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Commodity Price Optimization based on Price Elasticity of Demand

G SHIREESHA[1], SHAIK MAHAMMAD IRFAN[2], S PRASHANTH[3], TATIKONDA NARENDRA[4], SHAIK ALLA BAKSHU[5]

Assistant Professor, Department of Information Technology, Vasireddy Venkatadri Institute of Technology, Guntur, India[1]

Department of Information Technology, Vasireddy Venkatadri Institute of Technology, Guntur, India[2-5]

Abstract: Pricing strategies are essential for optimizing revenue, profitability, and customer happiness in the fiercely competitive retail sector of today. The goal of this project is to create a machine learning-based price optimization model that will allow merchants to identify the best prices for their products by examining a number of influencing factors, such as market circumstances, competition pricing, demand trends, and historical sales data. The suggested solution makes use of predictive analytics to comprehend how pricing and demand elasticity are related, determining the price points that optimize profits without offending clients. To forecast sales success at various price points and suggest the most lucrative pricing strategies, sophisticated regression algorithms like Gradient Boosting (XGBoost) are used. To improve the accuracy of the model, feature engineering will take into account consumer segmentation, inventory levels, promotions, and seasonality. The model will be trained and validated using publicly available or retailer-provided data, and its performance will be evaluated using metrics such as Mean Absolute Error (MAE) and Revenue Growth Rate (RGR). One of the top priorities will be creating a dynamic and adaptable system that can respond to changes in the market in real time. The expected outcome is a data-driven pricing strategy that helps businesses increase profit margins, reduce inventory costs, and improve customer retention. This initiative may have practical benefits for retail chains, e-commerce sites, and other consumer-focused firms seeking to enhance their pricing tactics.

Keywords: Demand prediction, price optimization, data driven machine learning, retailing.

INTRODUCTION

Pricing strategies are essential for striking a balance between revenue, profitability, and customer pleasure in the fiercely competitive retail industry. The goal of this project is to create a machine learning-based price optimization model that will help merchants identify the best prices for their products by examining a number of important variables, including demand trends, rival pricing, past sales data, and general market circumstances.

The method helps merchants find price points that optimize revenue without turning off customers by using predictive analytics to analyze the link between pricing and demand elasticity. This will be accomplished by using sophisticated regression algorithms to forecast sales success at various price points, especially Gradient Boosting (XGBoost). Toimprove forecast accuracy, feature engineering will also take into account consumer segmentation, inventory levels, promotions, and seasonality.

The model's performance will be evaluated using important metrics like Mean Absolute Error once it has been trained and verified using publicly accessible or retailer- provided datasets. (MAE) and the rate of revenue growth (RGR). Developing a dynamic and flexible pricing system that reacts to current market swings and guarantees the best possible pricing tactics at all times is a key component of this project.

A data-driven pricing optimization tool that increases profit margins, lowers inventory costs, and boosts client retention is the anticipated result. Retail chains, e- commerce sites, and other customer-focused companies looking to optimize their pricing strategies for optimal profitability can all benefit from this solution.

Conventional marketers often relied on intuition when setting prices, paying little attention to market trends, customer behaviour, the effects of promotions, holidays, or how these factors influenced how price-sensitive the products were. Due to improvements in high computing capabilities that enable the analysis of massive amounts of data over time, the majority of firms are using big data technology to optimize pricing choices. This is done in an attempt to offer more affordable prices while making sure that the highest possible clearing, revenue, and profit goals are reached.

Businesses must choose the optimal pricing for their goods in order to meet objectives like more revenue and profitability. Product pricing is by far the most significant determinant of sales and income. Therefore, businesses must choose the optimal pricing for their products in order to maximize revenue. Our approach uses an OLS linear regression model to read and analyze product data collected from retail sources in order to train and generate a demand curve. One can predict the product's optimal price by using the concept of price elasticity.

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I. LITERATURE REVIEW

The methods suggested by Rajan Gupta et al. [1] for forecasting and anticipating online buyers' purchases. This research presents an investigation of dynamic price changes in offline and online enterprises. The idea of selling products at varying costs based on consumer demand is known as dynamic pricing. The author discussed five different pricing strategies: segmented pricing, peak pricing, service time pricing, purchase time pricing, and pricing for fluctuating circumstances. Segmented pricing is the practice of adjusting the price of an item or service based on the customer's willingness to pay. Because customers are heavily charged during peak hours, peak user pricing is more commonly applied in the railroad and airline industries. The practice of charging exorbitant rates for brief service durations or set delivery dates is known as service time pricing. Pricing for the purchasing period refers to the time of purchase when the flight's take off time is shortest. When the market for a product is unclear, adjusting conditions pricing is the last resort

For prescriptive pricing optimization, Akhiro Yebe et al. [2] provide a unique resilient quadratic optimization paradigm. Because statistical evidence indicates that the estimation uncertainty in machine learning follows a matrix normal distribution, robust quadratic programming was created as a careful upper-bound reduction technique. The main contributions are divided into two steps. First, we show that uncertainty in prescriptive price optimization may be represented as a matrix normal distribution when the least squares approach is applied.

This provides a naturally robust formulation of a price optimization as a conservative lower-bound maximization. Second, we provide robust quadratic optimization techniques that use sequential relaxation to a non-robust counterpart that uses a subroutine of a non- robust algorithm. The sequential algorithms employed for robust quadratic programming converge rapidly both theoretically and practically, and they may be used to the development of non-robust price optimization strategies. Experimental results on both fictitious and actual price data show that the method allows users to get both safe and profitable pricing strategies in the prescriptive price optimization.

Three machine learning algorithms—support vector machine, random forest, and gradient boosting machine—are the foundation of the system developed by Winky K.O. Ho et al. [3] for the assessment of real estate prices. Using these three machine learning techniques, this study aims to experimentally estimate home prices before analysing the findings. Advanced machine learning algorithms are capable of properly estimating real estate prices based on performance metrics. First, the study has shown how property analysts may use state-of-the-art machine learning approaches to anticipate home prices. These algorithms themselves have certain limitations.

Second, compared to more established techniques like the hedonic pricing model, machine learning algorithms often need substantially longer computation times. While selecting the algorithm, several elements are taken into account, such as the amount of data, the processing power of the tools, and the duration of the waiting period for the complete findings.

In order to determine the optimal price point for every distinct product in the fashion e-commerce industry,this study [4] presents a progressive machine learning method and optimization technique. It is divided into three primary sections. First, the demand for each product is predicted for the next day at a certain discount rate using a demand estimate model. The price elasticity of demand concept is then used to create a range of demand values by altering the discount percentage. For each product, as a result, multiple price-demand pairings are made, and one of among them is chosen for the further computing. Ecommerce typically comprises millions of many products, therefore there are numerous arrangement possible. And for every combination, a different pricing point is set for all the products, adding up to a different income amount. Finally, one pricing range for each product is chosen using a linear programming optimization technique in order to maximize overall profit.

J. H. Zhang et al. [5] introduced a method that helps with revenue optimization and retail product pricing decision-making. The study utilized sales data from popular retailers in 45 locations during a two-and-a-half-year period. After redefining clustering and filtering using the R platform, the optimization model is used. Weekly demand is predicted using a machine learning system built on regression trees and random forests. Price, inventory, promotions, holidays, and other regional considerations are also taken into consideration while making decisions. Using several trees in a random forest reduced the range of errors.

II. METHODOLOGY

A. DATASET

For the purpose of demand forecasting and pricing optimization in the retail sector, a structured collection of product-related data is known as the retail dataset. Fresh fruit, dairy, drinks, and basic foods are just a few of the product categories it includes; each is impacted by important market variables. A thorough basis for price and demand research is provided by the dataset, which includes characteristics like demand, seasonality, competition pricing, historical sales, and promotions. For efficient machine learning applications, the data is pre-processed to guarantee consistency, using standardized formatting and standardization. Robust model training and assessment are made possible by the dataset's

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partitioning into training, validation, and test sets. This dataset is a useful tool for retail analytics and predictive modelling that enables practitioners and researchers to improve sales forecasts and pricing strategies. A responsible and cooperative research environment is promoted by recognizing the dataset sources and abiding by ethical usage norms.

B. Objective

Significant progress has been made in the development of machine learning models, especially in predictive analytics. One of the first models for predictive tasks was the decision tree, which provided a simple yet efficient method of data classification and prediction. However, overfitting—a condition in which the model learns the training data, including noise, too well—was a problem with classic decision trees. This results in poor generalization on unknown data. Furthermore, single decision trees were not robust enough to handle huge datasets with intricate feature interactions.

Techniques for ensemble learning were devised in order to overcome these constraints. A stronger prediction model is created by combining many weak learners using ensemble techniques. Gradient boosting stood out among these methods as a particularly successful and economical strategy, using an iterative procedure to gradually reduce errors in weak models. This led to the development of XGBoost (Extreme Gradient Boosting)—an optimized and scalable gradient boosting framework.

C. Proposed System

Creating a machine learning-based price optimization model that helps merchants identify the best product prices by examining past sales, rival pricing, and market dynamics is the main goal of the system design phase. Price suggestions are dynamic and data-driven because to the system's scalability, agility, and real-time decision-making capabilities. The system's integration of predictive analytics yields actionable insights that assist companies optimize revenue and maintain their competitiveness in the retail sector.

Additionally, the system has an intuitive user interface that makes it easy for users to interact with the model. Retailers may enter product information, modify prices, and get the best price recommendations based on machine learning predictions thanks to this interface. The system design process is defined by the following essential phases, which guarantee a methodical and effective implementation.

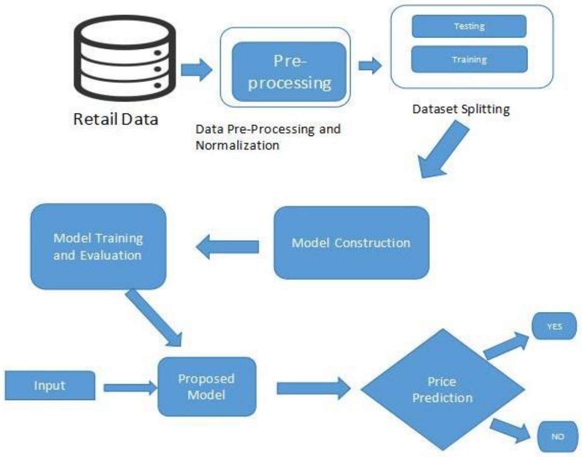

Fig. 1 Proposed System

D. ALGORITHM USED

XGBoost (Extreme Gradient Boosting) Model Architecture: The foundation of XGBoost is gradient boosting, which combines several weak learners into a powerful model to improve prediction performance. XGBoost uses an iterative learning approach to improve predictions across several training cycles, in contrast to conventional decision trees, which function independently. The model is especially well-suited for retail pricing optimization and demand forecasting since it is very effective, scalable, and tuned for handling big structured datasets.

1. Boosted Decision Trees:

XGBoost constructs an ensemble of decision trees in a sequential manner. Unlike conventional decision trees, where each tree operates independently, XGBoost builds trees iteratively, with each new tree attempting to correct the errors made by the previous trees. This ensures that the model continuously improves its accuracy. In this process, trees are

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assigned different weights based on their predictive performance, and subsequent trees focus more on the misclassified or error-prone observations. By aggregating the predictions of multiple trees, XGBoost minimizes residual errors and enhances overall accuracy. Additionally, pruning techniques and regularization prevent the model from overfitting, ensuring that it generalizes well to unseen data.
This technique is particularly beneficial for retail price optimization, where pricing trends and demand fluctuations require a dynamic and adaptive predictive approach. The use of boosted decision trees helps capture complex relationships between variables like historical sales, competitor pricing, and promotional impacts.

2. Gradient Boosting Mechanism

The core mechanism that powers XGBoost is gradient boosting, a technique that optimizes a machine learning model by iteratively minimizing prediction errors. In gradient boosting, each tree is trained on the residual errors (differences between actual and predicted values) left by previous trees. XGBoost optimizes a loss function using gradient descent, a mathematical approach that adjusts model parameters by computing gradients (slopes) to find the best possible predictive performance. By continuously adjusting weights and refining decision boundaries, the model improves its predictions in each iteration. This mechanism is particularly effective for structured data, where the relationship between variables is complex and non-linear. For retail businesses, gradient boosting enables more precise demand forecasting and price sensitivity analysis, leading to optimized pricing strategies that maximize revenue and customer engagement.

3. Handling Missing Values & Feature Selection:

One of the major advantages of XGBoost is its ability to automatically handle missing values and perform efficient feature selection.

- Instead of requiring imputation techniques (such as mean or median filling), XGBoost learns how to handle missing values dynamically, identifying optimal splits that minimize prediction errors.
- The model also applies feature selection, assigning importance scores to each variable. Less significant features are ignored, which reduces computational overhead and enhances efficiency.
- This built-in dimensionality reduction ensures that the model remains both lightweight and powerful, even when working with high-dimensional datasets containing many variables.

For retail applications, this capability is particularly useful as real-world sales data often contains missing entries, inconsistencies, or redundant attributes. By intelligently selecting the most relevant variables, XGBoost improves predictive performance while reducing unnecessary computation, making the system both accurate and efficient.

4. Fully Connected Layers (Deep Learning Integration):

Although XGBoost is primarily a tree-based model, it can also be integrated with deep learning architectures in hybrid machine learning models.

- Fully connected layers, commonly found in deep neural networks, can be incorporated into XGBoost models to enhance feature extraction and classification performance.
- In hybrid models, deep learning layers (such as those found in convolutional neural networks or ResNet architectures) can extract complex patterns from unstructured data, while XGBoost processes structured data to refine predictions.
- For example, in price optimization, a hybrid model might use deep learning to extract hidden patterns in consumer behaviour while using XGBoost to finalize price predictions based on structured sales data.

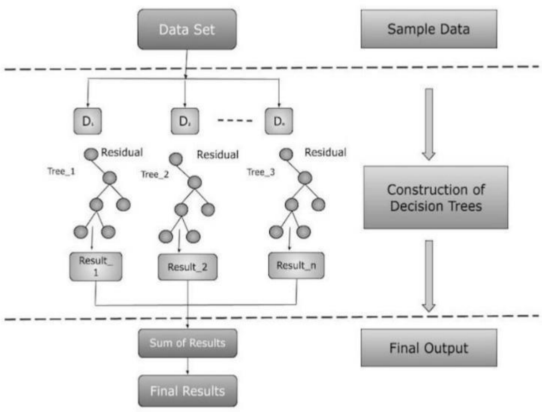

Fig 2: XGBoost Model Architecture

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III. IMPLEMENTATION

Tools and Technologies Used:
For effective development and deployment, a variety of tools and technologies are used in the pricing optimization system's implementation. Python 3 is the main programming language because of its ease of use and wide range of library support. An interactive online application that enables users to dynamically evaluate various pricing methods is built using Streamlit. Google Colab and Visual Studio Code are used to manage the development environment, offering cloud-based execution and effective debugging.

Dataset and Preprocessing:A structured retail dataset with characteristics including past sales, rival price, seasonality, promotions, and demand was employed in this investigation. It covers a wide range of product categories, including dairy, fresh vegetables, drinks, and essential foods. Handling missing data, eliminating duplicate entries, normalizing numerical properties, and encoding categorical variables are examples of preprocessing procedures. To guarantee model generalization and accuracy in performance evaluation, the dataset is divided into training (70%), validation (20%), and testing (10%) sets.

Machine Learning Model:
XGBoost (Extreme Gradient Boosting), the main technique for pricing optimization, builds a series of decision trees in order to improve demand forecasts. Through repeated weight adjustments and residual error minimization, the gradient boosting method improves the model. XGBoost is a strong option for predictive analytics in price optimization as it effectively handles structured data, selects features, and automatically handles missing values.

Model Training and Evaluation:
The model learns the link between price and demand elasticity through the use of previous sales and market-related data. To guarantee precise demand forecasts, training is carried out using the XGB Regressor from the XGBoost package, and performance is assessed using Mean Absolute Error (MAE). By reducing mistakes and dynamically modifying decision boundaries, the model gets better over time.

Price Optimization and Decision Support System:
Users may interactively change product price and see how it affects demand and income using the Streamlit- based interface. The trained XGBoost model forecasts demand based on user-inputted characteristics, including competitor pricing, seasonality variables, and promotional status. Additionally, the system estimates income and makes suggestions on whether the new pricing approach would boost sales or necessitate changes.

IV. RESULTS

Price Optimization Application Interface:
The price optimization application is designed to provide data-driven pricing recommendations using machine learning. The interface is built using Streamlit, allowing users to interact with the model and visualize demand predictions in real time. The application is based on an XGBoost model, which analyzes historical sales data, competitor pricing, and market conditions to generate optimal pricing strategies.
The interface consists of two key components:
1. Data Overview and Sample Dataset
2. Interactive Pricing Tool for Price Optimization These components allow users to explore historical sales data, modify pricing parameters, and receive revenue predictions, enabling them to make informed pricing decisions.

1. Data Overview and Sample Dataset:
The first image represents the application dashboard, displaying a sample dataset used for training the model. The dataset contains real-world product data, including:
- Product Name – The retail item for which pricing is being optimized.
- Historical Sales – Past sales volume, which serves as an indicator of product demand.
- Competitor Price – The price set by competing retailers for the same product.
- Seasonality – A categorical variable (Low, Medium, High) that reflects demand fluctuations based on seasons.

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- Promotion – A binary indicator (1 for active promotion, 0 for no promotion) to analyze the impact of discounts and marketing strategies.
- Price – The current price at which the product is being sold.
- Demand – The total quantity demanded for the product at the specified price.

This dataset is pre-processed and fed into the machine learning model, which learns patterns and relationships between pricing, demand, and external factors. The application then leverages this trained model to forecast demand and recommend price adjustments.

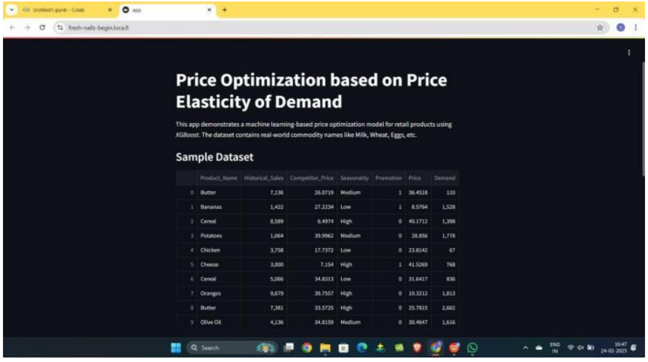

Fig 3: Home page of our Project

2. Interactive Pricing Tool for Price Optimization

The second image showcases the price optimization tool, allowing users to interactively adjust product pricing and observe its impact on revenue. This feature provides a real-time decision-support system for retailers, enabling them to experiment with different pricing strategies.

Key Features of the Pricing Tool:

1. User Input Fields:
- Users can select a product from the dropdown menu.
- They can manually input the competitor's price to see how it influences demand.The seasonality factor (Low, Medium, High) can be adjusted to reflect seasonal demand trends.
- Users can indicate whether a promotion is active or not.

2. Dynamic Price Adjustment:
- A slider widget allows users to set a new price for the selected product.
- The system calculates the corresponding predicted demand based on the input values.

3. Revenue Prediction and Decision Support:
- The application estimates Predicted Revenue at the New Price by multiplying the predicted demand by the set price.
- A decision box provides insights into the impact of the pricing change.
- If the new pricing strategy is expected to increase revenue, a green notification is displayed: *"The new price is expected to increase revenue."*
- If the price adjustment is not beneficial, a warning or alternative recommendation may be provided.

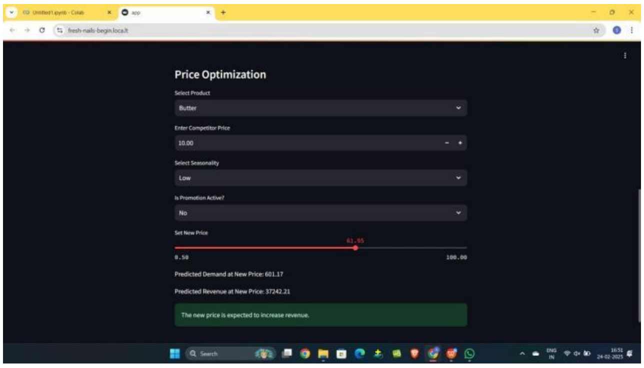

Fig 4: Price Optimization Result

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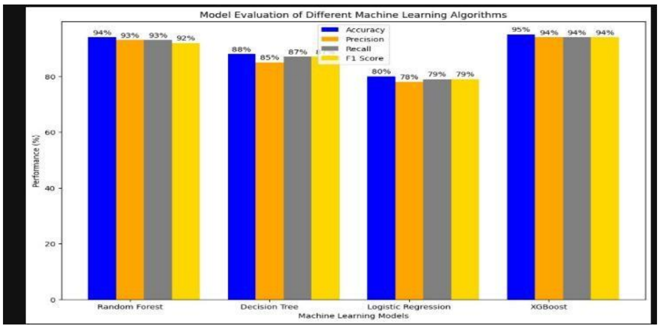

Fig 5: Performance Comparison of Machine Learning Algorithms Based on Evaluation Metrics

The machine learning models Random Forest, Decision Tree, Logistic Regression, and XGBoost are compared in Figure 6 according to the following important performance metrics: Accuracy, Precision, Recall, and F1 Score. According to the data, XGBoost is the most successful model for predictive analytics, outperforming all others with the greatest accuracy (95%) and balanced precision-recall scores (94% each). With an accuracy of 94%, Random Forest comes in second, while Decision Tree and Logistic Regression do worse, with accuracy scores of 88% and 80%, respectively. In contrast to ensemble-based models (XGBoost and Random Forest), which show excellent predictive capabilities, Logistic Regression suffers with complicated pricing patterns, as seen by its poorer accuracy and recall scores. This investigation demonstrates how well boosted decision trees work for pricing strategy optimization in retail demand forecasting.

V. CONCLUSION

The study's findings show how well machine learning-based price optimization may increase store profitability and client retention. Through the use of sophisticated predictive analytics, namely Gradient Boosting (XGBoost), the model effectively determines the best price plans that strike a compromise between maximizing revenue and accommodating client demand flexibility. Incorporating crucial elements like rival pricing and seasonality guarantees a more flexible and dynamic solution that can react to changes in the market in real time. The accuracy and business effect of the model are confirmed by performance evaluation utilizing indicators such as Mean Absolute Error (MAE) and Revenue Growth Rate (RGR). The suggested method offers a data-driven framework that helps consumer- focused companies, e-commerce sites, and shops efficiently improve their pricing strategies. Future research may concentrate on enhancing interpretability, including real- time data streams, and investigating reinforcement learning strategies for ongoing optimization. All things considered, this study emphasizes how important machine learning is to contemporary retail pricing tactics, providing a flexible and scalable option for companies looking to maintain their competitiveness in a changing market.

VI. FUTURE WORK

By continually learning and adjusting to new consumer behaviours and market trends, future versions can further improve the dynamic pricing approach by including cutting- edge AI techniques like reinforcement learning. In order to improve demand forecasts and price strategies, future innovations can include real-time data from external sources, like social media trends, weather, and economic factors. To improve pricing strategies globally, the model may be modified for worldwide markets, taking into account regional economic situations, cultural preferences, and currency variations.

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