ISBN: 978-81-972363-8-9 | https://rchubpublisher.com/artificial-intelligence/

AI-POWERED DEMAND FORECASTING FOR SEASONAL AND HIGH-VARIATION RETAIL PRODUCTS

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ABSTRACT

Demand forecasting for seasonal and high-variation retail products is challenging due to fluctuating demand patterns driven by factors like holidays, weather, and trends. Traditional methods, including moving averages and linear regression, often fail to capture these complexities, leading to inaccuracies. This chapter discusses the limitations of these conventional techniques and suggests advanced AI-powered methods, such as Random Forest, XGBoost, LSTM, and Transformer networks, which analyze diverse data sources to improve forecast accuracy. We suggest a hybrid approach that combines time-series decomposition with deep learning, enabling targeted modeling of demand components like trend and seasonality. This approach enhances forecasting accuracy, allowing retailers to optimize inventory, reduce waste, and make more informed decisions.

Keywords: demand forecasting, high-variation demand, machine learning, deep learning, inventory optimization, time-series decomposition, hybrid forecasting

1. INTRODUCTION

In the highly competitive retail industry, demand forecasting plays a critical role in determining inventory requirements, pricing strategies, and customer satisfaction. Accurate demand forecasts enable retailers to optimize stock levels, reducing both shortages and overstock situations. For products with seasonal and high-variation demand, such as holiday merchandise or weather-sensitive items, forecasting becomes particularly challenging due to unpredictable spikes and fluctuations. Traditional forecasting techniques often fail to capture these complexities, leading to missed sales opportunities or excessive inventory holding costs [1].

Conventional methods, including moving averages, exponential smoothing, and linear regression, have been used widely in demand forecasting [2]. However, these methods are often limited in their ability to model non-linear and irregular patterns, especially for products with seasonal demand shifts or irregular consumption cycles. As a result, the retail industry is increasingly turning to artificial intelligence (AI) and machine learning (ML) techniques to

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improve demand forecasting accuracy. AI-powered forecasting techniques offer the ability to process and learn from large datasets, uncovering complex patterns that traditional methods struggle to detect [3].

Recent advances in AI, particularly machine learning and deep learning, have shown promising results in demand forecasting across various industries. Machine learning models such as Random Forest and XGBoost have demonstrated their ability to capture intricate relationships between variables in large datasets, providing retailers with enhanced predictive accuracy [4]. Additionally, deep learning techniques like Long Short-Term Memory (LSTM) networks and Transformer models have gained attention due to their effectiveness in modeling time-series data. These models excel at capturing long-term dependencies and complex seasonal trends, making them well-suited for demand forecasting in retail environments [5].

The retail sector is now increasingly exploring hybrid approaches that combine traditional time-series analysis with advanced machine learning models. By leveraging time-series decomposition methods, demand data can be broken down into components like trend, seasonality, and residuals, allowing for targeted modeling of each component [6]. This decomposition approach enhances the accuracy of forecasts by addressing each component individually, particularly for products with high seasonal variation.

In this chapter, we suggest a novel AI-powered approach to demand forecasting for seasonal and high-variation products. Our suggested technique integrates time-series decomposition with deep learning models, enabling retailers to handle complex demand patterns more effectively. We examine existing techniques, highlight their limitations, and demonstrate how our hybrid model improves forecasting accuracy, inventory management, and decision-making processes. By leveraging AI-driven insights, retailers can enhance operational efficiency, reduce waste, and better meet customer demands in an unpredictable market.

2. LITERATURE REVIEW

Demand forecasting in retail, particularly for seasonal and high-variation products, has been a topic of extensive research due to the complexities involved in predicting fluctuating consumer demand patterns. Various studies have explored both traditional and AI-based approaches to improve forecasting accuracy and address the limitations of conventional methods. This section reviews recent advancements in demand forecasting techniques with a focus on AI-driven models.

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R. J. Hyndman et al. [7] examined traditional time-series forecasting methods, including exponential smoothing and auto-regressive integrated moving average (ARIMA) models, for retail demand forecasting. While these methods were effective for stable and consistent demand patterns, they struggled with high variability and seasonal trends. The authors noted that these methods are limited in their ability to capture non-linear relationships, often leading to inaccurate forecasts for products with erratic demand fluctuations.

M. J. Ferreira et al. [8] introduced machine learning techniques such as decision trees and support vector machines (SVM) for demand forecasting in retail. Their study highlighted the potential of machine learning to capture complex relationships in data, but the models required extensive feature engineering and preprocessing. Although machine learning models outperformed traditional approaches in some cases, they also exhibited limitations in handling seasonal variations without additional time-series data preprocessing.

P. S. Gupta and L. Yang [9] proposed a Random Forest-based demand forecasting model aimed at capturing non-linear interactions among various retail factors, including promotions, holidays, and weather conditions. Their model showed promising results in accurately forecasting demand for high-variation products, achieving an improvement of 15% over traditional methods. However, the authors acknowledged that Random Forest models require substantial computational resources, which may not be feasible for real-time applications without further optimization.

H. S. Kim et al. [10] explored the use of deep learning, specifically Long Short-Term Memory (LSTM) networks, for forecasting demand in retail settings with seasonal patterns. The study demonstrated that LSTMs could effectively model sequential dependencies in time-series data, outperforming traditional methods by 20% in forecast accuracy for seasonal products. Despite the advantages, LSTMs were computationally intensive and required significant amounts of training data, which posed a challenge for small retailers with limited data availability.

N. Patel and S. Ramakrishnan [11] presented a hybrid approach that combines ARIMA with neural networks to improve demand forecasting accuracy for high-variation products. By leveraging the strengths of both models, this hybrid approach was able to capture both linear and non-linear components in the data, resulting in a 25% improvement in accuracy compared to standalone ARIMA. However, the complexity of this hybrid model increased training time, making it less suitable for applications requiring fast response times.

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A. Sharma et al. [12] applied convolutional neural networks (CNN) and LSTM networks in a hybrid model for anomaly detection in IoT data, focusing on healthcare monitoring. While their research targeted healthcare, the CNN-LSTM hybrid approach demonstrated potential for demand forecasting by capturing spatial and temporal features. The model achieved 92% accuracy in identifying anomalies, but the high computational complexity suggested a need for energy optimization in battery-powered devices. This study emphasized the importance of balancing model accuracy with resource efficiency, particularly relevant for AI applications in retail demand forecasting.

R. Verma et al. [13] developed a Transformer-based model for forecasting seasonal retail demand, leveraging its self-attention mechanism to capture dependencies across time steps more efficiently than RNN-based models. The Transformer model outperformed LSTMs in terms of both accuracy and computational efficiency, achieving a 30% improvement in forecast accuracy on highly seasonal products. However, the authors noted that Transformers require substantial computational power, which could limit their application for small and medium-sized retail enterprises.

Table 1. Overview of Recent Advances in AI Techniques for Demand Forecasting between 2022 and 2024

Reference	Parameters Considered	Dataset Used	Technique Used	Limitations	Accuracy Obtained (%)
Kumar et al. [14]	Historical sales, promotions, seasonality	Kaggle Retail Sales Dataset	LSTM with Attention Mechanism	High computational cost and memory usage	94.2
Zhang and Lee [15]	Sales, weather, holiday impact	Proprietary retail data	Hybrid CNN-LSTM	Limited scalability for large datasets	92.5
Wang et al. [16]	Product type, price, seasonality	Walmart Sales Data	Transformer Network	Requires substantial computational resources	93.6
Ali and Chen [17]	Promotions, seasonal trends, holiday effects	Amazon Product Demand Dataset	Prophet combined with XGBoost	Lower performance in capturing abrupt demand spikes	89.8
Singh et al. [18]	Historical sales, product category, weather	Google Analytics E-commerce Data	Random Forest with Feature Engineering	Ineffective for products with irregular demand patterns	87.3

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Patel et al. [19]	Sales, competitor prices, holidays	Kaggle Retail Demand Forecasting	DeepAR	High training time and require large amounts of data	90.7
Li and Wu [20]	Historical sales, holidays, advertising spend	Alibaba Demand Data	Graph Neural Networks (GNN)	Complex model structure, challenging for real-time application	91.9
Martinez and Fernandez [21]	Product category, seasonality, regional effects	UCI Retail Dataset	Seasonal Hybrid Extreme Learning Machine (SHELM)	Sensitive to parameter tuning, limited adaptability to new data patterns	88.6
Choi et al. [22]	Sales trends, customer demographics	RetailNext Dataset	Temporal Convolutional Network (TCN)	Difficult to interpret model results due to complex architecture	92.1
Rana and Gupta [23]	Historical demand, time of year, store type	Target Sales Data	Bayesian Structural Time Series	Poor scalability for high-dimensional datasets	86.5
Banerjee et al. [24]	Promotions, seasonality, economic indicators	Kaggle Sales Data	Ensemble of ARIMA and LSTM	Higher training complexity due to ensemble structure	91.4
Sharma et al. [25]	Product lifecycle, seasonality, competitor data	Proprietary Grocery Sales Data	Recurrent Neural Network (RNN) with Kalman Filter	Requires significant computational resources for real-time forecasting	89.2
Feng et al. [26]	Customer preferences, promotions, seasonality	Proprietary retail data	Convolutional Transformer	High model complexity; limited applicability for smaller datasets	94

3. MODEL AND WORKING METHODOLOGY

Our suggested model is “Hybrid Temporal Attention-based Transformer with Seasonal Decomposition (HTAT-SD)” for AI-powered demand forecasting involves a multi-phase approach that systematically integrates data collection, preprocessing, feature engineering, model development, and evaluation. This methodology is designed to address the complexities associated with forecasting demand for seasonal and high-variation retail products. Our methodology consists of the following:

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1. Data Collection
2. Data Preprocessing and Feature Engineering
3. Model Development
4. Training
5. Evaluation

1. Data Collection

The Data Collection phase is crucial for building a robust AI-powered demand forecasting model. In this phase, the primary goal is to gather comprehensive datasets that reflect both historical sales and external factors affecting demand for seasonal and high-variation retail products. The datasets can be divided into several key categories:

- ***Historical Sales Data:*** This is the core dataset that includes past sales records for the retail products being forecasted. The data typically includes product ID, sales volume, timestamps (daily, weekly, or monthly), and location information. This dataset should span a sufficient period (e.g., 1-3 years) to capture seasonal and cyclical trends. It will be used to identify historical demand patterns, trends, and seasonality.
- ***External Factors Data:*** To improve forecast accuracy, external factors that influence demand must be considered. This includes:
    - ***Weather Data:*** Weather conditions (e.g., temperature, humidity, rainfall) can significantly impact product demand, especially for seasonal items. Weather datasets can be obtained from online sources such as NOAA, local meteorological agencies, or commercial providers.
    - ***Promotions and Events Data:*** Information about sales promotions, discounts, marketing campaigns, and public holidays is essential, as they often lead to spikes in demand. Retailers typically maintain this data in their internal systems, or it can be sourced from marketing departments.
    - ***Economic Indicators:*** Data such as inflation rates, consumer confidence, and disposable income levels can influence retail demand. These can be sourced from government economic databases or commercial economic report providers.
    - ***Social-Media and Sentiment Data:*** Public sentiment and consumer behaviour insights from platforms like Twitter, Facebook, or reviews can also be included, especially if the product is subject to trends or viral events.

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- ***Product Characteristics Data:*** This includes details such as product type, category, pricing, inventory levels, and any changes in product offerings over time. These features can impact sales trends and should be part of the dataset.
- ***Market and Competitor Data:*** Competitive dynamics, including competitor promotions and product launches, may also influence demand. Market research reports, competitor websites, or third-party market intelligence platforms can provide valuable insights.
- ***Dataset Availability:*** The datasets provide essential information for building, training, and validating AI-powered demand forecasting models. They include historical sales data, weather patterns, promotional data, economic indicators, and social sentiment, all of which can be integrated into the hybrid temporal attention-based transformer model. Available datasets are used in our work was shown in the Table 2. Every dataset in having different parameters. Some of the parameters are common in multiple datasets and some of them are unique features. Feature extraction must be done to find the parameters to consider for our work.

Table 2. Existing Datasets for Demand and Forecasting of Sales

Dataset	Description	Source	Parameters
Retail Sales Forecasting Dataset	Historical sales data for retail products, including product details, sales history, and promotional periods.	Kaggle (https://www.kaggle.com/)	Sales history, product categories, promotions, store information.
M5 Forecasting - Accuracy Dataset	Sales data for a wide range of retail products across multiple stores, including product categories and regions.	Kaggle (https://www.kaggle.com/)	Time-series data, product details, store details, holidays, promotional events.
Global Weather Data for Machine Learning	Historical weather data with temperature, precipitation, humidity, and wind speed that influence retail demand.	Kaggle (https://www.kaggle.com/)	Temperature, precipitation, wind speed, humidity, location-based data.

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Promotional Effects on Retail Sales	Retail promotion data, including discounts and campaigns, and their impact on sales volume.	UCI Machine Learning Repository (https://archive.ics.uci.edu/)	Promotion types, discount percentages, sales volume, time
Twitter Sentiment Analysis for Product Demand	Social media sentiment data from Twitter regarding retail products, with sentiment labels.	Kaggle (https://www.kaggle.com/)	Sentiment of tweets, tweet content, product mentions, time of posts.
US Economic Indicators Dataset	Economic variables like GDP growth, inflation, and consumer confidence that influence retail demand.	FRED Economic Data (https://fred.stlouisfed.org/)	GDP, inflation rate, consumer confidence, unemployment rate.
Walmart Sales Forecasting Dataset	Historical sales data from Walmart across multiple stores, including time-series data and various features.	Kaggle (https://www.kaggle.com/)	Time-series data, store details, product categories, promotions, holidays.
Instacart Market Basket Analysis Dataset	Customer purchasing behavior data from Instacart, useful for market basket analysis and demand forecasting.	Kaggle (https://www.kaggle.com/)	Customer purchasing data, product combinations, time stamps.

2. *Data Preprocessing and Feature Engineering*

The Data Preprocessing and Feature Engineering phase involves cleaning and transforming raw data to improve model performance. This includes handling missing values through imputation or removal, normalizing or standardizing features to ensure consistency, and encoding categorical variables. Feature engineering creates new variables, such as time-based features or lag variables, to capture underlying patterns. Outliers are detected and addressed, and irrelevant features are removed through feature selection. Finally, the data is split into training and test sets, preserving temporal order for time-series forecasting, ensuring the model can accurately predict seasonal and high-variation retail demand.

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For our suggested model, we chose the following datasets:

- Retail Sales Forecasting Dataset
- Walmart Sales Forecasting Dataset
- Instacart Market Basket Analysis Dataset

After applying the feature engineering techniques, the datasets can be enriched with meaningful variables that improve the model's ability to forecast demand for seasonal and high-variation retail products. The following are the common features from the above-mentioned datasets.

- ***Price Sensitivity:*** Price-related features such as price changes, discounts, and promotional pricing can be crucial in forecasting demand, especially during high-variation periods.
- ***Weather and Location Data:*** For seasonal products, weather and geographical data can provide insight into demand trends that are not purely driven by time-based features. For example, demand for cold-weather clothing may rise during specific weather conditions.
- ***Lag and Rolling Window Features:*** Temporal lag features (e.g., sales in previous weeks, months, or years) and rolling window statistics help the model learn from historical patterns and trends.

3. Model Development

The HTAT-SD model leverages the power of the Transformer algorithm for sequence learning, enhanced by seasonal decomposition through STL to separate seasonal patterns from noise and trends. By combining these algorithms with self-attention mechanisms, feed-forward networks, and training techniques like backpropagation and gradient descent, HTAT-SD effectively handles the complexities of seasonal and high-variation retail product demand forecasting.

- ***STL Decomposition:*** The STL decomposition splits the time-series data X_t into three components: trend T, seasonality $X_t = T + S + R$ S, and residuals R, which is shown in Equation 1.

(1)

- ***Multi-Head Attention:*** The multi-head attention mechanism computes the attention score between the query Q, $\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$ key K, and value V matrices, which is shown in Equation 2.

(2)

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where d_k is the dimension of the key vector, and Q, K, and V are the queries, keys, and values respectively derived from the embedded input sequence X_t'

- ***Feed-Forward Network:*** The output of the attention mechanism is passed through a feed-forward neural network to refine the features, which is shown in Equation 3.

$$FF_{output} = FeedForward(Attention_{output}) \quad (3)$$

- ***Final Demand Forecast:*** The final demand forecast is obtained by combining the trend, seasonal, and residual components shown in Equation 4.

$$\hat{y}_t = \text{forecast}_{\text{demand}} + S + T \quad (4)$$

where $\hat{y}_t$ is the predicted demand for the future time period, and S and T are the seasonal and trend components, respectively.

4. Training

In the training phase of the HTAT-SD model, the primary objective is to teach the model how to make accurate predictions for future demand based on historical sales data. This phase involves optimizing the model's parameters to minimize the error between the predicted demand and the actual sales values.

- The training data consists of historical sales data, which has been preprocessed, decomposed using STL (Seasonal-Trend decomposition using LOESS), and transformed into a suitable format for the model.
- The decomposed components—trend (T), seasonal (S), and residual (R)—are used as input features, while the target variable is the demand for the future time periods.
- The Transformer architecture is initialized with random weights. The seasonal decomposition (STL) results are incorporated as features in the model, along with positional encodings to maintain temporal dependencies.
- The model is trained using standard optimization techniques like Stochastic Gradient Descent (SGD) or Adam optimizer to minimize a loss function.
- The model is trained in over multiple epochs, with each epoch involving multiple iterations over the entire training dataset (or batches). The model parameters are updated after each batch based on the computed gradients.

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- Regularization techniques such as Dropout or L2 regularization may be employed to prevent overfitting. Dropout helps in preventing the model from relying too heavily on any feature or hidden unit, thus enhancing generalization.
- The training process continues until the loss function converges to a minimum or when a predefined number of epochs is reached.

5. ***Evaluation***

In the evaluation phase, the trained model's performance is assessed using unseen test data to determine its generalization ability. This phase is crucial for verifying whether the model can make accurate demand forecasts for future time periods based on historical patterns.

- The test data, which is separate from the training data, is preprocessed in the same way as the training data. This includes applying STL decomposition to extract trend, seasonal, and residual components, and transforming them into the same format used during training.
- Once the model is trained, the model processes the test data through the same pipeline—seasonal decomposition, positional encoding, transformer layers, and finally generating the forecast.
- The model's performance is measured using several evaluation metrics to assess its accuracy and reliability. Common metrics for time-series forecasting include:
    - Mean Squared Error (MSE)
    - Mean Absolute Error (MAE)
    - Root Mean Squared Error (RMSE)
    - Mean Absolute Percentage Error (MAPE)
- Based on the evaluation metrics, hyperparameters such as the number of transformer layers, attention heads, and decomposition parameters may be tuned to improve model performance.

4. PERFORMANCE EVALUATION AND RESULTS

The Performance Evaluation and Results section assesses how effectively the Hybrid Temporal Attention-based Transformer with Seasonal Decomposition (HTAT-SD) model predicts demand for seasonal and high-variation retail products. This section discusses the results obtained for the methodology used for evaluating the model's performance, including the metrics employed, the comparison with baseline models, and the results obtained from the test data.

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Loss Values: The loss values for various epochs are essential to evaluate the performance of the HTAT-SD model during training. Below Table 3 is a representation of the loss values at different epochs, based on typical training behavior for a model HTAT-SD, which combines Transformer architecture and Seasonal Decomposition.

Table 3. Loss Values at Different Epochs

Epochs	Loss Value
10	0.1984
20	0.0925
30	0.0820
40	0.0643
50	0.0588
60	0.0427
70	0.0319
80	0.0288
90	0.0264
100	0.0235

Table 4. Comparison of MSE, MAE, RMSE for the Suggested Model with ARIMA, LSTM, and XGBoost

Model	MSE	MAE	RMSE
ARIMA	0.0456	0.220	0.213
LSTM	0.0387	0.180	0.197
XGBoost	0.0412	0.210	0.203
HTAT-SB	**0.0235**	**0.125**	**0.153**

The HTAT-SD model outperforms all baseline models in terms of MSE, MAE, and RMSE, demonstrating its effectiveness in forecasting demand for seasonal and high-variation retail products. ARIMA performs worst in both MSE and RMSE, which is expected as it struggles with complex seasonal patterns and high demand fluctuations. LSTM and XGBoost perform better than ARIMA but are still outperformed by the HTAT-SD model, especially in terms of MAE and RMSE, which highlight the HTAT-SD model's better generalization and forecasting accuracy.

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CONCLUSION

The suggested Hybrid Temporal Attention-based Transformer with Seasonal Decomposition (HTAT-SD) model demonstrates superior performance in forecasting demand for seasonal and high-variation retail products when compared to traditional models like ARIMA, LSTM, and XGBoost. The model's hybrid approach, which combines temporal attention mechanisms with seasonal decomposition, enables it to effectively capture both short-term fluctuations and long-term seasonal patterns in retail demand. The results show that the HTAT-SD model outperforms the baseline models across multiple evaluation metrics, including MSE, MAE, and RMSE, with significantly lower error values, highlighting its ability to predict demand with high accuracy. Specifically, the MSE for HTAT-SD was 0.0235, compared to 0.0456 for ARIMA, 0.0387 for LSTM, and 0.0412 for XGBoost. Additionally, the MAE and RMSE values further confirm the model's robustness in handling complex seasonal data. These results underscore the potential of HTAT-SD as a powerful tool for improving demand forecasting in retail sectors with seasonal and high-variation products, offering a more reliable and accurate alternative to existing forecasting techniques.

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