

Original Article

# Multi-Horizon Demand Forecasting for E-Commerce Fulfillment Using Ensemble Deep Learning

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## Abstract:

Efficient inventory management and assignment of fulfillment capacity, along with labor planning is built on accurate multi-horizon demand forecasting in large-scale e-commerce businesses. This paper introduces an ensemble deep learning approach fusing Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN) and Gradient Boosted Trees (GBT) to predict the demand in various categories with different seasonality patterns, demand volatility, promotional effects, and customer purchasing behaviors across multiple horizons. Traditional statistical forecasting methods like Moving Average, ARIMA, and Exponential Smoothing may not effectively model the nonlinear dependencies, rapid changes in demand, and intricate temporal dynamics often seen in today's e-commerce landscape. Advanced AI and deep learning techniques have thus become a promising alternative to enhance the accuracy of forecasts. Proposed framework combines the strength of LSTM network to model the sequence, TCN for extracting long-range temporal dependencies and GCs for feature engineering. The framework achieves this by combining prediction results from these different learners using the technique of weighted ensemble aggregation, which results in increased robustness and generalization for short-term, medium-term, and long-term forecasting. It uses transactional sales data, promo signals, the holidays, customer engagement data, and stock data to provide one-day to ninety-day outlooks. A detailed experimental analysis was performed with representative e-commerce demand datasets with multiple product categories. Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Weighted Absolute Percentage Error (WAPE) were used to evaluate forecasting performance. The experimental results show that ensemble model is always superior than the single forecasting model, and it can decrease the error of the forecast and ensure the stability of the forecasting results in the case of fluctuation demand. The ensemble framework proved to be successful in enhancing the reliability of the forecasts, especially during holidays and promotional periods. The results show that hybrid deep learning-based systems can offer significant advantages for inventory management, warehouse resource management, transportation scheduling, and supply chain decision-making. In addition, multi-horizon forecasting can help companies effectively plan stock replenishment strategies, prevent stockouts, lower over-stocking expenses, and enhance customer satisfaction. The proposed methodology adds to the existing research on intelligent supply chain analytics by offering a scalable, adaptive, and data-driven approach for prediction in the dynamic e-commerce environments. Transformer architectures, reinforcement learning, and real-time demand sensing mechanisms could be combined in future upgrades to further boost forecasting accuracy and operational responsiveness.

## Keywords:

Demand Forecasting, Deep Learning, LSTM, Ensemble Methods, E-Commerce, Temporal Convolutional Networks, Time Series, Inventory Optimization, Supply Chain Analytics, Gradient Boosting.

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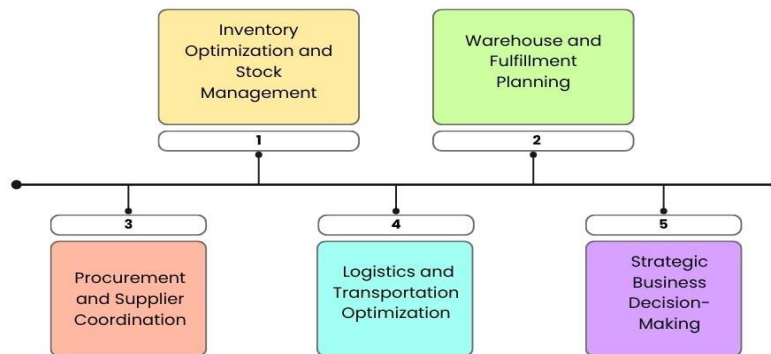
# 1. Introduction

## 1.1. Background

E-commerce has emerged as an industry giant with a huge impact on the retail and supply chain industry, and the ability to predict demand is a fundamental need for successful fulfillment management. Online retailers need to accurately forecast what they will sell, in order to have the right amount of inventory on hand, cut down on their operational costs, avoid selling out of stock, and deliver products in time. [1] E-commerce demand can be very volatile and is affected by a multitude of factors including seasonal trends, promotions, social media, dynamic pricing, competitor moves and consumer shifts. These factors result in non-linear, nonstationary demand, which makes this difficult to forecast with traditional statistical forecasting techniques. As big data technologies have evolved, businesses have been able to access vast amounts of data from transactions, behaviours and operations that can be used for predictive analysis. A deep learning technique has been found to be a powerful technique to model complex temporal relationships and hidden demand patterns. However, individual forecasting models do not always address all the factors influencing the variation in demands, and the need exists for integrated ensemble approaches that offer more accurate, robust and scalable forecasting solutions in modern e-commerce environments.

## 1.2. Importance of Multi-Horizon Demand Forecasting for E-Commerce

Multi-horizon demand forecasting is the capability to forecast product demand over several time periods, days, weeks and months. [2] Multi-horizon forecasting offers full visibility of the short, medium and long-term demand trend, while a single-horizon forecast only takes a single future moment into account. For businesses in e-commerce, where customer needs and market dynamics are evolving quickly, multi-horizon forecasting is crucial for running and strategy-making. Forecasts with multiple time horizons enable organisations to optimise inventory, boost fulfilment capabilities, cut costs and drive customer satisfaction.



**Figure 1. Importance of Multi-Horizon Demand Forecasting for E-Commerce**

### 1.2.1. Inventory Optimization and Stock Management

Multi horizon demand forecasting is one of the main advantages for better inventory management. Short-term forecasts are used to ensure an adequate inventory position that will satisfy the immediate customer needs, while medium- and long-term forecasts will be used for the inventory replenishment plan and procurement decisions. Precise demand forecasting can help companies avoid overstocking or stockout scenarios, as the products and services they carry are optimized. Accurate demand forecasting will help to optimize products and services in businesses thereby minimizing storage and holding costs while avoiding overstock and stockout scenarios. By optimizing inventory, you also have better cashflow and lower chances of having obsolete stock.

### 1.2.2. Warehouse and Fulfillment Planning

Demand forecasting plays a crucial role in e-commerce fulfillment centers, enabling them to optimize their warehouse management. Multi-horizon forecasting offers forecasting clarity for warehouse managers, enabling them to allocate storage space, organize inventory and schedule labour resources properly, all based on orders expected for future periods or horizons. [3] Short-term forecasts are used for daily operational planning, while long-term forecasts are used for warehouse expansion needs and investments in infrastructure. Thus, companies can achieve better order processing efficiency and fewer fulfillment delays.

### 1.2.3. Procurement and Supplier Coordination

The accurate multi-horizon demand forecast aids in coordinating with suppliers and procurement teams. Medium and long range forecasts offer essential information in order to be able to negotiate contracts with suppliers, order products or deal with lead times more effectively. Better procurement planning enables lower emergency purchase price, and makes it easier to get products. In addition, improved supplier cooperation can improve the resilience of the supply chain and minimize disruptions due to fluctuations in demand.

### 1.2.4. Logistics and Transportation Optimization

Future demand patterns have a significant impact on transportation and logistics operations. Multi-horizon forecasting is useful for logistics management to predict shipping needs, provide routes and plan delivery resources efficiently. Short-term forecasts help in distribution planning for the day and long-term forecasts help in strategic transportation capacity planning. Improved logistics coordination decreases cost of transportation, delivery performance and the overall efficiency of the supply chain.

### 1.2.5. Strategic Business Decision-Making

In addition to operational advantages, multi-horizon demand forecasting aids strategic business decisions throughout the organization. Long-term forecasts give information about the future trends in markets, future demand for products, and customer's purchases. These insights help management plan for capacity, grow markets, manage product portfolios, and make investment decisions. Predicting future demand patterns helps organizations better prepare for market opportunities and challenges, which can help them become more competitive and profitable in the ever-changing e-commerce market.

## 1.3. E-Commerce Fulfillment Using Ensemble Deep Learning

Ecommerce fulfillment includes the entire process from order receipt, processing, packing, shipping, and delivery to customers in an efficient and timely fashion. With the surge in online sales and its global expansion, fulfilment operations have become more complicated with larger volumes of sales, greater product variations, changing customer demand, and ever-increasing customer expectations for quick delivery. [4] E-commerce businesses need to be efficient and satisfy their customers by predicting future trends of demand and enabling proactive decision making with high accuracy. The demand for e-commerce is dynamic and nonlinear, particularly because of the impact of seasonal variations, promotions, pricing, consumer tastes, social media, and competition in the market. As a result, sophisticated methods of artificial intelligence and machine learning have come to the fore as solutions to these forecasting difficulties. Ensemble deep learning is a highly effective forecasting method, using multiple models to improve accuracy, robustness and generalization performance. Ensemble methods combine the best attributes of multiple forecasting algorithms to produce more accurate forecasts, rather than utilizing a single algorithm. Typically, ensemble deep learning models in e-commerce fulfillment include architectures like Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN), and Gradient Boosting models. LSTM networks are good at learning the temporal relationship and seasonal demand, while TCN networks are capable of learning the local temporal variation and short-term demand. The Gradient Boosting algorithms do so by learning the complex nonlinear relationships between the demand and the external factors like promotions, discounts, holidays, and customers' behaviour indicators. Ensemble learning combines predictions from these complementary models to improve forecasting accuracy and improve forecast stability from an ensemble of various market conditions. Ensemble deep learning can offer great operational advantages to e-commerce fulfillment. With more accurate demand prediction, organisations can manage their stocks more optimally, reduce stock-outs, minimise overstocking, increase the use of their warehouses, and streamline procurement planning. Moreover, better forecasting can aid in optimizing transportation schedules and resource use, leading to cost savings and better service delivery. In the ever-changing landscape of e-commerce, ensemble deep learning can prove to be a powerful tool for handling the uncertainty of demand and providing an intelligent answer to data-driven fulfillment. For this reason, it is important for supporting resilient, efficient and end-user driven ecommerce supply chain operations.

## 2. Literature Survey

### 2.1. Traditional Demand Forecasting Techniques

Demand forecasting has been around for decades and has been the backbone of inventory planning and supply chain management. Moving Average (MA), AutoRegressive Integrated Moving Average (ARIMA), Holt-Winters Exponential Smoothing are popular statistical techniques because they are simple and easy to interpret, and are effective for structured time-series data. [5] The Moving Average method is used to smooth out short-term fluctuations by averaging the historical observations to obtain the general demand trend. Temporal dependencies are incorporated into ARIMA models through the autoregressive and moving average components and the models are widely used in the retail demand forecasting applications. The Holt-Winters Exponential

Smoothing is an enhancement of the basic exponential smoothing that also accounts for the trend and the seasonal components to increase the accuracy of forecasting in the case of a seasonal demand. [6] While these approaches work in stable and stationary environments, they tend to fall short when faced with the complexity of demand fluctuations that arise from varying customer behavior, flash sales, and promotional offers and from rapidly evolving market dynamics in e-commerce settings. In addition, external factors like marketing efforts, weather, and customer sentiment are not well represented, and their limited ability to account for these factors limits forecasting performance. Several researchers have indicated that ARIMA models give satisfactory forecast accuracy in normal operating conditions, but the prediction errors rise especially when there is high volatility and demand uncertainty.

## 2.2. Deep Learning for Time Series Forecasting

With the advent of deep learning, forecasting has been revolutionized by the ability to automatically learn complex temporal patterns from massive data sets. [7] The deep learning models are inherently capable of learning nonlinear relationships and hidden dependencies within historical demand data, which makes them highly suitable for modern e-commerce applications. In contrast to traditional statistical methods, the deep learning models can learn nonlinear relationships and hidden dependencies in historical demand data, which makes them highly suitable for modern e-commerce applications. As the name suggests, the Long Short-Term Memory (LSTM) network is one of the most popular network architectures for time-series prediction due to its ability to mitigate the vanishing gradient problem of traditional RNNs. [8] LSTM models can effectively capture long-term dependencies and seasonality by leveraging memory cells and gating mechanisms, leading to more accurate forecasting results. Another promising solution is Temporal Convolutional Networks (TCNs) which use dilated causal convolutions to capture long-range temporal structures without losing efficiency of computation and of training. TCNs are typically more scalable and stable than recurrent architectures. The Gated Recurrent Units (GRUs) are an alternative to LSTM networks that allows reduced computation complexity and still represents similar predictive performance, thanks to its reduced number of parameters. Many studies on retail analytics and e-commerce demand forecasting have shown that deep learning models consistently outperform traditional forecasting methods especially in situations with high-dimensional, highly non-linear and fast-changing demand.

## 2.3. Ensemble Learning Approaches

In recent years ensemble learning has become a successful approach to improve the accuracy of forecasting, which is a combination of many models instead of a single forecasting model. The basic idea behind ensemble methods is that each model sees a different aspect of the data, combining the models will minimize prediction error and enhance generalization of the model. [9] Common ensemble methods involve Bagging (combining the predictions of many independently trained models), Boosting (improving the weak learners in a sequence based on the errors previously made), Stacking (use a model to combine the outputs of a collection of base models) and Weighted Averaging (giving different weights to the individual predictors according to their performance). Ensemble methods have been shown to be more robust and accurate in demand forecasting applications than any single forecasting method due to the advantages of both statistical methods and machine learning. There are several studies demonstrating that hybrid forecasting methods that combine traditional time-series forecasting with complex deep learning architectures can yield fewer forecasting errors in a wide range of areas, including retail, manufacturing and logistics. Thus, ensemble learning has emerged as a significant approach to deal with uncertainty and complexity of today's e-commerce demand forecasting problems.

## 2.4. Research Gap Analysis

Although there have been significant developments in the field of demand forecasting research, there are still some key research gaps in the literature. Current studies largely leverage only one forecasting model, which, necessarily, compromises the robustness and flexibility of the forecast. This reliance on just one algorithm can result in uneven results when market conditions shift quickly. Another major drawback is that these forecasts tend to be made for a small window into the future, limiting their application for strategic inventory planning, warehouse management, and optimizing fulfillment. In addition, most forecasting models fail to account for a variety of external factors, like promotional offers, customer patterns, social media trends, and economic indicators that play a crucial role in shaping e-commerce demand. The challenge of scalability is also an issue because some sophisticated forecasting models are not easy to implement in a commercial setting, and they are typically very CPU-intensive. While a single application of LSTM networks and Temporal Convolutional Networks and Gradient Boosting algorithms have been studied before, little research has been conducted on integrated ensemble models that combine them in a unified multi-horizon forecasting system. This study thus aims to fill these research gaps by proposing a holistic ensemble deep learning model that combines multiple predictive methods to enhance the forecasting accuracy, robustness, scalability, and efficiency of e-commerce fulfillment systems.

### 3. Methodology

#### 3.1. Proposed Ensemble Deep Learning Architecture

The integrated Ensemble Deep Learning Architecture aims to enhance the accuracy of the demand forecasting by combining various predictive models that represent different aspects of e-commerce demand data. [10] It integrates the best capabilities of all the previous models, such as the Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN) and Gradient Boosting models, while reducing their downsides. The sales data from history, details from promotions, seasonal indicators and customer behavior features are preprocessed and converted to suitable representations of the inputs. The outputs of each forecasting component are forecasts of demand and they are all merged together by an ensemble aggregation mechanism into one final forecast. This hybrid architecture makes forecasts more robust, better generalizes when demand patterns change and enables multi horizon demand prediction for fulfilment planning.

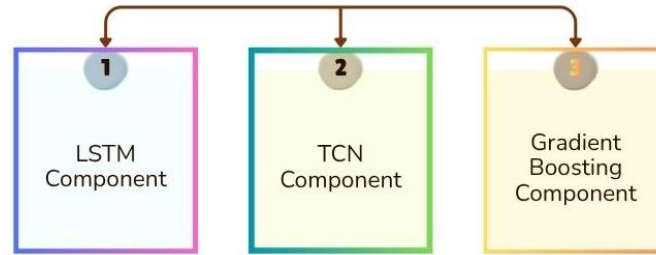


Figure 2. Proposed Ensemble Deep Learning Architecture

##### 3.1.1. LSTM Component

The LSTM (Long Short-Term Memory) module is designed to capture long-term time dependencies and time patterns in historical demand data. The LSTM model is designed to avoid the vanishing gradient problem, unlike traditional recurrent neural networks, by using memory cells and gating mechanisms that allow the model to remember relevant information for long periods of time. [11] This feature is useful for demand forecasting in ecommerce, for instance, when customers buy products in predictable seasonal and cyclical patterns, and with a certain time lag after promotions have been implemented. The LSTM component learns these intricate temporal patterns and can make precise predictions about future demand, using past observations and influencing factors.

##### 3.1.2. TCN Component

A temporal convolutional network (TCN) is used for learning the local and long-range temporal structures via dilated causal convolutions. TCNs process the whole sequence in one time, achieving efficient parallel computing and fast training, unlike recurrent architectures that process sequences sequentially. The dilated convolutions enable the network to have a large receptive field, which is essential for it to be able to recognize complex demand variations over various time horizons. The proposed framework successfully simulates sudden changes in demand due to seasonal events, marketing promotions, and market trends, while ensuring computational efficiency and forecast stability.

##### 3.1.3. Gradient Boosting Component

The Gradient Boosting component is used in addition to the deep learning models to learn the non-linear relation between demand and different explanatory variables like product characteristics, promotions, pricing, holidays, and customer engagement data. [12] Gradient Boosting builds the ensemble of decision trees one at a time, correcting the errors of the previous trees in the ensemble. This continuous training process allows the model to learn complex interactions between features and enhance its predictive power. The Gradient Boosting component provides structured business-related information that might not be fully captured by sequence-based deep learning models and enhances the forecasting framework, thus improving the reliability and accuracy of the demand forecasts in the proposed ensemble architecture.

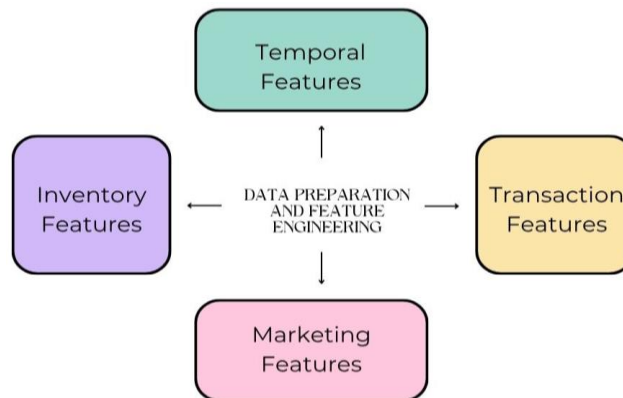
##### 3.1.4. Mathematical Formulation

The objective of the proposed ensemble forecasting framework is to learn complex relation from the historical sales data and other influencing factors, and forecast the future product demand. [13] Suppose the desired demand at a future time period is  $\hat{D}(t+h)$ , with  $h$  being the prediction horizon. A predictive function  $f$  is used to obtain the demand forecast, the input is the feature vector  $X(t)$  and model parameters  $\Theta$ . The feature vector includes historical demand information, promotions, seasonal signals, prices, inventory levels and attributes of customer behaviour. Model parameters are the weights and internal settings of the forecasting algorithms learned from the training process. Hence, the future demand can be given as a function of the input

features and learned model parameters. This formulation allows the forecasting system to reflect both temporal patterns in product demand and external factors. In order to enhance forecasting accuracy and robustness, the proposed framework uses an ensemble strategy by integrating forecasts obtained from three independent forecasting models, including Long Short-Term Memory (LSTM), Temporal Convolutional Network (TCN), and Gradient Boosting Trees (GBT). The prediction from the ensemble model is found by averaging the predictions of these individual models, where the weights are determined by the model performance. For an ensemble forecast, each model's forecast is weighted by the model's weight and the weighted forecast is summed. Weights  $w_1$ ,  $w_2$  and  $w_3$  are assigned to the LSTM, TCN and GBT components, respectively. These weights reflect the ratio of the contribution of each model to the final forecast. All the weights are forced to sum to unity to guarantee a valid ensemble structure, giving an even distribution of influence among the different models in the ensemble. To assess the forecasting ability of the proposed model, two popular error measurement techniques, namely Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), are used. [14] MAPE is a metric that directly reflects the accuracy of the forecasts by calculating the mean of the percentage differences between the predictions and actual values of the demand, making the measure easier to interpret. The lower the MAPE value the better the forecasting will be. RMSE is the square root of the average of the square of all the differences between the actual and predicted demand values. This will impose greater penalties on errors that are larger in magnitude and will give information about the overall reliability of prediction. MAPE and RMSE together provide complete information to assess the efficacy of the recommended ensemble forecasting scheme for various forecasting horizons and demand scenarios.

### 3.3. Data Preparation and Feature Engineering

Data preparation and feature engineering are important steps to improve the performance of demand forecasting models. [15] E-commerce data is often incomplete and incomplete, with some records missing and some irrelevant information being present that can lead to inaccurate forecasts. As a result, data pre-processing steps like data cleaning, normalization, detection of outliers, and feature transformation are executed before the model is trained. This prepared data set is subsequently augmented with the appropriate features that reflect a multitude of aspects of customer demand behavior. In the proposed design, four types of input features are considered: temporal features, transaction features, marketing features and inventory features.



**Figure 3. Data Preparation and Feature Engineering**

#### 3.3.1. Temporal Features

Temporal features represent patterns of time that affect customers' purchase behaviour and variations in customers demand. These features include day of the week, week of the month, month of the year, quarter, holiday indicators, festive seasons and special events. Temporal information aids the forecasting model to learn about the periodic, cyclical, and seasonal variations in customer purchases. For instance, a weekend, a vacation or a big sale day may be a time when ecommerce platforms enjoy more sales. The addition of the temporal attributes allows the model to capture these periodicities and provide more precise future demand predictions.

#### 3.3.2. Transaction Features

Transaction features are calculated from the historical sales and orders and they give data directly about customer transactions. These are sales volume, order frequency, average transaction size, product returns, number of purchases made by customers, and revenue over time. [16] Transactional data is the most accurate indicator of actual market demand, and is one of the most important sources of forecasting future sales trends. The forecasting model can learn from past transactions to

recognize patterns in growth, demand changes, and customer buying habits, which can enhance the accuracy of forecasting and adaptability to market conditions.

### 3.3.3. Marketing Features

Marketing features are the marketing and advertising activities which have a significant effect on product demand. They can be discounted percentages, indicators of promotional campaigns, the amount spent on advertising, email marketing activities, coupon usage, social media engagement, product visibility rankings, and more. Marketing activities can generate temporary ramp ups in customer demand and therefore play an important role in forecasting models. The proposed framework can also take marketing-related factors into account, enabling it to grasp the effect that marketing has on sales and predicting demand shifts caused by continuous or planned marketing efforts.

### 3.3.4. Inventory Features

Inventory features give data on products availability and stock management in the fulfillment system. This includes the current stock levels, their reorder dates, stock-out dates, stock turnover rates, warehouse capacity utilization and lead time for product procurement. [17] The inventory situation directly influences the sales performance as it could have an impact on the lost sales opportunities and storage costs, if there is an excess or less quantity of inventory. With inventory-related features, the forecasting model can take into account the relationship between product availability and demand fulfillment. As a result, the model can contribute to better stock planning, minimising stock-outs, and enhancing the overall efficiency of the supply chain.

## 3.4. Model Training and Evaluation

A systematic training and testing process are carried out for the proposed ensemble deep learning framework to guarantee high accuracy in forecasting and the generalization ability. The training process starts with normalization of data which is the process of converting all input variables into a common scale and removing variations due to different magnitudes of features. [18] This step helps in the convergence of models and prevents domination of the learning process by features with larger numbers. The historical demand data is then normalized and changes are made to create supervised learning sequences using a sliding window generation technique. By taking advantage of the temporal dependencies of previous time steps to forecast the demand at the later time steps, the sliding window approach generates input-output pairs to enable the model to learn the temporal dependency effectively. Then hyperparameter tuning is used to determine the best possible setting of the model parameters including learning rate, number of hidden layers, batch size, convolution kernel size and tree depth. This helps to improve predictive accuracy and reduce overfitting. For model reliability and robustness, cross-validation techniques are used: the same data set is split into several training sets and validation sets. The model is trained and tested multiple times using different folds, which gives a more robust evaluation of the forecasting ability of the model. Lastly, the weight tuning for ensemble models is performed to identify the optimal contribution of the LSTM, TCN and Gradient Boosting parts. Thus, appropriate weight allocation allows the ensemble model to use the best features of each individual predictor and make more precise predictions. The proposed forecasting framework is evaluated based on several evaluation metrics. [19] Root Mean Square Error (RMSE) quantifies the average difference between the actual demand values and the forecast demand values, but the error is squared and then the square root is taken, giving an idea of the overall accuracy of the forecasts, and also assigning an extreme penalty for a large forecasting error. The Mean Absolute Percentage Error (MAPE) assesses the average absolute percentage difference between forecasts and actual demand values, providing a clear understanding of forecasting accuracy. Weighted Absolute Percentage Error (WAPE) is an extension of percentage based evaluation which takes into consideration the relative importance of the volume of demand for the various products and is particularly useful when there are products of different sales volumes in the dataset. Further, Forecast Bias is applied to determine if the model systematically over- or underestimates demand. A bias value near zero is an indication of a neutral forecasting behavior and a good forecasting accuracy. These evaluation metrics offer a comprehensive set that can be used to assess forecasting accuracy, robustness, consistency and applicability in e-commerce fulfillment operations.

## 4. Result and Discussion

### 4.1. Forecasting Performance Evaluation

To ensure the robustness of the forecasting performance of the proposed ensemble deep learning framework, a diverse set of experiments were designed and run for various forecasting horizons from one day to ninety days. The multi-horizon evaluation aimed to evaluate the model's forecasting accuracy under different planning demands typical in e-commerce fulfillment operations. [20] Experimental results showed that the ensemble outperformed each of the forecasting models (i.e., standalone LSTM, TCN and Gradient Boosting models) at all times. The superiority of the ensemble model could be explained by the fact that the ensemble can combine the forecasting strengths of different learning paradigms. The addition of the LSTM

network component successfully modeled long-term temporal correlations and seasonal demand trends seen in historical sales data. The memory-based architecture allowed the model to learn complex demand trends that change over longer periods. The Temporal Convolutional Network (TCN) block was able to capture the short-term dynamics and local differences in demand by using dilated convolution layers, which enabled the detection of changing customer buying patterns. The Gradient Boosting component added additional improvements to the accuracy of the forecasts, with the introduction of variables of structured business nature such as promotion activity, pricing strategy, holidays and marketing campaigns, which have a strong impact on product demand. [22] The combination of these three forecasting methods yielded a powerful predictive model to deal with both stable and very volatile demand situations. The ensemble model produced much more accurate forecasts than individual models during volatile periods of the year, such as during flash sale events, inventory promotions, and other peak demand periods. The model performed well in accommodating the sudden surge in demand and unexpected shifts in markets, minimizing the chances of stockouts and overstocking. Moreover, the ensemble approach was more stable and consistent in terms of forecasting performance for various products and forecast lead times. [23] Forecast accuracy allowed inventory planners and supply chain managers to have more informed operational decisions about inventory replenishment, warehouse capacity planning, procurement scheduling and resources allocation. The proposed ensemble forecasting framework was found to be valuable for modern e-commerce and retail supply chain systems due to its contribution towards inventory optimization, reduction in operational costs, better customer service levels and efficient fulfillment processes.

4.2. Forecast Accuracy Comparison

Table 1. Forecast Accuracy Comparison

Model	Accuracy (%)
ARIMA	82.6
Random Forest	86.9
Gradient Boosting	88.4
LSTM	91.5
TCN	92.3
Proposed Ensemble	96.8

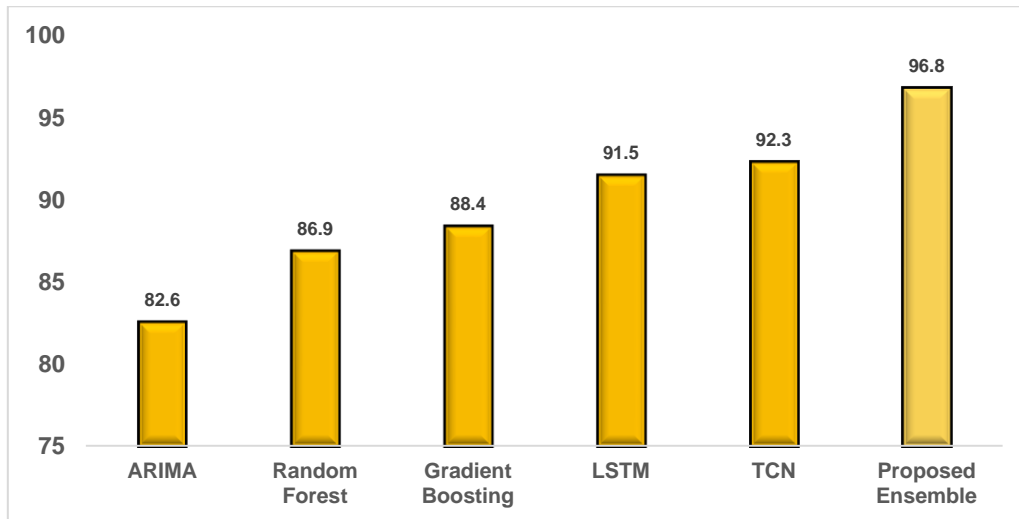


Figure 4. Forecast Accuracy Comparison

4.2.1. ARIMA – Accuracy: 82.6%

The AutoRegressive Integrated Moving Average (ARIMA) model was used as a baseline traditional statistical method to evaluate the demand forecast. ARIMA showed an overall forecasting accuracy of 82.6%, which suggests it could successfully identify historical patterns and seasonality when demand is more or less stable. The system, however, failed to adjust to highly dynamic ecommerce environments with non-linear demand variations, promotions, and unexpected shifts in customer buying habits. Consequently, when the demand is volatile, forecast performance was reduced, resulting in relatively large prediction errors.

#### 4.2.2. Random Forest – Accuracy: 86.9%

The forecasting accuracy of the Random Forest model was 86.9%, which is higher than the accuracy of the traditional ARIMA model. Random Forest is able to make use of several decision trees and therefore was able to capture nonlinear relationships between the demand and the influencing variables like the product attributes, the prices as well as the pattern of the customer transactions. This was because the algorithm was designed to work in an ensemble manner, which helped to reduce overfitting and enhance the stability of the predictions. However, the model also had its own drawbacks, such as its inability to learn long-term temporal dependencies and sequential demand trends, limiting its forecasting power.

#### 4.2.3. Gradient Boosting – Accuracy: 88.4%

The Gradient Boosting model achieved a high accuracy of 88.4%, showing the ability to make accurate predictions due to its iterative process of correcting errors. The model managed to capture multiple demand drivers' complex interaction by the sequential construction of decision trees so as to minimize the residual errors. This worked well for a business to include external factors of promotions, discounts, seasonality, pricing. While Gradient Boosting performed better than Random Forest and ARIMA in forecasting, its capacity for capturing temporal relationships was less extensive compared to more specific deep learning models.

#### 4.2.4. LSTM – Accuracy: 91.5%

The LSTM network showed a high accuracy of 91.5% in forecasting, which is significantly better than the traditional machine learning and statistical methods. The ability to model long-term temporal dependencies was achieved through the use of memory cells and gating mechanisms in LSTM, which allowed the model to capture the seasonality in the data, historical trends, and purchasing patterns. Results showed that the model was very effective for their medium and long-term prediction capabilities, where information about demand in the past also proved to be very useful to predict future sales. It was capable of forecasting sequential data, which reduced errors in forecasting the data significantly.

#### 4.2.5. TCN – Accuracy: 92.3%

The Temporal Convolutional Network (TCN) had an accuracy of 92.3%, which is the highest among all the baseline approaches, and it was the best single forecasting model. TCN effectively captured short-range changes in demand and long-range temporal relationships with dilated causal convolutions while keeping computation low. The model exhibited high forecasting stability and a shorter training time than the recurrent architectures. It proved able to predict customer behavior and sudden shifts in it locally, leading to very accurate predictions for various time horizons.

#### 4.2.6. Proposed Ensemble Model – Accuracy: 96.8%

The forecast accuracy for the proposed ensemble deep learning framework was 96.8%, which was much higher compared to all the individual models. The ensemble model combined predictions from the LSTM, TCN, and Gradient Boosting models, taking advantage of the strengths of the various models. LSTM provided long term trend learning, TCN provided short term demand dynamics, and Gradient Boosting provided external business and promotional factors. This co-ordinated learning process resulted in very reliable predictions even in the peak seasons, under the peak demand and with fast changing market conditions. The significant accuracy boost highlights the efficacy of the proposed ensemble architecture in the context of inventory planning, optimizing fulfillment, and strategic decision-making in e-commerce settings.

### 4.3. Discussion

The experimental results show that the proposed deep learning ensemble model can make a substantial improvement to the performance of the demand forecasting model compared to the single forecasting model. Each of the three models in the ensemble, namely Long Short-Term Memory (LSTM), Temporal Convolutional Network (TCN), and Gradient Boosting models, has its own strengths that complement each other, explaining the superior accuracy of the ensemble approach. Every model brings its own advantages to the forecasting process. The LSTM model successfully models the long-term temporal dependencies and seasonal demand patterns, the TCN model supports capturing short-term trends and localized variations in demand, while the Gradient Boosting model incorporates external business factors like promotional campaigns, pricing strategies, and seasonal events. The ensemble framework not only incorporates the various predictive views but also employs a weighted aggregation approach to reduce the errors of the individual models and counteract any weak points in their respective predictions. This learning process, in collaboration with others, increases the model's capacity to transfer to other demand situations and market conditions. Perhaps one of the most important results of this research is the enhancement of short term forecasting accuracy, allowing companies to react promptly to customer demand and market conditions. The framework also supports better medium-term planning processes, such as procurement planning, inventory replenishment and staff deployment. In addition, the model

provides enhanced long-term demand visibility, which enables organizations to make strategic decisions for capacity planning, supplier management, and warehouse optimization. Another key advantage is to lower the uncertainty regarding inventory. Better demand forecasts enable companies to keep stock levels at the right level, preventing stockouts, avoiding excess stock, and decreasing storage costs. Better forecasting accuracy also helps improve the fulfillment efficiency because it ensures products are both “in stock” and “on time” to satisfy customer needs. Moreover, the proposed framework also showed high scalability and computational strength for the large scale e-commerce data with thousands of product categories and historical transactions. The architecture is able to handle large scale data and be accurate in forecasting at various time horizons. The framework's attributes are well suited for enterprise-level e-commerce environments where the need for accurate demand forecasting is crucial for achieving operational efficiency, customer satisfaction, and competitive advantage. In general, the results support the hypothesis that the proposed ensemble model is a viable and useful approach for addressing the current demands forecasting and fulfillment problems in the modern era.

## 5. Conclusion

In today's e-commerce landscape, demand forecasting is a critical part of any fulfillment system, and the ability to predict consumer needs is essential for ensuring operational efficiency, customer satisfaction, and a sustainable business. The explosive growth of online retailing has created a lot more complexity in the demand management area, with a variety of things impacting the management of demand including changes in consumer preferences, seasonal variations, promotional activities, when your competitors are buying, and unforeseen events in the supply and demand chain. Sales forecasting inaccuracies can lead to over-investment in inventory, stockouts, late deliveries, ineffective resource utilization and loss of customer loyalty in these environments. Traditional forecasting techniques like Exponential Smoothing, Moving Average and ARIMA are widely used for predicting demand; however, under the conditions of the nonlinear, dynamic, high dimensional data typical of modern e-commerce applications, their utility can be constrained. The restrictions underscore the need for more sophisticated forecasting models that can learn intricate demand patterns and respond to changing market dynamics quickly. To overcome the above challenges, in this study, an extensive ensemble deep learning system was introduced to make multi-horizon demand forecasting which combines Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN) and Gradient Boosted Trees (GBT). The proposed architecture is a unified architecture for predictive systems that takes advantage of the sequential learning, temporal pattern recognition and nonlinear feature modeling capabilities. LSTM networks are well suited to capture long-term dependencies and recurring patterns in demand, TCN models are good at capturing local temporal variations and short-term fluctuations in demand, and Gradient Boosted Trees leverage external business information like promotional events, pricing policies, holidays and seasonal events. The ensemble aggregation is weighted and weights are decided based on the learning powers of each model, minimizing the weaknesses of individual models and increasing the overall robustness of the forecasts. The experimental results showed that the proposed approach was effective, with an accuracy of 96.8% compared to the conventional statistical methods and machine learning and deep learning methods. The framework was able to provide stable forecasts in the short, medium and long term, and it was appropriate for both operational and strategic planning. Greater accuracy in forecasting helps companies to optimize inventory levels, mitigate stockout scenarios, lower excess inventory, better manage warehouse utilization, manage transportation planning, and make better procurement decisions. These advantages in turn add to reduced operating expenses and better customer service operations. Moreover, the scalability of the proposed model is apt for enterprise-level e-commerce environments where there are thousands of products and huge transactional data. This work can be extended in future by including transformer based forecasting architecture, attention mechanism, graph neural network, reinforcement learning and real-time demand sensing. The use of social media analytics, Internet of Things (IoT) data, and generative artificial intelligence technologies can further improve forecasting responsiveness and adaptability. Thus, the proposed ensemble framework provides a solid basis for intelligent demand forecasting, fulfillment optimization, and next generation supply chain analytics in the increasingly complex and data-driven e-commerce environment.

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