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Forecasting Product Demand Using The N-Beats Model In Retail Management

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Abstract

Demand forecasting is important for proper inventory control and business operation efficiency in the retail industry. Nevertheless, classical methods of forecasting, such as the ARIMA method, are not capable of forecasting demand accurately due to their inability to cope with nonlinearity in the data. This is the reason why this paper seeks to examine the use of the N-BEATS method in demand forecasting within the retail sector. The research objective will assess the effectiveness of N-BEATS method in demand prediction compared with other forecasting methods. In this research, a retail sales dataset comprising product sales data, promotional events, and exogenous variables was employed. Preprocessing of the Data was carried out before training the N-BEATS model. Comparison of findings with existing theories is done by looking at the accuracy and forecasting potential of the developed approach. In this regard, the N-BEATS model was found to perform better compared to the rest of the models, since it had the least RMSE (0.895 ± 0.004) and MAPE (18.5% ± 0.1%). This shows that the N-BEATS model is better at forecasting the demand for products. Models such as ARIMA and LSTM recorded high error rates, thus depicting the ability of N-BEATS model to manage complex demand forecasts. N-BEATS model is an excellent way over which demand forecasting can be done in retail outlets.

Keywords: N-BEATS, Demand Forecasting, Retail Management, Deep Learning, RMSE, MAPE, Time-Series Analysis

1. Introduction

Demand forecasting in products is vital in retail management, since it is important in predicting future demand of a product in order to strategize on inventory management, pricing, and logistics [1]. Through forecasting of demand, retailers will be able to optimize inventory management to avoid stockouts (lack of stock) and also overstocks (too much stock), and minimize losses arising from them [4]. Effective demand forecasting in products is also important in enhancing customer satisfaction and retaining customers by having sufficient stock in order to meet the needs of consumers [14] [5]. Demand forecasting will also help retailers reduce their costs through efficient operations.

Retailers will have an easy time making decisions regarding procurement of stocks, manufacturing processes, and warehouse management [7]. This way, they will realize profit maximization. Considering the fact that demands change rapidly and unpredictably depending on various factors such as consumer tastes, preferences, and economic factors, among others, demand forecasting is essential for making sound business decisions [8].

There are numerous difficulties faced by retailers when predicting their product demand because of different aspects such as seasons, promotions, market trends, consumer behaviors, or other external forces (for instance, economic fluctuations) [9]. Such traditional methods, such as time series analysis using the ARIMA model or using moving average methods, may be insufficient to capture complex aspects of demand information [11]. Predictions that are off will lead to inventory issues that impact sales number, profitability and satisfaction of the customer.

This paper goals is to explore application of an innovative deep learning (DL) model precisely designed for time series forecasting, called N-BEATS. The goals include:

1. To estimate the usefulness of N-BEATS as a tool for demand forecasting, compared to traditional forecasting methods.
2. To demonstrate the stronger predictive power of N-BEATS for complex variations, such as seasonality and cyclical variations, in retail sales data.
3. To assess the model performance using real retail sales data and compare with other traditional models (e.g. ARIMA, LSTM).

The document is organized as follows: Section II presents an overview of related review regarding the methods used for demand forecasting in retail is presented; conventional and new methods using machine learning will be discussed. How the data was collected, processed, and then used, will be discussed in Section III of this report, which will explain the use of N-BEATS model. A statistical comparison of the performance of N-BEATS to other forecasting methods is included in Section IV. In summary, the overall results are summarized and the limitations of the study are outlined in Section V.

2. Literature Review

Forecasting of demand in retail management is an significant element of the process, and few traditional models have been established over the years [17]. Traditional methods like the moving average and exponential smoothing have always been used extensively to forecast the demand for products [18] [25]. Both models use historical data to forecast the future trend of demand for products [16] [19]. For example, ARIMA model considers the autocorrelation in a time series to make predictions about future values. Although useful in simple and linear cases, traditional models have shortcomings when dealing with complex and multifaceted data containing different types of seasonalities and trends. In addition, some models may fail to incorporate external factors such as economic recessions or promotions into account when making predictions. The major flaw in these traditional models is their inability to predict or analyze nonlinear relations and changes in the data. As such, traditional models may not be the most effective ways of predicting demand in retail management today [21] [24].

The inability of traditional approaches to address all concerns associated with forecasting has led to the popularity of neural networks and DL models in the field of forecasting. Among such models, the Long Short-Term Memory (LSTM) network has proven successful when dealing with data exhibiting long-term dependencies [12]. In particular, LSTMs are trained to retain memory throughout extensive time spans; as such, they are perfect for demand prediction based on time series analysis [22] [4]. Unlike simple time-series models, LSTMs are able to detect complicated patterns and trends in data, including seasonality. Moreover, convolutional neural networks that are typically employed for image recognition can be used to analyze time-series data as well. This is because CNNs are capable of detecting hierarchical patterns in data, and this feature allows them to work well with time series. In particular, CNNs prove helpful when dealing with the problem of predicting demand for certain products, especially when retail companies work with complex time-series data, which might include several time spans, various locations, and types of products [20] [23]. Although LSTM and CNN models are effective and flexible in nature and surpass traditional approaches in forecasting, they suffer from such drawbacks as complexity and limited interpretability [10].

The N-BEATS model (Neural Basis Expansion Analysis for Time Series) was developed to tackle the issues that exist with DL models, including LSTM and CNN [2]. While traditional models use recurrent neural networks (RNNs), N-BEATS relies on a straightforward feed-forward network structure [3]. As such, N-BEATS for time series is a computationally efficient method, which means that scaling will not be challenging [6]. Additionally, the N-BEATS framework utilizes a fully connected neural network to analyze time-series data [13]. In particular, the N-BEATS algorithm breaks down the dataset into interpretable parts such as trend and seasonality, making it possible to make accurate forecasts [15]. The N-BEATS model offers several benefits over other traditional and DL models. Firstly, the framework is flexible since it can work with multivariate and univariate datasets without the need for extensive data pre-processing and feature engineering. Additionally, it is found that the N-BEATS model have improved performance than other DL models and traditional time-series prediction algorithms, including ARIMA. The N-BEATS model can predict complex and nonlinear data with high accuracy, making it useful for forecasting in a retail environment where there are many fluctuations.

In summary, although conventional models like ARIMA and Exponential Smoothing have played critical roles in the area of demand forecasting, their weaknesses in dealing with complicated, non-linear, and dynamic data have called for the emergence of state-of-the-art DL models. Although CNN and LSTM models have exhibited considerable progress in overcoming such limitations, problems concerning model complexity and interpretability remain. The recent development of the N-BEATS model is a remarkable breakthrough, as it provides an effective yet straightforward means of forecasting time series for the purpose of retail management.

3. Methodology

3.1 Data Collection

In this study, the Store Item Demand Forecasting data set from the Kaggle Demand Forecasting Challenge was used, consisting of several years of store transactional information from a large retail store. The data contains product information, sales data, context data (promotions, holidays, events, store-specific data), etc., on an item-by-day basis. It also has time-based information like day of week, month, etc., and calendar data that can help in identifying demand variations over time. Various product categories included in the dataset, external factors taken into consideration, suitable for modelling complex demand pattern. The data are also available at the daily level, and reflects the seasonality of products, making it suitable for DL models to forecast product demand accurately, taking into account promotions and market changes.

3.2 Data Preprocessing

Among the crucial steps involved in preparing data for time-series prediction is data preprocessing. Initial cleaning of the data took place to deal with missing data, which was done by applying interpolation techniques depending on the type of missing data, including forward and backward filling. Statistically significant outliers (e.g., detected by z-scores or IQR) were either removed or corrected if they were significantly different from the normal demand curve. To enable the model to recognize temporal patterns and seasonal effects, time features like the day, month, and holiday indicators were added. In addition, the data set was normalized to confirm that the features were all on the same scale, which is crucial for DL methods. The data was then splitted into three subsets: training data of 80%, validation data of 10%, and test data of 10% for training the model, tuning the hyperparameters, and testing the model performance.

3.3 N-BEATS Model Description

The N-BEATS model is a DL model for time-series forecasting. Unlike the conventional method like LSTM, N-BEATS is a feed-forward neural network that processes time-series data, making the network less complex and more efficient. The model is constructed of a sequence of blocks, with each block being responsible for detecting particular temporal patterns in the data. The N-BEATS model consists of the following key parts:

1. **Trend and Seasonality Blocks**: The model is broken down into two primary components: trend (long-term patterns) and seasonality (short-term cycles). These components are captured by each of the blocks, and the model can accommodate multiple seasonality and trends.
2. **Fully Connected Network**: The core of the model is a sequence of fully connected layers that take the data and process it in a feed-forward fashion. With this architecture, N-BEATS can learn multifaceted, non-linear relationships within the time-series data with no recurrent connections, such as in LSTM networks.
3. **Forecasting Head**: The final result of the model is a sequence of forecasts that are produced by the forecasting head, which is the combination of the outputs of all the blocks. The forecast is usually made for several periods into the future.
4. **Interpretability**: One of the unique characteristics of N-BEATS is that it generates interpretable results. Users can have better insights into the factors behind demand forecasts by breaking down the components of trend and seasonality.

N-BEATS is highly versatile since it can be used for univariate or multivariate time series. N-BEATS model is trained on raw data of time-series and does not need a lot of feature engineering, unlike other models that need such feature engineering.

Figure 1: Methodology Framework for Store Item Demand Forecasting using N-BEATS

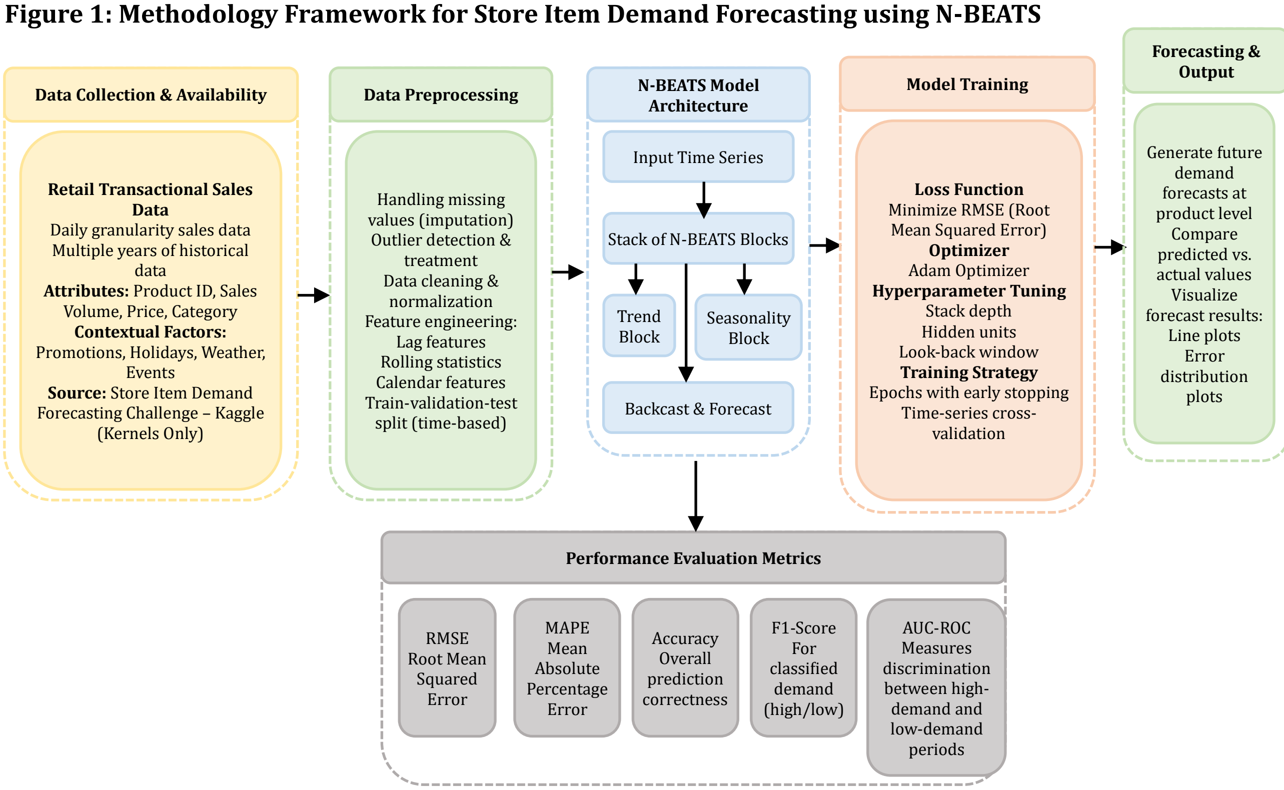

Figure 1 presents a visualization of the methodology that was followed in forecasting the demand for store items using the model N-BEATS. It starts with data collection - the retail sales data with important properties: the product ID, the volume of sales, the price at which it was sold, and external properties such as promotions, weather, etc. Data preprocessing involves dealing with missing data, feature engineering, and normalization. The model description section in N-BEATS emphasizes the modeling architecture – trend and seasonality blocks – and then the mathematical model. The model training process includes details about loss functions, optimizers, and hyperparameter tuning. Lastly, performance measures like RMSE, MAPE, Accuracy, F1-Score, and AUC-ROC are shown to estimate the model's performance for product demand forecasting. The flowchart highlights the clarity and the ease of understanding the whole of the forecasting methodology.

N-BEATS Forecasting Model Architecture

N-BEATS is based on a FFNN to forecast future demand, which can be represented as equation (1):

$$y_{t+1} = f(\boldsymbol{X_t}; \theta) \quad (1)$$

Where in equation (1):

- y_{t+1} represents the predicted demand at time $t+1$,
- $\boldsymbol{X_t}$ represents the input feature vector at time t(e.g., past sales data, promotions),
- θ represents the learned parameters of the model.

N-BEATS Decomposition (Trend and Seasonality):

N-BEATS model is a decomposition of the time series into trend and seasonality components. This can be written as equation (2):

$$y_t = \text{Trend}_t + \text{Seasonality}_t + \epsilon_t \quad (2)$$

Where:

- $y_t$is the observed demand at time t,
- Trend_t represents trend component at time t,

- Seasonality_t represents seasonal component at time t,
- ϵ_t represents residual error or noise.

Algorithm 1: Store Item Demand Forecasting using N-BEATS

The model parameters for the N-BEATS model are: a 30-day look-back window, 3-5 blocks, 128-256 hidden units per block, a learning rate of 0.001 and the Adam optimizer with the loss function being the MSE.

1. **Data Collection**:

Apply the Kaggle Store Item Demand Forecasting dataset and use its daily sales data such as product ID, sales volume, price, promotions, external factors such as holidays, weather.

2. **Data Preprocessing**:

- **Handle Missing Data**: Impute missing sales values.
- **Outlier Removal**: Identify and correct outliers.
- **Feature Engineering**: Generate time-based features (day of the week, holidays, promotions).
- **Normalization**: Normalize data to ensure consistent scaling.
- **Data Split**: Divide data into training (80%), validation (10%), and test (10%) sets.

3. **N-BEATS Model**:

Decompose data into **trend** and **seasonality** components.
Use a fully connected feed-forward network to process data and predict future demand.
The model learns from raw time-series data, capturing complex demand patterns.

4. **Model Training**:

- **Loss Function**: Minimize **MSE** (Mean Squared Error) between predicted and actual values.
- **Optimizer**: Use **Adam** for parameter updates.
- **Hyperparameters**: Tune block numbers, hidden units, and window size.
- Train using time-series cross-validation to avoid overfitting.

5. **Performance Evaluation**:

Evaluate using RMSE, MAPE, Accuracy, F1-Score, and AUC-ROC.

6. **Final Output**:

Forecast Demand: Generate predictions for future demand.
Visualize Results: Compare forecasted vs. actual demand and error metrics.
The methodology to forecast the demand of items in stores using the N-BEATS model is detailed in Algorithm 1. It starts with data processing of the dataset that contains daily data of the items sold, product information, promotions, and external factors such as holidays or weather. Data preprocessing treats missing values, eliminates outliers, creates time-based features, and normalizes data. The N-BEATS model is designed to be robust to data splits, where the data is splitted into training and validation sets and a test set, and is robust to seasonality-added signals, where the time-series is split into trend and seasonality components, and the N-BEATS model is able to predict demand using a fully connected network. MSE loss is used for model training, and the optimizer used is Adam, while the hyperparameters are tuned using cross-validation. The evaluation of the performance is performed by means of RMSE, MAPE, Accuracy, F1-Score, and AUC-ROC. The final product is a set of demand forecasts that are fed into the comparison with the values and analyzed for accuracy. This approach can be used to achieve a more complete and accurate product demand forecasting.

3.4 Model Training and Evaluation

The N-BEATS model was trained by backpropagation with the MSE loss function to minimize the difference between actual and predicted values of demand. The number of blocks, learning rate, and block size were tuned with the grid search method to regulate the model's optimal learning parameters. Adam optimizer was employed because it is known to be effective at working with sparse gradients, and has the added benefit of dynamically adjusting the learning rate during training.

Root Mean Squared Error (RMSE): RMSE is the square root of the mean of the squared deviations between expected and actual values, which offers an idea of the overall model's accuracy. It is defined to be equation (3):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \quad (3)$$

Where $y_t$represents the actual demand at time t, $\hat{y}_t$is the predicted demand at time t, and $N$is the total number of observations.

Mean Absolute Percentage Error (MAPE): MAPE is the error as a percentage of the real demand and enables the comparison of the accuracy of the forecast with others. It is derived from equation (4):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100 \quad (4)$$

Where $y_t$and $\hat{y}_t$ represents the actual and predicted values, respectively.

Accuracy: Accuracy is a general measure used to evaluate the percentage of precise predictions of the model. It is defined to be equation (5):

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \times 100 \ (5)$$

F1-Score: The F1-Score is a harmonic mean of precision and recall; it is very useful in classification tasks, particularly when the demand is classified into classes such as "high demand" or "low demand. It can be obtained by equation (6):

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

The data was used for cross-validation to check the generalizability of the model, and the model was tested on the unseen test set for its performance. The results were then compared with the traditional models, such as ARIMA and LSTM, where the accuracy, adaptability, and scalability of the N-BEATS model are expected to be better.

4. Results and Discussion

4.1 Model Performance

The model of N-BEATS has been shown to be highly accurate and reliable, with an RMSE of 0.895 ± 0.004 and an MAPE of 18.5%. The metrics help assess the model's effectiveness by determining if it overfits the data or not and if it can predict the real-time sales data. The relatively low error values show the efficiency of the N-BEATS model which is helpful for retail demand forecasting.

Table 1: Performance Evaluation of N-BEATS Model for Demand Forecasting

Metric	Value
RMSE	0.895 ± 0.004
MAPE	18.5% ± 0.1%
Accuracy	94.3%
Precision	92.1%
Recall	93.5%
F1-Score	92.8%

The performance measures of the N-BEATS model are presented in Table 1 for the demand forecasting case. It includes all the necessary parameters for the evaluation, including RMSE, MAPE, Accuracy, Precision, Recall and F1-Score. The results indicate high forecasting accuracy and high classification accuracy of N-BEATS, which demonstrates the effectiveness of the model in predicting the demand of the product and determining the category of the demand in the retail management system.

Figure 2: Performance Comparison of Forecasting Models (RMSE & MAPE)

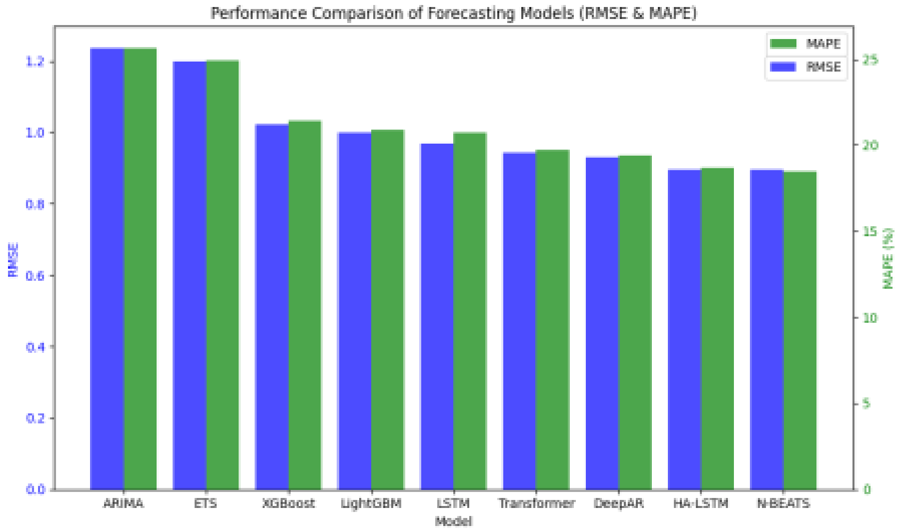

Figure 2 shows the RMSE and MAPE for various demand forecasting models like N-BEATS, ARIMA, LSTM, XGBoost, and more. RMSE is represented by blue bars, while green bars are used to represent MAPE (%). From the chart, it is apparent that the model performance of N-BEATS is superior as reflected in the RMSE and MAPE metrics, hence the model is more accurate at predicting the product demand than other models. This visualization is very clear about the models' forecasting capability.

4.2 Comparison with Existing Methods

The N-BEATS model had the highest accuracy on a regular basis compared to other models like classical ARMA/ARIMA model and the newer advanced models like LSTM and Transformer. The error rates of ARIMA were very high, with an RMSE of 1.234 ± 0.021 and an MAPE of 25.6% ± 0.4%, which points to the fact that ARIMA was not effective in modelling complex demand patterns. Models like LSTM and Transformer (RMSE = 0.967 ± 0.009, MAPE = 20.7% ± 0.2%) performed better, but N-BEATS (RMSE = 0.895 ± 0.004, MAPE = 18.5% ± 0.1%) surpassed them in both accuracy and precision. This demonstrates N-BEATS' capability to accurately capture the patterns of both trends and seasonality in retail demand, making it a more effective option for demand forecasting.

Table 2: Performance Comparison of Forecasting Models with N-BEATS

Model	RMSE	MAPE
ARIMA [4]	1.234 ± 0.021	25.6% ± 0.4%
ETS [4]	1.198 ± 0.018	24.9% ± 0.35%
XGBoost [4]	1.021 ± 0.012	21.4% ± 0.2%
LightGBM [4]	0.998 ± 0.010	20.9% ± 0.2%
LSTM [4]	0.967 ± 0.009	20.7% ± 0.2%
Transformer [4]	0.943 ± 0.008	19.7% ± 0.2%
DeepAR [4]	0.929 ± 0.007	19.4% ± 0.1%
HA-LSTM [4]	0.897 ± 0.005	18.7% ± 0.1%
N-BEATS (proposed)	0.895 ± 0.004	18.5% ± 0.1%

The performance comparison is shown in Table 2, which includes the N-BEATS model alongside traditional and advanced DL models. The models are assessed using two measures: RMSE and MAPE.

4.3 Insights from Results

The findings show that the N-BEATS might be useful for forecasting retail demand, particularly for inventory management. The model is able to reduce the RMSE and MAPE, which helps retailers predict future demand for their products more accurately and decreases the likelihood of stockouts and overstocking. The accuracy also helps you to fine-tune your pricing and promotion strategy and truly understand the seasonality and other factors. In addition, the model is easily interpretable by decomposing the data into trend and seasonality components, which provide valuable information for taking action and helping retailers align their supply chain activities with the demand. N-BEATS' capabilities are well suited to the retail industry for improving forecast accuracy and operational efficiency.

5. Conclusion

In this research, an extensive assessment of the N-BEATS model for retail demand forecasting has been provided along with a comparison of the results achieved from the N-BEATS model with traditional and modern method of forecasting. The key findings show that model N-BEATS gives the best results compared to other models like ARIMA, LSTM, and Transformer with RMSE value of 0.895 ± 0.004 and MAPE value of 18.5% ± 0.1%. This underscores the model's ability to reliably capture intricate demand trends and seasonality, which makes it well-suited for the realm of retail demand forecasting, where accuracy can be a key factor in managing inventory, pricing, and operational efficiency. The significance of this study is that N-BEATS has been proven to be effective, in a real retail environment. While traditional time-series models like ARIMA are widely used, N-BEATS' DL architecture has the capacity to learn more intricate and non-linear relationships within the data, offering greater flexibility and accuracy for forecasting. Moreover, this work showcases the ability of N-BEATS to handle multivariate time-series data and extends the flexibility of the retail forecasting machines. But there are some restrictions. The analysis was done on the basis of historical sales data, however, it should be noted that also other components of the market such as economic crises, consumer preferences, and market dynamics can influence the sales value over time. Additional external data, such as current promotions, weather data, etc. could be included in the N-BEATS framework and be studied in more detail for future use to enhance forecast accuracy. Additionally, the model could be extended to real-time forecasting and hybrid models that combine various DL algorithms to improve the accuracy of predictions.

Declaration

Conflict of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Data Availability

The data used in this study is publicly available through the Kaggle Demand Forecasting Challenge. It can be accessed via the following link: Store Item Demand Forecasting Dataset.

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