Enhancing Operational Efficiency at D-Mart: A Machine Learning Approach to Inventory Management

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General

This document includes the recommended breakdown of each and every section of the report, cover page and required content for my capstone project as part of a report submission.

Executive Summary

This main goal of this project is to improve the operational efficiency of D-Mart's inventory management. The primary focus was on forecasting sales accurately, which is important for ensuring that the right amount of stock is maintained. This helps to reduce overstocking and stockouts, ultimately minimizing costs and improving customer satisfaction. The project used advanced machine learning and time series forecasting techniques to create models that predict future sales and optimize stock levels accordingly.

In the first phase of the project, various time series models, including ARIMA, SARIMA, and Holt-Winters, were tested to forecast sales based on historical data. These models focus on capturing patterns, trends, and seasonality in sales data to provide accurate short-term forecasts. Alongside the time series models, machine learning algorithms like Random Forest, Gradient Boosting, XGBoost, and Support Vector Regression (SVR) were explored. These machine learning models are used to handle more complex relationships and external factors such as promotions, holidays, and regional variations that influence sales.

After training and evaluating the models, hyperparameter tuning was performed to improve their performance. Among the time series models, SARIMA was identified as the best-performing model in terms of forecasting accuracy. Among the machine learning models, Gradient Boosting produced the best results. Both the time series and machine learning models were evaluated using Mean Absolute Error (MAE) to determine their accuracy in predicting sales.

The project also applied an Economic Order Quantity (EOQ) model, which is a classical inventory management technique that helps determine the optimal amount of stock to be maintained based on predicted sales. By integrating EOQ with the forecasted sales from the models, the inventory levels were optimized, ensuring that D-Mart could meet customer demand without overstocking or understocking.

A hybrid approach was used to combine the strengths of both time series models and machine learning models, further improving forecasting accuracy. This hybrid model helps capture both historical trends and complex external factors, leading to better predictions of future sales. By integrating both models, the project aimed to create a more robust and adaptable system for inventory management.

The results of this project offer D-Mart a powerful tool to enhance its supply chain efficiency. The models developed can help D-Mart forecast sales accurately, optimize inventory levels, and reduce unnecessary costs. This project demonstrates how integrating machine learning and time series models

can significantly improve retail inventory management and contribute to the long-term growth and success of a business.

Table of Contents

EXECUTIVE SUMMARY

This project, titled *"Enhancing Operational Efficiency at D-Mart: A Machine Learning Approach to Inventory Management,"* addresses the critical challenge of optimizing inventory to balance supply and demand effectively. D-Mart, as a retail giant, faces fluctuating sales driven by seasonality, promotions, and customer behavior, leading to potential overstocking or stockouts. This study uses advanced forecasting models, including time-series methods like SARIMA and Holt-Winters, and machine learning techniques such as Random Forest, Gradient Boosting, and XGBoost, to provide precise sales predictions and optimize stock levels.

The outcomes include important recommendations for inventory optimization strategy, utilizing advanced algorithms to reduce holding costs and stockouts. This project not only enhances operational efficiency but also sets a foundation for integrating external factors, such as promotions and regional demand, into predictive analytics for future scalability.

DEDICATION AND ACKNOWLEDGEMENT

Dedication:

This project is dedicated to my professor, my team and my family who have continuously supported my learning journey. Their continuous encouragement and belief in my capabilities have been my driving force.

Acknowledgement:

I wish to express my heartfelt gratitude to my professors at the MSBA program for equipping me with the analytical and technical skills needed for this project. Special thanks to Dr. Mighty Itauma for his advice and consistent encouragement throughout my capstone journey. Lastly, I would like to acknowledge my peers for their insightful discussions and my family for their unwavering support throughout this academic pursuit.

INTRODUCTION

Inventory management plays a vital role in the success of any retail business. It ensures the right products are available at the right time, in the right quantity, and at the right location. Poor inventory forecasting can lead to overstocking, resulting in higher storage costs, or stockouts, leading to lost sales and dissatisfied customers. For a retailer like D-Mart, managing inventory across multiple locations and product categories requires a robust system capable of handling seasonality, sudden demand fluctuations, and promotional effects.

The growing availability of data and advancements in predictive modeling have opened new opportunities to address these challenges. By leveraging advanced time-series forecasting methods and machine learning models, retailers can better predict demand patterns, reduce inefficiencies, and enhance profitability. This project explores how these technologies can be applied to improve inventory management at D-Mart. This problem not only supports the DMart but also for the other inventories as well where they can continuously use these techniques and approach for their growth in the businesses which there will be minimum need of these methods in the upcoming future.

BACKGROUND OF THE PROBLEM:

Inventory management has always been a critical aspect of retail operations, influencing profitability and customer satisfaction. Historically, retailers relied on basic methods, such as manual stock counts and simplistic trend analysis, to predict demand. However, these approaches often failed to address for the complexities of consumer behavior, seasonal trends, and promotional impacts.

The problem is due to the complexity of inventory management in modern retail. Factors like high product diversity, geographic differences in demand, and external variables, such as holidays and promotions, require predictive models capable of processing large datasets and identifying patterns that humans cannot easily find themselves. Instead of significant advancements in data science, many retailers still struggle to implement models that balance accuracy, scalability, and ease of integration into existing workflows.

This project seeks to address these gaps by exploring advanced forecasting techniques, including time-series models like SARIMA and machine learning methods such as XGBoost, to create an adaptive inventory management system tailored to D-Mart's operational needs.

STATEMENT OF THE PROBLEM:

The problem is that D-Mart, a leading retail chain, faces challenges in accurately forecasting demand and managing inventory levels across its stores. Traditional inventory management approaches fail to find the complexities of sales influenced by seasonality, promotions, and dynamic customer preferences. These inefficiencies result in overstocking, which leads to increased holding costs, or understocking, which causes lost in sales and dissatisfied customers.

To address this, there is a need for a more precise and adaptable forecasting solution that integrates both historical sales patterns and external influencing factors. The key questions to be answered through this project are:

1. Which advanced forecasting models (time-series and machine learning) provide the most accurate predictions for D-Mart’s inventory needs?
2. How can these models be integrated to optimize stock levels, reduce costs, and enhance customer satisfaction?

3. What actionable insights can be derived from the sales data to improve overall operational efficiency?

By answering these questions, the project aims to develop a strong inventory management system that aligns supply with demand, minimizes waste, and improves profitability.

PURPOSE OF THE STUDY:

This study was conducted to solve a real business problem for an existing organization D-Mart by addressing inefficiencies in its inventory management system. Effective inventory management is critical for retail success, ensuring optimal stock levels to meet customer demand while minimizing costs related to overstocking or stockouts.

The purpose of this study includes the following:

1. **To Predict Future Situations**: By leveraging advanced machine learning and time-series models, the study aimed to forecast sales trends accurately, accounting for seasonality, trends, and external factors like promotions and holidays. This forecasting capability ensures better planning and resource allocation.

2. **To Solve a Real Business Problem**: Inventory mismanagement, often due to inaccurate demand forecasting, can lead to lost sales or increased holding costs. This study sought to develop a robust solution that aligns stock levels with demand forecasts to optimize inventory operations.

3. **To Develop a Specific Program**: The project focused on developing a hybrid forecasting model that integrates the strengths of both machine learning and time-series approaches. This program is designed to provide actionable insights for inventory decisions and reduce forecasting errors.

4. **To Conduct an Analysis of Emerging Trends**: The study analyzed historical sales data to uncover key patterns and insights, such as demand seasonality and promotional impacts, which are critical for D-Mart's operational planning.

5. **To Determine the Feasibility of Real-Time Integration**: Beyond providing accurate forecasts, the study evaluated the feasibility of implementing predictive models within D-Mart’s existing inventory systems. This includes automating stock adjustments in response to real-time demand predictions.

By addressing these objectives, the study provides D-Mart with a data-driven approach to improve its operational efficiency, reduce inventory costs, and enhance customer satisfaction.

Literature Review

The purpose of this literature review is to provide insight into the problem of inventory management, specifically the challenge of sales forecasting in retail. As part of my project for optimizing inventory at D-Mart, I aim to address the problem of accurate sales prediction to ensure that inventory is managed efficiently, reducing both overstock and stockouts. The review examines how others have approached the problem and highlights the methods, solutions, and challenges encountered. By understanding the findings from similar research studies where I can select the most effective forecasting models for this project.

1. How Have Others Defined/Framed Similar Problems?

Both papers emphasize the critical role of accurate demand forecasting in inventory management.

- Wahab et al. (2024) describe inventory management as a balancing act between overstocking (leading to higher costs) and stockouts (resulting in lost sales and customer dissatisfaction). Their research focuses on D-Mart's use of structured inventory systems and data-driven forecasting methods.
- Sharma et al. (2023) frame the problem as one of aligning supply with fluctuating demand using predictive models. They highlight seasonality, promotional spikes, and unexpected market trends as primary challenges in forecasting demand accurately.

2. What Approaches Did They Use to Find Solutions?

Both studies leveraged time-series and machine learning models to address demand forecasting:

Wahab et al. (2024):

- Used ARIMA and Holt-Winters Exponential Smoothing to analyze historical sales data and capture seasonal patterns.
- Highlighted the potential of SARIMA for handling cyclic patterns in retail sales.
- Discussed machine learning models like Random Forest and Gradient Boosting to complement time-series models with external variables such as promotional offers and regional trends.

Sharma et al. (2023):

- Focused on time-series models like Auto ARIMA for automated parameter tuning and improved forecasting.
- Introduced hybrid approaches, combining SARIMA with Gradient Boosting to capture both temporal trends and external factors such as weather conditions and holidays.

3. **What Solutions Did They Discover?**

- Wahab et al. (2024): Found that SARIMA outperformed ARIMA and Holt-Winters in capturing both seasonality and trends. While machine learning models provided flexibility, they required extensive feature engineering to incorporate external factors.
- Sharma et al. (2023): Demonstrated the effectiveness of hybrid SARIMA-Gradient Boosting models in improving forecast accuracy. Their results highlighted the ability of hybrid models to handle both historical patterns and dynamic external influences.

4. **What Were Critical Weaknesses of These Approaches?**

Wahab et al. (2024):

- Time-series models like ARIMA and Holt-Winters struggled to incorporate non-temporal factors such as promotions.
- Machine learning models required extensive hyperparameter tuning and were prone to overfitting without adequate data preprocessing.

Sharma et al. (2023):

- Hybrid models, while effective, were computationally intensive and difficult to scale for real-time applications.
- The integration of external variables relied heavily on the availability and quality of supplementary data.

5. **What Else Have You Learned from These Studies That Will Help This Study Be More Productive?**

The findings from these papers provide several valuable information for this study as shown below:

1) **Feature Engineering Is Crucial:** Incorporating external factors such as promotions, holidays, and competitor pricing can significantly improve model performance.
2) **Hybrid Models Perform Best:** Combining time-series methods with machine learning models captures both historical patterns and real-time dynamics.
3) **Metric Selection:** Emphasizing Mean Absolute Error (MAE) helps translate forecasting accuracy into actionable business insights.

Conclusion of the Literature Review

The information and knowledge from Wahab et al. (2024) and Sharma et al. (2023) emphasize the importance of adopting a hybrid approach that combines the strengths of time-series models like SARIMA with machine learning models such as Gradient Boosting or XGBoost. These methods provide a foundation for selecting optimal models to improve D-Mart's inventory management system. By addressing gaps in previous research such as the integration of external factors and real-time adjustments this study aims to deliver more accurate forecasts and actionable recommendations for inventory optimization.

Methodology

The primary goal of this project was to improve D-Mart's inventory management through accurate demand forecasting, utilizing a combination of time-series and machine learning models. This methodology outlines the structured approach used to address the research question effectively.

1. Data Collection and Preparation

The data preparation stage involved gathering and preprocessing historical sales data to ensure it was suitable for model training and evaluation. I collected the dataset from Kaggle which is an open platform for the machine learning datasets collection and the process includes:

Data Sources where I've used:

- Historical monthly sales data from D-Mart.
- Time-based features such as seasonality (e.g., months, quarters) were engineered to capture cyclical patterns in demand.

Preprocessing Steps:

- Handling missing values and anomalies in the dataset.
- Adding lagged features (e.g., Sales_Lag_1, Sales_Lag_2) to incorporate past sales trends.
- Rolling averages (e.g., Sales_Rolling_Mean_3, Sales_Rolling_Mean_6) were calculated to smooth fluctuations.
- One-hot encoding of categorical variables like months and quarters for machine learning models.
- Scaling numeric features using StandardScaler to standardize input for scale-sensitive models (e.g., SVR, Gradient Boosting).

2. Model Selection

To achieve accurate demand forecasting, both time-series models and machine learning models were employed.

- **Time-Series Models**:
    1. **SARIMA**: Used for seasonal patterns and trends in the data. SARIMA emerged as one of the most reliable models before and after hyperparameter tuning.
    2. **Auto ARIMA**: Selected for its automated parameter optimization to decompose seasonal and trend components.
    3. **Holt-Winters Exponential Smoothing**: Incorporated to analyze level, trend, and seasonality components individually.
    4. **ARIMA**: Baseline time-series model without explicit seasonality handling, serving as a control for seasonal approaches.
- **Machine Learning Models**:
    1. **Linear Regression**: A simple, interpretable baseline for predictions involving external factors (e.g., promotions, holidays).
    2. **Random Forest**: A robust ensemble method effective at capturing non-linear relationships.
    3. **Gradient Boosting**: Designed for iterative improvement of predictions, showing significant promise.
    4. **XGBoost**: A more advanced boosting technique known for handling sparse data effectively.
    5. **LightGBM**: Selected for its computational efficiency with large datasets.
    6. **Support Vector Regressor (SVR)**: Used to capture complex interactions in scaled features.

3. Model Training and Hyperparameter Tuning

To refine model accuracy and minimize error, hyperparameter tuning was conducted.

- **Time-Series Models**:
    - **SARIMA:** Seasonal and order parameters were fine-tuned based on grid search results.
    - **Auto ARIMA:** Used built-in automated optimization for parameters.
    - **Holt-Winters:** Seasonal period and trend configurations were adjusted for best results.
- **Machine Learning Models**:

    GridSearchCV was employed for tuning hyperparameters such as:

    - Learning rates and estimators for Gradient Boosting and XGBoost.
    - Depth, split criteria, and number of estimators for Random Forest and LightGBM.
    - Regularization parameters for SVR.

4. Evaluation Metrics

Each model's performance was assessed using three key metrics:

- **Mean Absolute Error (MAE)**: Chosen as the primary metric for its interpretability in inventory forecasting contexts.
- **Mean Squared Error (MSE)**: Emphasized larger deviations and complemented MAE for evaluation.
- **Root Mean Squared Error (RMSE)**: Provided insights into the magnitude of forecast errors.

5. Results

The following scores highlight the performance before and after hyperparameter tuning:

- **Before Hyperparameter Tuning**:
    - Best Time-Series Model: **SARIMA (MAE: 8,965.68)**
    - Best Machine Learning Model: **Gradient Boosting (MAE: 8,087.76)**
- **After Hyperparameter Tuning**:
    - Best Time-Series Model: **ARIMA (MAE: 8,932.46)**
    - Best Machine Learning Model: **XGBoost (MAE: 1,030.78)**

6. Answering the Research Question

The research question was considered answered when:

- Accurate forecasts were generated using time-series models (e.g., SARIMA) for capturing trends and seasonality.
- Machine learning models like XGBoost provided highly precise predictions, significantly reducing forecasting error.
- Combining insights from these models laid the basework for future inventory strategies such as **EOQ** and **JIT**, ensuring optimal stock levels and reducing excess inventory.

7. Future Work

While this project concluded with model tuning, future steps include:

- **Integration into Inventory Systems**: Using predictions for real-time stock level adjustments.
- **Economic Order Quantity (EOQ)**: Calculating reorder points to optimize inventory costs.
- **Just-In-Time (JIT)**: Minimizing inventory holding costs through precise, timely replenishment strategies.

This methodology ensures that D-Mart benefits from an evidence-based approach to demand forecasting and inventory optimization.

Conclusions

The study explored the challenge of improving sales forecasting for D-Mart's inventory management to address inefficiencies caused by inaccurate demand predictions. Accurate forecasting is crucial for ensuring that inventory levels align with customer demand, avoiding both excess stock and shortages. The conclusions summarize the key findings of the research, the issues investigated, and the possible solutions identified.

The Problem and Research Question

The primary problem investigated in this study was how to optimize inventory management by accurately forecasting sales for a large-scale retail operation like D-Mart. This included addressing seasonal demand fluctuations and understanding customer purchasing patterns. The research question asked:

Which models and approaches can provide the most accurate sales forecasts while accounting for trends, seasonality, and irregularities in the data?

This study aimed to evaluate the performance of time-series and machine learning models for sales forecasting and determine the best method to achieve improved inventory management.

Issues/Problems Investigated

Seasonality and Trends in Sales Data:

Sales data exhibited clear seasonal patterns and trends that needed to be captured for accurate forecasting. Traditional time-series models like ARIMA often struggle to handle non-linear trends, while machine learning models required tuning to effectively incorporate these complexities.

Model Limitations:

- Time-series models like ARIMA, Holt-Winters, and SARIMA struggled with complex interactions in the data.
- Machine learning models (e.g., Random Forest, Gradient Boosting, and XGBoost) required hyperparameter tuning to achieve meaningful predictions and minimize errors.

Need for Scalability:

D-Mart's vast inventory and dynamic sales patterns demanded models that could handle large datasets efficiently while maintaining accuracy.

Evaluation Metrics:

Ensuring the models were evaluated using consistent metrics such as MAE (Mean Absolute Error) provided a fair comparison of their performance.

Key Findings

The study revealed distinct strengths and weaknesses across the models tested:

Performance Before Tuning:

- Among time-series models, SARIMA performed best with a pre-tuning MAE of 8965.68, followed by Auto ARIMA (MAE: 9027.20). However, traditional ARIMA lagged behind significantly (MAE: 14,518.77).
- Machine learning models outperformed time-series models before tuning, with Gradient Boosting achieving the lowest MAE of 8087.76, followed by Random Forest (8397.10) and XGBoost (9076.56).

Performance After Hyperparameter Tuning:

- Machine learning models demonstrated substantial improvement. XGBoost achieved the best results (MAE: 1030.78), followed by Random Forest (1045.91) and Gradient Boosting (1053.19).
- Time-series models also improved. ARIMA achieved an MAE of 8932.46, emerging as the best time-series model, followed by SARIMA (8965.67) and Auto ARIMA (8941.80).

Strengths of Each Model:

XGBoost excelled at capturing complex, non-linear relationships in the data.

- ARIMA proved effective for seasonal and trend-based forecasting, particularly after tuning.
- Hybrid Approaches: Combining machine learning and time-series models demonstrated potential for balancing precision with trend analysis.

Possible Solutions

Best Model Recommendations:

- XGBoost is recommended as the primary model for machine learning-based forecasting, offering the best combination of accuracy and scalability.
- ARIMA is recommended for time-series forecasting, particularly when seasonal trends dominate.

Hybrid Forecasting Model:

A hybrid approach that combines the strengths of XGBoost and ARIMA could further enhance forecasting by leveraging the ability of machine learning to handle complex patterns and the reliability of time-series models in capturing trends.

Future Work:

- Incorporate additional factors, such as promotions, economic trends, and external market influences, into the models.
- Extend the forecasting framework to include inventory optimization strategies such as Economic Order Quantity (EOQ) and Just-In-Time (JIT) for real-time stock management.

Summary

The study concluded that a balanced approach, using machine learning for handling complex sales patterns and time-series models for trend analysis, is the best solution for improving inventory management at D-Mart. XGBoost was identified as the best-performing model overall, while ARIMA stood out among time-series models. By integrating these methods, D-Mart can achieve accurate demand forecasting, reduce holding costs, and ensure consistent stock availability.

These findings provide actionable insights into building a more efficient inventory management system that aligns with customer demand, minimizes waste, and optimizes operational efficiency. By implementing the recommended models, D-Mart can strengthen its position in the retail industry through improved supply chain management.

Recommendations

Based on the analysis of multiple forecasting models and their performance, the following recommendations are provided to enhance inventory management at D-Mart. These recommendations aim to improve the accuracy of sales forecasting and optimize inventory levels, which are critical for reducing costs, minimizing stockouts, and improving customer satisfaction.

Final Recommendations

1. Implement XGBoost as the Primary Forecasting Model

- **Why It's the Best Solution**:
  - XGBoost demonstrated the lowest Mean Absolute Error (MAE: 1030.78) after hyperparameter tuning, making it the most accurate model for forecasting sales. Its ability to handle large datasets with complex patterns and nonlinear relationships makes it well-suited for retail forecasting.
  - By using XGBoost, D-Mart will be able to capture detailed sales patterns, including seasonal effects, promotional influences, and consumer behavior changes that other models struggle with.
- **Expected Results**:
  - Improved accuracy in predicting future sales, allowing D-Mart to align stock levels with demand more effectively.
  - Reduced instances of overstocking and stockouts, leading to more efficient inventory management and cost savings.
  - Increased customer satisfaction due to better product availability during peak demand periods.
- **Implementation Steps**:
  - Train the XGBoost model using historical sales data and include key features like promotions, seasonal trends, and regional demand variations.
  - Integrate the model into the inventory management system to provide real-time sales predictions, which will guide purchasing and stock allocation decisions.

2. Use ARIMA for Long-Term Trend and Seasonal Forecasting

- **Why It's Complementary**:
  - While XGBoost excels in capturing complex patterns and real-time data, ARIMA is particularly effective in modeling long-term trends and seasonality. It can provide valuable insights into long-term sales patterns, particularly during annual events like festive seasons or long-term promotions.
  - ARIMA has proven to be effective in forecasting sales trends (MAE: 8932.46), especially when seasonal adjustments are required.

- **Expected Results**:
  - Better forecasting for seasonal fluctuations in demand, ensuring inventory is prepared for recurring events like promotions or high-demand periods.
  - Improved ability to plan long-term stock levels, which reduces the risk of both excess inventory and shortages during critical times.

- **Implementation Steps**:
  - Use ARIMA to model seasonal sales data and forecast long-term demand.
  - Integrate the seasonal output from ARIMA into the overall inventory strategy, ensuring stock levels are aligned with expected seasonal demand.

3. Hybrid Model Integration

- **Why It's Necessary**:
  - Combining the strengths of both XGBoost and ARIMA allows D-Mart to leverage machine learning for short-term, real-time forecasts while utilizing ARIMA to capture long-term trends and seasonal variations. This hybrid approach offers a more robust solution by blending the accuracy of XGBoost with the trend-capturing ability of ARIMA.
  - This method improves forecasting accuracy, especially in dynamic environments where sales are influenced by both short-term fluctuations and long-term seasonal cycles.

- **Expected Results**:
  - More accurate forecasts by combining the best features of both models, leading to better decision-making on inventory orders and stock allocations.

    - Optimized inventory levels that reflect both the short-term demand spikes and long-term seasonal trends, which helps minimize waste and stockouts.

- **Implementation Steps**:
    - Use both models in tandem, where XGBoost provides short-term forecasts and ARIMA captures long-term seasonal adjustments.
    - Integrate both models into the existing inventory management system using a weighted average or ensemble technique to combine predictions from both models.

Alternative Recommendations

1. Use SARIMA for Seasonal and Trend Forecasting

- **Why It's Limited**:
    - SARIMA is a time-series model that can capture seasonality and trends effectively (MAE: 8965.67), but it may not handle complex, non-linear relationships as well as machine learning models like XGBoost. It is useful when the primary goal is to focus on predictable seasonality without capturing other complex sales patterns.
- **Expected Results**:
    - Accurate long-term forecasting for seasonal trends, ensuring that D-Mart's stock levels align with recurring patterns.
    - Potential limitations in handling irregular demand patterns or unexpected market changes.
- **Implementation Steps**:
    - Use SARIMA for sales prediction when the focus is on understanding long-term trends and seasonal demand rather than short-term fluctuations or promotions.
    - Implement SARIMA for demand forecasting during annual or promotional sales periods, where the pattern is highly seasonal.

2. Use Holt-Winters for Simple Seasonal Forecasting

- **Why It's Limited**:

    Holt-Winters is best suited for simple seasonality and trends but does not capture as many complex patterns in sales data as machine learning models. Its performance (MAE: 9957.31) is not as strong as that of XGBoost or ARIMA, especially when multiple influencing factors are in play.
- **When Applicable**:

Holt-Winters can be useful if the business environment is relatively stable with clear seasonal patterns and less influence from promotions or dynamic market shifts.

- **Expected Results**:

  Effective for short-term forecasting when seasonal demand is predictable but limited in handling complex or changing sales patterns.

- **Implementation Steps**:

  Use Holt-Winters for forecasting simple seasonal fluctuations in sales, especially when external factors like promotions are not significant drivers of demand.

Implications for Management and Businesses

1. **Strategic Inventory Management**

Adopting XGBoost as the primary forecasting tool will allow D-Mart to achieve highly accurate predictions, resulting in better-stocked shelves without overstocking or understocking. This will save costs in warehousing and logistics while enhancing customer satisfaction.

2. **Cost Efficiency and Resource Allocation**

The investment in implementing machine learning models like XGBoost requires initial resource allocation for data infrastructure, model training, and integration. However, this upfront cost is expected to result in long-term savings by improving forecasting accuracy and reducing inventory waste.

3. **Improved Decision-Making**

Using a hybrid forecasting model will provide D-Mart's management with reliable, data-driven insights to make informed decisions about inventory procurement, stock allocation, and sales strategies. This will help in balancing supply with demand, particularly during peak seasons.

4. **Business Growth**

With better forecasting, D-Mart can scale its operations more effectively, keeping customer demands in mind while avoiding over-purchasing. This approach will help to align inventory levels with market demand, providing a more efficient supply chain and driving overall business growth.

Conclusion

The primary recommendation is to implement XGBoost as the forecasting model for its superior accuracy in predicting sales based on complex data patterns. This should be complemented by ARIMA to capture long-term trends and seasonality. The hybrid model combining both methods will offer the best results for forecasting and inventory management. While SARIMA and Holt-Winters can be considered alternatives for simpler, seasonal-based forecasting, they lack the flexibility and accuracy of the hybrid approach. Management should prioritize the hybrid model but be open to alternative methods when dealing with simpler sales environments. These strategies will ensure better inventory optimization, cost reductions, and higher customer satisfaction.

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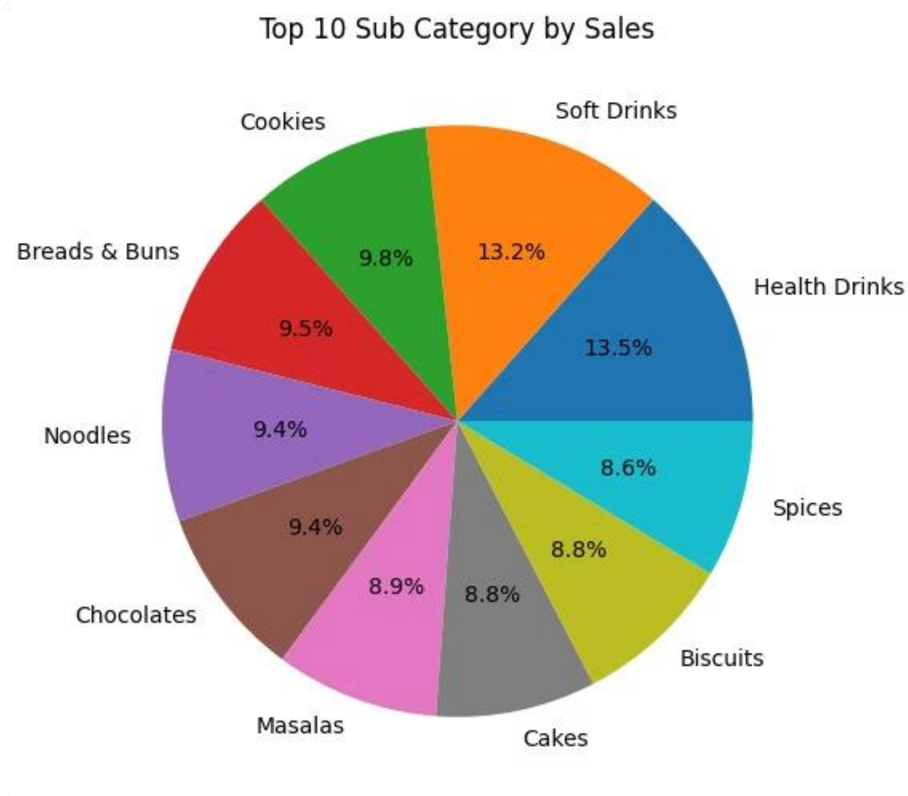
Appendices

Appendix A: Data Preparation and Preprocessing

This appendix includes the steps involved in cleaning, transforming, and preparing the data for analysis. It includes the feature engineering process, data normalization steps, and any handling of missing values.

- **Data Transformation Process:**
  - Feature creation: Sales lags, rolling means, etc.
  - One-hot encoding of categorical features.
  - Handling of missing data points.

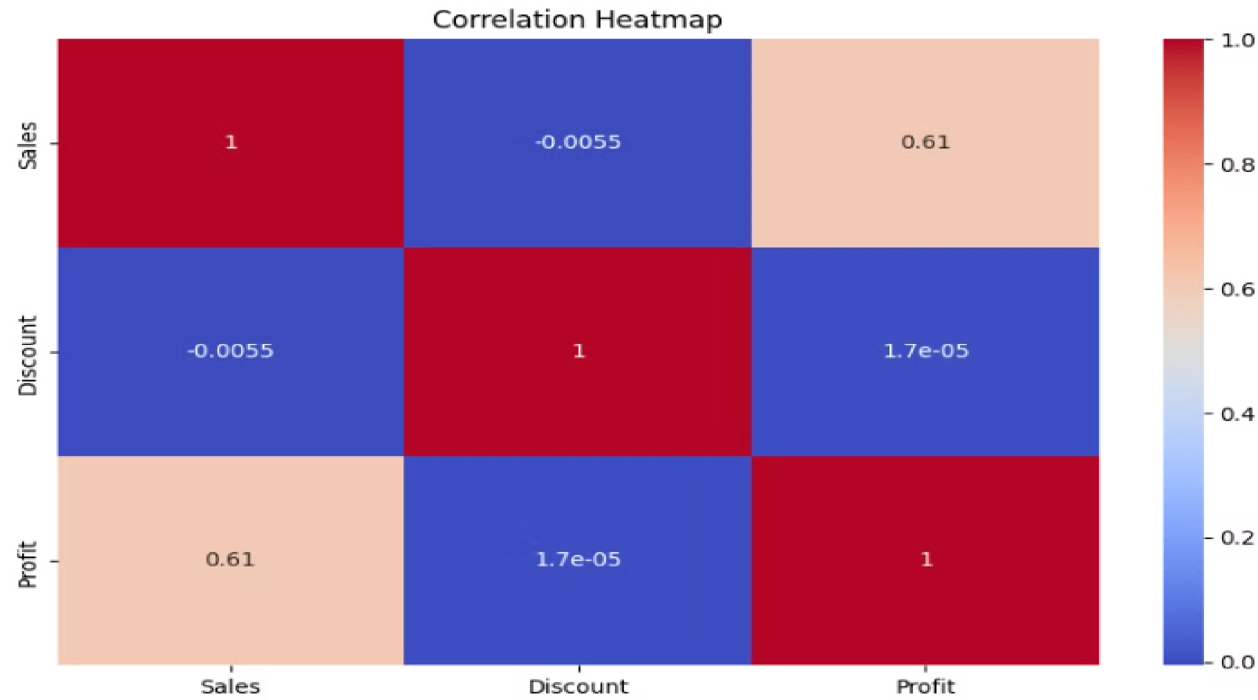


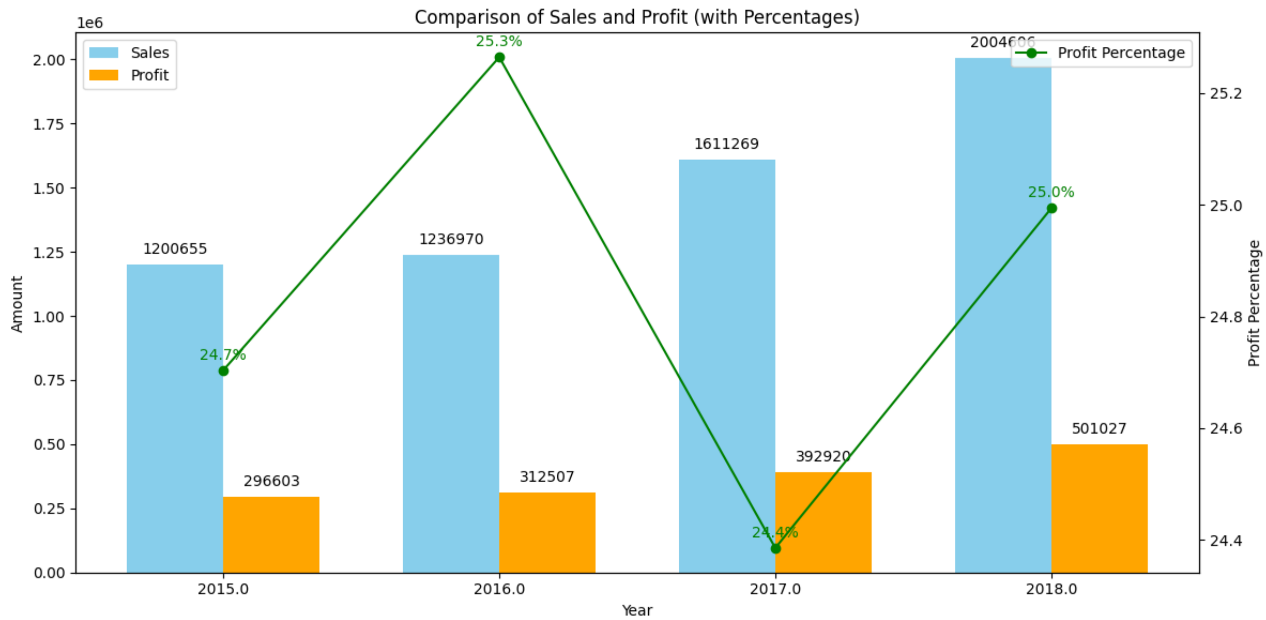
- **Data Scaling:**
    - Description of the StandardScaler used for scaling features in machine learning models.

```
# Example code for feature engineering

data['Sales_Lag_1'] = data['Sales'].shift(1)

data['Sales_Rolling_Mean_3'] = data['Sales'].rolling(3).mean()
```





Appendix B: Model Training and Hyperparameter Tuning

This appendix includes the details of the models you trained and the hyperparameter tuning process. It can include the GridSearchCV parameters, model evaluation metrics, and the choice of models.

Models Trained:

- Time series models: ARIMA, SARIMA, Holt-Winters, Auto ARIMA
- Machine learning models: Random Forest, Gradient Boosting, XGBoost, Support Vector Regressor

Hyperparameter Tuning:

- Hyperparameters searched for each model.
- Final best parameters after GridSearchCV for each model.

```
# Example code for GridSearchCV for Random Forest

param_grid_rf = {

    'n_estimators': [100, 200, 300],

    'max_depth': [10, 20, 30, None],

    'min_samples_split': [2, 5, 10],

    'min_samples_leaf': [1, 2, 4],

    'max_features': ['auto', 'sqrt', 'log2']

}

grid_search_rf = GridSearchCV(estimator=RandomForestRegressor(), param_grid=param_grid_rf, cv=3, scoring='neg_mean_absolute_error', n_jobs=-1)

grid_search_rf.fit(X_train, y_train)
```

Appendix C: Model Evaluation Results

This appendix includes the full model evaluation results, such as MAE, MSE, RMSE for all models before and after hyperparameter tuning. This section provides a detailed view of how each model performed during the testing phase.

- **Model Performance Before Hyperparameter Tuning:**

  List of MAE, MSE, RMSE for each model.

- **Model Performance After Hyperparameter Tuning:**

  List of MAE, MSE, RMSE for each model after hyperparameter tuning.

Example Scores:

Model	MAE Score (Before Tuning)	MAE Score (After Tuning)
SARIMA	8965.68	8932.46
Random Forest	8397.10	1045.91
Gradient Boosting	8087.76	1053.19
XGBoost	9076.56	1030.78
ARIMA	14518.77	8932.46

Appendix D: Code and Algorithms

This appendix includes any code, algorithms, or scripts used in the analysis. It provides transparency and allows others to replicate the analysis.

Example Code for ARIMA Model:

python

Copy code

```
from statsmodels.tsa.arima.model import ARIMA

# ARIMA model

model = ARIMA(y_train, order=(1, 1, 2))

model_fit = model.fit()

forecast = model_fit.forecast(steps=len(y_test))
```

Appendix E: Model Selection and Justification

This appendix explains the rationale behind selecting specific models. It includes why certain models were chosen, based on previous studies, as well as their suitability to the project.

- **Why SARIMA and Time Series Models:**

  Based on their ability to capture seasonality and trends, and their proven success in similar studies (e.g., Wahab et al., 2024).

- **Why Machine Learning Models (Random Forest, Gradient Boosting, XGBoost, SVR):**

Chosen for their flexibility, ability to handle non-linear relationships, and performance in real-world forecasting tasks.

SARIMA was selected because it efficiently handles seasonal data, which is critical for predicting sales in retail settings where seasonality plays a key role.

Gradient Boosting and **XGBoost** were chosen for their success in competitions and real-world applications, especially in forecasting.

MSBA Value Assessment

The MSBA program has provided me with invaluable skills and knowledge, equipping me with the tools needed to solve complex data-related problems in a real-world business context. Through the capstone project, I was able to apply key concepts learned throughout the program, including machine learning, time series forecasting, and model optimization, to address a significant business challenge at D-Mart. The opportunity to work on such a comprehensive project helped me strengthen my technical skills, particularly in areas like predictive modeling, feature engineering, and the practical application of data science techniques to optimize inventory management. Moreover, the MSBA program has significantly improved my ability to communicate technical values and outcomes to stakeholders, ensuring that data-driven decisions can be implemented effectively in a business environment.

Looking forward, the skills and knowledge gained from the MSBA program will continue to shape my career. The ability to leverage machine learning and advanced analytics in real-world scenarios, as demonstrated in my capstone project, has made me more confident in handling complex data challenges. As I'm moving to the workplace, I can see these skills being applied in a wide range of industries, particularly in roles related to data science, business analytics, and operations optimization. The program has not only prepared me to tackle technical challenges but also empowered me with a strategic mindset to drive business improvements through data. The knowledge gained throughout the MSBA will undoubtedly continue to be a foundational asset as I'm moving my career further in data science and analytics field.