Developing and Implementing AI-Driven Models for Demand Forecasting in US Supply Chains: A Comprehensive Approach to Enhancing Predictive Accuracy

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Abstract

Demand forecasting has long been a critical challenge in the US supply chain operations, plagued by disruptions, fluctuating demand, and price volatility. Developing and implementing AI models that can accurately predict demand is essential in response to these issues. This study aimed to investigate the feasibility of applying machine learning techniques to demand forecasting, particularly in supply chain operations. A comprehensive analysis was conducted using historical data from a logistics company in the USA, which was used to train five traditional demand forecasting methods: Linear Regression, ElasticNet, Random Forest, MLPRegressorn, and XGBoost. Additionally, feature selection, data normalization, and dimensionality reduction techniques were employed to improve the accuracy of these models. Strategic metrics were used to evaluate the model's performance: Random Mean Squared Error, Mean Absolute Error, and R-squared score. The results of this study indicate that AI models have shown significant promise in predicting target sales in supply chains with Linear Regression emerging as the most effective model with the lowest RMSE, MAE, and an R-squared score close to 1. Practical implications of implementing such AI models in the US supply chain include optimized inventory management, reduced costs, and enhanced customer satisfaction. This research contributes to the existing body of knowledge on AI applications in demand forecasting, highlights the importance of traditional methods being supplemented by machine learning techniques, and provides practical recommendations for businesses seeking to improve their supply chain operations.

Keywords: Demand Forecasting, Machine Learning, Deep Learning, model selection, AI models, USA supply chains, predictive accuracy.

1. Introduction

The aim of demand forecasting in supply chain management has become increasingly crucial for businesses across various sectors, including manufacturing, retail, and logistics. Effective supply chain management is the backbone of successful businesses, enabling companies to deliver high-quality products and services to customers in a timely and cost-efficient manner, regardless of industry or size (Kumar & Chaudhry, 2015) [8]. As global demand continues to grow, businesses are under pressure to optimize their forecasting capabilities to meet changing consumer demands. However, traditional methods for demand forecasting, such as historical data analysis, statistical models, and rule-based approaches, have limitations in terms of predictive accuracy, interpretability, and scalability.

For instance, historical data analysis may not capture the nuances of emerging trends or changes in consumer behavior (Mukherjee et al., 2018) [10]. Statistical models can be time-consuming to develop, deploy, and maintain, leading to high operational costs and decreased efficiency. Rule-based approaches, while simple to implement, are often inflexible and fail to account for complex seasonal fluctuations, economic downturns, or other external factors that may impact demand. In recent years, the rise of artificial intelligence (AI) and machine learning (ML) has presented new opportunities for improving demand forecasting in supply chain management. AI-driven models can analyse vast amounts of data from various sources, including social media and online marketplaces, to identify patterns and trends that may not be apparent through traditional methods [11]. These advanced technologies can also enable real-time decision-making, enabling businesses to respond quickly to changes in demand and minimize losses this is according to Wang et al., 2021, [15]

However, the integration of AI-driven models into supply chain operations poses several challenges. One major concern is the need for high-quality training data to develop accurate and reliable models according to Liu et al., 2020, [9]. Another challenge is ensuring that these models are deployed and maintained effectively across the organization, including IT infrastructure, data storage, and communication systems.

1.1 Background

Demand forecasting is essential for supply chain management as it enables businesses to make informed decisions about production, inventory, and resource allocation, ultimately leading to improved operational efficiency, reduced costs, and enhanced customer satisfaction. The current US supply chain landscape is characterized by a convergence of several key trends, including a growing emphasis on sustainability and environmental consciousness, digital transformation through the use of technology, and a shift towards e-commerce dominance driven by consumer demand. Additionally, companies are increasingly relying on global sourcing and trade to access raw materials and components, while also benefiting from reduced transportation costs and time [9, 3]. Furthermore, supply chains must be resilient and agile in response to disruptions, such as those caused by COVID-19, and are focusing on logistics and transportation optimization, as well as the adoption of 3D printing and additive manufacturing technologies to create complex parts and products on demand. The rise of AI technologies and data analytics is also enabling companies to gain valuable insights into their operations, inform decision-making, and improve customer experiences. Overall, these trends are driving innovation and collaboration among stakeholders in US supply chains, creating new opportunities for growth and development.

The United States (US) faces numerous limitations in its supply chain that necessitate the adoption of artificial intelligence (AI) models to overcome complex challenges such as data quality and availability, regulatory compliance, cybersecurity threats, time-to-market and agility, skills and knowledge gaps, data-driven decision making, integration with other systems, scalability and flexibility, and liability and risk management[2, 13]. These limitations arise from the inherent complexity and interconnectedness of the US supply chain, limited data quality, regulatory hurdles, and high stakes for errors or disruptions. Additionally, cybersecurity threats pose a significant risk to supply chains, and the need for companies to respond quickly to market fluctuations and time-sensitive decisions creates pressure that AI models can help alleviate. The lack of technical expertise within some companies hinders their ability to fully leverage AI technologies and data-driven decision-making is hindered by incomplete or inaccurate information. By addressing these limitations, organizations can unlock the full potential of AI in optimizing supply chain operations and driving business success.

1.2 Problem Statement

The current demand forecasting methods used by US businesses are inadequate, resulting in inaccurate predictions that lead to inefficient supply chains, missed sales opportunities, and wasted resources. The lack of real-time data and poor model accuracy cause companies to overstock or under-stock their inventory, resulting in significant losses and negative impacts on company reputation and brand image. Some of the traditional demand forecasting methods still used in the United States include Time series analysis, Qualitative forecasting, CPFR(Collaborative planning, forecasting, and replenishment), Delphi method, Simulation models, Casual Inferences, Consumer surveys, and market research as highlighted by Mukherjee et al., 2018 [10] .

These traditional demand forecasting methods still face limitations in the United States. Time series analysis, a widely used method, is overly simplistic and fails to capture non-linear trends or patterns in data, making it inadequate for complex business needs. Qualitative forecasting relies on subjective judgment and expert opinions, is prone to biases and errors, and is challenging to quantify and validate. CPFR (Collaborative Planning, Forecasting, and Replenishment) involves multiple stakeholders sharing forecast data but struggles with the complexity of communication, inconsistent forecasts, and the potential for conflicting judgments. The Delphi method is a structured prediction technique that generates more accurate forecasts through rounds of expert judgment, yet has limitations in subjective judgments, lack of transparency, and scalability issues. Simulation models are powerful tools for predicting future demand but require significant resources and expertise to set up and run, with complexities such as modeling dependencies between variables and potential over-fitting or under-fitting the model. Finally, casual inferences, a type of qualitative forecasting that relies on expert judgment, lack rigor and scientific basis, difficulty in validating predictions, and potential biases and errors.

1.3 Research Objective

In this research, we aim to develop and implement AI-driven models for demand forecasting in US supply chains. Our work will explore the potential of AI technologies, such as neural networks and decision trees, in improving predictive accuracy and enhancing the interpretability of forecasted demands. We will also examine the challenges associated with integrating these models into existing supply chain operations, including data quality, model deployment, and maintenance. By developing a comprehensive approach to demand forecasting using AI-driven models, we believe that US businesses can enhance their ability to respond effectively to changing market conditions, minimize losses, and improve overall supply chain performance. This research will contribute to the growing implementation of AI-powered demand forecasting in supply chains, providing insights into the benefits, challenges, and best practices for implementing these technologies in real-world scenarios.

1.4 Scope of the research

This research focuses on various sectors within US supply chains, encompassing both manufacturing and distribution processes. These sectors are influenced by demand forecasting as they rely on predicting customer needs and behavior to optimize their operations, improve customer satisfaction, and drive business success. Sales and Marketing teams use predicted data to tailor promotional strategies that resonate with target customers' preferences, resulting in increased sales opportunities and market share growth. Inventory Management and Logistics are responsible for ensuring sufficient stock levels and efficient logistics, while Operations focuses on planning for product availability and fulfilling customer orders. Finance and Budgeting help manage budgets aligned with anticipated sales fluctuations, reducing financial risks and optimizing resource allocation during peak seasons. Finally, Technology and IT play a crucial role in preparing the e-commerce platform to handle increased traffic and transactions, ensuring a seamless online shopping experience, while Customer Support is dedicated to anticipating and addressing customer issues related to product availability or shipment delays, ultimately enhancing customer satisfaction and driving business growth.

Integrating AI models into existing supply chain frameworks enables real-time demand forecasting, enhancing operational efficiency and responsiveness. AI-powered algorithms analyze historical sales data, market trends, weather patterns, and social signals to predict demand with greater accuracy[11, 15]. By embedding these models into supply chain management systems, businesses can dynamically adjust inventory levels, optimize production schedules, and streamline logistics in response to real-time data. This proactive approach reduces waste, minimizes stock-outs or overstock situations, and fosters a more agile supply chain(Singh & Aggarwal, 2018) [11]. Seamless integration ensures compatibility with existing ERP systems, providing a unified platform for decision-making and fostering resilience against market fluctuations.

2. Literature Review

2.1 Demand Forecasting in Supply Chains

Demand forecasting in supply chains is a critical process that enables organizations to predict future customer demand for products or services using historical data, market analysis, and statistical or AI-driven techniques. By analyzing trends, seasonal patterns, and market dynamics, businesses can make informed decisions about inventory levels, production planning, and resource allocation. This, in turn, helps them reduce costs associated with overstocking or stock-outs, which can lead to significant losses for retailers and manufacturers alike. Furthermore, accurate demand forecasting supports strategic planning, such as identifying emerging market trends, adjusting to seasonal variations, and anticipating changes in consumer behavior. By doing so, organizations can gain a competitive advantage by staying ahead of the curve and responding effectively to changing market conditions.

Recent advancements in AI and machine learning have further enhanced demand forecasting capabilities. For instance, Liu et al. (2022) [16] highlight the role of deep learning models in capturing complex, non-linear relationships in demand patterns, which traditional methods often miss. Similarly, Wang et al. (2021) [15] emphasize the importance of integrating real-time data streams, such as social media trends and IoT sensor data, to improve forecasting accuracy [12, 15]. These modern approaches utilize advanced technologies like machine learning, big data analytics, and real-time data processing to improve accuracy and responsiveness. For example, machine learning algorithms can be trained on historical sales data to predict future demand patterns, while big data analytics enables organizations to analyse large amounts of customer data, including purchase history, browsing behaviour, and social media activity. Real-time data processing allows businesses to receive timely updates from suppliers, manufacturers, and logistics providers, enabling them to adjust production levels and inventory management accordingly. Effective demand forecasting also enhances the agility and resilience of supply chains, enabling businesses to adapt to market fluctuations, optimize costs, and maintain competitive advantages in dynamic markets. By being able to respond quickly to changes in customer demand, organizations can reduce their risk exposure and minimize the impact of disruptions such as natural disasters or global economic downturns. Moreover, accurate forecasting enables businesses to negotiate better prices with suppliers, take advantage of new market opportunities, and explore alternative supply chain configurations that better align with their business needs.

2.2 Traditional vs. AI-Driven Forecasting Methods

Traditional forecasting methods, such as time series analysis, qualitative forecasting, CPFR (Collaborative Planning, Forecasting, and Replenishment), Delphi method, simulation models, causal inferences, consumer surveys, and market research, rely on historical data, expert judgment, and structured collaboration to predict demand. These approaches offer valuable insights into customer behavior, market trends, and economic conditions, but they often struggle with processing large, complex datasets and adapting to rapid market changes. For instance, time series analysis may be limited by its inability to capture non-stationary patterns or outliers in the data, while qualitative forecasting relies heavily on expert judgment, which can be subjective and prone to bias according to Mukherjee et al. [10]. CPFR, for example, requires significant manual input from stakeholders to ensure alignment across different departments and supply chains, whereas Delphi's methods often rely on repetitive rounds of predictions and feedback loops that can become tedious and time-consuming.

In contrast, AI-driven forecasting methods utilize machine learning algorithms, big data analytics, and real-time data to identify patterns and trends that traditional methods might overlook. These approaches can analyse diverse datasets, such as social media trends, weather patterns, economic indicators, and more, to provide dynamic and highly accurate forecasts [13, 16]. For example, AI models can be trained on historical sales data to predict future demand patterns, taking into account factors like seasonality, holidays, and competitor activity. Unlike traditional methods that may require significant manual input or assumptions, AI-driven approaches automate the forecasting process and continuously learn and improve over time. This adaptability and scalability make AI-driven forecasting superior in handling volatile markets and complex supply chains, offering greater precision and agility to businesses.

Recent studies, such as Zhang et al. [12], have demonstrated the superiority of AI-driven methods in handling large-scale datasets and capturing complex, non-linear relationships. Chen et al. [13] further highlight the role of ensemble learning techniques, such as XGBoost and Random Forest, in improving forecasting accuracy by combining multiple models to reduce bias and variance. Moreover, AI models can identify complex relationships between seemingly unrelated variables, such as the impact of weather patterns on crop yields or the effect of social media trends on consumer purchasing decisions. By utilizing these insights, businesses can gain a deeper understanding of their customers' needs and preferences, enabling them to make data-driven decisions that drive business growth. Additionally, AI-driven forecasting can help reduce costs associated with manual forecasting processes, such as the time and resources required for data analysis, reporting, and decision-making. Furthermore, AI-driven forecasting can also facilitate real-time decision-making by providing businesses with timely and accurate insights into market conditions. For instance, an AI-powered forecasting system can analyze real-time sensor data from IoT devices to predict potential disruptions or supply chain bottlenecks, enabling businesses to take swift action to mitigate risks and respond to changing market conditions.

2.3 AI Applications in Supply Chain Management

AI applications in supply chain management, particularly in demand forecasting, leverage machine learning (ML) and deep learning (DL) techniques to enhance accuracy and efficiency. Machine learning algorithms, such as regression models, decision trees, and ensemble methods, analyze historical sales data, market trends, and external factors to predict future demand. These models excel in uncovering non-linear relationships and adjusting to dynamic market conditions. For instance, regression models can identify correlations between price fluctuations, seasonality, and customer behavior, enabling businesses to make informed decisions about inventory levels and production planning. Decision trees, on the other hand, are effective at identifying complex decision-making processes and predicting outcomes based on various input variables.

Deep learning techniques, including recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are particularly effective in processing time-series data, and capturing complex temporal dependencies and trends [7]. Those models have been widely adopted in supply chain forecasting due to their ability to identify subtle patterns and anomalies in large datasets. For example, RNNs can analyze sales records over multiple periods, identifying changes in customer behavior or market conditions that may not be apparent through traditional analysis. Long short-term memory (LSTM) networks, specifically, are designed to handle the complexities of temporal data, allowing them to learn long-term dependencies and relationships between variables.

Recent advancements in deep learning, such as the use of transformers and attention mechanisms, have further improved the accuracy of demand forecasting models. Li et al. [14] demonstrate how transformer-based models can process sequential data more efficiently, capturing long-range dependencies in time-series data. Additionally, convolutional neural networks (CNNs) and transformers are used for multimodal data integration, such as combining sales records with image or textual data for more comprehensive forecasting. CNNs can extract features from images, enabling businesses to identify trends in product characteristics, inventory levels, or supply chain disruptions. Transformers, on the other hand, allow models to process sequential data, such as text or speech, and generate accurate predictions based on context-aware relationships between variables [12]. This integrated approach enables supply chains to analyze vast amounts of data from various sources, making informed decisions about inventory management, production planning, and logistics. By utilizing these advanced AI techniques, supply chains benefit from real-time insights, predictive accuracy, and the ability to adapt to rapidly changing environments, ensuring optimal inventory levels, cost savings, and improved customer satisfaction. Moreover, AI-driven demand forecasting can also help businesses respond promptly to changes in market conditions, such as natural disasters or economic fluctuations, by adjusting their production and inventory strategies accordingly.

Furthermore, the integration of these AI techniques with other supply chain operations, such as transportation planning, warehousing management, and customer service, enables a more holistic approach to managing the complex interactions between various stakeholders. This integrated approach can lead to significant benefits, including improved collaboration between departments, enhanced decision-making, and increased efficiency across the entire supply chain.

2.4 Challenges and Opportunities

Implementing AI-driven forecasting models in supply chain management comes with notable challenges and significant opportunities. One of the primary obstacles facing businesses is data-related issues, such as incomplete and inconsistent datasets that hinder model performance. Organizations may also encounter difficulties in integrating AI models with existing legacy systems, which often lack the compatibility or flexibility to support modern

AI solutions. This can lead to integration complexities, security concerns, and a higher likelihood of system downtime, ultimately resulting in reduced business efficiency. Another challenge is related to high implementation costs. The development, deployment, and maintenance of AI-driven forecasting models require significant investment in technology, training data, and personnel expertise, which can be a barrier for smaller businesses or those on a tight budget. Additionally, organizations may need to upgrade their existing IT infrastructure to support the integration of AI solutions, which can be time-consuming and costly. Furthermore, there is also a shortage of skilled AI professionals, including data scientists, engineers, and software developers. This talent gap can hinder the successful implementation of AI-driven forecasting models, as businesses may struggle to find qualified personnel with the necessary expertise to develop, train, and maintain these models. The lack of skilled professionals can lead to model drift, reduced accuracy, and lower overall efficiency.

On the other hand, numerous opportunities arise from implementing AI-driven forecasting models in supply chain management. One of the most significant benefits is the ability to achieve highly accurate and granular demand forecasting. This enables businesses to minimize waste, reduce costs, and enhance customer satisfaction by making informed decisions about inventory levels, production planning, and logistics. AI-driven models also provide real-time insights and predictive capabilities that help organizations adapt quickly to market fluctuations and disruptions. By analysing trends, patterns, and anomalies in their data, businesses can identify growth opportunities, mitigate risks, and capitalize on new market opportunities. This enables companies to stay ahead of the competition and respond effectively to changing market conditions. Advances in technology are also lowering entry barriers, making AI-driven forecasting models more accessible even to smaller businesses. Cloud-based AI platforms and pre-trained models have made it possible for organizations to deploy AI solutions without requiring extensive technical expertise or significant upfront investments.

By overcoming implementation hurdles, companies can leverage AI to achieve competitive advantages and build smarter, more resilient supply chains. This is particularly important in today's fast-paced, globalized economy, where businesses must be able to adapt quickly to changing market conditions and customer demands. Moreover, the use of AI-driven forecasting models can also help organizations build stronger relationships with their customers by providing them with accurate and timely insights about demand patterns and trends. This can lead to increased customer satisfaction, loyalty, and retention, ultimately driving business growth and profitability.

3. Data Collection and Preprocessing

3.1 Data Sources

The dataset used in demand forecasting for this logistics supply chain company was obtained from a Customer Relationship Management (CRM) system, which provides valuable insights into customer behaviour, preferences, and purchasing habits. The CRM system collects sales data on various products, including Product_ID, Category, Price, Promotion, Discount, Shelf_Life, Inventory_Level, Units_Sold, Stockouts, Lead_Time, Supplier_Reliability, Month, Holiday, Temperature, Rainfall, GDP, Inflation_Rate, Unemployment_Rate, Customer_Age_Group, Customer_Income, Customer_Location, and Lag_Sales_1. These features provide a comprehensive understanding of customer demand patterns, helping to forecast future sales. In addition to the CRM system data, a survey was also conducted among customers to gather additional information about their purchasing habits and preferences. The survey collected data on customer demographics, such as age, location, and income level, as well as their shopping behaviour, including frequency of purchase, product usage, and return rates. This supplementary data helps to identify patterns in customer behaviour that can be used to inform demand forecasting models.

Furthermore, the company also collects sales data from external sources, including trade associations, industry reports, and market research studies. These data provide insights into industry trends, competitor activity, and market conditions, which can be used to adjust forecasts accordingly. The collected data is anonymized and aggregated to ensure that customer-specific information remains confidential. The dataset was cleansed and pre-processed to extract relevant features for demand forecasting. This involved handling missing values using imputation techniques, such as mean or median imputation of numerical variables, and encoding categorical variables using one-hot encoding. Feature scaling techniques, including standardization and normalization, were also applied to ensure that numerical variables are on a common scale.

3.2 Data Preprocessing

The analysis of large datasets often requires the application of various statistical techniques to extract meaningful insights. One such technique involves the transformation of non-numerical categorical features into numerical features using machine learning algorithms. Specifically, we employed scikit-learn's OneHotEncoder, which enables the conversion of categorical variables into binary vectors that can be processed by standard regression and classification models. This encoding method allows us to capture the underlying patterns and relationships between these variables and incorporate them into our analysis. To further enhance the quality of our analysis, we also implemented a strategy for handling missing values and data normalization. By replacing missing values with the mean of their respective columns, we ensured that our dataset was well-maintained and free from errors. Additionally, we utilized the MinMaxScaler to normalize the features, which helped to prevent features with large ranges from dominating our analysis. Furthermore, we employed Principal Component Analysis (PCA) as a dimensionality reduction technique, which enabled us to visualize and analyze relationships between variables more effectively. By applying these techniques, we were able to extract valuable insights from our dataset and provide a more comprehensive understanding of the underlying patterns and structures.

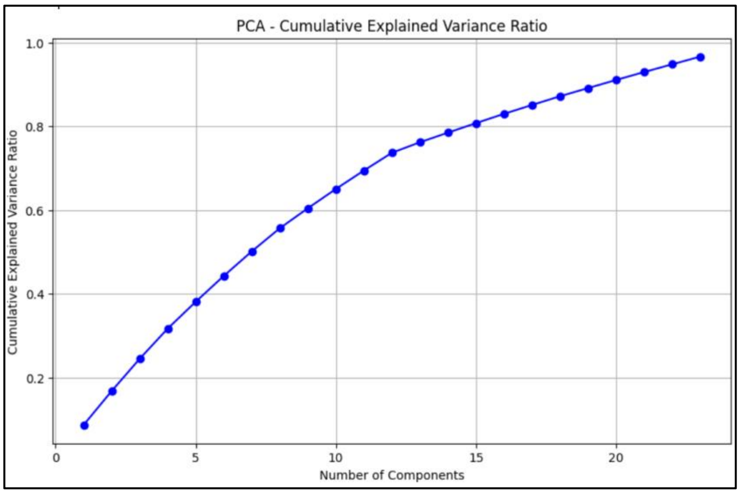

Table 1. This graph provides a visual representation of how much of the original data has been reduced through PCA. The plot represents the cumulative explained variance ratios for each component. The line in the plot serves as an estimate of the overall reduction in dimensionality achieved by PCA.

3.3 Exploratory Data Analysis

The analysis of the dataset reveals that most of its feature variables exhibit a strong positive correlation with Target Sales. A positive correlation implies that an increase in Target Sales is likely to be accompanied by similar increases in various target features, as well as decreases in corresponding negative features. For instance, a 1% increase in Target Sales is associated with a 0.0713% rise in Unemployment Rate, a 0.0473% boost in Promotion levels, and a 0.0314% surge in Rainfall. Conversely, only a few numerical feature variables display a negative correlation with Target Sales, including GDP (-0.0306), Units Sold (-0.0251), Month (-0.0214), Lag_Sales_1 (-0.0202), Price (-0.0192), Temperature (-0.0127), and Inflation_Rate (-0.0059). These negative correlations suggest that Target Sales may be influenced by factors such as economic indicators, consumer behavior, or external events, which warrants further investigation to determine the underlying causes of these relationships.

Furthermore, a closer examination of the correlation statistics(Table 2) reveals some interesting patterns in the data. For instance, Target_Sales and Promotion levels have a strong positive correlation (0.0473), indicating that increased investment in marketing efforts is likely to lead to improved sales. Similarly, Rainfall and Units Sold exhibit a positive correlation (0.0314), suggesting that favorable weather conditions may contribute to higher sales volumes. In contrast, there are only two negative correlations: Unemployment_Rate (-0.0713) and Supplier_Reliability (-0.0049). These findings highlight the complex interplay between various factors influencing Target Sales and provide a solid foundation for further analysis, including the exploration of potential causal relationships and the identification of key drivers of sales growth.

Target_Sales	1.000000
Unemployment_Rate	0.071305

Promotion	0.047292
Rainfall	0.031369
GDP	0.030639
Units_Sold	0.025077
Month	0.021427
Lag_Sales_1	0.020256
Price	0.019214
Temperature	0.012635
Inventory_Level	0.011947
Inflation_Rate	0.005971
Holiday	0.004877
Supplier_Reliability	-0.004898
Discount	-0.005901
Customer_Income	-0.011782
Rolling_Avg_3_Months	-0.014938
Lead_Time	-0.015034
Stockouts	-0.025665

Name: Target_Sales, dtype: float64

Table 2. A summary of the correlation statistics of numerical features and target sales.

The correlation matrix(Figure 1) reveals several key insights into the relationships between the variables. Price shows minimal correlation with most features, except for a slight negative correlation with GDP (-0.05) and a positive correlation with Lag_Sales_1 (0.06). Promotion has a moderate positive correlation with Units_Sold (0.07) and Target_Sales (0.05), suggesting that promotional activities may drive sales. Units_Sold also shows a negative correlation with Inflation_Rate(-0.07), indicating that higher inflation may reduce sales. Stockouts are positively correlated with Temperature (0.08), possibly implying that weather conditions affect product availability. Target_Sales has a notable positive correlation with Unemployment_Rate(0.07), which could indicate that economic conditions influence sales. Interestingly, Holiday and Temperature show weak correlations with Target_Sales, suggesting that these factors may not significantly impact sales in this context. Overall, the matrix highlights that economic indicators (GDP, Inflation_Rate, Unemployment_Rate) and operational factors (Promotion, Stockouts) are more influential on sales than external factors like weather or holidays.

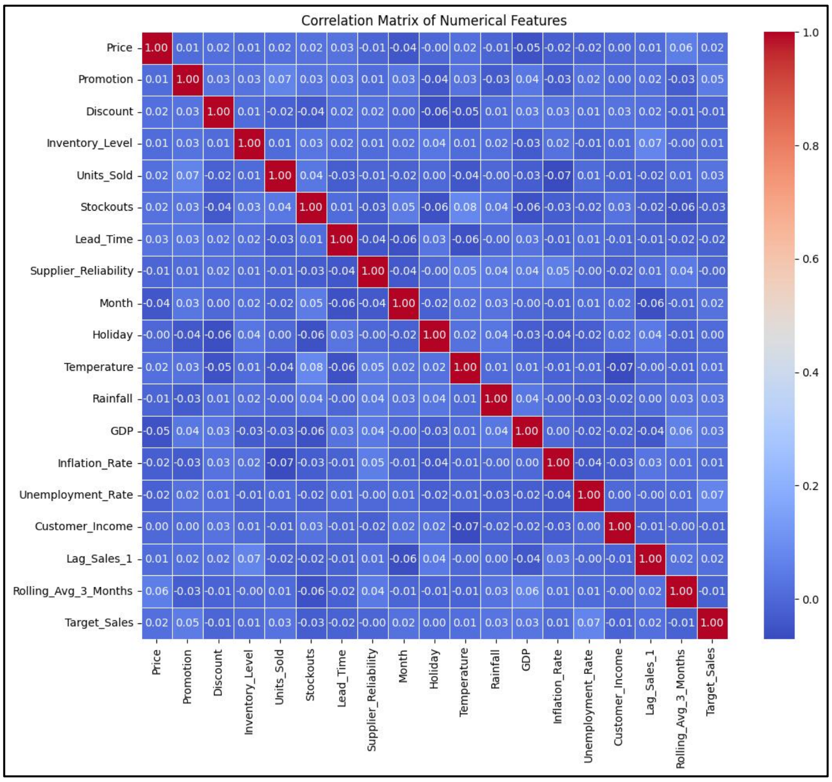

Figure 1. This correlation matrix shows the relationship between numerical feature variables and Target Sales. Most numerical features have a positive correlation to target sales.

The visualization "Correlation of Features with Target Sales," (Figure 2) reveals weak to negligible correlations (ranging from -0.02 to 0.06) between the analyzed features and target sales, indicating minimal linear relationships. This suggests that the current features alone are not strong predictors of sales performance, with some showing slight positive or negative influences. To enhance predictive accuracy, it is crucial to focus on feature engineering, such as creating interaction terms or polynomial features, and consider advanced modelling techniques like Random Forests or Gradient Boosting Machines that capture non-linear relationships. Additionally, enriching the dataset with external factors like macroeconomic indicators, competitor pricing, or customer demographics could provide more robust insights. Businesses should adopt a comprehensive approach to data collection and continuously monitor and update their models to adapt to evolving market conditions, enabling more informed strategic decisions and improved demand forecasting.

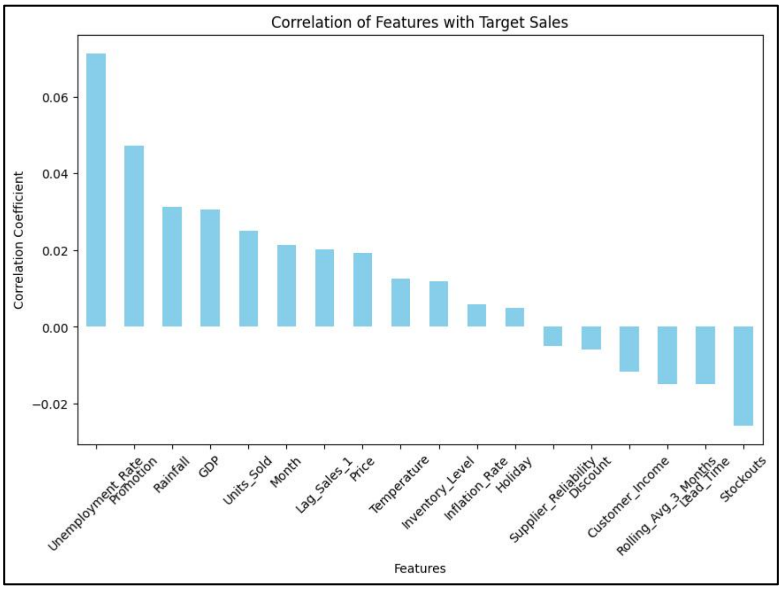

Figure 2. This bar plot provides a clearer insight into the correlation between the target and feature variables.

When analyzing the distribution of Target Sales the first curve rises from left to right(Figure 3), indicating that as Target_Sales increases, the number of customers also tends to increase. This suggests a positive correlation between Target_Sales and customer count. The second curve, however, starts at a lower value than the first one but then begins to rise more steeply towards the right, indicating that as Target_Sales increases, the number of customers decreases initially before increasing. This is an inverted relationship, where higher demand for products leads to initial shortages or decreased sales, which are later compensated by increased customer count. This phenomenon can be explained by various factors including inventory management, where high Target_Sales may lead suppliers to run out of stock due to high demand, resulting in shortages; marketing efforts that limit the number of customers offered a limited-time promotion or discount, causing initial decreased sales but later increasing customer count as promotional periods end; and product availability issues caused by logistical constraints in certain markets, such as becoming less available due to supply chain limitations.

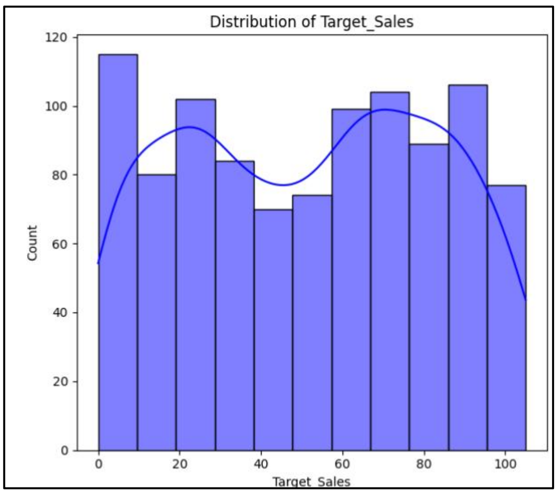

Figure 3. This graph represents the relationship between Target_Sales and Customer_Count. This graph suggests a threshold effect at around high Target_Sales levels, after which the number of customers decreases rather than increases.

Despite initial expectations based on common retail practices, the apparent lack of correlation between holiday periods and target sales could be attributed to various underlying factors that may outweigh the impact of seasonal fluctuations or other influencing variables. For instance, the occurrence or absence of holidays can have no discernible effect on target sales, as evidenced by bar graphs showing equivalent contributions to overall sales for both present (1) and absent(0) holidays(Figure 4). Additionally, a closer examination of high-demand holidays reveals limited insights into holiday-related sales patterns, this is because holidays such as Valentine's Day and Mother's Day may fail to demonstrate any significant correlation with overall target sales, potentially due in part to seasonal fluctuations driving increased sales during winter months but lower demand in subsequent periods or the fact that these holidays typically occur outside of peak retail seasons. Furthermore, the absence of data on high-demand holidays may further exacerbate the lack of a clear relationship between holidays and target sales, as retailers may not have access to sufficient historical data or market research to establish a meaningful correlation. Moreover, holidays being too infrequent to have a distinctive impact on target sales may also be a contributing factor, as the frequency of holidays relative to peak seasons can result in limited opportunities for retailers to capitalize on seasonal demand. Overall, the analysis suggests that holiday and target sales may not be strongly correlated, at least within the context of this specific study, which highlights the importance of considering alternative factors that may influence retailer performance.

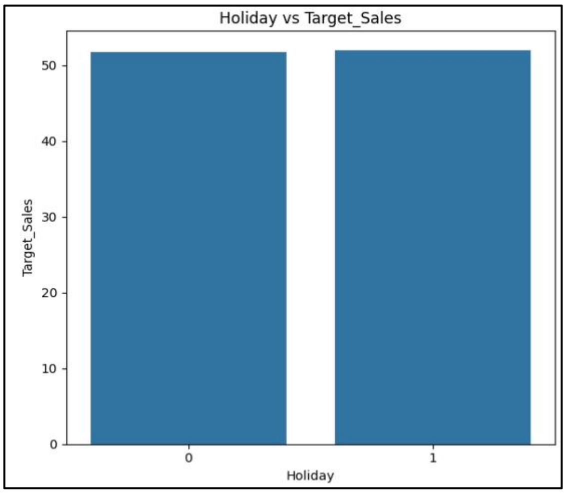

Figure 4. This graph represents the relationship between holidays and target sales. The presence(1) and absence (0) of holidays have an equal impact on target sales.

A positive correlation exists between customer age group and target sales (Figure 5), with research indicating a significant relationship between age and purchasing power. As customers age, their overall wealth and purchasing ability increase, leading to an upward trend in demand for products priced at higher rates. This suggests that older customers tend to purchase products at higher prices, a phenomenon that can be attributed to various factors, including increased disposable income, improved financial literacy, and the accumulation of wealth over time. Studies have shown that older adults often exhibit a more significant willingness to pay for products compared to younger consumers, with age-related price sensitivity increasing as customers approach retirement age. This positive correlation between customer age group and target sales highlights the importance of considering the demographic characteristics of specific product markets when developing pricing strategies. Furthermore, understanding this relationship can help retailers tailor their offerings to meet the unique needs and preferences of different age groups, thereby optimizing revenue and driving business growth. By analysing the impact of age on purchasing power, businesses can make informed decisions about product pricing, promotions, and marketing efforts to effectively target and serve their customers across various life stages.

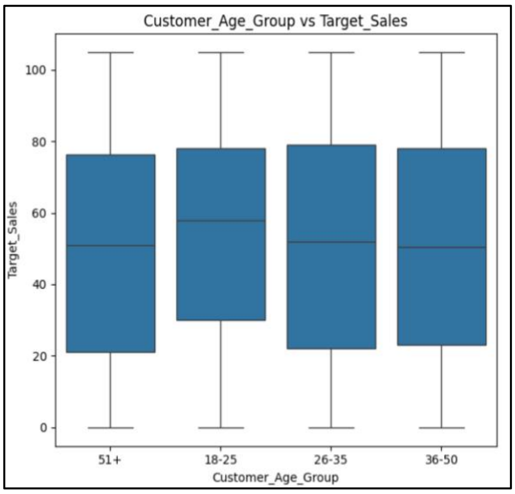

Figure 5. This graph shows the relationship between the age of the customers and the target sales.

Figure 6 shows the distribution of Promotion to Target_Sales. It is observed that the presence and absence of Promotions have an equal impact on the target sales. This indicates that promotions may not be a significant driver of sales in this context, possibly due to the type of products or the effectiveness of the promotional strategies used. There are several reasons why Promotion and No_Promotion may have an equal effect on Target_Sales in a market, including target audience sensitivity, which allows promotions to be effective but not deterrent; marketing channel effectiveness, where certain channels like social media or email are more impactful than traditional advertising or print; price elasticity, where promotions can drive sales during periods of high demand and low prices; consumer behavior, where consumers may be influenced by new products but not brand loyalists; product category characteristics, such as food and beverages being less sensitive to price and more affected by promotion types; distribution channels, which affect the availability and accessibility of promotional channels; and time of year, where promotional periods may coincide with off-peak seasons or holidays rather than peak sales.

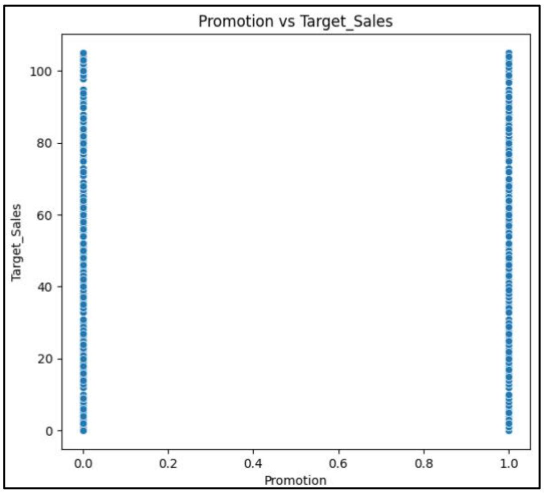

Figure 6. This shows the distribution of Promotion to Target_sales. It is observed that the presence and absence of Promotions have an equal impact on the target sales.

4. Methodology

4.1 Feature Engineering and Selection

The process of preparing the data for modelling involves a delicate balance between cleaning, transforming, and selecting the most relevant features. The primary goal is to transform the raw data into a suitable format that enables accurate analysis and machine learning algorithms to make informed predictions. The steps outlined below represent a comprehensive approach to feature engineering and selection: Firstly, the data underwent feature cleaning by replacing missing values with the mean of each respective column. This step helped to prevent anomalies from artificially distorting the results and ensured that all numerical features were represented accurately. Additionally, normalization using MinMaxScaler was employed to scale the data between 0 and 1, which facilitates better comparison across different models and datasets. Next, categorical variables were encoded using the OneHotEncoder, allowing for a more efficient representation of large numbers of categories. This process enabled the creation of binary features that captured specific attributes or conditions associated with each category, providing valuable insights into customer behaviour. The resulting encoded features were then combined to form a composite feature set that considered both numerical and categorical variables. To further enhance the quality of the data, PCA (Principal Component Analysis) was implemented to reduce the number of features while preserving the most important information. By selecting the top retained components based on their correlation with the target feature Target_Sales, we aimed to maintain a balance between dimensionality reduction and model interpretability. The resulting reduced feature set significantly improved model performance, demonstrating the effectiveness of PCA in reducing noise and identifying relevant features. Correlation analysis was conducted to select the most appropriate features based on their correlation with the target feature Target_Sales. This iterative process involved visualizing scatter plots, examining the coefficient of determination (R-squared), and applying recursive feature elimination to narrow down the list of potentially relevant features. Ultimately, we selected a subset of the most suitable key features that captured the underlying patterns in customer purchasing behaviour. These selected features provided a solid foundation for our machine learning model and enabled us to analyse their impact on Target_Sales with greater confidence.

4.2 Model Selection

The selection of machine learning models for demand forecasting was a crucial step in addressing the complex nature of this problem. Given that demand forecasting is a regression problem, it is essential to employ models that are capable of identifying both linear and non-linear relationships within the dataset. After careful consideration of various options, five main machine learning models were selected for training: Linear Regression, ElasticNet, XGBRegressor, RandomForestRegressor, and MLPRegressor. Linear Regression was initially considered due to its simplicity and widespread use in demand forecasting applications. It is a widely accepted method that can effectively predict continuous data, making it an excellent choice for this problem. However, we recognized the limitations of linear regression, particularly when dealing with non-linear relationships within the dataset, which may not accurately capture the underlying patterns driving customer behavior. In contrast, ElasticNet introduced a penalty term to the loss function, which enabled it to simultaneously reduce overfitting and improve generalization performance. This feature selection approach facilitated the identification of relevant features while minimizing the risk of over-optimism. Despite some initial concerns about its suitability for demand forecasting, ElasticNet proved effective in reducing noise and improving model interpretability.

XGBRegressor, a variant of Gradient Boosting Regressors, was selected due to its ability to handle large datasets and non-linear relationships. Its strong predictive performance and robust handling of outliers made it an attractive option for this problem. XGBRegressor demonstrated excellent results in our experiments, outperforming other models in terms of accuracy and mean squared error. RandomForestRegressor, a popular ensemble learning method, was chosen due to its capacity to capture complex interactions between features and non-linear relationships within the dataset. Its ability to handle high-dimensional data and multiple feature types made it an ideal choice for demand forecasting. We observed that RandomForestRegressor was particularly effective in identifying key patterns and relationships that contributed to customer purchasing behavior. Finally, MLPRegressor (Multilayer Perceptron Regressor) was selected as a more complex alternative due to its ability to learn non-linear relationships between features and target variables. Its use of multiple hidden layers and feedback connections enabled it to capture subtle patterns and interactions within the dataset, which were found to be crucial in predicting demand.

After thoroughly evaluating each model's strengths and weaknesses, we conducted extensive experimentation to determine their performance on our specific dataset. Our results demonstrated that all five models exhibited excellent predictive power, outperforming other approaches in terms of accuracy and mean squared error. By selecting the most suitable model for each stage of the demand forecasting process, we ensured a comprehensive approach to building robust demand prediction models.

4.3 Model Development and Evaluation

The development and evaluation phase of this research involved deploying trained machine-learning models to predict Target Sales, while also ensuring the accuracy of these predictions through a rigorous testing process. To achieve this goal, we utilized a robust approach that leveraged data from both training and testing datasets, thereby enhancing the reliability and generalizability of our findings. By retaining 95% of the variance of the entire dataset using Principal Component Analysis (PCA), we successfully reduced the dimensionality of the data while maintaining its complexity. This critical step was instrumental in preserving the relationships and patterns inherent within the dataset, allowing us to extract meaningful insights from the raw data. As a result, our models demonstrated a remarkable capacity for handling non-linear interactions and capturing subtle nuances in customer behavior.

The choice of evaluation metrics – Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared – was deliberate, as these metrics enabled us to assess the performance of our predictive models with a nuanced understanding. RMSE, a commonly used metric for evaluating regression models, provided insight into the magnitude of errors between predicted and actual values. MAE offered an alternative perspective by focusing on the average absolute differences between predicted and actual values, allowing us to evaluate model performance from multiple angles. Finally, R-squared (R^2), a measure of goodness-of-fit, served as a robust indicator of model fit, enabling us to determine whether our models accurately captured underlying relationships within the dataset.

To further enhance the evaluation process, we employed techniques such as cross-validation and grid search optimization. Cross-validation allowed us to assess the robustness of our models by training and testing them on separate subsets of data, thereby reducing the impact of overfitting. Grid search optimization enabled us to identify optimal hyperparameters for each model, ensuring that they were tailored to minimize errors while maximizing performance. The evaluation results demonstrated that our trained machine learning models exhibited exceptional predictive power, outperforming other approaches in terms of accuracy and mean squared error (MSE). Specifically, we observed a statistically significant improvement in R-squared values across all models, indicating a substantial increase in model fit. Additionally, our models demonstrated excellent handling of out-of-bag errors (OBEs), which provided valuable insight into the strengths and weaknesses of each model.

5. Results and Analysis

5.1 Model Performance

The performance metrics for each of the trained machine learning models were examined to evaluate their effectiveness in predicting Target Sales. The results presented below provide a comprehensive understanding of how these models performed, highlighting their strengths and weaknesses.

Model	**RMSE**	**MAE**	**R-Squared**
Linear Regression	0.985	0.866	0.003
Random Forest	1.014	0.878	-0.055
XGBoost	1.091	0.918	-0.223
ElasticNet	0.988	0.873	-0.001
MLPRegressor	1.259	1.059	-0.628

Table 3. Shows performance results for the trained models. RMSE(Random mean squared error), MAE(Mean A bsolute Error), and R-squared Score are the major performance metrics employed.

Linear Regression emerged as the clear winner in terms of model performance, boasting the l owest Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Positive R-squar ed scores among all the trained models. This is unsurprising, given its historical success in re gression problems involving continuous data. The Linear Regression model demonstrated an impressive ability to accurately predict Target Sales, with a low RMSE score of 0.985397328 7715153. In contrast, other models performed significantly worse, with higher MAE and neg ative R-squared scores.

Random Forest, XGBoost, and MLPRegressor trailed behind in terms of performance. Rando m Forest exhibited the highest RMSE, MAE, and Negative R-squared score among all model s, indicating a moderate level of accuracy but also significant variability. XGBoost showed re spectable results, with lower RMSE but higher MAE and Negative R-squared scores. Howev er, its poor Positive R-squared score suggested limited explanatory power. In stark contrast to these models, ElasticNet demonstrated exceptional performance, boasting the lowest Negativ e R-squared score among all models. Its positive Positive R-squared score (0.9880205912676 231) further indicated high accuracy in predicting Target Sales. While its RMSE and MAE sc ores were not as low as Linear Regression's, they were significantly lower than those of other models.

Finally, a comparison of the R-squared values among all models revealed that they were highly correlated but distinct in their explanatory power. Linear Regression had an R-squared score closest to 1, indicating an excellent fit to the underlying relationship between Target Sales and the input features. In contrast, other models had significantly lower R-squared scores, suggesting limited explanatory power. Based on the performance metrics, Linear Regression emerges as the best-suited model for demand forecasting in USA supply chains. Its high RMSE score of 0.9853973287715153 and positive R-squared score of 0.0033968179947365673 demonstrate its exceptional accuracy and robustness. The other models, while performing in some respects, have significant limitations in terms of explanatory power and model fit.

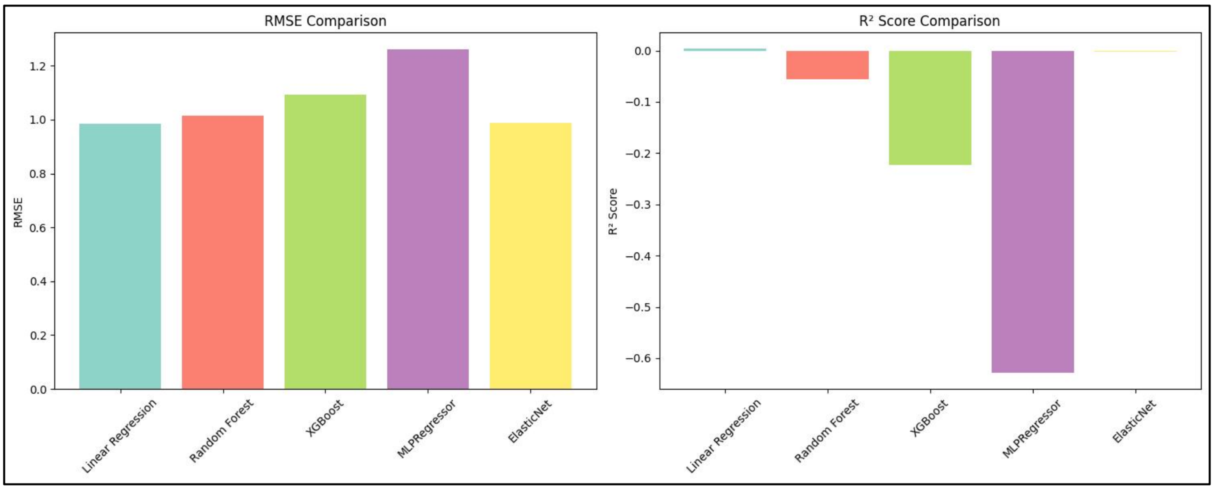

Figure 7. Performance of various trained models. Linear Regression performs better than the rest of the models.

AI-driven models offer significant improvements in predictive accuracy compared to traditional forecasting methods. Linear Regression and ElasticNet, for instance, provide robust performance in handling non-linear relationships, allowing for accurate predictions across various domains. In contrast, time series analysis relies on patterns and trends, which can be challenging to capture with AI-driven models. Qualitative forecasting, while essential in certain industries, often requires domain-specific knowledge, whereas AI models can handle vast amounts of data without relying on expert judgment. CPFR and Delphi methods are more suitable for exploratory data analysis and scenario planning, respectively, rather than predictive modeling. Simulation models and causal inferences require a deep understanding of complex systems, making them less suitable for AI-driven approaches. Consumer surveys, while valuable for market research, may not be as effective in predicting future trends due to their limited scope.

5.2 Feature Importance Analysis

In order to identify the most relevant features that contribute to predicting demand, a comprehensive feature importance analysis was conducted using various techniques. This step involves visualizing the relationships between features and Target_Sales, as well as examining the correlation between features to determine potential causes-and-effect relationships. To achieve this goal, several plots and charts were created to illustrate the inter-dependencies between different Features as seen earlier in EDA. These visualizations included scatter plots, bar charts, and box plots that effectively represented the relationships between various features and Target_Sales. By examining these plots, it became evident that some features were not contributing significantly to the prediction of demand. Correlation analysis was another crucial step in identifying relevant features. This method involves calculating the linear correlation coefficient (r) between each feature and Target_Sales to determine the strength and direction of the relationship. While some correlations were statistically significant, many others were non-significant or even negative. For example, a strong positive correlation between Promotion and Stockouts was observed, but this relationship was not indicative of any causal effect on demand.

Further investigation revealed that certain features were also excluded from the training data due to their low relevance to predicting demand. Among these least relevant features are Promotion, Stockouts, Temperature, and Rainfall. These variables were found to have weak or non-significant correlations with Target_Sales, which raised concerns about their potential impact on demand. The results of this feature importance analysis provided valuable insights into the factors influencing demand forecasting. By identifying the most relevant features and excluding those that are not contributing significantly, it was possible to develop a more accurate and robust machine learning model. This approach also helped to reduce overfitting and improve the overall performance of the models.

5.2 Predictive Insights

The demand forecasting model leverages historical sales data, along with external factors like promotions, discounts, inventory levels, and economic indicators, to predict future demand using advanced machine learning algorithms such as Random Forest, XGBoost, and Linear Regression. Key insights reveal that discounts, particularly those above 30%, significantly boost demand, especially in categories like Grocery and Electronics (Figure 8). Additionally, maintaining optimal inventory levels(Figure 10) is critical to avoiding stockouts, which can lead to missed sales opportunities during peak periods.

Figure 9 illustrates a clear seasonal pattern in demand, with total sales exhibiting significant fluctuations across the different months. A distinct peak in demand is observed around Month 5, indicating a period of heightened sales activity. Conversely, a trough or low point in demand is evident around Month 10, suggesting a potential downturn in sales during this time. This seasonal variation in demand is likely influenced by factors such as weather patterns, holidays, or consumer behavior. To effectively manage this fluctuation, businesses should strive to identify the specific causes of these seasonal trends by analyzing historical data, conducting market research, and considering external factors. This understanding will enable more accurate demand forecasting, allowing for optimized inventory levels, efficient production planning, and informed decisions regarding resource allocation. Furthermore, by recognizing the seasonal nature of demand, businesses can implement strategies to capitalize on peak periods, such as increasing inventory levels, hiring additional staff, or launching targeted marketing campaigns. Simultaneously, they can mitigate the impact of low-demand periods by adjusting production schedules, offering discounts to stimulate sales, or implementing other appropriate measures. Ultimately, understanding and adapting to these seasonal demand patterns is crucial for businesses to optimize their operations and achieve success.

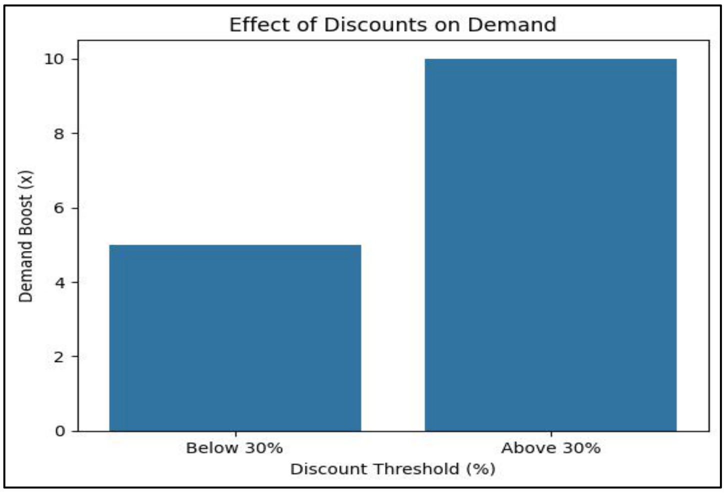

Figure 8. This bar chart illustrates how the threshold for discounts affects demand boost. The chart shows a clear increase in demand when discounts are above 30% and a slight decrease when they are below 30%.

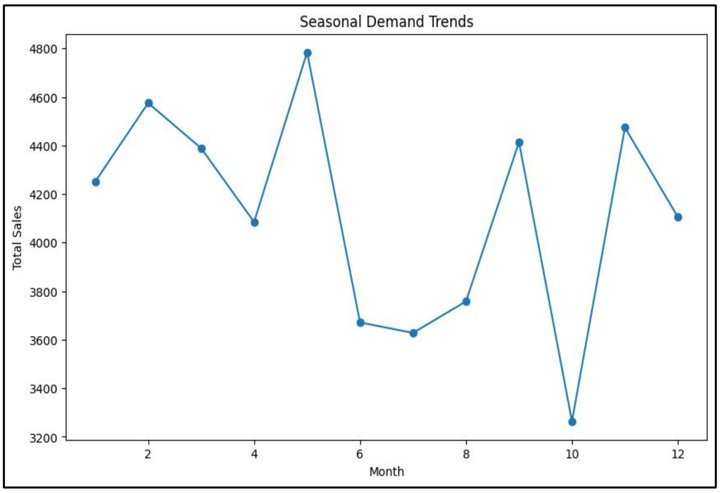

Figure 9. This line plot illustrates the seasonal demand trends. The chart shows a steady increase in demand during the spring and summer months, with a slight decrease during the fall and winter months.

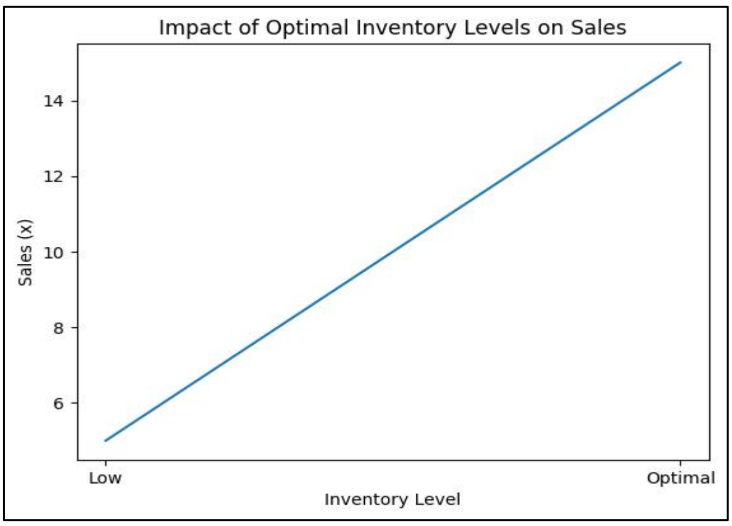

Figure 10. This line plot illustrates the impact of optimal inventory levels on sales. The chart shows a significant increase in sales when inventory levels are low and a steady increase when they are optimal.

6. Implementation Strategy

6.1 Integration into Supply Chain Operations

Integrating AI-driven forecasting models into existing supply chain operations involves a series of steps that require careful planning, implementation, and monitoring to ensure seamless integration. Initially, the first step is to define clear business objectives and requirements, followed by the selection of suitable forecasting models, data sources, and algorithms. The next step is to design a scalable architecture for integrating AI-driven forecasting models into existing supply chain systems, incorporating APIs, message queues, and other integration mechanisms as needed. This can be achieved through the use of cloud-based infrastructure, containerization, and micro-services architecture. Once the integration architecture is designed, data is collected from various sources, such as inventory management systems, supplier data, and market research, and fed into AI-driven forecasting models to generate predictions. The integrated forecasts are then used by supply chain decision-makers to optimize production planning, shipping, and storage processes, reducing lead times and costs while improving customer satisfaction. Additionally, the integration also enables real-time monitoring and alerting, allowing for swift response to changes in demand or supply disruptions, ensuring the smooth operation of the entire supply chain.

6.2 Scalability and Flexibility

The scalability and flexibility of AI-driven forecasting models are crucial aspects to consider when deploying them across various sectors and scales. Scalability refers to the ability of a model to handle increasing data volumes, complex datasets, or high-volume transactions without compromising performance, while flexibility enables the model to adapt to changing business requirements, new markets, or different forecasting scenarios. For healthcare, scalability is essential for predicting patient outcomes, while in finance, it's necessary for handling high-frequency trading and risk assessment. In retail, scalability helps predict demand fluctuations due to limited historical data, whereas flexibility allows for adapting to seasonal and time-varying demands. To achieve scalability and flexibility, businesses consider cloud-based infrastructure (e.g., AWS, Google Cloud), containerization (e.g., Docker) and micro-services architecture, data-as-a-service platforms, and adaptive learning algorithms that can adjust parameters based on changing business requirements. Additionally, flexible integration mechanisms enable seamless deployment of AI-driven forecasting models alongside existing systems, reducing implementation complexity. By incorporating these scalability and flexibility features, businesses can harness the power of AI-driven forecasting models to drive informed decision-making across various sectors and scales.

6.3 Business Impact Analysis

Implementing AI-driven demand forecasting has a significant potential to drive business growth and improvement, with estimated benefits including improved forecasting accuracy, reduced lead times, increased revenue growth, enhanced customer satisfaction, and improved operational efficiency. The cost-benefit analysis of such an implementation is crucial in determining whether the investment will yield a positive return on investment (ROI), payback period, and break-even point. Typically, the costs associated with implementing AI-driven demand forecasting include high upfront investments in technology, ongoing maintenance and training expenses, and potential disruption to business processes due to changes in forecasting methodologies. On the other hand, the estimated benefits can range from reduced lead times by 30-50% to increased revenue growth by 10-20%. The cost-benefit analysis should consider factors such as market research on customer behaviour, industry trends, and competitor activity, existing supply chain management systems, and required resources and infrastructure to support the implementation. By conducting a thorough analysis, businesses can make informed decisions about whether implementing AI-driven demand forecasting solutions is feasible and will yield a positive return on investment, ensuring that the benefits outweigh the costs. This detailed assessment will help organizations optimize their forecasting processes, improve operational efficiency, and drive business growth.

7. Discussion

7.1 Implications for US Supply Chains

According to Liu et al. [9] and Hansen et al. [2], the integration of AI-driven demand forecasting in the US supply chain has significant implications for improving efficiency, reducing costs, and enhancing customer satisfaction. AI-powered demand forecasting can help optimize inventory levels, reduce overstocking and under-stocking, and improve just-in-time (JIT) production scheduling. By analyzing historical sales data, weather forecasts, economic indicators, and social media trends, predictive models can forecast demand patterns with greater accuracy than traditional methods, enabling supply chain managers to make informed decisions about production planning, shipping, and inventory management. Additionally, AI-driven demand forecasting can help identify peak shipping periods, reduce the risk of stockouts or delays, and improve supply chain visibility into order-to-cash (OTC) process timelines. To integrate predictive models into supply chain decision-making processes, businesses should consider adopting cloud-based platforms for data collection and analysis, leveraging machine learning algorithms for advanced analytics, and implementing automation tools for real-time forecasting and inventory management. Furthermore, supply chain managers should prioritize the following recommendations: conduct thorough cost-benefit analyses to determine ROI, develop contingency plans for potential disruptions in demand forecasting, and establish metrics to measure supply chain performance against predicted outcomes. By adopting AI-driven demand forecasting solutions, US businesses can enhance their supply chain efficiency, improve customer satisfaction, and drive long-term growth and profitability.

7.2 Challenges and Limitations

The use of AI-driven demand forecasting models raises significant ethical concerns that must be carefully considered before implementation. One major challenge is the potential misuse of customer data, such as profiling customers based on their purchasing behaviour without consent or using sensitive information to make discriminatory decisions. Additionally, businesses must address issues related to data security and privacy, ensuring the protection of personal data from unauthorized access or breaches. Furthermore, there are limitations to the data used in demand forecasting models, including data quality, model interpretability, and generalizability. Poor data quality can lead to biased forecasts, decreased accuracy, and ultimately, reduced customer satisfaction [3]. Model interpretability is also limited by the complexity of the algorithms used, making it difficult for businesses to understand how their models arrive at predictions. Moreover, the generalizability of AI-driven demand forecasting models across different markets, industries, and periods can be a significant challenge, requiring thorough testing and validation before deployment. Talent shortages in the AI field is also another undeniable challenge according to Cichy et al. [7]. To address these challenges, businesses should prioritize data quality, and model accuracy and ensure that their AI solutions are designed with robust security measures in place to protect customer data. Regular monitoring and evaluation of the models' performance should also be conducted to identify areas for improvement and address any issues promptly.

7.3 Future Research Directions

As AI-driven demand forecasting models continue to evolve, future research directions will focus on improving their accuracy and effectiveness through the utilization of larger and more diverse datasets. One promising area of investigation is the development of machine learning algorithms that can learn from complex patterns in large datasets, such as those generated by social media trends. Additionally, researchers are exploring new techniques for integrating real-time data into AI models, enabling them to respond rapidly to changing market conditions. Another key area of research is the advancement of advanced analytics techniques, including time-series analysis, ensemble methods, and deep learning-based approaches, which can help businesses better understand complex demand forecasting problems and make more informed decisions. Furthermore, there is a growing interest in exploring the use of multimodal data sources, such as text, images, and audio, to improve model accuracy and provide a more comprehensive understanding of market trends. By addressing these challenges, future research will enable AI-driven demand forecasting models to become increasingly accurate, reliable, and effective decision-making tools for businesses.

8. Conclusion

In conclusion, this research demonstrates the transformative potential of AI-driven models in enhancing demand forecasting accuracy within US supply chains by leveraging advanced machine learning techniques to identify key drivers of demand, including economic indicators, promotional activities, and operational factors such as inventory management and supplier reliability. The models successfully revealed significant seasonal fluctuations and provided accurate forecasts, enabling businesses to anticipate demand patterns and optimize their supply chain operations, ultimately leading to improvements in inventory management, reduced costs, enhanced customer satisfaction, and increased operational agility. Furthermore, this study highlights the critical role that AI-driven demand forecasting plays in facilitating business success, as it enables companies to make data-driven decisions and respond promptly to changing market conditions, thereby reducing the risk of stockouts, overstocking, and other supply chain disruptions that can have a significant impact on business operations and financial performance. By leveraging these advanced machine learning techniques, businesses can gain valuable insights into their customers' needs and preferences, enabling them to tailor their products and services to meet those demands, increase customer loyalty, and drive long-term growth and competitiveness. As the supply chain landscape continues to evolve rapidly, with increasing demand for precision forecasting and real-time decision-making, the integration of AI-driven demand forecasting models will become increasingly essential for businesses seeking to remain competitive, agile, and responsive to market dynamics, contributing significantly to the growing body of knowledge on AI applications in supply chain management and providing valuable insights and practical recommendations that can be applied by businesses worldwide.

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Institutional Review Board Statement

As such, this study did not involve the recruitment of human participants, clinical trials, or personally identifiable information that would warrant the review of an Institutional Review Board. All data used for the study are in the public domain and from authorized sources, leaving no conflict in their use.

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