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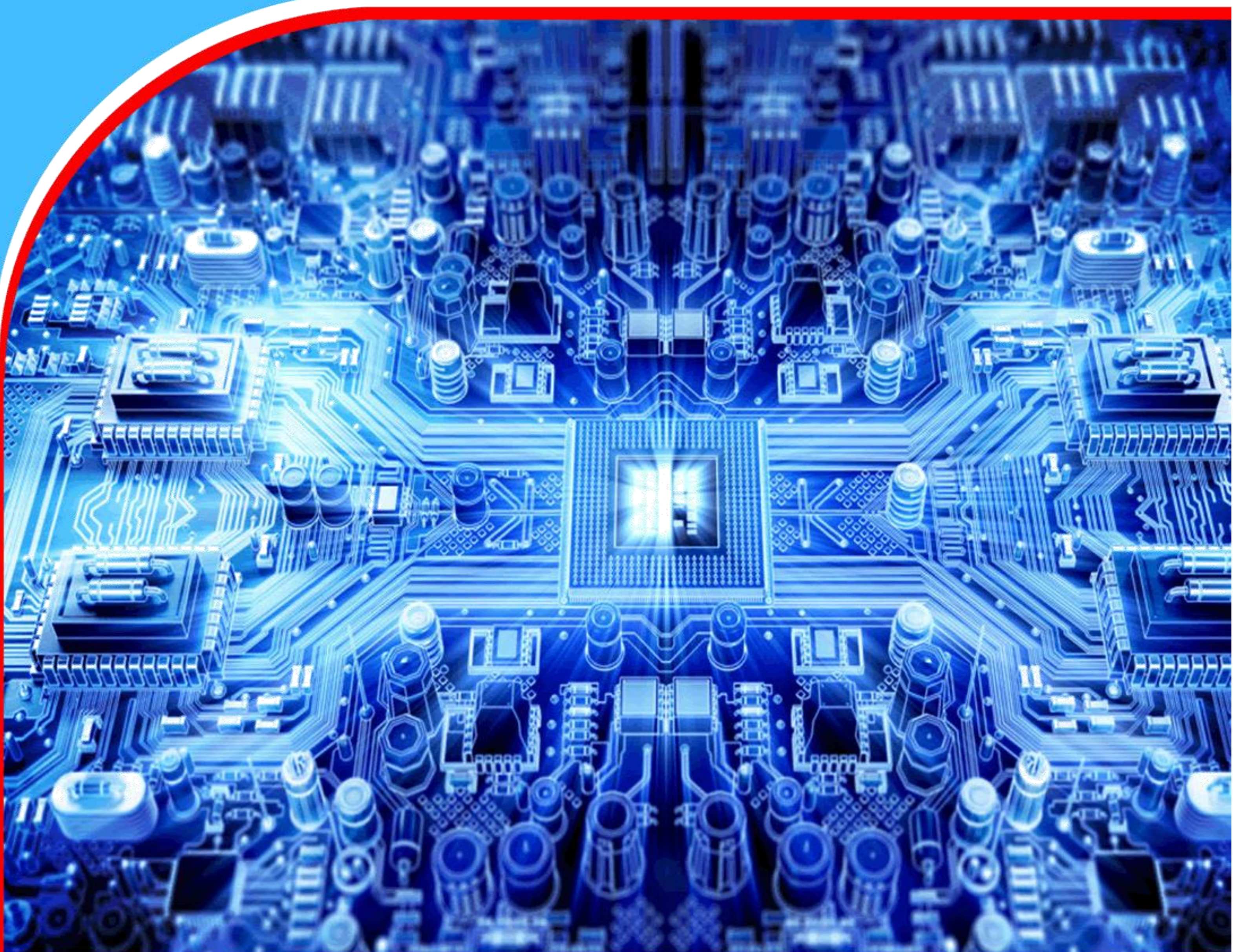

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Abstract

Purpose: Accurate demand forecasting is critical for optimizing inventory management, improving customer satisfaction, and maximizing profitability in the retail sector. Traditional forecasting models predominantly utilize micro-level variables, such as historical sales data and promotional activities, often neglecting the influence of macroeconomic conditions.

Materials and Methods: This study addresses this gap by integrating Freight Transportation Services Index (TSI) which is an indicator for overall economic health with time series data of retail product sales. Utilizing an advanced neural networks model, we demonstrate that incorporating macroeconomic variables significantly enhances the model's predictive accuracy and explanatory power.

Findings: The results reveal that the model with the TSI index outperforms conventional models, highlighting its potential for practical application in the industry.

Implications to Theory, Practice and Policy: This approach offers a more comprehensive understanding of demand dynamics, enabling businesses to make more informed decisions, adapt to market fluctuations, and maintain a competitive edge.

Keywords: *Neural Networks (C45), Inventory Management (G31), Demand Forecasting (C53), TSI, Economic Environment (O11), Explainable Artificial Intelligence*

1.0 INTRODUCTION

Inventory management is crucial for firms as it directly impacts their financial performance. By predicting future demand, firms can align their operations with market needs, thereby gaining a competitive edge in the highly globalized market environment. To improve supply chain management, an increasing number of firms are adopting advanced prediction models. This shift has spurred a significant body of literature focusing on forecasting future demand, utilizing a wide array of statistical methods as well as advanced Machine Learning approaches, including neural network algorithms.

Traditionally, demand forecasting models have relied on time series data of customer demand for retail products, incorporating variables such as product prices, store features, any special offers or deals, etc. However, firms operate within a macroeconomic environment that significantly influences household spending. Despite empirical evidence suggesting that economic conditions greatly affect household shopping behavior and spending patterns [Scholdra et al., 2022], current literature mostly fails to account for this influence when forecasting future customer demand. Haque (2023) strives to address this concern by incorporating macroeconomic variables. In our proposed study, we further improve the methodology proposed by Haque (2023) and incorporate Freight Transportation Services Index (TSI) along with historical customer demand data. The Freight Transportation Services Index (TSI) measures the volume of goods moved by the for-hire transportation industry each month, and it can reflect changes in demand for goods and services. During periods of economic expansion, demand for goods and services usually increases, which can lead to an increase in the TSI. Empirical evidence by Bureau of Transportation Statistics (BTS) suggest that changes in the freight TSI can sometimes happen before changes in the economy. These evidences demonstrate that TSI is a clever and innovative choice for representing overall economic conditions of a country.

This study addresses this gap by enriching time series data of customer demand with TSI data along with macroeconomic variables such as the Consumer Price Index (CPI), Consumer Sentiment Index (ICS), and unemployment rate, reflecting the economic environment. Using this enriched data, a multi-layer Deep Neural Networks model is developed for forecasting future demand, specifically implementing a Long Short-Term Memory (LSTM) model. The LSTM model is adept at capturing unobserved non-linear trends from observed data through its hidden layers and memory of past information. The results of this study show our proposed model outperforms the conventional models with a reasonably low prediction error, with a Root Mean Square Error (RMSE) of 1.22.

Long Short-Term Memory (LSTM) networks are particularly effective for demand forecasting due to their unique architecture and capabilities. Demand forecasting involves time series data, where the order of observations matters. LSTMs are specifically designed to work with sequential data, making them a natural fit for predicting future demand based on past patterns. One of the main strengths of LSTMs is their ability to capture long-term dependencies in the data. Traditional neural networks and even some other types of recurrent neural networks (RNNs) can struggle with long-term dependencies due to issues like vanishing or exploding gradients. LSTMs use a special gating mechanism to regulate the flow of information, which helps them remember information over long periods.

Problem Statement

Current research predominantly relies on historical data to train forecasting models, often overlooking comprehensive macroeconomic data that significantly influences consumer purchasing behavior. Our approach incorporates Freight Transportation data, which provides insights into the overall demand within the broader economy. By integrating historical demand data with macroeconomic factors, we train sophisticated neural network models to enhance forecasting accuracy.

2.0 LITERATURE REVIEW

Accurate demand forecasting is crucial for effective supply chain management, influencing critical decisions such as production planning and inventory optimization. This literature review synthesizes key findings on demand forecasting methodologies, documenting the transition from traditional statistical approaches to advanced machine learning techniques. Additionally, it emphasizes the emerging integration of macroeconomic and consumer indicators to enhance the accuracy of retail sales forecasting.

Historically, statistical methods like SARIMA (Seasonal Autoregressive Integrated Moving Average) have dominated demand forecasting due to their maturity and ability to capture both seasonal and trend components in time series data. For instance, Abellana et al. (2020) highlight the widespread adoption of SARIMA due to its interpretability and effectiveness. Chuang (1991) applied SARIMA to forecast computer part demand, demonstrating its superiority over simple smoothing methods. Similarly, Velos et al. (2020) successfully used SARIMA for sales forecasting in the alcoholic beverage industry, where it outperformed baseline models. However, as data complexity increases, the limitations of linear statistical models have become evident.

In response to the constraints of traditional statistical techniques, machine learning has emerged as a flexible and powerful approach for modeling complex nonlinear relationships in demand data. Makridakis et al. (2018) conducted a benchmark study comparing statistical methods with machine learning algorithms, finding that Random Forests significantly reduced forecast errors. Bousqaoui et al. (2021) further demonstrated that Support Vector Regression (SVR) substantially improved the accuracy of forecasts compared to SARIMA and Exponential Smoothing. The potential of ensemble methods in demand forecasting is highlighted by Mitra and Sahu (2022), who conducted a comparative study of five machine learning regression techniques. They found that a hybrid model combining Random Forests, Extreme Gradient Boosting, and linear regression provided superior forecasting accuracy, underscoring the effectiveness of combining multiple machine learning approaches.

The superiority of machine learning techniques over classical methods in demand forecasting is further supported by studies in various industries. Lorente-Leyva et al. (2020) compared machine learning techniques, such as Artificial Neural Networks, with traditional forecasting methods in the Ecuadorian textile industry, demonstrating that machine learning models significantly outperformed classical approaches in terms of accuracy and overall performance. Similarly, Mbonyinshuti and Kim (2021) applied machine learning algorithms, including linear regression, Artificial Neural Networks, and Random Forest, to predict the demand for essential medicines in Rwanda, showcasing the effectiveness of these approaches in improving demand forecasting accuracy and contributing to better healthcare resource planning.

Traditional time-series methods, such as Exponential Smoothing and ARIMA, have been widely used for demand forecasting in offline retail, as observed by Punia et al. (2020). However, their study suggests that advanced machine learning approaches offer significant advantages over traditional methods, highlighting the potential benefits of adopting these techniques in demand forecasting.

In addition to machine learning advancements, the integration of macroeconomic indicators into predictive models has become an emerging approach to enhance forecasting accuracy. Grzywińska-Rąpca and Ptak-Chmielewska (2023) investigated the determinants of the Consumer Confidence Index (CCI) and its influence on consumer spending behavior. Their study emphasized the importance of respondent expectations in shaping the CCI and its potential contribution to forecasting consumption and retail sales. Ye and Le (2023) focused on the factors influencing automobile sales, particularly macroeconomic determinants such as residents' disposable income. By incorporating these variables into their forecasting model, they provided a more comprehensive understanding of the dynamics driving automobile sales and improved forecasting precision.

The predictive power of macroeconomic indicators is further illustrated by Bakas and Triantafyllou (2019), who explored the relationship between macroeconomic uncertainty and commodity market volatility. Their findings suggest that incorporating macroeconomic uncertainty into forecasting models enhances the accuracy of volatility forecasts in commodity markets. Liu et al. (2022) proposed a regional economic forecasting method using recurrent neural networks, advocating for the adoption of advanced machine learning techniques to capture the complex relationships between macroeconomic and consumer indicators, thereby improving regional sales forecasts.

Haque (2023) introduced the integration of external macroeconomic variables, such as the Consumer Price Index (CPI), Consumer Sentiment Index (ICS), and unemployment rates, with retail product sales time series data. By incorporating these indicators into a Long Short-Term Memory (LSTM) model, Haque demonstrated that the enriched predictive framework significantly improved forecasting performance compared to models without macroeconomic contextualization.

The literature reviewed in this paper highlights the growing interest in leveraging machine learning models for demand forecasting across various industries. As businesses seek greater forecasting accuracy to inform supply chain decisions, combining the predictive power of machine learning with macroeconomic and consumer data presents a significant opportunity. While Haque (2023) provided evidence of the superior performance of forecasting models that include external economic conditions, there is a notable gap in the literature regarding the use of TSI (Total Sales Index) data in predicting retail demand. The current study is among the first to introduce TSI data in retail demand forecasting, with promising results indicated by an outstanding RMSE value of 1.22.

The Freight Transport Services Index can provide valuable insights into the overall economic condition due to its close relationship with economic activity. For instance, the TSI measures the volume of freight transported by various modes of transport, such as rail, road, sea, and air. Since freight transport is a crucial component of the supply chain, fluctuations in the index often reflect changes in economic activity. An increase in freight transport typically indicates higher production and consumption levels, suggesting a growing economy. Conversely, a decline may signal reduced economic activity. Hence, freight transport is closely tied to both consumer and business spending. When consumers increase their spending, demand for goods rises, which in turn boosts freight transport volumes. Similarly, businesses often ramp up their inventory and production in response to economic growth, leading to more freight movement. Thus, the TSI can be a useful proxy for changes in spending patterns and economic growth. Furthermore, the efficiency and volume of freight transport can indicate the health of the supply chain. Disruptions or inefficiencies in freight transport can signal problems in the supply chain, such as production bottlenecks or inventory issues, which can have broader economic implications. Monitoring the TSI helps assess how well the supply chain is functioning and how it might impact overall economic performance. Freight transport volumes often correlate with industrial production levels. When industrial production is high, more raw materials and finished goods need to be transported, leading to increased freight activity. Conversely, a slowdown in industrial production typically results in reduced freight volumes. As a result, changes in the TSI can provide insights into trends in industrial production and overall economic health. And, finally, TSI can act as an early indicator of economic trends. Since freight transport data can reflect changes in economic activity before they are visible in other economic indicators, tracking the TSI can help anticipate shifts in the economic cycle. For example, a sudden drop in the TSI might precede broader economic downturns, giving early signals of potential economic slowdowns.

Data Collection and Preparation

This study utilizes historical sales data for 3,049 products sold across ten Walmart stores located in three states: California (CA), Texas (TX), and Wisconsin (WI). The dataset spans five years, providing a comprehensive view of sales trends and patterns over 1,913 days. Each store in these states carries the same set of products, ensuring consistency across locations. The data is structured into three main datasets: historical sales data, calendar data, and product price data.

Historical Sales Data: This dataset is wide, with each row representing a unique product and each column representing a unique day over the 1,913-day period. It includes information such as product ID, product category, and store location.

Calendar Data: This dataset contains information about special events, holidays, promotions, and event types for each day in each state. This helps in identifying external factors that might influence sales.

Product Price Data: This dataset provides the daily prices of each product at each store, allowing for the analysis of price fluctuations and their impact on sales.

Additionally, the study incorporates macroeconomic variables such as TSI data along with the Consumer Price Index (CPI), the Index of Consumer Sentiment (ICS), and unemployment rates. Historical CPI and unemployment data were sourced from the World Bank's World Development Indicators (WDI) database, while historical ICS data was obtained from the University of Michigan's website.

The data preparation process involves several steps:

Data Integration: The calendar dataset is first joined with the macroeconomic data using the "date" column, creating a combined dataset that contains a row for each day, including special events, promotions, and macroeconomic indicators.

Merging Datasets: This combined dataset is then merged with the product price dataset and the sales dataset. The resulting dataset includes detailed information on product sales, prices, and promotions for each of the 3,049 products across the ten stores over 1,913 days.

Data Restriction: To focus on recent trends and avoid outdated patterns, the dataset is restricted to the most recent 600 days of data.

Feature Engineering: Rolling averages and rolling standard deviations of several lag values of sale prices are calculated and included as input features. This approach helps in capturing the temporal dynamics and variability in the data.

To forecast product demand, this study employs the Long Short-Term Memory (LSTM) Neural Networks algorithm, a specialized type of Artificial Neural Network (ANN) well-suited for time-series data. Neural Networks are designed to mimic the human brain's structure and learning process, consisting of interconnected nodes arranged in layers—input layers, hidden layers, and output layers. Each node in the network functions similarly to a linear regression model, with initial weights assigned at the beginning of the training process. During training, the network undergoes cycles of forward and backward propagation, where the weights are adjusted to minimize the cost function. The rate at which these weights are adjusted is controlled by a parameter known as the learning rate.

LSTM networks, a variant of recurrent neural networks (RNNs), are particularly effective for time-series forecasting due to their ability to retain information over time. This is achieved through their memory cells, which allow the network to learn dependencies across different time steps. In this study, a multilayer LSTM neural network is used to train the forecasting model, leveraging its capacity to capture complex, non-linear relationships in the sales data. The LSTM model is trained on the prepared dataset, utilizing the rolling features and macroeconomic indicators to enhance its predictive accuracy.

3.0 FINDINGS

The performance of various demand forecasting models was evaluated using Root Mean Squared Error (RMSE) as the primary metric. Table 1 presents a comparative analysis of the RMSE values for four different models: Lasso, LightGBM (LGBM), Random Forests, and Long Short-Term Memory (LSTM) networks. The models were tested both with and without the inclusion of the TSI and other macroeconomic variables.

Table 1: Comparative Model Performances

Model Name	**RMSE**	
	Without TSI and Other Macro Variables	**With TSI and Other Macro Variables**
Lasso	3.50	3.49
LGBM	2.88	2.84
Random Forests	2.59	2.50
LSTM	1.34	1.22

The results indicate that incorporating TSI and other macroeconomic variables consistently improves the performance of all models. For the Lasso model, the inclusion of these variables results in a marginal reduction in RMSE from 3.50 to 3.49. Similarly, the LightGBM model sees a slight improvement, with RMSE decreasing from 2.88 to 2.84.

The Random Forests model shows a more notable enhancement, with RMSE dropping from 2.59 to 2.50 when TSI and macroeconomic variables are included. However, the most significant improvement is observed with the LSTM model. The RMSE of the LSTM model decreases from 1.34 to 1.22, showcasing the model's superior ability to leverage TSI and macroeconomic data for more accurate demand forecasting.

Overall, these results highlight the effectiveness of integrating TSI and macroeconomic variables in improving forecasting accuracy, particularly for more complex models like LSTM. The findings suggest that the inclusion of these external factors allows models to better capture the underlying patterns and trends in the data, leading to more precise predictions.

4.0 CONCLUSION AND RECOMMENDATIONS

This study aimed to enhance retail demand forecasting by developing an LSTM model that incorporates macroeconomic variables, including the Freight Transportation Services Index (TSI), alongside other demand-related features. The key findings demonstrate that the inclusion of TSI and macroeconomic variables significantly improves forecasting accuracy across all models tested. As shown in Table 1, the LSTM model, in particular, exhibited the most substantial performance improvement, with the RMSE decreasing from 1.34 to 1.22 when these variables were included.

The comparative analysis of various models, including Lasso, LightGBM, Random Forests, and LSTM, underscores the robustness of the proposed approach. The LSTM model outperformed other models, highlighting its superior ability to capture complex relationships in the data when enriched with macroeconomic insights. These results provide strong evidence for the effectiveness of integrating macroeconomic variables into demand forecasting models.

This study contributes to the existing literature by offering a practical solution that enhances forecasting capability, thereby creating opportunities for firms to improve supply chain management and financial performance. By leveraging the predictive power of machine learning, particularly LSTM networks, combined with relevant macroeconomic indicators, businesses can achieve more accurate and reliable demand forecasts, ultimately leading to more informed decision-making and optimized operations.

Statements and Declarations

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

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