CHAPTER

4

COMPARING MACHINE LEARNING METHODS FOR DEMAND FORECASTING

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4.1 INTRODUCTION

Demand forecasting is essential across all business sectors to predict future product demand accurately. This practice aids in inventory optimisation, minimising holding expenses. Accurate forecasts are pivotal for supply and demand equilibrium; misjudgements can result in oversupply or shortages. Leading companies like Reynolds Aluminium, Eastman Chemical, Ocean Spray, and Wal-mart have effectively managed inventory and lead times through demand forecasting. Conventional methods have encountered various limitations in demand forecasting. Hence, a reliable forecasting model is needed in the industry to obtain an accurate demand prediction for improving business efficiency and customer satisfaction. The causal method employs machine learning (ML) techniques to yield more accurate estimations by considering additional factors likely to influence demand in the supply chain. The conventional methods fail to consider these factors. Therefore, researchers and practitioners have recently garnered significant interest in demand forecasting from ML methods. This study intends to evaluate the performance of various ML methods, such as multilayer perceptron (MLP) and recurrent neural network (RNN), for demand forecasting in the supply chain of an e-commerce business. y.

4.2 MACHINE LEARNING IN DEMAND FORECASTING

The industry commonly uses three demand forecasting methods: causal, time series, and judgmental (Carbonneau et al., 2009). Time series analysis determines the data's trends, cycles, and seasonality and assumes that the prediction will follow a similar pattern. Extensive research on supply chain demand forecasting employs time-series methods like exponential smoothing, moving averages, and box-jenkins techniques. However, these approaches rely solely on historical demand data and do not account for other factors that may influence future product demand.

The causal forecasting approach is used when historical data is available, and the demand values have been forecasted based on several features such as advertising cost, price of the product, and sales promotion values to improve demand forecasting accuracy significantly (Benkachcha et al., 2014). ML is a type of artificial intelligence (AI) used as a causal forecasting approach to supply chain demand. Nguyen's (2023) survey indicates a clear upward trend in the use of AI techniques in demand forecasting research from 2019 to 2023. Supporting this, Seyedan and Mafakheri (2020) and Aamer et al. (2020) highlight that neural network are among the leading methods used for supply chain demand prediction forecasting.

Various neural network techniques have been proposed, such as RNN and multilayer feed-forward neural networks (MLFFN). Au et al. (2008) employed an evolving neural network method and obtained improvements in forecast accuracy in the fashion retail industry. In recent years, long short-term memory (LSTM), a type of RNN, has become a preferred approach in demand prediction studies, demonstrating robust performance (Kavya et al., 2023).

Moroff et al. (2020) compared the demand forecasting results between the time series methods and ML techniques. The study found that the MLP method outperformed LSTM, XGBoost, random forest (RF), SARIMAX, and holt-winters, achieving an overall accuracy of 81.9%. Muhaimin et al.

(2021) introduced RNN and deep neural networks (DNN) for predicting intermittent demand data. Their results showed that RNN outperformed DNN, Croston, and single exponential smoothing methods. Therefore, this paper aims to compare the performance of LSTM and MLP in demand forecasting.

4.3 DESIGN OF COMPARATIVE STUDY LSTM AND MLP

A comparative study of demand forecasting methods, focusing on LSTM and MLP, is conducted following the research framework illustrated in Figure 4.1. The process begins with reviewing relevant literature on demand forecasting. Next, demand data is collected from open sources, followed by a data pre-processing phase to clean the dataset before performing the exploratory data analysis (EDA) and predictive analytics.

(1) Data collection

The supply chain dataset by DataCo Global company, obtained from Kaggle, is used as the dataset for demand forecasting in this study. DataCo Global is an e-commerce retailer offering clothing, sports gear, and electronics, with 11 departments such as fitness, footwear, apparel, books, golf, and outdoors. To remain competitive in the online market, the company must implement changes. The dataset consists of 180,519 records and 53 attributes that contain information regarding the company's product orders, shipping, customers, products and stores. Table 4.1 represents the detailed information for several attributes in the dataset.

The order item quantity attribute represents customer demand in this study. Generally, Various causal factors influence customer demand, including the product's price, shipping, discounts, payment options, delivery time, reviews, and more (Bucko et al., 2018). The optimal order quantity is predicted based on several potential factors, such as discounts on the order item, estimated shipping time, and product price. These factors are in ratio-type form. This demand forecast does not consider other potential factors in this dataset, such as the risk of delivery delays, payment type, and actual delivery time. The