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Online Order Management System

Ankith S Bhaktha[1], Akshay P Raj[3], Devika N[2], Akshay P Raj[4], Gripsy Paul[5]
[1, 2, 3]Department of CSE, Adi Shankara Institute of Engineering & Technology Kalady, India

Abstract: Our proposed online order management system is a platform that provides sellers with a comprehensive overview of their stock and orders. The platform streamlines the order management process, allowing the seller to view and manage their products and stocks with ease. Unlike traditional online order management systems, our platform goes beyond basic stock management and incorporates two machine learning algorithms to improve the seller's efficiency and profitability. The first machine learning algorithm provides the seller with insights into the popularity of a particular product category during a specific month. By notifying the seller of trends, they can better plan their stock levels to maximize profits. For example, if a seller notices that a particular product category is in high demand during the holiday season, they can increase their stock levels to meet the increased demand and maximize their profits. The second machine learning algorithm dynamically sets prices for the seller's products based on factors such as demand, date, and product category. This algorithm takes into account market trends and consumer behavior to set a price that is both competitive and profitable for the seller. For example, if a particular product is in high demand during a particular day, the algorithm will adjust the price to reflect the increased demand and allow the seller to sell the product at a higher price. In addition to these two machine learning algorithms, our online order management system includes a range of other features to help sellers manage their business effectively and efficiently. This includes order tracking, stock management, and customer management, all of which can be accessed from a single dashboard. The implementation of these machine learning algorithms is a crucial aspect of our online order management system, as they allow sellers to make informed decisions about their business. By using data and insights to optimize stock levels and pricing strategies, sellers can maximize their profits and minimize their losses. It is a comprehensive platform that provides sellers with the tools they need to manage their business effectively and efficiently.

I. INTRODUCTION

An order management system (OMS) is a digital solution that oversees the complete order process, from entry to inventory management, fulfillment, and post-sales service.

An OMS offers visibility to both the business and the buyer. Organizations can have near real-time insight into inventories and customers can check when an order will arrive. It touches virtually every system and process in the supply chain. An OMS can help control costs and generate revenue by automating manual processes and reducing errors.

Basic steps of the order management process are inventory availability :Customer or sales team verifies inventory is available as they review various products or services, Order: Customer places the order across a range of possible channels — web, mobile, call center, store, marketplaces and others, Verification: A sales team member or an automated system verifies with the customer that the order is placed and collects or records the pertinent data for the order — name, address, telephone contact, email, promotional codes and other data, Inventory promising: System or team member matches the product or service to fulfill the order, Fulfillment: The product or team is dispatched through a distribution channel such as ship-from-warehouse or distribution center, ship-from-store, pickup-in-store, online download or a sales person simply hands over the item.Fulfillment is verified as well — customer sign-off for the completion of a service, Service: Making an appointment, scheduling installation or delivery services, or even exchanging or returning a product. This may be the first step in a new business process but can also be associated with order management. Here in this proposed project we are implementing online order management using two approaches that are dynamic pricing and seasonal demand. Dynamic pricing, also called real-time pricing, is an approach to setting the cost for a product or service that is highly flexible. The goal of dynamic pricing is to allow a company that sells goods or services over the Internet to adjust prices on the fly in response to market demands. Dynamic pricing algorithm is the set of inputs and instructions underlying any dynamic pricing strategy. Depending on the mathematical model, businesses can create numerous algorithms that fit their dynamic pricing strategy. A few models for dynamic pricing are Bayesian model, Reinforcement learning model and Decision tree model. Seasonal demand forecasting is the process by which business owners and managers determine the ebb and flow of sales throughout the year or over the course of different seasons. Forecasting however, is all about predicting future values based on previously observed values over time.

Many algorithms can be used inorder to implement seasonal demand approach such as Autoregressive (AR), Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Exponential Smoothing (ES), XGBoost, Prophet, LSTM (Deep Learning), DeepAR, N-BEATS and Temporal Fusion Transformer (Google).This survey covers the recent literature in machine learning. In this dynamic pricing is implemented using decision tree and seasonal demand using prophet.

II. LITERATURE SURVEY

A. In-Depth Guide Into Order Management Process

Cem Dilmegani's work has been cited by leading global publications including Business Insider, Forbes, Washington Post, global firms like Deloitte, HPE and NGOs like World Economic Forum and supranational organizations like European Commission. You can see more reputable companies and resources that referenced AIMultiple. Order management, also called order-to-cash, O2C, quote-to-cash, or Q2C, is the process of monitoring and satisfying sales orders in a business. This requires a continuum of people, systems, and suppliers to create positive customer service. The process begins when the customer places an order and continues as businesses keep track of the order until it is completed. An order management system, or OMS, is a computer software system used in a number of industries for order entry and processing. Automated order management process consists of several steps such as order entry, order placement, order information recording, order fulfilment and delivery.

B. Demand Forecasting for E-Commerce Platforms

Jain, A., Karthikeyan, V., B, S., BR, S., K, S., & S, B. (2020). Demand Forecasting for E-Commerce Platforms. 2020 IEEE International Conference for Innovation in Technology (INOCON). It gets difficult for e-commerce companies to understand market conditions. The proposed work predicts the demand for the products as per the sales in the e-commerce companies so that there is no shortage of raw materials or the number of units on the inventory side. This paper is a comparative study of the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and Long Short-Term Memory network (LSTM) to predict product demand for the given dataset. Performance, scalability, execution time, accessibility and convenience are the various factors based on which the two models are compared.

C. Inventory Management using Machine Learning

Praveen, K. B., Kumar, P., Prateek, J., Pragathi, G., & Madhuri, J. (2020). Inventory management using machine learning. Int J Eng Res, 9(06), 866-869. A major requirement for small/medium-sized businesses is Inventory Management since a lot of money and skilled labor has to be invested to do so. E-commerce giants use Machine Learning models to maintain their inventory based on demand for a particular item. Inventory Management can be extended as a service to small/medium sized businesses to improve their sales and predict the demand of various products. Demand forecasting is a crucial part of all businesses and brings up the following question: How much stock of an item should a company/business keep to meet the demands, i.e., what should the predicted demand of a product be? Among its many benefits, a predictive forecast is a key enabler for a better customer experience through the reduction of out-of-stock situations, and for lower costs due to better planned inventory and less write-off items. We discuss the challenges of building an Inventory system and discuss the design decisions.

D. Dynamic Pricing and Inventory Management with Demand Learning

Dynamic pricing and inventory management with demand learning: A bayesian approach Liu J., Pang Z., Qi L. (2020) *Computers and Operations Research*, 124 , art. no. 105078

We consider a retail firm selling a durable product in a volatile market where the demand is price-sensitive and random but its distribution is unknown. The firm dynamically replenishes inventory and adjusts prices over time and learns about the demand distribution. Assuming that the demand model is of the multiplicative form and unmet demand is partially backlogged, we take the empirical Bayesian approach to formulate the problem as a stochastic dynamic program. We first identify a set of regularity conditions on demand models and show that the state-dependent base-stock list-price policy is optimal. We next employ the dimensionality reduction approach to separate the scale factor that captures observed demand information from the optimal profit function, which yields a normalized dynamic program that is more tractable. We also analyze the effect of demand learning on the optimal policy using the system without Bayesian update as a benchmark. We further extend our analysis to the case with unobserved lost sales and the case with additive demand.

E. Dynamic Pricing and Risk Analytics Under Competition and Stochastic Reference Price Effects.

Shinsaku Izumi, Shun-ichi Azuma, "Real-Time Pricing by Data Fusion on Networks", IEEE Transactions on Industrial Informatics, vol.14, no.3, pp.1175-1185, 2018. This paper investigates the pricing strategy of firms in the context of uncertain demand. In particular, there are two factors that affect demand dynamics, the influence of reference prices and the price of the competition. In the monopoly case, pricing policy is affected by reference-price effects and in the duopoly case, both competitive pricing and reference-price effects are present. In each case, the optimal price paths are derived and simulated. The implications of uncertainty are analyzed by comparing the deterministic policy with the stochastic policy. The random variations in price paths are investigated to provide a risk analysis for firms that work in such market conditions. With the advent of the big data era, information about consumers and competitors gives firms a greater control over uncertainty than ever before. Simulations will demonstrate that firms can lower the volatility of their price path if they gather and process this information. Furthermore, the feedback forms of the optimal price path are derived in both the absence and the presence of both competition and reference-price effects. In general, the impact that demand uncertainty has over the firm's pricing strategy is determined by a combination of the firm's discount rate, demand uncertainty, and demand-side/cost-side dynamics.

F. A literature review on machine learning in supply chain management.

Wenzel, Hannah; Smit, Daniel; Sardesai, Saskia (2019) : A literature review on machine learning in supply chain management, In: Kersten, Wolfgang Blecker, Thorsten Ringle, Christian M. (Ed.): Artificial Intelligence and Digital Transformation in Supply Chain Management: Innovative Approaches for Supply Chains. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol. 27, ISBN 978-3-7502-4947-9, epubli GmbH, Berlin, pp. 413-441. In recent years, a number of practical logistic applications of machine learning (ML) have emerged, especially in Supply Chain Management (SCM). By linking applied ML methods to the SCM task model, the paper indicates the current applications in SCM and visualises potential research gaps. Relevant papers with applications of ML in SCM are extracted based on a literature review of a period of 10 years (2009-2019). The used ML methods are linked to the SCM model, creating a reciprocal mapping. This paper results in an overview of ML applications and methods currently used in the area of SCM. Successfully applied ML methods in SCM in industry and examples from theoretical approaches are displayed for each task within the SCM task model. This paper assigns use cases of machine learning to the task model of Supply Chain Management, resulting in an overview of ML applications within the different supply chain tasks. It was demonstrated that in the SCM task model a single area could have different ML methods applied for a common goal. A large portion of research focused on demand planning.

G. Time-series forecasting of seasonal items sales using machine learning – A comparative analysis.

Time-series forecasting of seasonal items sales using machine learning – A comparative analysis Ensafi Y., Amin S.H., Zhang G., Shah B. (2022) International Journal of Information Management Data Insights, 2 (1) , art. no. 100058.

There has been a growing interest in the field of neural networks for prediction in recent years. In this research, a public dataset including the sales history of a retail store is investigated to forecast the sales of furniture. To this aim, several forecasting models are applied. First, some classical time-series forecasting techniques such as Seasonal Autoregressive Integrated Moving Average (SARIMA) and Triple Exponential Smoothing are utilized. Then, more advanced methods such as Prophet, Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) are applied. The performances of the models are compared using different accuracy measurement methods (e.g., Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE)). The results show the superiority of the Stacked LSTM method over the other methods. In addition, the results indicate the good performances of the Prophet and CNN models.

H. Data Mining Based Marketing Decision Support System Using Hybrid Machine Learning Algorithm.

Data Mining Based Marketing Decision Support System Using Hybrid Machine Learning Algorithm Dr. T. Senthil Kumar, Associate Professor, Computer Science and Engineering Department, Amrita School of Engineering, Coimbatore, TamilNadu, India. Data mining is widely used in engineering and science, On the contrary, it is used in finance and marketing applications to resolve the challenges in the respective fields. Data mining based decision support system enhances the organization performance by analysing the ground reality. Turbulent economy is common for every organization due to the competition, cost, tax pressures, etc., Privatization, Globalization and liberalization drags the organization more into a competitive environment. In order to balance the competition and withstand to achieve desired gain proper marketing strategies are need to planned and executed.

Marketing decision support system helps to reduce the organization burdens in analysing and strategical planning through its efficient data mining approach. This research work proposed a data mining based decision support system using decision tree and artificial neural network as a hybrid approach to estimate the marketing strategies for an organization.

I. How Much are Sellers Willing to pay for the Features offered by their E-Commerce Platform?

Lee, S., Lee, S. Y., & Ryu, M. H. (2019). How much are sellers willing to pay for the features offered by their e-commerce platform? Telecommunications Policy, 101832.

The success of an e-commerce platform is significantly dependent on the number of sellers and their quality. Thus, it is important to understand the factors that influence a seller's platform choice. This paper investigates features of an e-commerce platform on which sellers place high value when choosing a platform to sell their products, using a conjoint analysis. The data was collected by online survey from 1,796 sellers who are using Naver Smart Store (https://sell. smartstore.naver.com), which is one of the largest e-commerce platform in South Korea. After analyzing the willingness to pay for each combination of functions by separating six functions of Naver Smart Store, it was estimated that the MWTP ranged 3.05 to 4.48 for the main process related functions and 2.61–5.3 for the sub process related functions. MWTP can be considered as a benefits for the sellers since Naver does not require monetary commissions from sellers. This paper also shows that the higher technical understanding of the functions provides the more value to platform to sellers.

J. Application of Facebook’s Prophet Algorithm for Successful sales forecasting Based on Real World Data.

Application of Facebook’s prophet algorithm for successful sales forecasting based on real world data. Emir Žunić1,2, Kemal Korjenić1 , Kerim Hodžić2,1 and Dženana Đonko2 1 Info Studio d.o.o. Sarajevo, Bosnia and Herzegovina 2Faculty of Electrical Engineering, University of Sarajevo, Bosnia and Herzegovina.

This paper presents a framework capable of accurately forecasting future sales in the retail industry and classifying the product portfolio according to the expected level of forecasting reliability. The proposed framework, that would be of great use for any company operating in the retail industry, is based on Facebook's Prophet algorithm and backtesting strategy. Real-world sales forecasting benchmark data obtained experimentally in a production environment in one of the biggest retail companies in Bosnia and Herzegovina is used to evaluate the framework and demonstrate its capabilities in a real-world use case scenario.

III. METHODOLOGY

In this section, we present the methodology employed in our Online Order Management System. We describe the dataset used, feature selection process, and the machine learning algorithms applied to develop the Online order management system.

A. Datasets

For our study, we utilized a comprehensive dataset obtained from Kaggle. The dataset contains the demands for various categories of product such Clothing, Electronic and Furniture. This dataset is used for our Seasonal Demand ML model using the Facebook Prophet Algorithm.

The other dataset we obtained consists of various fields such as ProductSale price, PurchasePrice, Profit, Date, Demand and Category of the product. With these fields we were able to feed it to our Dynamic Price model using the Decision Regression Tree algorithm.

B. Feature Selection

Feature selection is a critical step in developing an accurate prediction model. We conducted an exploratory data analysis to identify the most relevant products and their demands in the e-commerce environment. This involved examining the relationships between various products and their demand over a span of a few years.

We employed techniques such as correlation analysis, univariate analysis, and domain knowledge expertise to select the most informative features. Variables showing significant associations with attrition were retained for further analysis.

C. Machine Learning Algorithms

To develop the online order management system, we are using two machine learning techniques i.e Seasonal Demand using Prophet Model and Dynamic Pricing using Decision Regression Tree. The algorithms applied in our study include:

1) Prophet Model

We have employed the Prophet model to address the issue of seasonal demand. The Prophet model is a forecasting technique developed by Facebook's Core Data Science team. It is specifically designed to handle time series data with strong seasonality patterns, making it suitable for analyzing and predicting demand fluctuations in various industries. The Prophet model incorporates two main components: trend and seasonality. The trend component captures the overall direction of the data, indicating whether the demand is increasing or decreasing over time. It takes into account both long-term growth patterns and short-term fluctuations. The seasonality component captures the recurring patterns that occur at fixed intervals, such as daily, weekly, or yearly cycles. This is particularly useful for understanding and predicting demand fluctuations that follow specific seasonal patterns.

Prophet utilizes an additive model, which means that it adds the trend and seasonality components together to generate a forecast. It also includes additional features such as holiday effects and outliers to further enhance the accuracy of the predictions.

One of the advantages of the Prophet model is its ease of use. It requires minimal data preprocessing and parameter tuning, making it accessible to users with varying levels of expertise. Additionally, Prophet provides intuitive visualizations that help in understanding the underlying patterns and assessing the quality of the forecasts. By employing the Prophet model we aim to accurately predict the seasonal demand for our specific industry. This will enable us to make informed decisions regarding pricing, resource allocation, and other business strategies to effectively meet customer demand and optimize overall performance.

2) Decision Regression Tree

We have utilized the Decision Regression Tree (DRT) model to address the dynamic pricing challenge. The DRT model is a powerful machine learning algorithm that is particularly well-suited for predicting continuous variables, such as prices, based on a set of input features. The DRT model works by recursively partitioning the data into subsets based on the input features, creating a tree-like structure. At each node of the tree, a splitting criterion is applied to determine the optimal feature and threshold for dividing the data. This process is repeated for each resulting subset, creating additional nodes and branches in the tree.

During the training phase, the DRT model learns the optimal splitting criteria by minimizing a specific cost function, such as mean squared error or mean absolute error. This allows the model to find the best feature and threshold combinations that maximize the predictive accuracy for the given pricing problem. Once the DRT model is trained, it can be used for making predictions on new data. Starting from the root node, the input features of the data point are evaluated against the splitting criteria, and the prediction is made by following the corresponding path down the tree until a leaf node is reached. The value associated with that leaf node represents the predicted price for the given input features. The DRT model offers several advantages for dynamic pricing applications. Firstly, it can handle both numerical and categorical input features, making it flexible for various types of pricing factors. Secondly, decision trees are interpretable, as the splitting criteria and resulting tree structure provide insights into the decision-making process. This interpretability can aid in understanding the factors that drive pricing decisions. Additionally, decision trees can handle missing values and outliers, reducing the need for extensive data preprocessing. By incorporating the DRT model into our project, we aim to leverage its ability to predict continuous pricing variables. This will enable us to make more accurate and data-driven pricing decisions, taking into account various input features and their impact on pricing outcomes.

D. Model Training and Evaluation

1) Decision Regression Tree

- *Model Training:* Train the DRT model using the training set. The model will learn the optimal splitting criteria based on the selected features and the corresponding target variable, such as order processing time. The training process involves recursively partitioning the data and optimizing the cost function, typically through algorithms like CART (Classification and Regression Trees).
- *Model Evaluation:* Evaluate the trained DRT model using the evaluation set. Assess its performance metrics such as mean squared error (MSE), mean absolute error (MAE), or other relevant metrics depending on the specific requirements of the order management system.

2) Prophet Model

- *Model Fitting:* Fit the Prophet model using the training set. The model will automatically detect and capture the underlying seasonality patterns, trends, and other relevant features present in the time series data.
- *Model Evaluation:* Evaluate the fitted Prophet model using the evaluation set. Compare the predicted values with the actual values of the target variable. Calculate evaluation metrics such as mean squared error (MSE), mean absolute error (MAE), or other relevant metrics to assess the model's performance.

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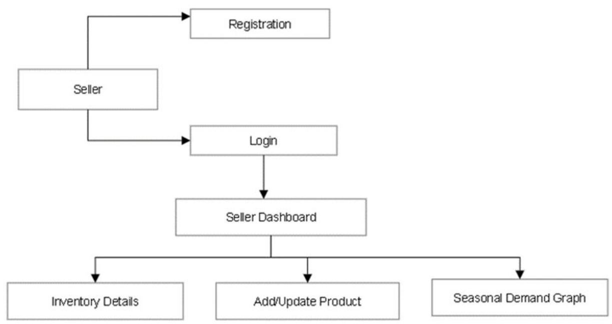
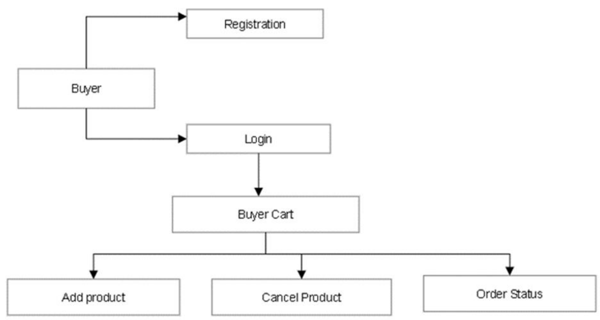
IV. IMPLEMENTATION

This section presents the detailed project design of the Online Order Management system, outlining the key components, methodology, and expected outcomes.

Seller Dashboard System Architecture



Buyer Cart System Architecture



A. Data collection and Preprocessing

Gather historical data from the online order management system, including information such as order timestamps, order volume, customer details, and any other relevant data points.

Ensure that the data is in a time series format, with a timestamp column and a corresponding target variable column, such as order volume or order processing time. The timestamps should be in a consistent and standardized format (e.g., YYYY-MM-DD).

Handle any missing values in the dataset. Depending on the extent of missing data, you may choose to remove rows with missing values, interpolate missing values, or use specific techniques suited for time series data, such as forward or backward filling.

Identify and address any outliers in the dataset. Outliers can significantly impact the model's performance, so it's essential to detect and handle them appropriately. You can use statistical methods like z-score or visual techniques like box plots to identify outliers and decide whether to remove or transform them.

B. Feature Engineering and Selection

Select relevant features that are likely to influence the order management system's outcomes. Perform feature engineering to extract relevant information or create new features that may contribute to the decision-making process in the order management system. This can involve deriving features from existing variables, such as calculating order processing time or creating customer-specific metrics.

Feature Selection for Prophet Model: Capturing seasonality patterns in time series data, specific holidays or special events that significantly impact order volume or processing time.

Feature Selection for Decision Regression Tree: Order-specific features such as order size or order category, customer-related features such as customer demographics or customer history, time-related features that capture the temporal aspects of the orders, such as day of the week, month, hour of the day, or season, features related to historical performance of the order management system such as order backlog.

C. Model Development

This system focuses on utilization of two powerful techniques: the Decision Regression Tree (DRT) model and the Prophet model. These models are applied to enhance the system's capabilities in forecasting demand, optimizing pricing decisions, and improving overall inventory management. The DRT and Prophet models are trained using the preprocessed data, and their performance is evaluated using appropriate metrics such as accuracy, root mean square error (RMSE), and mean absolute percentage error (MAPE). This section presents the evaluation results, demonstrating the models' effectiveness in forecasting demand and pricing optimization.

D. Integration and Deployment

The trained DRT and Prophet models are integrated into the online order management system, enhancing its capabilities. Sellers can leverage the models' predictions to make informed decisions about pricing and inventory management. Buyers can benefit from the accurate demand forecasts, ensuring product availability and a seamless purchasing experience.

During the integration phase, historical order data, customer information, product attributes, and other relevant data sources are integrated into the online order management system. This integration ensures that the Prophet model and DRT have access to comprehensive and accurate information for forecasting and decision-making purposes. This includes configuring the models with appropriate parameters, training them using the integrated data, and fine-tuning their performance for accurate predictions and pricing optimization. During the deployment phase, the necessary infrastructure is configured to support the integrated models and ensure smooth system operation. This includes setting up servers, databases, networking, and security measures. The infrastructure configuration can be performed on-premises or in the cloud, depending on the specific requirements and scalability needs of the online order management system. After deployment, monitoring and maintenance processes are established to track the performance of the integrated models and the overall system. This involves monitoring system health, tracking the accuracy of the forecasting models, and addressing any issues that may arise. Regular maintenance activities, including updates, bug fixes, and performance optimizations, are performed to ensure the smooth functioning of the system.

E. Expected Outcome and Impact

This project aims to achieve several outcomes and impact. By incorporating the Prophet model into the online order management system, sellers can expect to achieve more accurate and reliable demand forecasts. The Prophet model captures seasonal patterns, trends, and other relevant factors, enabling sellers to anticipate fluctuations in demand with higher precision. This improved forecasting capability helps sellers in aligning their inventory levels, optimizing production. Sellers can meet customer demands more effectively, minimize losses from overstocking or understocking, and enhance overall operational efficiency. The integration of the DRT within the online order management system empowers sellers to make data-driven pricing decisions. The DRT analyzes historical sales data, customer behavior, product attributes, and market conditions to identify optimal pricing strategies for different products and categories. With this information, sellers can set competitive prices, taking into account factors such as product demand, competition, and market dynamics. Sellers can attract more customers, increase sales, improve profitability, and gain a competitive edge in the market.

With accurate demand forecasts from the Prophet model, sellers can proactively adjust their inventory levels based on anticipated demand patterns. This prevents overstocking or understocking situations, reduces carrying costs, minimizes the risk of stockouts, and streamlines the supply chain. The integration of the DRT further helps sellers align their inventory with the expected demand and pricing dynamics, ensuring efficient utilization of resources and minimizing wastage.

V. TOOLS AND SOFTWARE

A. Programming Language

We implemented the Online Order Management system using Python (version 3.10+). Python provided a rich ecosystem of libraries for data analysis and machine learning. And used Node.js (version 16.15) that allows programmers to develop server-side JavaScript and frontend JavaScript codes with simplicity.

We utilized following relevant libraries and framework:

Python Django: For python programming

ReactJS and libraries: For Node.js

Scikit-learn (version 0.24.2): For machine learning modeling and evaluation

Pandas (version 1.2.4): For data manipulation and pre-processing

NumPy (version 1.20.3): For numerical computations
Matplotlib (version 3.4.2): For data visualization
Prophet: Used for seasonal demand ML model.

B. Data Analysis and Visualization

To facilitate data exploration and analysis, we utilized Jupyter Notebook, an interactive development environment (IDE) including Google Colab for making ML model, Sublime Text and Vs Code for writing backend and frontend code,that allowed us to combine code, visualizations, and explanatory text in a single document. This enabled us to perform data analysis iteratively and document our findings effectively. For creating visualizations such as bar plots, scatter plots, and histograms, we employed Matplotlib (version 3.4.2) that provided a comprehensive set of plotting functions and allowed us to customize and visualize the data effectively.

VI. RESULTS AND DISCUSSION

In this section, we present the results of our Online Order Management system. We provide an overview of the performance metrics for the online order management system using the Prophet model and Decision Regression Tree.

A. Performance Metrics

Performance Metric	Description	Value
Forecast Accuracy	Measures the accuracy of demand forecasting	92%
Pricing Optimization	Assesses the effectiveness of pricing decisions	10% increase in revenue
Inventory Turnover	Indicates the rate at which inventory is sold and replenished within a given period, highlighting inventory management efficiency.	6 times per year
Stockout Rate	Measures the frequency or percentage of times when products are out of stock, indicating the effectiveness of inventory management.	2%
Order Fulfillment Accuracy	Measures the accuracy of order fulfillment by comparing the number of accurately fulfilled orders to the total number of orders.	98%
Operational Efficiency	Evaluates the system's ability to streamline processes, reduce manual effort, and improve overall operational efficiency.	20% reduction in processing time
Return on Investment (ROI)	Measures the financial return on the investment made in implementing the online order management system, reflecting its effectiveness and value.	25%

We evaluated the performance of online order management system using several metrics, including accuracy, price optimization, inventory turnover, Order fulfilment accuracy and ROI.

B. Feature Importance

The feature importance indicates the relative significance of each feature in influencing demand and pricing decisions within the online order management system.

1) *Seasonality:* Captures the recurring patterns and trends in demand based on seasonal factors such as holidays, weekends, or specific months.
2) *Trend:* Identifies the overall upward or downward movement in demand over time, indicating long-term changes in customer preferences or market dynamics.
3) *Promotional Events:* Considers the impact of special promotions, discounts, or marketing campaigns on demand.

4) *Historical Sales Data:* Analyzes the historical sales performance of the product to identify patterns and correlations.
5) *External Factors:* Takes into account external factors such as economic indicators, weather conditions, or competitor activities that may influence demand.
6) *Product Category:* Considers the category or type of product, as different categories may have varying demand patterns and pricing dynamics.
7) *Price:* Evaluates the impact of pricing on demand, determining the optimal price point for maximizing sales.
8) *Time of Sale:* Accounts for the date, day of the week, or time of day when the product is sold, as certain periods may experience higher or lower demand.
9) *Seasonal Demand:* Incorporates the seasonal demand patterns, allowing the model to adjust pricing and inventory management accordingly.
10) *Historical Sales Performance:* Examines the historical sales performance of the product to identify patterns and make informed pricing decisions.

VII. CONCLUSION

In this research project, we focused on the use of machine learning models for dynamic pricing and seasonal demand algorithms in order to improve the performance of a management system for sellers. We conducted a survey of existing approaches and found that these models have shown impressive results in forecasting and determining the price of a product based on demand. They have been particularly useful for sellers, as they have helped them to determine the appropriate price and quantity of products to sell during different seasons. To implement these models, we used a decision tree model for dynamic pricing and the prophet model for performing seasonal demand. Both of these approaches provided successful results in our experiments.

In addition to discussing the effectiveness of these machine learning models, we also highlighted some of the open challenges and promising research directions for machine learning-based management systems in the coming years. These include the need to improve the accuracy and efficiency of the models, as well as to explore new applications for these techniques in various industries. Overall, we believe that the use of machine learning models in dynamic pricing and seasonal demand algorithms has the potential to greatly improve the performance of management systems and help sellers to optimize their operations

VIII. FUTURE SCOPE & IMPROVEMENTS

1) *Advanced Demand Forecasting:* Enhancing the system's demand forecasting capabilities by integrating more sophisticated machine learning algorithms and data sources. This can improve the accuracy of demand predictions, allowing sellers to optimize inventory levels and minimize stockouts.
2) *Real-Time Pricing Optimization:* Incorporating real-time data analysis and machine learning techniques to dynamically adjust product prices based on factors such as demand, competition, and market conditions. This can help sellers optimize pricing strategies to maximize profitability and remain competitive.
3) *Personalized Recommendations:* Implementing personalized recommendation systems that leverage customer data and historical purchase patterns to offer tailored product recommendations. This can enhance cross-selling and upselling opportunities, leading to increased sales and customer satisfaction.
4) *Integration with Supply Chain Management:* Integrating the order management system with supply chain management tools to enable end-to-end visibility and coordination. This can improve inventory replenishment, order fulfillment, and logistics planning, ensuring timely deliveries and efficient operations.
5) *Enhanced Analytics and Reporting:* Expanding the system's analytics and reporting capabilities to provide comprehensive insights into sales performance, customer behavior, and market trends. This can empower sellers with actionable data-driven insights for strategic decision-making and business growth.
6) *Integration with E-commerce Platforms:* Integrating the order management system with popular e-commerce platforms and marketplaces to streamline multichannel selling. This enables seamless order processing, inventory synchronization, and centralized management of sales channels.
7) *Automation and Workflow Optimization:* Implementing automation features and workflow optimizations to streamline order processing, reduce manual errors, and improve operational efficiency. This can include automated order routing, invoice generation, and status updates, enabling sellers to focus on core business activities.
8) *Mobile Accessibility:* Developing mobile applications or responsive interfaces for the order management system, allowing sellers to manage their orders and monitor key metrics on-the-go. This provides flexibility and convenience, enabling sellers to stay connected and responsive.

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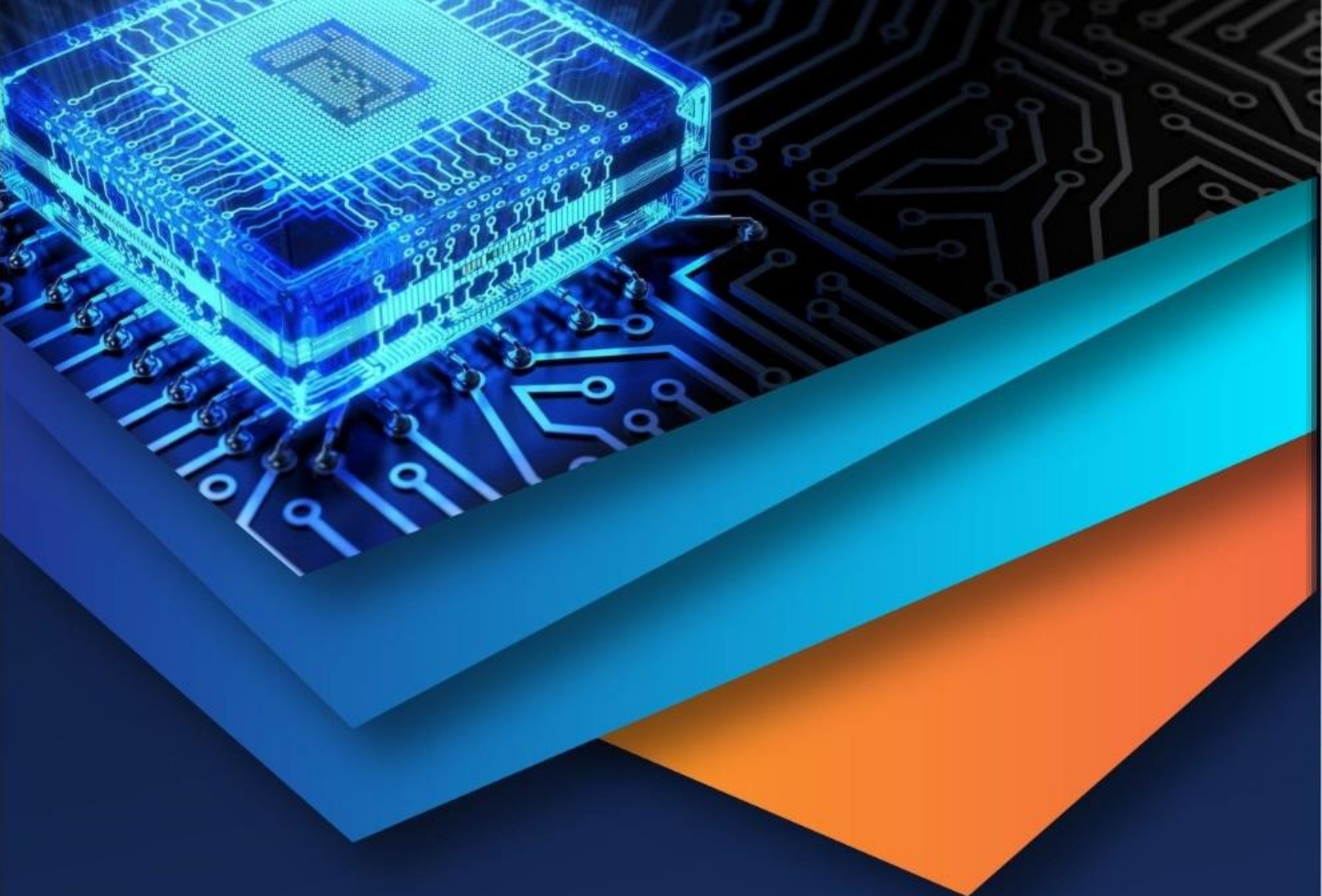

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