation networks, allowing for more efficient logistics management. Mechanical engineering students can prepare for these future advancements by acquiring skills in ML, data analysis, and IoT, among other relevant technologies. By staying informed and being adaptable, they can take advantage of the future opportunities that ML presents in supply chain management.

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