IFERP

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Volume 11 Issue 7 July 2024

Optimizing Bullwhip Effect in Hotel Management Systems Using Artificial Intelligence

[1] Yogesh Kumar B, [2] Sharon Priya S, [3] Aisha Banu W, [4] Aarthi G

[1] [2] [3] [4] Computer Science and Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, Chennai
Corresponding Author Email: [1] yyogeshkumar996@gmail.com, [2] sharonpriya@crescent.education, [3] aisha@crescent.education, [4] gaarthii@gmail.com

Abstract— ***The Bullwhip Effect, a distortion of demand fluctuations inside a supply chain, continues to test traditional supply chain management. This study investigates the revolutionary potential of AI algorithms in minimizing the Bullwhip Effect using Artificial Intelligence Techniques for demand forecasting, dynamic inventory management, supplier relationship management, and real-time data exchange provides a comprehensive approach to optimize successful deployments, with real benefits such as cost savings, increased efficiency, and increased customer satisfaction. This work speaks about the demand fluctuation caused by hotel industry consumers and efficiently predicts the demand using an ensemble machine learning model. Inheriting the ensemble stacking the incorporation of two base learners (KNN and K means clustering) who have different characteristics are used to analyse the meal movement analysis and food type classification both combined to be the input of meta-model linear regression and with these factors, the meta-model predict the demand. Firstly using the k means clustering as a base learner which type of meals are consumed by whom is found and the food type classification is undertaken by the KNN base learner.***

Both of them are then given to meta-learner linear regressor to predict the food demand of the given region. Outputs look promising and the Mean Square Error (MSE) is used for performance evaluation.

Index Terms— ***Artificial Intelligence, Machine Learning, Demand Prediction, Ensemble Learning, Bullwhip Effect.***

I. INTRODUCTION

The Bullwhip Effect (BWE) is a circumstance where a small fluctuation action causes a huge impact on the other actioners in a closed chain environment [1]. The bullwhip effect raises operating costs in food supply networks, particularly when perishable goods are involved. Here in the food Industry the small fluctuation in demand raised by customers which effectively affects the stockholders like retailers, distributors, Raw materials, and inventory is studied and resolved by predicting the demand using the artificial ensemble technique.

For online food enterprises to maximize inventory, food demand forecasting is essential. Regression, Random Forest, and XG Boosting are examples of machine learning models that precisely estimate demand, minimizing waste and shortages [2]. Forecasting helps to make long-term business decisions. It also makes it easier to check, estimate, and analyze data to achieve calculable results. It leads to regular investigations of different facets of manufacturing as well as leadership both within and outside of the company. Forecasting lays the groundwork for future operations and improves coordination, cooperation, and management within the organization. Prognostication involves accurately weighing and studying future possibilities, stability, and disparities. This enables management to eliminate any impediments that may arise in the management process. Restaurants use Machine Learning (ML) to estimate demand for different food goods at different locations, which helps with waste reduction and ideal ingredient storage [3].

Thus, corporate results are contrasted with calculable ones, highlighting the opposite component of prognostication. When a significant difference is discovered, further study is conducted to determine the causes of the gap.

Time series analysis provides insight into the numerous features of underlying key patterns, as well as the breakdown of different trends and periodicity. Regression and time-series forecasting are two machine learning strategies that are used to predict demand in food-related industries accurately [4]. Forecasting with time series is essential for forecasting the sales of food. Forecasting has become complex due to the abundance of data and business competition. An attempt is made to estimate sales of the shop's daily sales data. Monthly and yearly data item charts take into account various trends and seasonal variations. Techniques from ML are used to achieve this by ensemble the different characteristics of ML algorithms to learn and drive the outcome that's expected.

In this study, store-based demand forecasting was implemented. One of the most significant contributions is that the dataset comprises time series characteristics, but we turned it into a regression dataset during the feature engineering step. Regression ML algorithms which are the family of prediction-type machine learning algorithms and also traditional techniques were applied to the dataset, which is the output of data pre-processing and feature engineering stage. After that, the data set is driven into base learners and fitted into a meta-model for forecasting.

ISSN (Online) 2394-2320
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II. LITERATURE REVIEW

Demand forecasting for any goods is one of the notable aspects of improving the balance in stock [5]. Then analyzed the harvest of wheat on a national using an ensemble learning method. Methodical creation of the exponential weighted moving average forecasting expressions. Similarly, seasonal and non-seasonal series with additive or multiplicative error structures are covered by the approaches and Estimating ratio seasonal, wherein sales figures are determined via integrating recent seasonally fluctuating sales with the preceding period's sales rate, utilizing exponential weights that decrease over succeeding periods [6]. Also, it investigates projecting a ratio trend, focusing on scenarios without seasonal changes, where the sales rate is generated by combining current sales and the preceding time's sales rate compensated for trend revisions. For retail sales forecasting, ARIMA models are examined, and model selection is done using Akanke's Information Criteria. Single and multi-step approaches were drafted for the projections of retail sales. The evaluation metrics used here are RMSE, MSE, and MAPE State space and ARIMA models generate coverage probabilities near nominal rates for both one-step and multi-step forecasts [7].

Unreliable inventory control in convenience stores causes consumer discontent and revenue loss. Leading to shortages or over-ordering, highlighting the significance of accurate order control to meet client expectations properly. Efficient inventory control in fast food restaurants is important for increasing customer happiness and income this endeavor seeks to construct a sales forecasting model known as the Cluster and Forecast Model (CFM), which uses a hybrid artificial neural network forecasting model [8]. The research proposes a novel way to scale the KNN classification approach for large datasets that begins with k-means clustering for data splitting. The issue of efficiently training from big data sets in a variety of real-world applications, including classification and clustering. [9] This research proposes a novel way to scale the KNN classification approach for large datasets that begins with k-means clustering for data splitting. The training phase selects the nearest cluster for each test instance as its new trained dataset, and the testing phase uses the KNN algorithm to classify each test instance inside its nearby cluster. Landmark-based Spectral Clustering (LSC) is a clustering approach that is introduced to scales linearly and has low processing complexity. There has been little debate of the suggested algorithm's scalability to highly massive or high-dimensional data areas which may be a problem in realistic applications utilizing big data. Inventory management in the food industry is vital for enterprises to convert raw resources into finished commodities for profit. Inventory management is critical since meeting the needs of customers is key for client retention. Understanding current trends assists in preserving adequate quantities to cover orders and avoid shortages. It focuses on forecasting demand to avoid out-of-inventories and excess inventories in the food the company Uses the Random Forest ensemble method in ML algorithms to successfully estimate client wants [10]. The precision of forecasts is determined by the Root Mean Squared Logarithmic Error (RMSLE) measure, which assesses prediction accuracy.

Demand projection is essential in managing supply chains for improving operations and lowering storage costs. Conventional strategies like ARIMA models have issues with dynamic supply chain features, resulting in the use of AI techniques such as SVR for increased forecasting accuracy. Support Vector Regression (SVR) and Particle Swarm Optimization (PSO) are introduced for reliable supply chain demand forecasting [11]. The performance of the SVR-PSO technique can vary because of stochastic elements in the algorithm used for PSO, resulting in different outcomes for each run. The research paper performs an empirical analysis of the supply chain based on 100 different retail items across 10 locations, drawing on a 5-year sales data history from 2013 to 2018. The study applies time-series forecasting methods, such as decomposition, ARIMA, Prophet, and Box-Cox transformation, to the collected data to estimate sales and evaluate the efficacy of these models in real-time transactions in stores. Examines three criteria to help with model selection decisions and assesses the precision of ML models in projecting future sales for logistics stores. These contrasting results indicate that an integrated model comprising Prophet and ARIMA performs better than individual models. Fuzzy time series (FTS) forecasting in interrupted supply chains demonstrates its advantage over other methods. High-order FTS are suggested for higher tiers to match the auto-regressive integrated moving average approaches for supply chain disruptions but does not dive into the specific industries or sorts of disruptions where FTS may be less effective, providing potential for more research into the generalizability of the findings [12]. Intends to overcome the issues with handling inventory systems with periodic demand patterns, enabling dynamic decisions in inventory control for intelligent supply chains. To increase demand prediction precision in semiconductor supply chains, a hybrid forecasting model employing recurrent neural networks & linear approaches is proposed [13]. The framework might not operate optimally in certain cases due to implementation limitations or computational complexity. Further investigations or experimentation may be required to investigate the adaptability, stability, and adaptability of the suggested strategy across other semiconductor supply chain environments and demand patterns. The movement of goods and data in a supply chain is critical for good supply chain management, ensuring all company operations work nicely together. Utilizes an ensemble model for predicted demand in the retail market, specifically deployed in SOK Markets, a hard discounting chain in Turkey [14]. While the article highlights several aspects that can affect forecasting accuracy, like as seasonality, promotions effects, and competition activity, it does not go fully into how these elements are

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ISSN (Online) 2394-2320
International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Volume 11 Issue 7 July 2024

folded into the ensemble methodology.

III. DATASET EXPLORATION AND PREPROCESSING

The "Food Demand Forecasting" dataset, which includes 145 weekly purchase orders for 50 meals. The data is separated into three files, totaling approximately 4, 50,000 items and 15 features. Fulfillment_center_info.csv includes details for each fulfilments center with attributes such as center_id, and op_area which contains the area of service details, city_code, centre_type, and regional_code.

Meal_info.csv Provides information for each fulfilments center. It includes the meal_id, which is the unique identifier for each meal, Meal type (e.g., beverages, snacks, soups), and Cuisine (e.g., Indian, Italian, etc.). Weekly Demand Data provides historical sales data for specific meals in a specific center. The following information is included id: A unique order ID is associated, week (1-145), meal_id a unique ID for each meal, center_id a unique ID for each fulfilments center, checkout_price and base_price.

This section seeks to examine each characteristic independently. Categorical and numerical features are thoroughly investigated. Plotting histograms illustrates the distribution of each feature. Figure 3.1 shows that the majority of "num_orders" values are grouped around 0. The distribution has a spread of more than 20,000, suggesting the potential of an outlier. Data down-sampling, also known as subsampling or under-sampling, is a machine learning and statistics technique that reduces the size of a dataset by deleting samples from the majority class(es) to produce a more balanced distribution. This method is especially beneficial when the classes are uneven, which means that one or more classes are much more common than others. Down-sampling attempts to address class imbalance by equalizing the representation of each class, which can improve the performance of machine learning models, particularly those that are sensitive to class distribution [15].

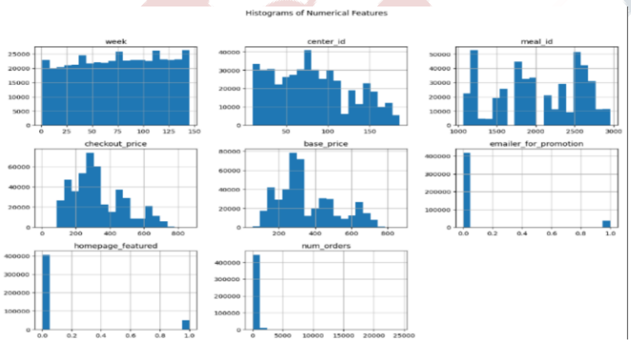

Figure 3.1. Variable distribution of each feature

IV. PROPOSED MODEL

The proposed system represents a paradigm shift from conventional forecasting approaches. By incorporating advanced clustering techniques and food type classification, the project aims to address the identified challenges and introduce a more adaptive and accurate forecasting model [16]. The choice of clustering analysis is motivated by the need to identify intricate patterns in meal movements across different centers. This segmentation is crucial for tailoring forecasting models to regional demand dynamics. Simultaneously, the incorporation of food type classification introduces a finer granularity to the analysis, capturing specific preferences that contribute to the overall demand picture [17].

The proposed system's adaptability is a key feature, allowing it to evolve with changing consumer behavior and market trends. This section provides a comprehensive overview of the methodologies chosen and their alignment with the project's objective. The classification models will analyses the meal movement and both inputs are clipped with each other and given to the forecasting model for future demand.

V. METHODOLOGY

The proposed system comprised two base learners firstly the classification learner KNN and the clustering analysis model K-means model acts as base learners and then the meta-model is used to predict the demand with the help of meta-learner linear regression. Figure 5.1 shows the overall workflow of the system.

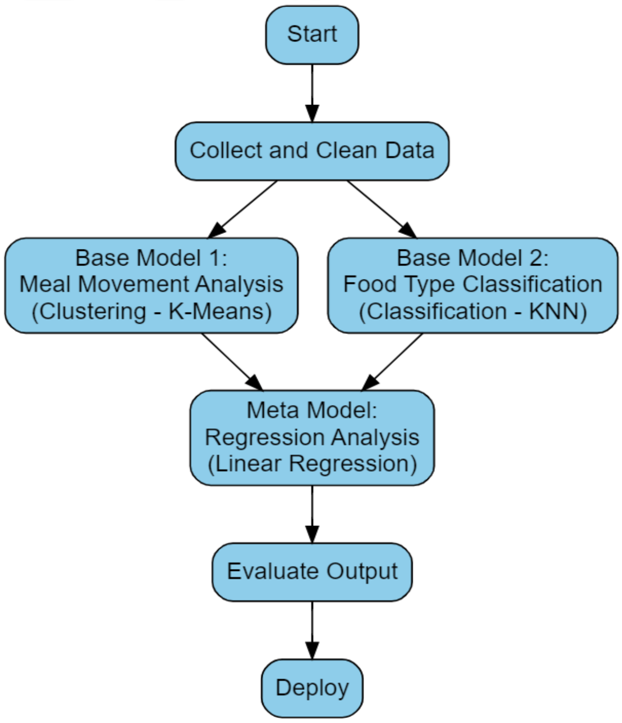

Figure 5.1. Flow Diagram

A. Predictive Modelling

Machine learning algorithms make use of historical data on sales (no of order) placed to build predictive models. These models can also identify the key factors that contribute to stock, region, communication, and user feedback.

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

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B. Base Model 1: Clustering Analysis

It is possible to classify food types into several clusters according to their cuisine using machine learning algorithms. This can help identify which groups of dishes are moving better or worse in certain regions, and changes need to be made to improve sales. Here K-means clustering is used to group foods according to their cuisine. K-means clustering is an unsupervised learning method that groups similar data according to similarity [18].

C. Base Model 2: Classification Analysis

Moving forward, the Food Type Classification Module emerges as a pivotal base model, employing sophisticated machine learning classifiers for categorizing food types. The intricacies of the classifier KNN algorithm is thoroughly explored [19]. This enriches our understanding of consumer preferences, contributing vital information for subsequent stages of the work.

D. Meta-Model: Regression Analysis

The ultimate goal is to seamlessly incorporate cluster and food-type data into a meta-model designed for demand prediction. This meta-model represents the pinnacle of our analytical efforts, trying to deliver a comprehensive and accurate forecast. Using regression methods, particularly adaptive linear regression, the meta-model expertly combines geographical demand patterns and client preferences. This integration goes beyond the limitations of individual patterns, offering a full understanding of meal demand that takes into account the complex relationships between different components of consumer behaviour[20]. In essence, the meta-model emerges as a strong and adaptable tool for companies, offering not only precise predictions but also profound insights into the complex factors influencing meal demand.

VI. RESULTS AND DISCUSSIONS

The model is evaluated using test splits and promising results are obtained in all three models Figure 6.1 shows the results of cluster analysis prediction Figure 6.2 promotes the classification analysis prediction and the final regression model gives the number of orders that may be placed in Figure 6.3 and Figure 6.4 respectively. Since the bullwhip effect is a user-side demand fluctuation our model tried to cope with the test model because of the deterministic behaviour of user patterns. The test MSE is approximately 80 which shows the good and shining results. Where the mean square error is the average of squares between actual and predicted outcomes [21].

```
Base Model 2 (K-Means Clustering) Train Clusters:
[0 2 1 ... 2 1 0]

Base Model 2 (K-Means Clustering) Test Clusters:
[1 3 3 ... 3 3 0]
```

Figure 6.1: Cluster analysis performance

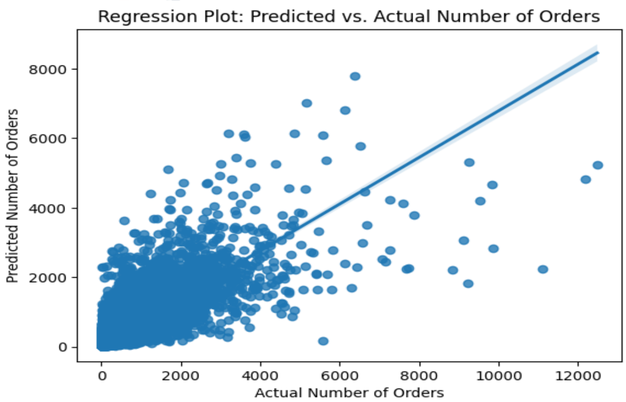
```
Predicted orders : [  44  103   39 ...  101 1584   63]
Actual orders  : [  14   96   55 ...   69 1608   82]
```

Figure 6.2: Food type classification performance

```
Enter meal_id: 1885
Enter center_id: 55
Enter week: 111
Predicted number of orders: 429.78285536141055
55
```

Figure 6.3: Final food demand prediction

In the future, the complex structure of the ensemble model will be reduced and will try to predict the demand even more closely with the help of some improvised models like AutoML and Analytical AI which is under study. Also will try to build an AI-based recommendation system and alert applications using GenAi.



VII. CONCLUSION

In this paper, the proposed system for the advancement of forecasting by leveraging advanced cluster and classifying techniques. The system provides an improved and adaptable forecast model by recognizing complex patterns and combining market regional dynamics. Implementing K-mean clustering and KNN classification as base learners, paired with a meta-model based on adaptive linear regression, enables thorough analysis and demand prediction. As indicated by a modest mean square error, the positive results demonstrate the system's ability to address customer demand

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Volume 11 Issue 7 July 2024

changes and improve forecasting accuracy. This comprehensive strategy gives important insights into customer behavior, making it an effective tool for businesses to improve demand forecasting and decision-making processes.

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