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Research Article
Araştırma Makalesi

Development of machine learning based demand forecasting models for the e-commerce sector

E-ticaret sektörü için makine öğrenimi tabanlı talep tahmin modellerinin geliştirilmesi

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Abstract: The e-commerce sector has undergone rapid and dynamic growth in recent years. For companies aspiring to lead in this competitive industry, it is crucial to efficiently and cost-effectively respond to evolving consumer demands. In this context, the ability to accurately forecast future product demand becomes imperative. This study aims to develop forecasting models utilizing machine learning-based techniques, specifically Multi-Layer Perceptron (MLP), Multi-Horizon Quantile Recurrent Neural Network (MQRNN), and Random Forest (RF), to predict future product demand. The demand forecasting models were developed for the months of July and August, based on daily sales data for Fast-Moving Consumer Goods (FMCG) products spanning from January 1, 2023, to August 25, 2024. The models' performances were evaluated using Mean Absolute Percentage Error (MAPE). Upon examining the forecasting models developed using MLP, MQRNN, and RF, it has been observed that MQRNN exhibited the superior performance.

Keywords: E-Commerce, Demand Forecasting, Machine Learning

Özet: E-ticaret sektörü son yıllarda hızlı ve dinamik bir büyüme göstermiştir. Bu rekabetçi sektörde lider olmayı hedefleyen şirketler için değişen tüketici taleplerine verimli ve maliyet etkin bir şekilde yanıt vermek büyük önem taşımaktadır. Bu bağlamda, gelecekteki ürün talebini doğru bir şekilde tahmin etme yeteneği hayati hale gelmektedir. Bu çalışma, gelecekteki ürün talebini tahmin etmek amacıyla, Çok Katmanlı Algılayıcı (MLP), Çok Ufuklu Çeyrek Tekrarlayan Sinir Ağı (MQRNN) ve Rastgele Orman (RF) gibi makine öğrenimi tabanlı teknikler kullanılarak tahmin modelleri geliştirmeyi amaçlamaktadır. Hızlı Tüketim Ürünleri (FMCG) için günlük satış verilerine dayalı olarak 1 Ocak 2023 ile 25 Ağustos 2024 tarihleri arasındaki dönemi kapsayan bu modeller, Temmuz ve Ağustos aylarına yönelik talep tahmini yapmak için oluşturulmuştur. Modellerin performansları Ortalama Mutlak Yüzde Hatası (MAPE) metriği kullanılarak değerlendirilmiştir. MLP, MQRNN ve RF kullanılarak geliştirilen tahmin modelleri incelendiğinde, en iyi performansı MQRNN modelinin gösterdiği gözlemlenmiştir.

Anahtar Kelimeler: E-Ticaret, Talep Tahmini, Makine Öğrenimi

1. Introduction

E-commerce is a form of trade involving the sale and purchase of goods and services over the Internet (Albérico Rosário, and Ricardo Raimundo, 2021). Rapid technological developments, combined with changing consumer behavior, have caused a significant transformation in this sector (Shiwangi Singh and Tata Sai Vijay, 2024). In recent years, several rapid changes have been observed in e-commerce, such as the rise of mobile commerce, fast delivery services, artificial intelligence, and personalization, the growth of social commerce, sustainability-focused applications, and subscription-based models. The COVID-19 pandemic further accelerated this transformation, with mobile shopping, in particular, seeing an increase. Additionally, innovations in logistics, the spread of omnichannel strategies, eco-friendly solutions, and sales opportunities via social media platforms have significantly reshaped e-commerce.

In this dynamic environment, companies must take various strategic steps to gain a competitive advantage. The most important of these steps is ensuring customer satisfaction. To achieve this effectively, meeting customer needs accurately becomes critical. Meeting customer needs also strengthens the likelihood of purchase when the customer has access to the product they demand. This typically leads to positive feedback, which positively

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influences the behavior of other potential customers. In this context, competitive advantage is achieved, and customer loyalty can be maximized.

Effective inventory management is essential to accurately meeting customer needs. Proper inventory management directly impacts business success by ensuring that customer demands are met promptly. Additionally, it enables cost optimization and supports efficient use of company resources. Managing inventory effectively allows businesses to minimize inventory costs and improve cash flow. The success of this process relies on accurately predicting future product demands. Product demand forecasting is an analytical method that aims to predict future demand levels for products over a specific period, and it plays a critical role in supporting accurate inventory management. Furthermore, demand forecasts consider a wide range of factors, such as past sales data, market trends, seasonal fluctuations, and consumer behavior. While excess inventory leads to unnecessary costs, stock depletion results in customer loss and dissatisfaction. Accurate forecasting methods reduce costs by preventing these negative outcomes. Furthermore, the ability to respond quickly to market changes and sudden demands is crucial for gaining a competitive advantage. Especially in dynamic markets where customer expectations and demands change rapidly, effective demand forecasting provides businesses with flexibility and helps them achieve a stronger competitive position.

The aim of this study is to develop machine learning-based forecasting models to predict future product demand for companies operating in the e-commerce sector. To achieve this, the product demand forecasting models were developed using MLP, MQRNN, and RF.

This study is organized as follows: Section 2 includes relevant literature. Methodology is presented in Section 3. Section 4 presents datasets overview. Development of forecast models are presented in Section 5. Results and discussion are given in Section 6. Section 7 concludes the paper.

2. Literature Review

(Yashar Ahmadov and Petri Helo, 2023) presented an artificial intelligence-based model for demand forecasting of intermittent online sales. In this study, data from 17 different sellers, comprising approximately 3,000 orders, were used. It was noted that due to their multilayer structure, Deep Neural Networks provided up to 35% better prediction accuracy compared to classical models such as Moving Average, Exponential Smoothing, Croston's method, and Auto Regressive Integrated Moving Average (ARIMA). Additionally, it was determined that the arrival times and sizes of the orders followed an exponential distribution. For this reason, it was highlighted that the Poisson Exponential distribution is a good option for modeling intermittent sales processes, with an error margin of less than 7%.

(Yong Chen et al., 2024) proposed an e-commerce sales forecasting stacking method based on the integration of Gated Recurrent Unit (GRU) and Light Gradient Boosting Machine (LightGBM) to predict the sales of products with a short shelf life. GRU's ability to capture temporal features was combined with LightGBM's capability to solve multivariate problems. The proposed model was compared with other forecasting methods such as ARIMA and Support Vector Regression. The results indicated that the GRU-LightGBM model had higher accuracy in predicting sales for short-shelf-life products.

(Yujie Chi et al., 2024) proposed a wavelet-based forecasting framework for demand forecasting during major promotions. The sparsity of wavelet coefficients and feature sets was utilized, and the Bayesian Least Absolute Shrinkage and Selection Operator method was employed to address the high dimensionality of the parameters. The model's forecasting performance was evaluated using data from JD.com, demonstrating a reduction in forecasting errors.

(Indrayani Daulat Desale, 2024) aimed to analyze three time series methods ARIMA, Facebook (FB) Prophet, and Long Short Term Memory (LSTM) to forecast e-commerce sales. LSTM is a specialized type of network used within artificial neural networks for analyzing sequential data, particularly time series, and belongs to the class of Recurrent Neural Networks.The stages of dataset preparation, model creation, hyperparameter tuning, and performance evaluation were applied. Model performances were assessed using Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE), with the Prophet model exhibiting superior performance.

(Alp Ecevit et al., 2024) aimed to evaluate short-term sales forecasting performance using deep learning models based on LSTM and the FB Prophet model. The performance of the proposed models was compared with the Seasonal ARIMA model, using real-life data from an e-commerce site. Model performance was measured using Weighted Mean Absolute Percentage Error (wMAPE), RMSE, and Determination Coefficent (R^2). The results showed that the LSTM model achieved higher forecasting accuracy in hourly sales predictions than the other models.

(Mesi Febima and Lena Magdalena, 2024) aimed to optimize product demand forecasting by combining K-Means clustering and the K-Nearest Neighbors (KNN) algorithm. Similar products were grouped into two clusters using K-Means, and demand forecasting within each cluster was performed using KNN algorithms. The results indicated a 96% Accuracy rate in sales forecasting for Shopee marketplace products.

(M.D. Tanvir Islam et al., 2024) proposed a hybrid framework using RF, Extreme Gradient Boosting (XGBoost), and Linear Regression (LR) for demand forecasting. The framework was compared with various machine learning methods such as Adaptive Boosting, RF, XGBoost, and Artificial Neural Networks (ANN). Model performances were evaluated using MAE, MSE, and R^2, with RF-XGBoost-LR demonstrating superior performance.

(Dmitry Ivanov, 2024) examined the principles and applications of supply chain analytics related to demand forecasting, production planning, and inventory control. Demand and lead time uncertainty management were analyzed, and statistical demand forecasting methods alongside inventory control policies were discussed. The study also presented production planning methods using linear programming.

(Pooja Kaunchi et al., 2021) proposed a hybrid combination of Convolutional Neural Networks (CNN) and LSTM methods for future product sales forecasting. The model was tested on a real-time BigMart dataset from local market shops. In the results, the maximum Accuracy rate was over 97%, and the minimum Accuracy rate was above 82%.

(Taiyu Lu, 2024) presented a sales forecasting system-based machine learning to improve businesses' market competitiveness and economic benefits. A dataset was created by processing large sales data through tasks such as data cleaning, label encoding, and outlier handling. Multiple regression models, such as RF and Extra Trees (ET), were tested, and their performances were evaluated through cross-validation. To address data imbalance, a combination of oversampling using Random Over Sampler and normalization processes was applied. The results showed that ET was the best-performing model, evaluated on the training set.

(Santiago Mejía and Jose Aguilar, 2024) proposed a system for forecasting product demand to improve inventory management efficiency. Products were clustered using an unsupervised learning approach, and a feature engineering process was applied. Demand forecasting was performed using ensemble machine learning models for each cluster, and performance was evaluated using R^2, MSE, and Mean Absolute Scaled Error metrics. The results showed that the proposed system improved demand forecasting accuracy.

(Subramani Neelakandan et al., 2023) aimed to develop deep learning algorithms for e-commerce sales forecasting. The Continuous Stochastic Fractal Search method was proposed to optimize the parameters of the Deep Learning-Modified Neural Network (DLMNN). The DLMNN model was compared with a model that does not use deep learning, and its performance was evaluated using RMSE, Mean, and Standard Deviation. The results indicated that the proposed model showed superior performance.

(Bohdan M. Pavlyshenko, 2022) introduced a deep learning approach for forecasting non-stationary time series by integrating time trend adjustment into a Neural Network (NN) model. A subnetwork block has been integrated into the NN model to account for the time trend term, which has been added to the predicted sales value. The time trend term has been calculated as the product of the predicted weight and the normalized time value.The results showed that this approach significantly improved forecasting accuracy for sales data affected by time trends.

(Kritika Swaminathan and Rakesh Venkitasubramony, 2023) provided a literature review of various demand forecasting techniques used in the fashion industry. Forecasting methods were classified into qualitative, statistical, artificial intelligence, and hybrid techniques, and challenges in demand forecasting were identified.

(Mehran Nasseri et al., 2023) explored a tree-based ensemble forecasting application using ET and LSTM networks. A dataset containing more than six years of historical demand data for over 330 products (totaling 5.2 million records) was created. Model performance was evaluated using MAPE, MAE, RMSE, and R^2, with ET outperforming the LSTM network. ET results were also compared with three other tree-based ensemble methods: XGBoost, RF, and Gradient Boosting.

(Peijian Wu et al., 2023) proposed a Nonlinear Auto Regressive (NAR) - NN model that uses smart decision-making technology to enhance demand forecasting accuracy by simulating historical sales data. The simulated results were compared with the forecasting results of the AR model, demonstrating that the NAR - NN provided more accurate forecasts.

3. Methodology

3.1. Multi-Layer Perceptron

A Artificial Neural Networks (ANN) are generally divided into two main types: recurrent (feedback) networks and feedforward networks. One of the most common types of ANN, the Multilayer Perceptron (MLP), follows a feedforward network structure. The MLP does not make assumptions regarding the data distribution, the linearity of the predictor and output functions, or the structure of the output variable. It consists of multiple layers of parallel nodes connected by weights: the independent variables are in the input layer, the processing units are in the middle (hidden) layer, and the output variables are in the output layer. For example, an MLP model may consist of an input layer with five input units, three hidden layers with 64, 32, and 16 neurons, and an output layer (Agaraoli Aravazhi, 2021).

3.2. Multi-Horizon Quantile Recurrent Forecaster

The MLP in MQRNN uses context vectors generated by the LSTM, which acts as a convolutional encoder for each prediction horizon. This technique is based on Seq2SeqC architecture and consists of three main components:

1. Encoder: It generates a feature vector that represents the input time series. Patterns in the time series are discovered and extracted using these feature vectors. The encoder is typically implemented using a Convolutional Neural Network (CNN) or a Recurrent Neural Network (RNN) with one or more layers.

2. Context Vector (Intermediate Vector): This vector, produced by the encoder to summarize the features of the input time series, is known as the context or

intermediate vector. The decoder uses this vector to make predictions representing the time series.

3. Decoder: The decoder usually consists of an RNN or a similar model with one or more layers. It takes the feature vector provided by the encoder and predicts values for subsequent time steps. The decoder can be trained to model a specific percentage or distribution of the time series and can perform these predictions using various techniques. It relies on the feature vector generated by the encoder to make value predictions for future time periods (Xiao-Yu Zhang et al., 2022).

3.3. Random Forest

Breiman's Random Forest (RF), an ensemble learning technique favored for classification, clustering, regression, and interaction detection, is particularly effective in understanding complex structures in data. A single Decision Tree (DT) is usually not an effective classifier due to high variance and bias issues. However, RF generally produces more robust models by mitigating these problems through an ensemble approach that consists of multiple trees. To create a forest, RF generates hundreds of random binary decision trees. These trees are structured using randomly selected variables at each node to perform classification and regression operations. Each tree is constructed from samples obtained through the bootstrap method; in this process, data not included in the bootstrap sample are used to calculate the Out of Bag (OOB) error rate, which evaluates the model's accuracy. In model development and classification processes, the final decision is made based on the majority vote of all trees. In RF models, the average decrease in the Gini coefficient and the average decrease in accuracy are calculated to determine variable importance. These two criteria are commonly used for variable ranking and selection in various studies. To run the RF model with optimal performance, the user can minimize the OOB error by adjusting two key parameters: the number of variables to be evaluated at each node and the total number of trees in the forest (Soyoung Park, and Jinsoo Kim, 2019).

4. Dataset Generation

The dataset was obtained from a customer of Innovance. The daily sales data for two different products, A and B, from January 1, 2023, to August 25, 2024, were created. The attributes and descriptions of the datasets are listed in ▶**Table 1**.

5. Development of Forecast Models

In this study, the demand forecast models were developed for products A and B in the FMCG sector. The models were developed using MLP, MQRNN, and RF for the months of July and August. The best value of hyperparameters was found with grid search.The hyperparameter ranges used as a basis for developing prediction models are given in ▶**Table 2**.

Table 1. Attributes in the datasets

Attribute Name	Description
Quantity	Quantity of the products sold
Year	Year
Month	Month
Quarter	Quarter of the year
Specialday	Special days of the year
Price	Product prices during the sales period
Campaign_Status	Campaign status during the sales period
USD_Open	USD opening value
USD_High	Highest value of USD
USD_Low	Lowest value of USD
USD_Close	USD closing value
EURO_Open	Euro opening value
EURO_High	Highest value of Euro
EURO_Low	Lowest value of Euro
EURO_Close	Euro closing value
BIST_Open	BIST opening value
BIST_High	Highest value of BIST
BIST_Low	Lowest value of BIST
BIST_Close	BIST closing value

Table 2. Hyperparameter ranges

Method	Hyperparameter Range
MLP	"Percentage_Of_Rows_In_Train_Set": [70 - 95] "Lag_Options": [1 - 9] "Number_Of_Hidden_Layer": [1, 2] "Neurons_In_1_Layer": [15 - 64] "Neurons_In_2_Layer": [16 - 128] "Epoch": [100, 120] Batch_Size": [32, 64] "Learning_Rate": [0.001, 0.002]
MQRNN	"Percentage_Of_Rows_In_Train_Set": [70 - 100] "Lag_Options": [1 - 9] "Number_Of_Hidden_Layer": [1, 2] "Neurons_In_1_Layer": [16 - 128] "Neurons_In_2_Layer": [64, 128] "Epoch": [100] Batch_Size": [16, 64] "Learning_Rate": [0.001- 0.007]
RF	"Percentage_Of_Rows_In_Train_Set": [70 - 100] "Lookback_Value": [4, 8] "Seasonal_Period": [2, 4] "Seasonal_Value": [4] "N_Estimators": [75 - 150] "Max_Depth": [5 - 15] "Min_Samples_Split": [2, 3] "Min_Samples_Leaf": [1, 3]

6. Results and Discussion

The graphs comparing the real and forecasted values of the models developed using MLP, MQRNN, and RF for two different products in July and August are presented in ▶**Figures 1-12**.

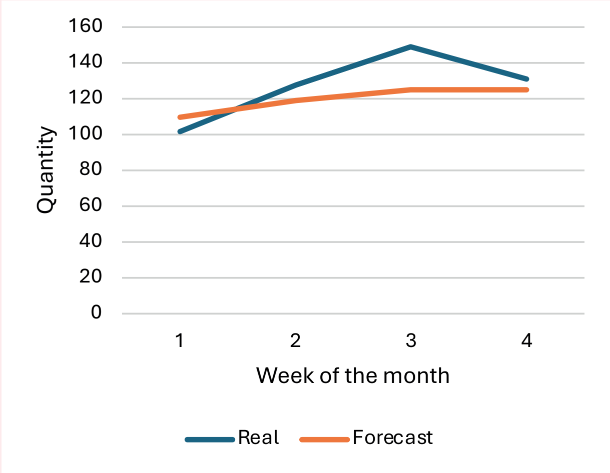

Figure 1. Real and forecasted values for product A using MLP in July

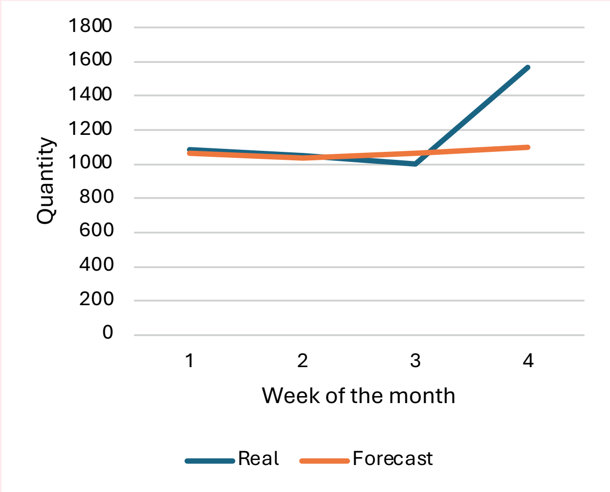

Figure 2. Real and forecasted values for product B using MLP in July

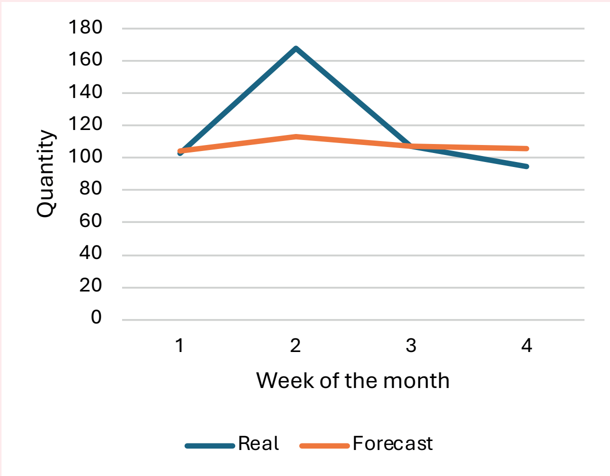

Figure 3. Real and forecasted values for product A using MLP in August

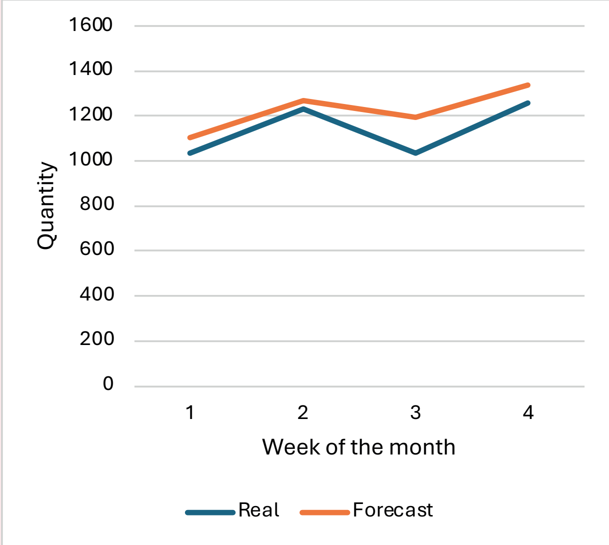

Figure 4. Real and forecasted values for product B using MLP in August

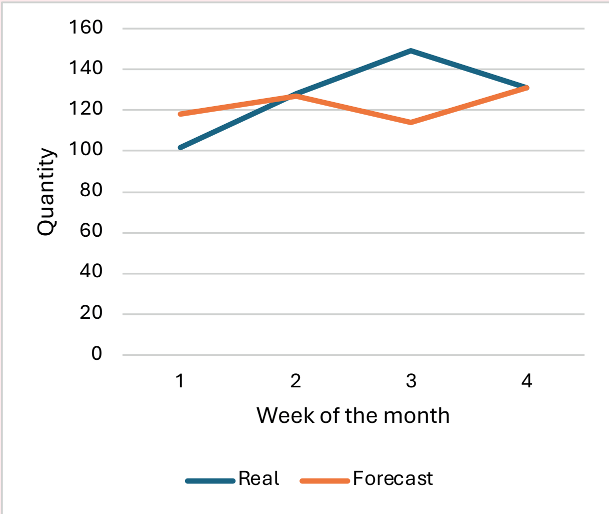

Figure 5. Real and forecasted values for product A using MQRNN in July

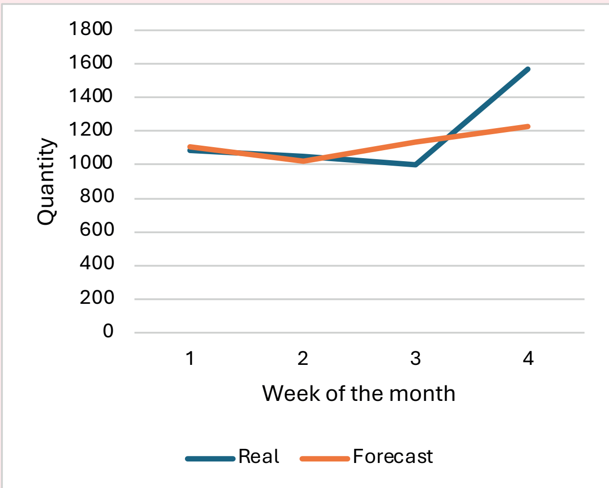

Figure 6. Real and forecasted values for product B using MQRNN in July

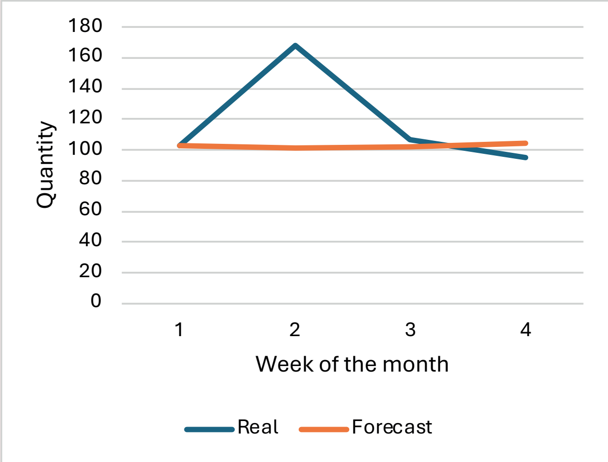

Figure 7. Real and forecasted values for product A using MQRNN in August

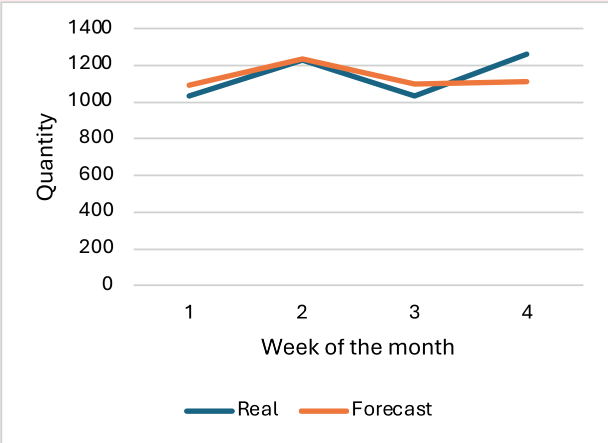

Figure 8. Real and forecasted values for product B using MQRNN in August

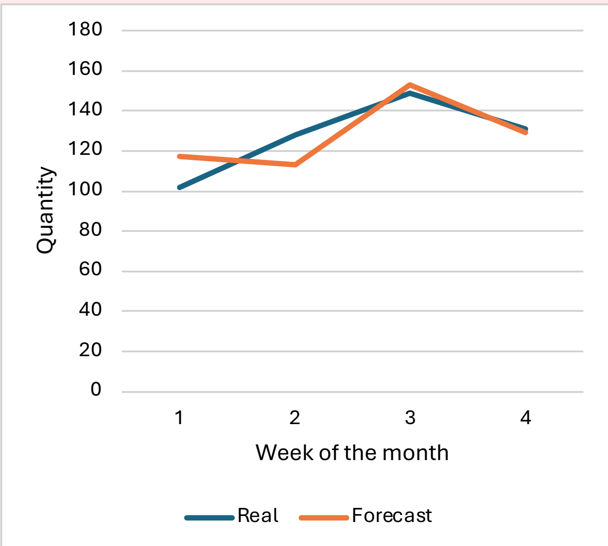

Figure 9. Real and forecasted values for product A using RF in July

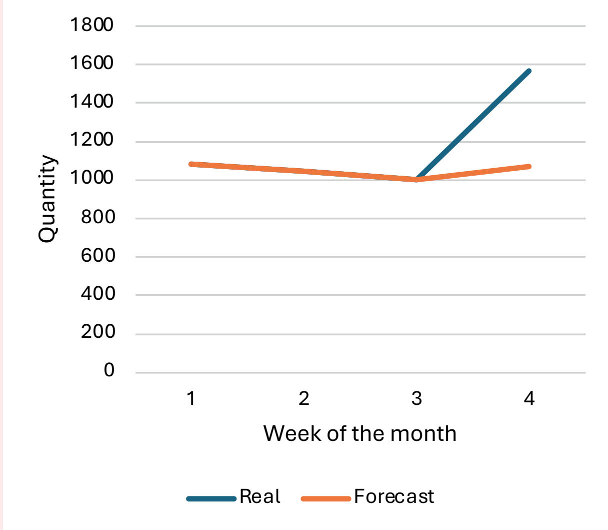

Figure 10. Real and forecasted values for product B using RF in July

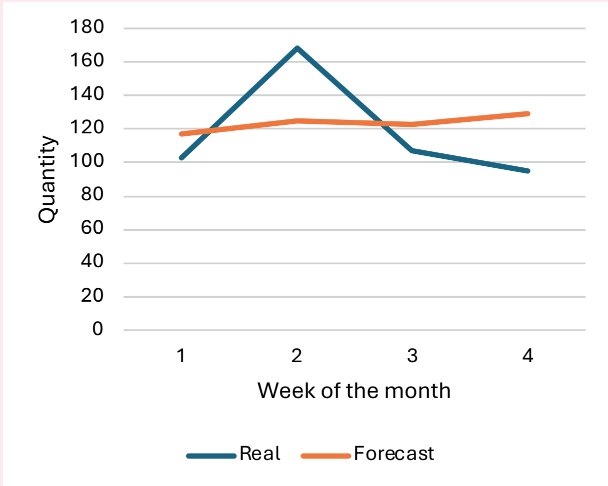

Figure 11. Real and forecasted values for product A using RF in August

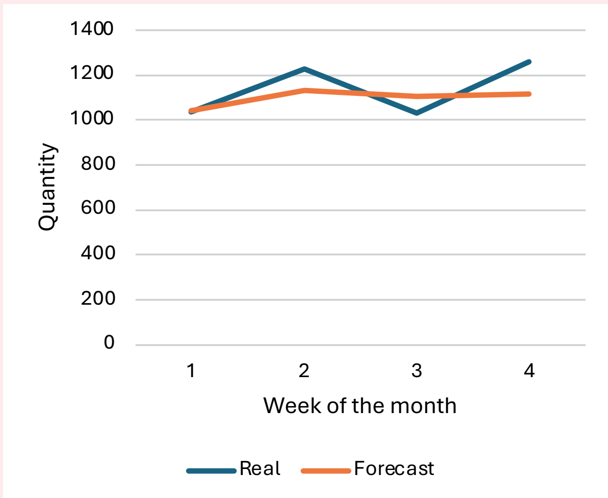

Figure 12. Real and forecasted values for product B using RF in August

MAPE is an error metric used to evaluate the accuracy of forecast models and is defined as the mean absolute percentage error. Since the problem is a regression problem, the MAPE metric was chosen as the error metric. The MAPE values of the models developed for the month of July are presented in ▶**Table 3**, while the MAPE values of the models developed for the month of August are shown in ▶**Table 4**.

Table 3. The MAPE values of the models developed for July

Algorithms	MAPE (%)	
	Product A	Product B
MLP	8.89	9.83
MQRNN	9.99	9.96
RF	7.66	8.22

Table 4. The MAPE values of the models developed for August

Algorithms	MAPE (%)	
	Product A	Product B
MLP	11.32	7.78
MQRNN	13.51	5.9
RF	22.48	6.65

The results allow for the following discussions to be made:

- The model developed using MLP in July produced successful results for Product A, however had a higher error rate for Product B.
- The model developed with MQRNN provided similar MAPE values for both Products A and B, also exhibited higher error rates compared to the other models for both products.
- The RF model yielded the lowest error rates, with a MAPE value of (7.66) for Product A and (8.22) for Product B, indicating that RF showed the best performance for both products in July.
- Among the models developed in August, the most successful prediction performance for Product A has been achieved with the MLP model.
- The MQRNN model recorded the highest error rate (13.51) for Product A, however stood out as the most successful model for Product B, with the lowest MAPE value (5.9).
- The model developed with RF for Product A did not meet expectations in August, with a highly error rate (22.48).
- In general, RF gave the best results for both products in July. In August, MQRNN delivered the best performance for Product B however showed the worst performance for Product A.

These findings reveal that the performance of the models varies significantly depending on the time period and the product. The performance of various methodologies exhibits significant variability contingent upon specific temporal contexts. In particular, machine learning-based approaches are influenced decisively by factors such as economic fluctuations, and consumer behavior, all of which substantially impact model efficacy. Furthermore, the effectiveness of the model is contingent upon the specific product categories under examination, as the demand dynamics for one product group may differ markedly from those of another. The temporal interval within which the selected product is forecasted emerges as a critical factor that directly influences the MAPE value. Consequently, when formulating demand forecasting models, it is imperative to consider the characteristics of the product in question, the designated forecasting time frame, and the methodologies employed. Additionally, incorporating seasonal variations into the model enhances the applicability of the resultant forecasts, thereby facilitating more accurate and reliable predictions. In this context, the differing results across various products and periods underscore the importance of considering both the forecast period and the product type when selecting a model.

7. Conclusion

The e-commerce sector has undergone significant transformation due to technological advancements and shifts in consumer behavior. To gain a competitive advantage in this rapidly evolving landscape, businesses must implement a variety of strategic measures. Among these, accurate demand forecasting is crucial for enhancing customer satisfaction and optimizing operational costs. This study aims to develop machine learning-based models to forecast future product demand in the e-commerce sector. To this end, the demand forecasting models were developed using MLP, MQRNN, and RF. These models were trained on daily sales data for products A and B, spanning the months of July and August. The model performance was evaluated using the MAPE. The results indicated that the forecasting models for product B provided the most accurate predictions for August, while the models for product A exhibited the highest MAPE values. Upon further analysis, it has been observed that the MQRNN-based forecasting model for product B demonstrated the most successful performance for August, whereas models developed using RF generally yielded higher MAPE values.

Research Ethics

Not applicable.

Author Contributions

Conceptualization: [Alim Toprak Fırat, Onur Aygün, Mustafa Göğebakan, Ceren Ulus, M. Fatih Akay], Methodology: [Alim Toprak Fırat, Onur Aygün, Mustafa Göğebakan, Ceren Ulus, M. Fatih Akay], Formal Analysis: [Alim Toprak Fırat, Onur Aygün, Mustafa Göğebakan, Ceren Ulus, M. Fatih Akay], In-

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Competing Interests

The authors states no conflict of interest.

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Data Availability

Not applicable.

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