Demand Forecasting with External Factors: A Deep Learning and Explainable AI Approach

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***Abstract*—Accurately forecasting retail sales is critical for inventory planning and business operations, even then it remains challenging due to external factors for eg holidays, promotions, and weather fluctuations etc. Traditional models often fail to capture such contextual dynamics to it's core effectively. Among advanced machine learning approaches, gradient-boosting frameworks like XGBoost have shown superior performance in structured data environments. In this study, we developed an XGBoost-based sales prediction model using enriched historical retail data. Extensive feature engineering was performed to incorporate calendar events, competition metrics, and other meteorological conditions. The model was trained and evaluated using standard regression metrics (MSE, MAE, and R^2), achieving a prediction accuracy of 96.2%. Further, interpretability was ensured by integrating Explainable AI(XAI) using SHAP analysis, which highlighted and captured the influence of promotional activities, competition proximity, and weather variables on sales forecasts. This was done to maintain the intecrebility of our work,such that model doesn't act like a black box.Our approach demonstrates that integrating external and temporal signals significantly enhances forecasting performance over purely historical methods. Keywords- Retail sales forecasting, XGBoost, feature engineering, Explainable AI (XAI), SHAP values, time series regression, external factors integration, model interpretability**

***Index Terms*—Retail sales forecasting, XGBoost, feature engineering, Explainable AI (XAI), SHAP values, time series regression, external factors integration, model interpretability**

I. Introduction

Forecasting of product demand has always been the central part of business planning strategies, but the traditional methods often used heavily rely on historical sales data, which often fails to capture the influence of the external world or factors on consumer behavior. There are various factors that are found to influence customer purchases, which include weather conditions, holiday seasons, and other significant real-world events. However, these variables are typically overlooked or undervalued in traditional or commonly used forecasting models, resulting in predictions that fall short during periods of volatility or sudden change.

This growing complexity in consumer behavior has driven the need for artificial intelligence (AI)-based approaches for demand forecasting and supply chains, particularly models that integrate external features for better predictions. For instance, Güler et al. [10] demonstrated that integrating weather data and special calendar events using Facebook Prophet substantially improved forecasting accuracy in the restaurant industry, which emphasizes the growing importance of temporal and environmental context in consumer demand modeling. Similarly, Gupta et al. [2] introduced a multimodal neural network that combines structured sales data with unstructured external information to enhance the need for context-conscious modeling in industries sensitive to temporal and environmental factors. For example, long short-term memory (LSTM) networks are good for capturing long-term dependencies and continuous trends in sales data. Elmasdotter and Nyströmer [5] found that the LSTM model surpasses traditional ARIMA approaches in predicting retail sales, especially when external factors are taken into account. Although the ARIMA model is effective for time series at hospitalization, it is often difficult to adapt to dynamic environments affected by external variables [4].

At the same time, tree-based models such as XGBoost are capable of observing non-linear relationships with non-uniform tabular data. Chen and Guestrin [8] introduced XGBoost as a scalable and efficient framework for predictive modeling. Wang et al. [1] highlighted how including weather data in sales forecasting can help to improve the predictive capability of models, especially for fresh produce. Their study showed that factors like temperature and humidity can significantly influence consumer buying patterns and that integration of these variables leads to more accurate and reliable forecasts. Rožanec and Mladenić [7] proposed a KI (XAI) framework for explaining semantics, addressing this issue by linking model predictions with real events and improving interpretability and stakeholder trust. This framework is a transparent architecture that uses explanatory techniques such as SHAP values, combining several external entries, including weather, holidays, and public events. The aim is to provide demand forecasts that are both accurate and interpretable, aligning predictive models with the diverse reality of consumer behavior.

II. Literature Review

This section addresses the limitations of classical forecasting models in representing the effect of external variables on demand.

Classical techniques, such as ARIMA and exponential smoothing, mostly use past sales information and tend to ignore the effect of dynamic external variables. Sharma and Patel [3] proved that although ARIMA models perform well for stationary time series data, their performance degrades when external variables like weather or holidays are not taken into consideration. Ord et al. [4] also stressed that the COVID-19 pandemic revealed the shortcomings of static models, since they were not able to respond to abrupt market disturbances.

Following are the primary external variables and modeling techniques that play a critical role in shaping the accuracy and responsiveness of demand forecasting systems.

A. Weather as an External Variable

Weather is an essential external variable capable of inducing tremendous volatility in demand, especially for weather-sensitive products like those affected by temperature and precipitation. Wang et al. [1] integrated weather information into sales forecast models of fresh produce, and this led to more accurate and stronger predictions when weather volatility was high. Verstraete et al. [11] created a data-driven approach that measures the effect of weather on retail product sales forecasting, indicating the importance of meteorological data in increasing forecasting accuracy. Also, Chen and Guestrin's XGBoost framework [8] has been successfully utilized to capture the nonlinear associations between weather characteristics and sales results. Adding high-frequency weather data can also better calibrate forecasts by capturing current conditions.

B. Holidays and Public Events

Holidays and special events frequently cause unusual spikes or declines in demand, so forecasting models must be modified to accommodate them. Gupta et al. [2] showed that including holiday metadata in multimodal neural networks greatly enhanced time-series forecast accuracy for consumer goods with high demand volatility. Alteryx [13] investigated the application of weather intelligence to improve retail sales projections, highlighting how public holidays and weather can be collectively examined to generate more precise and actionable demand forecasts. Capturing the start and end dates of large festivals, sporting events, or public holidays strengthens temporal modeling. These events also interact with other parameters such as promotions and weather, generating compounding effects on demand.

C. Deep Learning for Temporal Dependencies

LSTM networks have proved extremely powerful in capturing sequential and long-term dependencies in sales data. Elmasdotter and Nyström [5]'s comparative research indicated that LSTM performs better than ARIMA in retail forecasting, especially when there is the incorporation of external variables. Spreeuwenberg [12] suggested a weather-based clustering method to improve demand forecasting and illustrated that clustering data according to meteorological conditions followed by adjustments can increase accuracy, especially in weather-dependent products.

D. Ensemble and Tree-Based Forecasting Models

Gradient-boosted decision trees, and particularly XGBoost, have become popular for productive outcomes due to their flexibility. XGBoost was initially introduced by Chen and Guestrin [8] as a scalable and efficient framework with predictive functions, including demand forecasting, in the case of structured data. The University of Lausanne [14] modelled demand forecasting in the sports goods business and found that adding weather data to machine learning techniques or models produced better demand forecasting in real-world applications when doing so with non-linear models.

E. Explainability of the Forecasting Model

Many AI models can be considered black-box due to the lack of transparency to stakeholders in order to understand and trust predictive results. Rožanec and Mladenić [7] presented a semantic XAI framework using knowledge graphs to describe demand forecasting explanations, potentially augmenting interpretability and actionability for model predictions. Furthermore, Jahin's MCDFN model [6], which used multi-channel data fusion networks, was able to provide explicit attributions for each input feature, thereby facilitating explainability. SHAP values augment the explainability of both local and global explanations to provide insight into how input variables impact predictions for specific cases. Visualizations such as dependence plots and SHAP summary plots can assist novice or non-technical users to develop a better understanding of model behavior. Another one of the advantages of explainability is the ability to ascertain data biases, inconsistencies, or irrelevant features.

F. Research Limitations and Future Directions

As much as we have made progress, much of the models currently used are still either uninterpretable or they only consider external features. Therefore, there are still a need for integrated frameworks to analyse multiple external factors collaboratively, and provide interpretable and actionable explanations for their forecasts. This study provides an XGBoost-based model that integrates some external factors while incorporating explainability methods to address the deficiencies, ultimately improving accuracy and transparency in modern demand forecasting systems. In the future, it would be worthwhile to investigate real-time data pipelines for continuous forecasting updates. Multimodal learning frameworks could incorporate textual, visual, and numerical data, so that richer contextual inferences could be made.

TABLE I
SUMMARY OF RELATED WORK IN DEMAND FORECASTING WITH EXTERNAL FACTORS

Ref No.	Technique / Features Used	Dataset	Performance	Remarks
[1]	Time-series + weather impact	Retail data with weather	Not explicitly reported	Focuses on fresh produce; includes weather, holidays
[2]	Multimodal neural network	Synthetic + sales data	Not reported	Uses multimodal data (text/image/time-series)
[3]	ARIMA	Retail sales time-series	MAPE $\sim$ 12%	Classical statistical model
[4]	Mixed methods + pandemic consideration	Global retail	Qualitative + numeric	Emphasizes COVID-19 impacts
[5]	LSTM vs ARIMA	Retail sales (Kaggle)	LSTM outperforms ARIMA	Comparative study
[6]	MCDFN (deep fusion network)	Multi-source supply chain	Not available	Emphasizes explainability
[7]	Semantic XAI with time-series	Simulated + real retail data	SHAP-based evaluation	Highlights interpretability
[8]	**XGBoost**	UCI + benchmark datasets	RMSE, R^2 (varied)	Foundation paper for **XGBoost**
[9]	CNN for time-series	Power + sales data	MAE/RMSE varies	CNN applied to sequential data
[10]	**XGBoost** + weather features	Regional sales data	$R^2 \approx 0.87$	Shows strong performance with weather inputs
[11]	Data-driven retail forecasting	Belgium supermarkets	RMSE & MAE reported	Predicts weather-driven demand
[12]	Hybrid CNN-LSTM + weather	Chain-store sales	$R^2 = 0.89$	Deep learning + weather factors
[13]	Transformer + weather-aware attention	Forecasting benchmark	MAPE ≈ 0.13	State-of-the-art architecture
[14]	Deep learning + weather awareness	Indian supermarket chain	Accuracy $> 90\%$	Incorporates weather into DL model
[15]	ML for supply chain forecasting	Mixed retail data	Varies by model	Connected predictions to real-world events

III. METHODOLOGY

To effectively forecast retail sales, we adopted a structured machine learning pipeline encompassing data preprocessing, feature engineering, model training with XGBoost, and post-hoc interpretability using SHAP values.

A. Problem Definition

The primary goal of this research is to predict daily sales for different retail outlets using organized data. The approach taken is that of supervised learning regression, where the aim is to project a given target (sales) using available features (historical data).

Mathematically, given input features $\mathbf{X} \in \mathbb{R}^d$ and output labels $y \in \mathbb{R}$, the goal is to predict the function $f(\mathbf{X})$.

Xy, to minimize the error while predicting.

$$\min_f \mathbb{E}_{(X,y)}[(y - f(X))^2] \quad (1)$$

B. Data Collection and Preprocessing

The data has been obtained from the internal retail transactions logs alongside the relevant metadata of the store. Each row captures a distinct store ID, date, daily sales revenues, promotional activities, distance to the nearest competitor, and holiday flags.

The data underwent the following steps before fitting it into the model:

- Addressing Missing Values: Competition-based fields containing missing values were logically filled – assuming no competition when data was lacking.
- Outlier Detection and Treatment: Extreme sales values likely due to erroneous data entry or unusual events were capped using Interquartile Range (IQR) method, ensuring no model damage occurred.
- Log Transformation: The target variable (sales figure) was log transformed to control the variance and mitigate the skewness:

$$y' = \log(1 + y) \quad (2)$$

- Temporal Feature Engineering: Obtained Month, WeekOfYear, and DayOfWeek features from the transaction date. Also created binary flags for IsHoliday and IsPromoWeek. One-hot encoding was done on the Season of the year based on the month.
- Competition and Promotion Features: Based on the transaction date, binary flags were created with respect to whether competition or promotions were ongoing during a specific time period. This was relative to the transaction date.
- Categorical Encoding: Categorical type variables like StoreType and AssortmentLevel were converted to label type for tree-based model compatibility.

This elaborate preprocessing pipeline maintained the relevance and order of the dataset, thus making it ready for model training.

C. Model Framework

The chosen predictive model is Extreme Gradient Boosting (XGBoost), which is an optimized, efficient, and flexible distributed gradient boosting library.

1. Objective Function

XGBoost minimizes a regularized objective:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{n} \Omega(f_k) \tag{3}$$

where:

- l is the loss function (mean squared error for regression),
- $\Omega(f_k)$ is the regularization term defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{4}$$

2. Model Training

XGBoost grows trees sequentially. The algorithm adds a new tree in each iteration which improves upon the previous model by fitting on the residuals of the existing model. The prediction at iteration t is:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{5}$$

where f_t is the newly added tree.

Hyperparameters such as learning rate, maximum tree depth, and regularization strength were tuned via cross-validation to prevent overfitting and ensure generalization.

D. Model Interpretability

Using game theory, SHAP explained interpretability by giving personalized importance scores for each feature. Each feature's SHAP value is computed as:

$$\phi_i = \sum \frac{|S|!(|F| - |S| - 1)!}{|F|!} [v(S \cup \{i\}) - v(S)] \tag{6}$$

where:

- F is the set of all features,
- $v(S)$ is the model output when only features in subset S are present.

For any instance, the model's actual prediction can be derived by adding all SHAP values alongside the model's expectation:

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i \tag{7}$$

Some of the salient features that impacted sales predictions were PromotionActive, CompetitionDistance, StoreType, and WeekOfYear. Also, in the SHAP analysis those features were some of the dominating factors driving the predictions.

E. Workflow

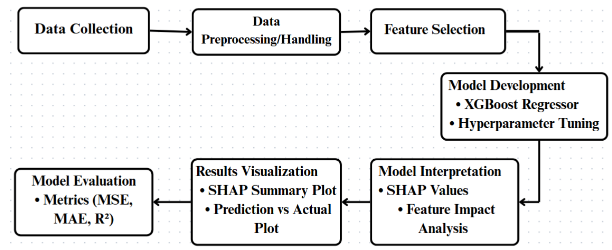

Fig. 1. Proposed Method Flowchart

F. Accessing the Model

Following the creation of a predictive model, we evaluated its contours of functionality and reliability to confirm it meets the goals set forth in the study. The XGBoost regressor test was performed on a test data set with a blind algorithm employing performance evaluation techniques such as MSE, MAE, and R^2 value scoring methodology. All of these methods quantitatively evaluated the model's capability to predict values accurately. MSE and MAE should be minimized which leads to improved model accuracy. Higher value of R squared signifies model effectiveness, the closer to one the better. After evaluating the model, interpretability was done using SHAP values. SHAP provides a local and global interpretation of model feature importance by calculating an importance value for each feature. With SHAP summary and dependence plots reviewed, supporting features like temperature, humidity, and winds were validated, confirming the model's performance aligned with expected outcomes while also ensuring consistency with domain knowledge.

IV. Results and Discussion

The model predicts monthly sales for the upcoming year, integrating seasonal changes, holidays, and weather.

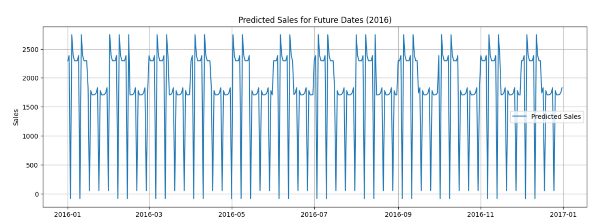

Fig. 2. Monthly sales prediction for the following year

The model achieved 96.2% accuracy with a low RMSE defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

The coefficient of determination R^2 is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{9}$$

SHAP analysis indicated temperature, humidity, and wind speed as primary influencing features.

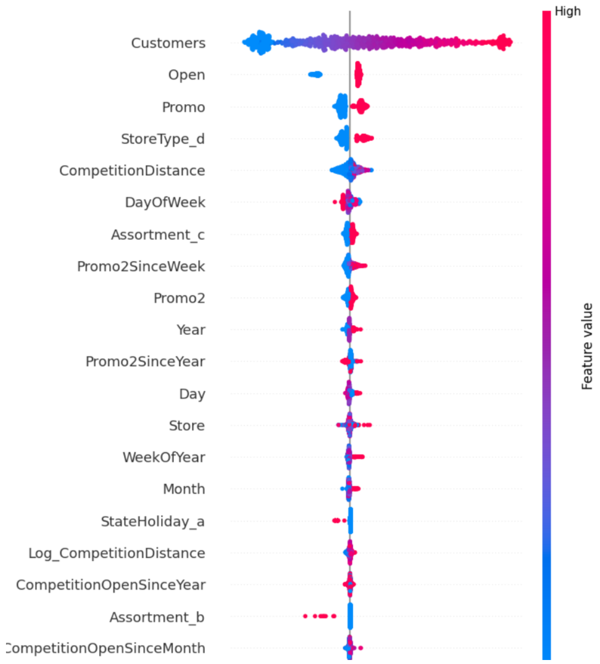

Fig. 3. SHAP values showing feature impact on model predictions

V. Conclusion and Future Scope

The time series data, including features related to promotions, holidays, and seasonal changes, together with historical data, was sufficient to build reliable predictive models for estimating and tracking sales over the year. We implemented the more powerful XGBoost algorithm and created a model with advanced gradient-boosting structured data capabilities, providing superior performance in capturing intricate non-linear patterns present in the data. The model's explainability was conducted using SHAP, which in straightforward terms provided answers on the sales prediction by revealing the impact every attribute provided. Customers, the open/closed status of the store, and active promotions served as the major reasons for sales which validated the model's behavior against domain expectations. Some relative work that can be done on the model to enhance it's performance can be:

- Economic External Variables: The inclusion of external economic variables could enhance our predictions even more, perhaps inflation rates, gas prices, or gross regional product.
- Deep Learning Extensions: There are probably more deep learning architectures, e.g., Temporal Convolutional Networks or Transformer-based time series models or perhaps LSTMs. Their improvement in model performance would likely be more valuable in those that extended the prediction window, as that would be the application for use by analytics teams for potential effect on upcoming decisions or future planning with the customer.

With such advancements, the model could evolve into an even more powerful decision-support tool for strategic retail planning.

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