
| RESEARCH ARTICLE

Optimizing Regional Business Performance: Leveraging Business and Data Analytics in Logistics & Supply Chain Management for USA's Sustainable Growth

Md Sumon Gazi

MBA Business Analytics, Gannon University, USA

Corresponding Author: Md Sumon Gazi, **E-mail:** sumonmkt87@gmail.com

| ABSTRACT

The logistics and supply chain management (SCM) sector plays a paramount role in the economic development and growth of countries. In the USA, the effectiveness and efficiency of logistics and SCM functions directly influence regional organizational performance and long-term economic sustainability. The prime objective of this research is to explore the phenomenon of optimizing regional business performance through the application of data and business analytics in logistics and supply chain management for the sustainable growth of the US economy. In this study, the researcher employed machine learning methodologies, specifically ANN, RNN, and SVM, to forecast lead times for purchasing aluminum products. In the research, historical data was collected from the database of one of the aluminum-producing companies in the USA for the last 10 years. In particular, a sample of 38,500 orders of aluminum profiles was adopted for the current study. Retrospectively, the Recurrent Neural Network and the Support Vector Machine displayed the most favorable outcomes in predicting lead time in the supply chain. Particularly, RNN had the least Mean Average Error (MAE) on the testing set (447.72), followed by SVM (453.04), MLR (453.22), and NN (455.41). By deploying these algorithms, the government can optimize inventory degrees, minimize stockouts, and reduce excess inventory. This results in enhanced efficiency, diminished carrying costs, and elevated consumer satisfaction, leading to cost savings and heightened profitability for government companies within the supply chain.

| KEYWORDS

Business Analytics; Logistic; Supply Chain; Recurrent Neural Networks; Support Vector Machines (SVM); Artificial Neural Network (ANN).

| ARTICLE INFORMATION

ACCEPTED: 02 April 2024

PUBLISHED: 20 April 2024

DOI: 10.32996/jbms.2024.6.2.14

1. Introduction

According to Aljohani (2023), the United States is a worldwide economic powerhouse, and its logistics and supply chain management play an instrumental role in sustaining its competitiveness and growth. In the recent past, businesses in the USA have been increasingly leveraging organizational and data analytics to reinforce their regional performance in the supply chain and logistics sector. As per Biazon (2022), Logistics and supply chain management are pivotal functions that guarantee the effective flow of services and goods from manufacturers to consumers. It revolves around the synchronization of various activities such as warehousing, transportation, order processing, and inventory management. Effective logistics and supply chain management can lead to cost savings, enhanced consumer satisfaction, and elevated competitiveness in the market. This study aims to examine the phenomenon of optimizing regional business performance through the application of data and business analytics in logistics and supply chain management for the sustainable growth of the US economy.

Biazon (2022) indicates that the logistics and supply chain management (SCM) sector plays a paramount role in the economic development and growth of countries. In the USA, the effectiveness and efficiency of logistics and SCM functions directly influence regional organizational performance and long-term economic sustainability. With the progression of advanced technologies and

the growth of data, optimizing business and data analytics has arisen as a paramount strategy for leveraging logistics and SCM processes. The essence of Logistics and Supply Chain Management entails the management of the flow of services and products from the point of origin to the point of consumption. Effective logistics and SCM functions are tantamount to minimizing costs, enhancing client satisfaction, and improving competitiveness. In the USA, the huge geographical area and diverse market demand robust logistics and SCM strategies to affirm smooth product flow and timely delivery.

2. Literature Review

2.1 Current State of Logistics and Supply Chain Management in the USA

The USA has a relatively complex and interconnected supply chain network and logistics. It comprises various means of transportation, encompassing rail, road, water, and air, which streamlines the movement of products across the nation. Retrospectively, the logistics and SCM sector is a big contributor to the American economy. According to the *Bureau of Economic Analysis (BEA)*, the warehousing and transportation industry contributed approximately \$1.6 trillion to the American GDP in 2023, accounting for 8.3% of the overall GDP (Gonuguntla, 2023). This reiterates the significant economic effect of logistics and SCM activities in the USA.

Moreover, the logistics and SCM industry is a big employer in the USA, offering employment opportunities to millions of American citizens across various roles and functions. In particular, as per the US Bureau of Labor Statistics (BLS), the warehousing and transportation sector employed approximately 5.9 million citizens in 2023, accounting for approximately 4% of the overall nonfarm employment (Aljohani, 2023). These statistics demonstrate the substantial workforce involved in managing logistics and SCM operations across the nation.

IntelliSoft. (2024) contends that technological advancements and infrastructure investment play a pivotal role in shaping the efficiency and competitiveness of logistics and SCM in the United States. The *American Society of Civil Engineers (ASCE)* approximates that the American government needs to invest approximately \$2.6 trillion in infrastructure by 2020 to streamline the depleting transportation networks, enhance connectivity, and boost supply chain resilience. Moreover, the employment of digital technologies such as blockchain, Internet of Things (IoT), business analytics, and artificial intelligence (AI) is gradually gaining momentum, with companies increasingly deploying these tools to optimize supply chain processes and enhance visibility.

2.2 Key Challenges in Logistics and Supply Chain Management

Logistics and supply chain management in America experience several key challenges that influence profitability, efficiency, and competitiveness. These challenges emerge from various fronts comprising technological advancements, global trade dynamics, market shifts, and regulatory requirements (Matta, 2024). Below are some of the key challenges experienced in logistics and SCM in the USA:

2.2.1 Supply Chain Disruptions and Resilience:

Matta (2024) holds that one of the prime challenges confronted in logistics and supply chain management is the escalating severity and frequency of supply chain disruptions. Occurrences such as geopolitical tensions, pandemics, natural disasters, and trade disputes consequently disrupt global supply networks, causing shortages, delays, and increased costs. In that regard, building resilience against such disruptions demands proactive risk management strategies, entailing robust contingency planning, supply chain diversification, and real-time monitoring systems to pinpoint and combat potential disruptions promptly.

2.2.1 Infrastructure Constraints:

The USA's dilapidating infrastructure causes significant challenges to logistics and SCM operations. In particular, outdated ports, congested roads, and ineffective transportation networks can cause bottlenecks, delays, and heightened transportation costs. Besides, insufficient investment in infrastructure modernization and maintenance worsens these challenges, hampering the sector's capability to satisfy the evolving demands effectively (Sarkar, 2019). Resolving infrastructure restraints requires substantial investment in upgrading and expanding port capacities and transportation networks, as well as enhancing connectivity to enhance the flow of goods across the country.

2.2.3 Evolving Consumer Expectations and E-commerce Growth:

The escalating e-commerce and changing consumer preferences have reshaped the dynamics of logistics and Supply Chain Management in America. Customers now anticipate flexible fulfillment alternatives, faster delivery times, and seamless order tracking experiences. Therefore, satisfying these evolving anticipations demands logistics providers to invest in warehouse automation, enhance last-mile delivery, and improve visibility throughout the supply chain (Sarkar, 2019). Additionally, the upsurge in e-commerce sales has stressed logistics networks, causing inventory management challenges, capacity constraints, and increased competition for warehouse space.

2.3 Role of Business Analytics in Logistics and SCM:

Business analytics employs statistical techniques, predictive modeling, and data analysis methods to get insights and make informed decisions. In SCM and logistics, business analytics assists companies in optimizing inventory management, forecasting, route planning, demand, and resource allocation (Shete, 2022). By evaluating real-time and historical data information, companies can pinpoint patterns, anticipate demand fluctuations, and mitigate supply chain risks.

As per Swami (2020), accurate demand prediction is instrumental for efficient resource allocation and inventory management. Predictive modeling methodologies such as machine learning algorithms can analyze market trends, historical sales data, and external components to forecast future demand patterns. By optimizing predictive analytics, companies can streamline inventory levels, enhance procurement processes, and reduce carrying costs while ensuring adequate stock availability to meet customer demand.

3. Methodology

In this study, the researcher employed machine learning methodologies to forecast lead times for purchasing aluminum products. The dimension of this research paper approaches the investigation as a regression challenge, targeting to predict a single real number ($y \in \mathbb{R}$) based on a set of features ($x \in \mathbb{R}^d$). Supervised machine learning methods facilitate the learning of a function (f) that produces an approximated value (\hat{y}) from a provided input vector (\hat{x}). The algorithm is trained on a dataset (D) entailing N pairs (x_i, y_i) , where every input scenario x_i is paired with its equivalent target y_i , signifying the predicted value. In this research, the investigators assess various regression algorithms commonly adopted in machine learning and statistics to pinpoint the most efficient model for real-world datasets, evading the need for more complex methodologies.

3.1 Dataset

In this study, historical data was collected from the database of one of the aluminum-producing companies in the USA for the last 10 years. In particular, a sample of 38,500 orders of aluminum profiles was adopted for the current study. The data comprised all company info such as order history, product manufacturing history, company turnover as well as sales history. In the database, every sample was evaluated concerning eight independent variables that made up the input vector, represented as x , for the machine learning algorithm adopted for the forecasting lead times. These variables comprised:

- The specific day of the month when the client order was made ranged from day 1 to day 31.
- The weekday of the client order, portrayed numerically from 1 to 5, is equivalent to Monday through Friday.
- The specific month when the client order happened is represented by values ranging from 1 to 12.
- The specific identifier for the supplier code is related to the order.
- The identifier for the particular item being ordered.
- The aluminum product type category to which the ordered product belongs.
- Order Quantity
- Distance between the supplier and the warehouse in km.

3.2 Preprocessing

In preparing data for both lead time prediction and demand forecasting, several fundamental preprocessing stages were performed. Firstly, anomaly and outlier detection techniques were employed to detect any unexpected variations or irregularities within the dataset. Secondly, efforts were adopted to resolve missing values by applying appropriate imputation techniques to guarantee data accuracy and completeness. Thirdly, lag features and rolling windows were developed to capture temporal dependencies and patterns within the data, facilitating more robust predictive models. Fourthly, categorical values presented in the dataset were encoded into numerical depictions, enabling their consolidation into machine learning models. These preprocessing stages are collectively targeted to reinforce the reliability and quality of the data, laying a strong foundation for efficient forecasting and prediction tasks.

3.3 Feature Engineering and Selection

Multiple analyses were performed to comprehensively analyze the supply chain dynamics and pinpoint distinct factors impacting the lead time for product orders. These evaluations explored the intricate details to obtain a holistic comprehension of the supply chain's operation. In these inspections, numerous features were assessed to determine their impact on lead times. The evaluations included a meticulous assessment of order-associated particulars, such as the date of order placement and the special attributes of the items being ordered. Moreover, substantial emphasis was imposed on consolidating real-time data from the accessories' capacity planning software, also known as Material Requirements Planning (MRP), into the analysis.

Feature	Description
Order Date	Refers to the specific date the order was placed by the client
Order Number	Denotes the unique ID of each order
Order Quantity	Represents the ordered quantity for every item
Line Number	Every order may have one or more lines. Each line in the order must have a special identifier.
Item Code	Refers to the item's code
Line of Business	Denotes the description of the difference between the values of the line of business
Log Category	This attribute articulates if the item is delivered by an external supplier or manufactured in-house.
Commercial Code	Refers to a detailed categorization using a unique identifier.

3.4 Algorithms Used

3.4.1 Artificial Neural Network

An artificial neural network acts as a computational algorithm motivated by the human brain's cognitive processes. At its core, it depends on mathematical algorithms and models, with its apparent exhibition being computer software. Corresponding to how matter comprises atoms, a neural network encompasses numerous interrelated units called neurons. Figure 1 showcases the essential operational principle of neurons, with their behavior mathematically expressed as follows:

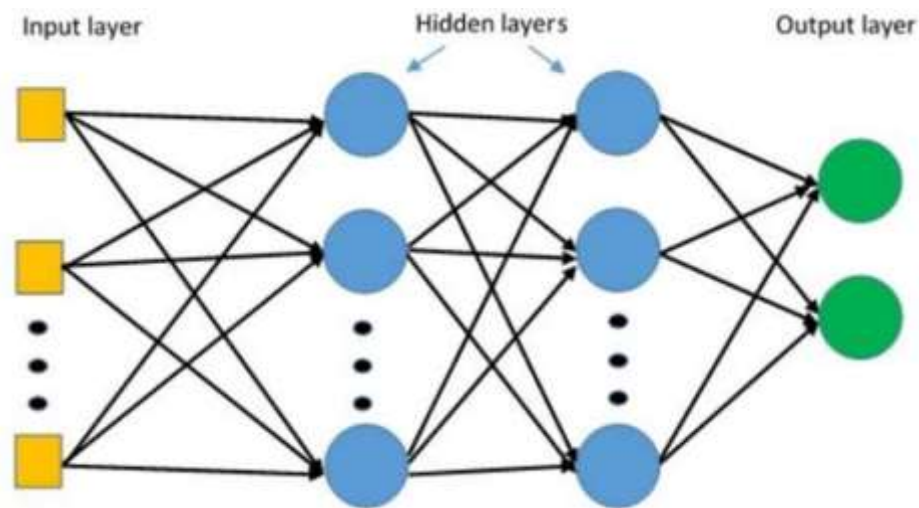


Fig 1: Showcases the architecture of the Artificial Neural Network

$$y = f(\sum w_i x_i)$$

In the expression above, "xi" denotes the input, "y" represents the output, and "wi" stands for the weight coefficient related to every input. The function "f" acts as the attributes function, representing the mapping association between outputs and inputs. Normally, this expression is nonlinear, facilitating the neural network to capture complex associations between outputs and inputs.

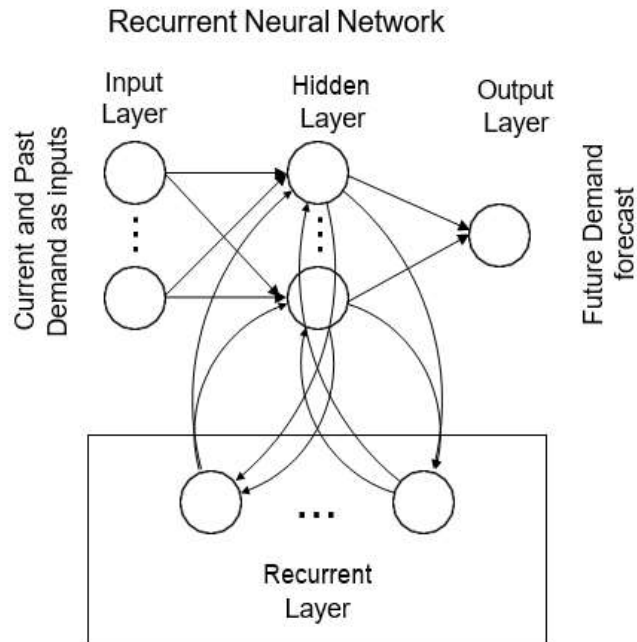
3.4.2 Support Vector Machines (SVM)

Support Vector Machines (SVMs) are potent supervised learning algorithms employed for regression and classification tasks. At the center, SVM aims to locate the optimal hyperplane that best splits data points belonging to distinct classes in attribute space. This hyperplane is placed to optimize the margin, which is the space between the hyperplane and the closest data points of every class, considered as support vectors. SVMs are specifically efficient in high-dimensional distances and are versatile in handling linear and non-linear categorizing tasks via the use of kernel functions.

3.4.3 Recurrent Neural Network (RNN)

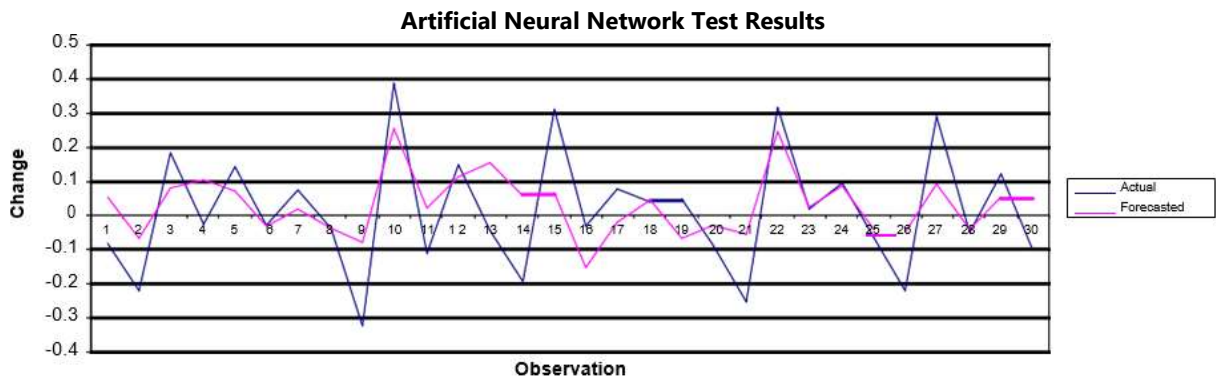
Recurrent neural networks have the unique capacity to enable output signals from particular neurons to flow back and behave as inputs for neurons within similar layers or those from previous layers. This recursive structure renders the Recurrent Neural Network

a powerful tool for handling a myriad of complex issues, specifically those comprising time series data. The training method labeled as "back-propagation through time" can be adapted to train RNNs employing an assigned training dataset. Figure 2 offers a schematic depiction of the RNN structure, particularly tailored, to address the demand prediction challenges within the supply chain domain.

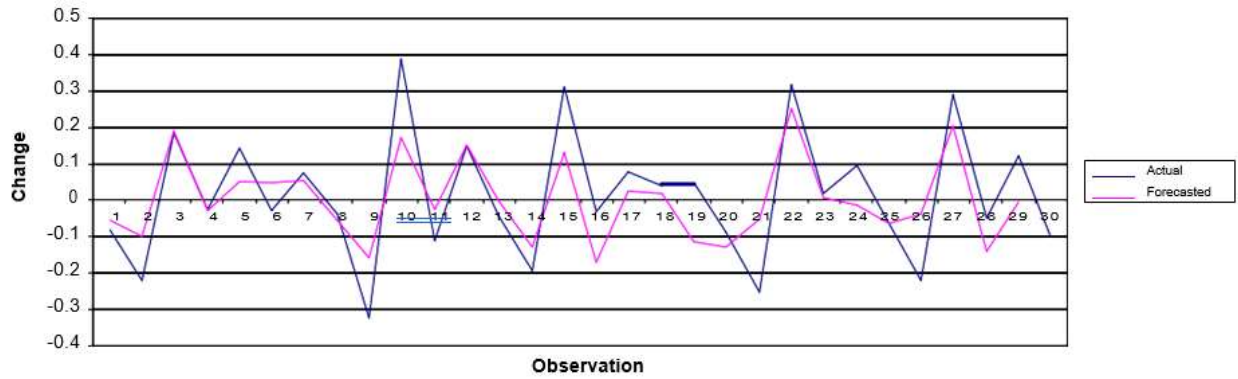


3.5 Experimental Result

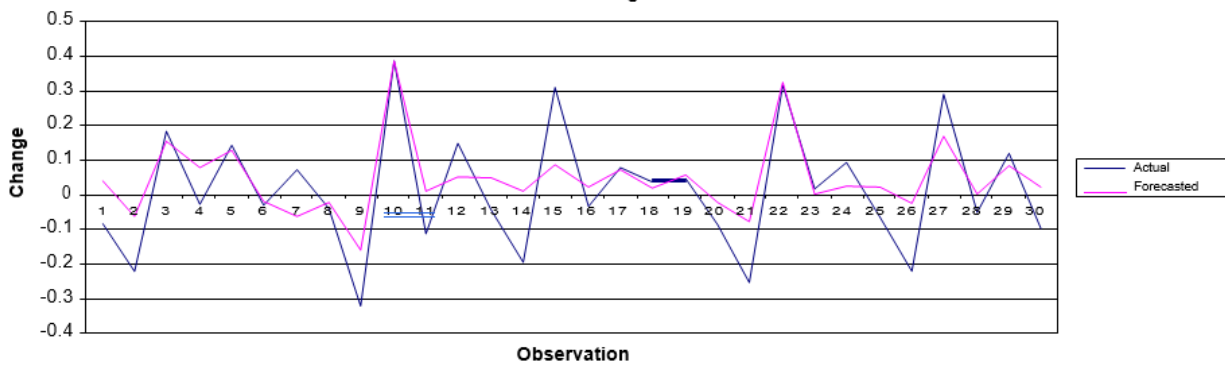
To guarantee fair comparisons, similar testing and training datasets were adopted across all predicting models. The datasets were retrieved from the daily manufacturer orders produced by the supply chain simulation, acting as the primary data for designing the forecasting models. The first 30 days of the dataset were visually exhibited as follows.



RNN Test Results

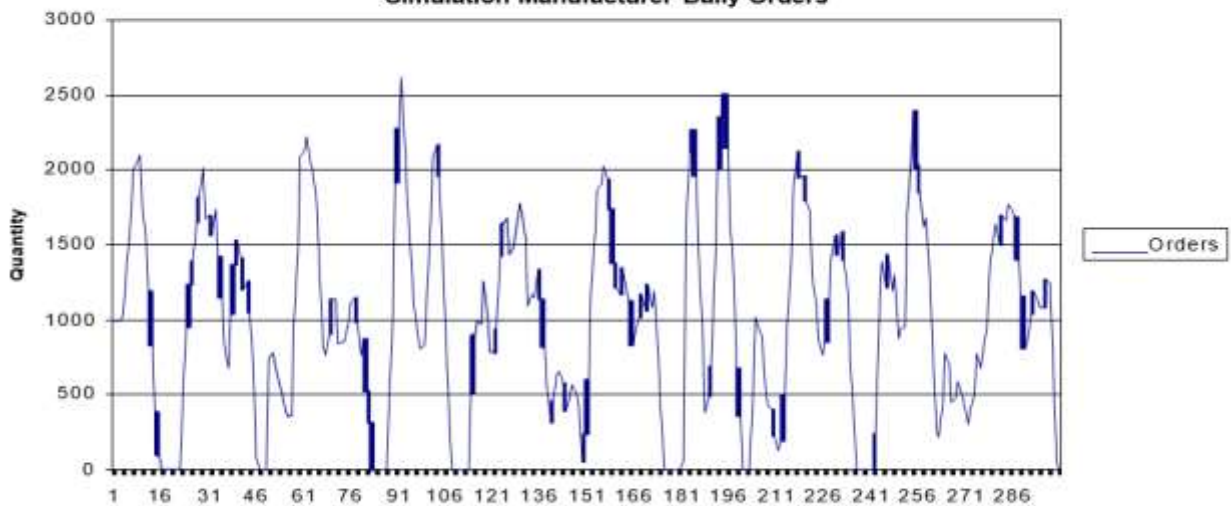


SVM Test Results



The comparison and contrast of prediction outcomes across different algorithms are exhibited in Tables 3 and 4. Results have been displayed in ascending order as per the Mean Average Error (MAE) from the test set. Retrospectively, the Recurrent Neural Network and the Support Vector Machine displayed the most favorable outcomes in predicting lead time in the supply chain. Nevertheless, their increased accuracy is relatively more noticeable for the Foundries' demand data series contrasted to the simulated demand data.

Simulation Manufacturer Daily Orders



Comparison of MAE Performance of the predicting algorithm on the Simulation data set

Forecasting technique	Testing set		Training set	
	MAE	Std. dev.	MAE	Std. dev.
RNN	447.72	328.23	461.66	350.35
LS-SVM	453.04	341.88	449.32	365.01
MLR	453.22	343.65	464.62	375.62
NN	455.41	354.40	471.03	383.29

Comparison of MAE Performance on the Predicting algorithm on the foundries data set

Forecasting technique	Testing set		Training set	
	MAE	Std. dev.	MAE	Std. dev.
RNN	447.72	328.23	461.66	350.35
LS-SVM	453.04	341.88	449.32	365.01
MLR	453.22	343.65	464.62	375.62
NN	455.41	354.40	471.03	383.29

By referring to the above table, it was evident that the Recurrent Neural Network (RNN) and the Support Vector Machine (SVM) exhibited the most favorable results. Particularly, RNN had the least Mean Average Error (MAE) on the testing set (447.72), followed by SVM (453.04), MLR (453.22), and NN (455.41). It is worth noting that the distinction in MAE between these methods is relatively small.

4. Business Impact

4.1 How to Use the Model

- **Step 1: Data Preparation:** Gather and preprocess your dataset from all the avenues of the organization. This may include tokenizing, cleaning, and normalizing the text data or conducting any essential feature engineering for time series data. Subsequently, the dataset is divided into validation, training, and testing sets.
- **Step 2: Preparing Input Sequences:** Transform time series or text into data into sequences that can be inserted in the RNN and SVM model. Afterwards, employ any fundamental encoding methods (such as word embeddings or one-hot encoding) to exhibit your input data.
- **Step 3: Building the RNN and the SVM Model:** Select a deep learning framework such as PyTorch or TensorFlow. Subsequently, build the architecture of your RNN and SVM model. One can employ renowned RNN variants such as Gated Recurrent Unit (GRU) or Long Short-Term Memory (LSTM). Specify the number of layers, hidden units, and activation operations for the RNN and SVM model.
- **Step 4: Training the RNN Model:** Train the RNN and SVM algorithm utilizing the training data. Experiment with the training data for a specified number of epochs, modifying the algorithm's weights to reduce the loss. Monitor and assess the performance of the validation set to mitigate overfitting.
- **Step 5: Evaluating and modifying the Model:** Evaluate the trained algorithm on the testing set to examine its performance. Assess the model's outputs and make any essential modifications or enhancements based on the evaluation results.

4.2 Benefits of the Proposed Models on the USA Economy

- ✓ **Demand Forecasting and Inventory Management:** SVM and RNN algorithms can be used to predict demand accurately, taking into consideration factors such as market trends, historical sales data, and external variables. By deploying these algorithms, the government can optimize inventory degrees, minimize stockouts, and reduce excess inventory. This results in enhanced efficiency, diminished carrying costs, and elevated consumer satisfaction, leading to cost savings and heightened profitability for government companies within the supply chain.
- ✓ **Efficient Supply Planning and Procurement:** RNN and SVM algorithms can help the government in procurement and supply chain processes. By assessing market conditions, supplier performance, and historical purchasing data, these algorithms can offer insights regarding optimal procurement techniques, such as ascertaining appropriate quantity, timing, and sourcing locations. Consequently, this may assist the government in negotiating better contracts, making informed decisions, minimizing lead times, and affirming a solid supply of materials. Consequently, it improves operational efficiency and cost-effectiveness throughout the supply chain.
- ✓ **Warehouse Optimization and Logistics Management:** SVM and RNN algorithms can streamline warehouse operations and logistics management. By assessing historical data on order trends, delivery times, and transportation routes, these algorithms can help in route optimization, scheduling, and load planning. These outcomes result in diminished transportation costs, enhanced delivery accuracy, and faster order fulfillment for the government supply chain. Besides, effective logistics

management leads to streamlined operations, better customer service, and less carbon footprint, profiting the environment and the economy.

4.3 Business Side Benefits:

- **Expedite Order Processing:** Machine learning automation can enhance order processing, minimizing manual effort and fast-track fulfillment. SVM algorithms can be trained to categorize routes and order them through the ideal workflows, while the RNN algorithm can assess order histories to forecast processing times.
- **Enhanced Accuracy and Decreased Human Error:** Machine learning models such as RNN and SVM thrive at pattern recognition and can process massive volumes of data with accuracy and precision, consequently reducing errors that often arise from manual data entry and processing.
- **Predicting Seasonal Demand:** Predictive, descriptive, and analytical algorithms utilizing machine learning, big data, and AI can pinpoint historical patterns and correlations to predict seasonal demand fluctuations. This enables organizations to optimize inventory, production, and staffing levels.
- **Optimized Inventory Levels and Minimized Stock-Outs:** By assessing supplier lead times, sales data, and other variables, SVM and ANN models can recommend optimal inventory levels to satisfy demand while reducing excess stock and stock-outs.

4.4 Customer Side Benefits:

- **First Delivery and Time Saving:** Effective supply chain management fortified by big data and AI/machine learning, such as RNN and SVM, facilitates accurate delivery estimates, faster order processing, and effective route planning. Consequently, this leads to timely delivery success and saves time for the consumer, enhancing their overall experience.
- **Beneficial for the Physically Challenged Population:** Enhanced supply chain management optimizing technology boosts the physically challenged population by offering more convenient and accessible shopping experiences. For instance, fortified inventory management and precise delivery tracking facilitate clients to easily find and purchase products they need without physical exertion.

Green Initiatives and Reduction of Carbon Footprint:

4.5 Reduction of Carbon Footprint:

Big data and AI/machine learning algorithms such as the RNN and SVM can boost green initiatives by enhancing transportation routes, diminishing fuel consumption, and reducing overall carbon emissions. By accessing data on traffic trends, delivery schedules, and weather conditions, companies can plan more effective logistics operations, leading to less carbon footprint. Furthermore, effective supply chain management reinforced by machine learning algorithms can have a positive effect on local and regional economic development in the USA. Particularly, faster order fulfillment contributes to streamlined logistics, job creation, increased productivity, and improved competitiveness, benefiting local businesses and communities.

4.6 Business Case Studies

- ❖ Wassan et al. (2021) indicate that Amazon employs predictive analytics and machine learning on its massive transaction and consumer data to predict demand and optimize its inventory levels. As a result, this helps Amazon to diminish the risks of excess inventory and stockouts. They also use robots in their warehouses to automate order packing and fulfillment. In that respect, My proposed SVM and RNN models could help further improve Amazon's demand forecasting and streamline warehouse operation and logistic management.
- ❖ Niu (2020) contends that Walmart gathers point-of-sale, supply chain, inventory, and other operational data from its suppliers and stores. Particularly, Walmart employs big data analytics to attain strategic insights into purchasing patterns, streamline replenishment, and optimize product assortment in stores. RNNs could help Walmart better predict customer demand trends. In that regard, our proposed algorithms, notably SVM and RNN algorithms, can be used jointly with big data to predict demand accurately, considering factors such as market trends, historical sales data, and external variables.
- ❖ According to Bar-Gill (2024), eBay analyzes seller and buyer behavior data using Big Data to recommend personalized products, optimize shipping logistics, and detect fraud. Besides, they adopt automated warehouses fortified by robotics to assist in the effective process of handling high volumes of orders. My SVM model could help eBay enhance its product recommendation system. In connection with that, our proposed models can assist ebay in route optimization, scheduling, and load planning. These outcomes result in diminished transportation costs, enhanced delivery accuracy, and faster order fulfillment for the government supply chain.

5. Conclusion

This study aimed to examine the phenomenon of optimizing regional business performance through the application of data and business analytics in logistics and supply chain management for the sustainable growth of the US economy. In this study, the researcher employed machine learning methodologies, specifically ANN, RNN, and SVM, to forecast lead times for purchasing

aluminum products. In the research, historical data was collected from the database of one of the aluminum-producing companies in the USA for the last 10 years. In particular, a sample of 38,500 orders of aluminum profiles was adopted for the current study. Retrospectively, the Recurrent Neural Network and the Support Vector Machine displayed the most favorable outcomes in predicting lead time in the supply chain. By implementing these algorithms, the government can optimize inventory degrees, minimize stockouts, and reduce excess inventory. This results in enhanced efficiency, diminished carrying costs, and elevated consumer satisfaction, leading to cost savings and heightened profitability for government companies within the supply chain.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

- [1] Aljohani, A. (2023). Predictive analytics and machine learning for Real-Time supply chain risk mitigation and agility. *Sustainability*, 15(20), 15088. <https://doi.org/10.3390/su152015088>
- [2] Bar-Gill, S., Brynjolfsson, E., & Hak, N. (2024). Helping Small Businesses Become More Data-Driven: A Field Experiment on eBay. *Management Science*.
- [3] Biazon, M. (2022). Lead Time Forecasting with Machine Learning Techniques for a Pharmaceutical Supply Chain. *www.academia.edu*. https://www.academia.edu/73265581/Lead_Time_Forecasting_with_Machine_Learning_Techniques_for_a_Pharmaceutical_Supply_Chain
- [4] Gonuguntla, V. (2016). Application of machine learning techniques for supply chain demand forecasting. *www.academia.edu*. https://www.academia.edu/26506366/Application_of_machine_learning_techniques_for_supply_chain_demand_forecasting
- [5] IntelliSoft. (2024, March 1). Supply chain data Analytics for efficient operations. *Medium*. <https://medium.com/@IntelliSoft/supply-chain-data-analytics-for-efficient-operations-55a366137029>
- [6] Kharwal, A. (2023, April 3). *Supply Chain Analysis using Python*. Thecleverprogrammer. <https://thecleverprogrammer.com/2023/04/03/supply-chain-analysis-using-python/>
- [7] Matta, N. (2024). Forecasting supply chain demand approach using knowledge management processes and supervised learning techniques. *www.academia.edu*. https://www.academia.edu/113375227/Forecasting_Supply_Chain_Demand_Approach_Using_Knowledge_Management_Processes_and_Supervised_Learning_Techniques
- [8] Niu, Y. (2020, October). Walmart sales forecasting using the xgboost algorithm and feature engineering. In 2020 International Conference on Big Data & Artificial Intelligence & Software Engineering (ICBASE) (pp. 458-461). IEEE.
- [9] Sarkar, P. (2017). Forecasting model of supply chain management based on neural network. *www.academia.edu*. https://www.academia.edu/32263072/Forecasting_Model_of_Supply_Chain_Management_Based_on_Neural_Network
- [10] Shete, K. (2022). Analytics for Manufacturing DecisionsIn Supply Chain Management. *www.academia.edu*. https://www.academia.edu/69213072/Analytics_for_Manufacturing_DecisionsIn_Supply_Chain_Management
- [11] Swami, D. (2020). Predicting Future Sales of Retail Products using Machine Learning. *Usc*. https://www.academia.edu/73000420/Predicting_Future_Sales_of_Retail_Products_using_Machine_Learning
- [12] Wassan, S., Chen, X., Shen, T., Waqar, M., & Jhanjhi, N. Z. (2021). Amazon product sentiment analysis using machine learning techniques. *Revista Argentina de Clínica Psicológica*, 30(1), 695.