MASTER THESIS

IU University of Applied Sciences

Study program: Master of Science in Data Science

Predictive Inventory Management for Retail Using Advanced Machine Learning Techniques

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Date of Submission: 12th September 2024

Abstract

Stock control is one of the essential activities that need to be conducted efficiently in organizations to ensure that they meet their goals and objectives in resource utilization, particularly in retail businesses. Stock management defines the best ways of making sure that adequate stock is available to meet the needs of customers while at the same time ensuring that there is no massive accumulation of stocks that is likely to attract more expenses towards holding them. In the past, inventory management practices used to rely more on educated guesses or manual methods with the help of basic forecasting tools. Currently, with the growing possibilities in technologies in the store and managing corporate data, for instance, in machine learning and predictive modelling, there are possibilities of improving approaches to inventory management.

This study explores how modern and improved machine learning technologies can better manage inventory in retail stores. It looks at how accurately forecasting sales numbers can help stores organize their stock better, which increases customer satisfaction. By applying the predictive models to historical sales data, the current study assesses the accuracy of the machine learning models as compared to traditional models in accurately predicting stock levels. Our findings indicate that the proposed hybrid models are more accurate than the traditional models, especially during times of high traffic like festive seasons and on promotions. They can accurately find these patterns, which helps improve performance and make better decisions in retail sales. The paper also offers important advice like using real-time data, keeping an eye on models, and adopting more adaptable inventory management methods to cut costs and increase efficiency. Furthermore, it emphasizes the importance of ethical practices and training for retail workers to ensure positive results and prevent negative effects from predictive analytics.

Keywords: Predictive inventory management, Retail sales forecasting, Machine learning models, Inventory optimization, SARIMA, Prophet, Random Forest, Sales trends analysis, Seasonal demand forecasting, Hybrid forecasting models, Retail stock management.

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List of Abbreviations

AI - Artificial Intelligence

ARIMA - Autoregressive Integrated Moving Average

DS - Data Science

GB - Gradient Boosting

MAE - Mean Absolute Error

ML - Machine Learning

MSE - Mean Squared Error

PA - Predictive analytics

RF - Random Forest

RMSE - Root Mean Squared Error

R^2 - Coefficient of Determination

SARIMA - Seasonal Autoregressive Integrated Moving Average

Chapter 1: Introduction

Historically, inventory control has always been an essential part of the retail industry, dating back to its infancy. During ancient civilizations, vendors and merchants employed naïve recording methods to account for the stock and determine the requisite amounts for consumption in the marketplace (Jr & Hébert, 2013). However, several centuries later, trade routes were established that stimulated the growth of economies, leading to the realization that inventory management required more effective methods. An important transition was the Industrial Revolution which introduced various technological improvements in the manufacturing process and transportation and resulted in a larger scale of production and distribution (Allen, 2017). These early management practices, which began emerging during that period, were centred on inventory control to plan production schedules and manage stock levels to meet the rising consumer demand.

1.1 Research Background

Throughout the 20th century, the way stores manage their stock changed significantly due to global changes, advancements in technology, and shifts in what customers want. As online shopping grew, consumers began to expect faster deliveries and more product choices (Wagner et al., 2020). This development put a lot of pressure on retailers to have products available in various locations while also keeping the costs of storage and delivery in check. Traditional methods like Economic Order Quantity (EOQ) and Just In Time (JIT) that depend on predictable demand patterns have found it challenging to adapt to these shifts (Nemtajela, 2016). Consequently, many stores have faced issues such as running out of stock, which not only results in lost sales but also lowers customer satisfaction (Turk, 2012).

Additionally, retailers now have access to new markets as a result of globalization, which enables them to serve a variety of clients and accommodate differing regional preferences (Wrigley & Lowe, 2010). Because of this growth, inventory management must become more flexible and quick to react to shifts in consumer demand across various markets and product categories. Additionally, businesses are looking for better ways to manage their supplies as a result of the growing costs associated with managing inventory. Predictive analytics and machine learning are vital techniques to use because of the high expenses associated with storage and the potential consequences of having excessive or insufficient stock. By examining historical sales data and present consumer purchasing patterns, these technologies assist merchants in more precisely forecasting demand and preventing problems such as supply shortages or excess inventory (Tirkolaee et al., 2021).

1.2 Problem Definition

In today's retail world, where profits are slim and operating costs matter more than ever, adopting advanced inventory management methods is essential for staying competitive. Predictive analytics offers significant advantages by helping retailers cut costs, increase how quickly items sell, and quickly adapt to market trends and consumer preferences. According to Chuang et al. (2021), retailers who use predictive analytics for demand forecasting can eliminate up to 20% of holding costs and increase inventory turnover by 30%. These advances are crucial in an industry where productivity, effectiveness, and responsiveness to market forces are decisive factors for long-term competitiveness and profitability.

The concern of this thesis, therefore, is to investigate and establish a reliable prediction model designed for application in inventory control within the retail business context. This study intends to improve upon existing models and approaches by using a large historical sales dataset that span several years and includes a range of product categories. This is because many parts of the business must be controlled on a vast and complex scale. The research entails using historical sales data to forecast future sales quantities, utilizing patterns and trends to increase predictive accuracy, comparing the performance of the model during periods of high demand to regular times, and evaluating the results of implementing predictive inventory management into practice.

1.3 Significance

This research is significant because it applies advanced machine learning techniques to enhance inventory management in the retail sector. This study improves decision-making concerning inventory control by using predictive models like SARIMA, Prophet, and Random Forest to predict future sales trends in a range of retail product categories. Retailers can minimize expenses related to overstocking and understocking by maintaining optimal levels of inventory through the implementation of these models, which also ensures customer satisfaction by meeting demand more effectively. This work offers an outline for future investigations into hybrid models, which may be able to provide inventory management with even more accuracy, thereby advancing the field's logical and practical aspects.

1.4 Research questions

Central to this research are several key questions that guide the investigation:

1. How effectively can historical sales data be leveraged to predict future sales quantities across diverse retail product categories?

2. What underlying patterns and trends within the sales data can be identified and utilized to enhance the accuracy of the predictive model?
3. How does the predictive model perform during periods of heightened demand, such as holidays or promotional events, compared to regular periods?
4. What are the impacts of adopting predictive inventory management on inventory holding costs and customer satisfaction levels?

1.5 Structure of Dissertation

This dissertation is structured into six chapters, each addressing specific research questions. Chapter 1 introduces the research background, providing an overview of the significance of predictive inventory management in the retail industry, along with the research questions, objectives, and scope. Chapter 2 reviews existing literature, covering both traditional and contemporary approaches to inventory management, the limitations of old methods, and the emergence of predictive analytics. It also explores various machine learning models applied to inventory management. Chapter 3 describes the research methods, including how data is collected and prepared, features are engineered, and how predictive models are developed and assessed. Chapter 4 shows the analysis results, shedding light on sales trends and how well different models perform in various retail categories. Chapter 5 evaluates the performance of these models, considering how they impact inventory management in retail. The final chapter, Chapter 6, wraps up the study by summarizing the findings, discussing the significance of predictive analytics in retail inventory management, and suggesting directions for future research and practical implementations in the industry.

Chapter 2: Literature Review

The objective of this chapter is to review inventory management historically within the field of the retail sector, with an emphasis on the use of predictive analytics. The section will start with an overview of traditional methods used for managing inventories and discuss how these methods often struggle to keep up with changes within the industry due to environmental factors such as globalization, the emergence of e-commerce giants, and changing customer preferences. In addition, the literature review will focus on identifying predictive analytics and elaborating on them, along with use cases in the retail industry before delving into the machine learning models used in predictive analytics. This will be achieved by a critical review of each model and comparing the models' strengths and limitations using case studies. Further, it will discuss the issues that arise and the limitations in the retail business when dealing with the concept of predictive analytics. Based on the identified sources and analyzed gaps in the literature, this literature review aims to provide a strong background for the current study to discuss the need for and significance of enhanced predictive inventory management systems in the retail industry.

2.1 Traditional Inventory Management Practices

Inventory management has been a crucial process implemented in the retail business for numerous years while undergoing drastic changes due to the shift in business and technological developments. In the past, retailers have used basic techniques like EOQ and JIT for inventory and stock management.

The EOQ model, including ordering cost and carrying cost, was developed by Ford W. Harris in 1913 and this model is used to minimize the total cost of ordering and holding inventories (Andriolo et al., 2014). This model calculates EOQ as (Andriolo et al., 2014):

Equation 1, EOQ

$$Q* = \sqrt{\frac{2KD}{h}}$$

Where:

$Q*$ is the optimal order quantity (EOQ),

K is the cost of placing one order (set-up cost),

D is the annual demand,

h is the unit stock holding cost per item per year.

This model presupposes a constant rate of demand and lead time, which permits the identification of an order quantity that would be most cost-effective to the retailers. Still, the use of EOQ depends considerably on fixed assumptions concerning demand and lead time and therefore is much less appropriate for modern retail environments because they are subjected to significant volatility.

Another traditional system of managing inventories is the Just-In-Time (JIT) inventory system which was developed at Toyota Motor Company in 1987 (Basodan, 2016). JIT intends to minimize inventory holding costs since it develops supply schedules to match demand needs. It helps minimize waste and, at the same time, results in better organizational capacity by having less inventory at any given time. Conversely, JIT implies that the company sticks to the small lot size and frequently purchases inventory in small quantities. However, JIT depends solely on a company's supply chain and hence the suppliers must also maintain a consistent quality and delivery standard (Green et al., 2014). Meanwhile, in practice, disruptions to the supply chain cause a range of problems that affect JIT, for instance, issues in production and stockouts, which limit JIT in situations with significant volatility and risk.

Along with EOQ and JIT, other conventional inventory management systems have been used to control the inventory. Systems such as safety stocks and reorder points, for instance, are standing safety measures that help in equalizing volatile demands and supplies (Ross, 2015). Safety stock is the additional stock that is maintained to avoid at least one stockout in a given period because of fluctuations in demand or lead time. The reorder point is calculated as (Gupta et al., 2022):

Equation 2, Re-order Point

$$ROP = Safety\ Stock + Lead\ Time * Q$$

Where:

ROP is Re-order Point,

$Lead\ Time$ is Watch Time

Q is Average material sales per month

These methods are more flexible as compared to EOQ because they include some aspects of uncertainty in their calculations. Nevertheless, they still contain a set of historical data and expectations for future sales, which can be inapplicable in real-life situations, especially in the rapidly evolving sphere of retail sales.

Finally, ABC analysis is another traditional approach that has been widely used in categorizing inventories with consideration of their significance. Items are classified into three categories: This classification includes; the high-value, low-turnover category A, the moderate value, moderate turnover category B, and the low-value, high turnover category C (Flores & Clay Whybark, 1986). This categorization is useful in stock management since it directs more attention to the management of articles that highly influence overall retail profits. ABC analysis is beneficial in strategy implementation for inventory management; however, it does not address problems related to demand estimation and does not take into account the conditions of fluctuating consumer behavior and constantly evolving markets that are characteristic of the contemporary retailing landscape (Nemtajela & Mbohwa, 2017).

2.2 Challenges of Traditional Inventory Management Models

The conventional inventory management techniques, as we have seen are impersonal and are considered as the bedrock of retailing, but they have some major problems that hinder their functionality in contemporary commerce. Some of the issues include the inability to adapt quickly to the changing customer trends and market conditions. According to Lukinskiy et al., (2020) EOQ, JIT, and other similar stock management techniques rely heavily on what may be called static demand and lead time, which do not address the fluctuations and thus the uncertainty characterizing the contemporary retail sector. Issues such as swollen demand in summer and low demand in winter, changes in sales due to promotions, and shifts in client preference can cause a huge disparity between the actual and expected demand levels, leading to overstocking or stock-out conditions.

Another more vital issue is related to the consequences of the globalization process and the broadening of the market sphere. Thus, when retailers expand their operations to different areas and countries, they find different consumer buying behaviors, preferences, and market demand. The traditional methods of inventory management do not meet the complexity of managing stock at multiple locations with different patterns of demand (Bonney & Jaber, 2011). The global nature of supply chains as a result of globalization raises the challenges of having to coordinate several supply chain systems across different geographical locations, thus making it harder to achieve accurate supply chain inventories.

Moreover, stock management is highly susceptible to supply chain disruptions. Issues like floods, political instability, or any other unpredictable changes in the economic cycle affect the supply chain, thus causing delays and stock-out threats (Herold & Marzantowicz, 2023). Conventional approaches such as JIT, which relies on raw materials' timely delivery to schedule production, are greatly exposed to such interferences. For instance, the COVID-19 outbreak demonstrated the weaknesses of supply chain networks and the inapplicability of conventional stock control techniques to cope with such disruptions.

The conventional method of inventory control leads to high inventory holding costs and transportation expenses (Gurtu, 2021). For instance, a firm invests capital in inventory and incurs losses from storing excess inventory, whereas having less inventory results in missed sales opportunities and lower customer satisfaction. These costs have to be negotiated by the retail businesses at the same time as they try to satisfy the supply-demand chain. The use of historical data and the review at some specified interval can then make these methods slow in responding to changes that are real-time, hence worsening the above costs.

Despite these challenges, the usage of more sophisticated methods like advanced predictive analytics in combination with machine learning is becoming the essence of inventory management for retailers to improve the accuracy of the predictions and better match stock levels with the actual demand in the market. This shift is a major development in stock management methodologies because the earlier strategies were developed from reactive thinking rather than proactive thinking that uses data analysis.

2.3 Introduction to Predictive Analytics

The concept of predictive analytics refers to the ability to anticipate future occurrences by using data mining and statistical modeling. It allows organizations to make better decisions based on insights derived from data analysis. It is therefore a great leap in the field of business analytics. The core of predictive analytics as defined by Mitchell (1997):

"A computer program is said to learn from experience E for some class of tasks T and performance measure P if its performance in T as measured per P is better from experience E."

This learning process forms the foundation of the basic working mechanism that enables predictive models to enhance their capabilities and demonstrate higher efficiency and performance when trained on large volumes of data.

Predictive analytics leverages various forms of machine learning, which can be broadly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning (Udousoro, 2020). Supervised learning is a type of machine learning where the function to be learnted is a classifier that maps a given input space G to an output space F. In this case, every training example is associated with an output label (Sen et al., 2020). This type of learning is extensively used for classification and regression problems, where the task is to predict the label or value for unseen data based on what the learning algorithm learns from the training data.

On the other hand, unsupervised learning handles data that does not contain labels or target variables. Unlike other machine learning techniques, such as decision trees, where the algorithm is told which aspects of the data to focus on, algorithms for unsupervised learning are not given such instructions. Clustering and association are common tasks in this category of learning and are usually applied in market basket analysis and outlier detection. This type of learning is used to find relationships that are hidden in data and not easily discoverable (Alsharif et al., 2020).

Finally, reinforcement learning is a type of machine learning that is used to determine the best choice of action in a given environment by practicing certain behaviors and gaining feedback in the form of a reward or penalty (Zai & Brown, 2020). This method is very useful where the best strategy is hard to identify and dependent on the information gathered through learning by doing. Reinforcement learning fields of use are in situations that involve decision-making.

These machine learning techniques are used in predictive analytics to develop effective tools for analyzing trends and behaviors. Based on sales data, customer behavior, and other factors, predictions can be made to support strategic business decisions. In the retail environment, such applications of PA include inventory management, demand forecasting, targeted marketing, and overall performance improvement. Given the probability of market changes based on the collected data, predictive analytics can be used as a primary method for successful retail management.

2.4 Application of Predictive Analytics in Retail

Predictive analytics has proven to be a game-changing tool for the retail sector today, enabling businesses to change their operations, formulate new strategies, or even concentrate on offering value-added client services. Big data and machine learning, when used in retail management, give businesses a way to analyse consumer trends, market dynamics, and store performance.

The first and most important use of predictive analytics in retail is demand forecasting (Punia & Shankar, 2022). PA can use historical sales data to forecast demand for products, trends in seasons, and even the effects of the stock market and climatic conditions to determine demand for the future. This capability makes it possible for retailers to manage their stocks more efficiently, avoid stock losses due to stockouts, and avoid excessive stocking of products, hence making their operations more effective and profitable.

Another area that would not be possible without the help of predictive analytics is a targeted marketing approach. Using customer data, including purchase history, preferences, interests, demographics, and web history, retailers can develop highly targeted marketing tactics (Artun & Levin, 2015). PA can help to provide targeted discounts, offers, and recommendations to specific customers through these campaigns, ultimately increasing sales.

In addition, predictive analytics help determine the ideal pricing strategies to be used by retailers (Fildes et al., 2022). Relative to competitors' prices, the price sensitivity of consumers, and trends in the marketplace, retailers can employ dynamic pricing models, which, if well implemented, would optimize the revenue as well as the competitiveness of retail businesses. That way, pricing can be changed depending on the demand and the intensity of competition once established in the market.

Finally, PA also fosters the optimization of supply chain management. To optimize the logistics and inventory replenishment, retailers can apply predictive models. This greatly helps in aspects like supplier lead times, choosing efficient delivery routes, and spotting existing disruptions in the supply chain (Aljohani, 2023). This approach reveals the immense potential to have supply chains that enable retailers to cut costs, have better stock availability, and deliver products at the right time to the consumers.

2.5 Machine Learning Models for Predictive Analytics

Predictive analytics in retail are centered on machine learning (ML) models, which allow companies to gather insights from vast amounts of data and forecast future events with high accuracy. These models anticipate consumer behaviour, optimise operations, and enhance decision-making processes by using algorithms that learn from previous data to find patterns, trends, and interactions. An overview of machine learning and its usage in retail predictive analytics is provided in this section, along with a discussion of some of the most widely used prediction models.

2.5.1 Time Series Models

ARIMA (Autoregressive Integrated Moving Average)

ARIMA is a widely recognized statistical method for time series analysis applicable to forecasting (Siami-Namini et al., 2018). It addresses the problems associated with the usual economic practices such as the EOQ and JIT that fail to incorporate the time series data's autocorrelation and trend analysis. ARIMA models are special in that they can accommodate changes and cycles that affect retail sales over time. One of the advantages of the use of historical sales data is that ARIMA models can produce forecasts that reflect the changes that have occurred in a particular business due to past historicity (Siami-Namini et al., 2018). This is different from EOQ and JIT because they completely rely on static assumptions and the use of the periodic review system, which can cause stockouts or overstocking since such systems cannot respond quickly to environmental changes.

SARIMA (Seasonal ARIMA)

SARIMA further develops the functionality of ARIMA by incorporating seasonality into the model. It is useful when adopted in solving problems involving datasets with cyclical patterns and would be especially useful in the retail business where sales have cyclical trends such as during the festive periods or promotions (Ren et al., 2022). The model excels at accurately forecasting and addressing seasonal fluctuations while other methods might fail to do so. This means that the retailers can be in a position to be able to forecast the stock demands effectively and take action before they are faced with stock-out situations while also being in a position to optimize the incurred costs of exercising the warehousing.

Prophet

Prophet is a robust prediction tool created by Facebook for datasets that involve daily occurrences and multiple seasonal trends (Atasever et al., 2022)(Atasever et al., 2022). Prophet stands out in recognizing changes in patterns called changepoints and handling the impacts of holidays or events on sales effectively. Its flexibility and automatic identification of patterns distinguish it from forecasting methods that have fixed periods in place. This feature allows retailers to achieve precise outcomes that mirror real life situations. When retailers utilize Prophet to refine their forecasts with accuracy and adjust promptly to changes in market demand trends accordingly, this can result in better store outcomes and heightened customer contentment overall.

2.5.2 Regression Models

Linear Regression

Linear regression creates a model that represents a line to predict values of outcome or target variables using past values of independent or input variables. In the retail sector, simple linear regression is applied to predict sales or demand by taking into account elements, like advertising costs, pricing tactics, and customer traits (Kumar et al., 2020). In contrast, to methods that summarize factors in an equation, linear regression offers a precise mathematical forecast formula obtained from historical sales evaluations. Retailers can use this ability to improve their marketing strategies and promotions adjust prices as needed and efficiently allocate resources to boost profit margins and gain a competitive advantage.

Random Forest Regression

Random forest is a type of bagging model that constructs decision trees in training and then combines their outputs to make predictions more reliable and accurate by leveraging the diversity of the trees decisions (Hegelich, 2016). Unlike methods that struggle for managing inventory in settings where it is hard for them to capture complex relationships between variables or nonlinear patterns effectively due to their rigid structures and predetermined assumptions about sales behavior and market dynamics. Random forest regression offers more flexibility in analyzing retail patterns by adapting to diverse factors such, as customer preference shifts and seasonal trends more effectively. Enhancing prediction accuracy enhances the ability of businesses to make decisions regarding stock management and optimize overall business operations effectively.

Gradient Boosting Regression

Gradient boosting combines weak classifiers, typically decision trees, and constructs each subsequent tree to minimize the misclassification error of its predecessor (Cai et al., 2020). Its most common application is in retail, where it is particularly useful for demand forecasting and inventory management. By gradually improving prediction accuracy and reducing errors, gradient boosting regression models have replaced labor-intensive traditional methods that lack the learning ability and high predictive potential of machine learning. This learning cycle empowers retailers to predict shifts in consumer behavior, prevent disruptions, and optimally manage their supply chain, reducing costs associated with excess inventory or stock shortages.

2.5.3 Other Relevant Models

Neural Networks (e. g., LSTM for Time Series)

Other types of recurrent neural networks, particularly Long Short-Term Memory (LSTM) networks, have great capabilities for modeling temporal dependencies and long-term relationships in time series data. In retailing, LSTM models analyze past sales data to identify patterns that are useful for forecasting future sales and seasonality trends with a minimal error margin (Lai et al., 2018). Unlike traditional time series methods, which struggle to handle non-linear connections or diverse patterns, LSTM networks can learn from these patterns and adjust predictions based on previous observations. This ability allows retailers to forecast demand more accurately and manage inventories more effectively, leading to improved operational efficiency in the fast-paced retail industry.

Support Vector Machines (SVM)

SVM is a type of supervised learning algorithm that is applied in the categorization of data and also in regression. In retail, SVMs are used to forecast customer behavior, market trends, and categorize products, particularly based on the sales rate or clients' preferences (Sen et al., 2020). The SVMs help kernel functions to map the data to a higher dimension in which all these points can easily be classified. This makes it possible to practice differentiated marketing communications, manage product range effectively, and control for the risks relating to volatility of demand leading to better business outcomes for retailers.

2.6 Comparative Analysis of Predictive Models

Studying these models side by side is important to see how useful and appropriate they are for managing inventory situations. Recent research shows examples of comparing how well different prediction models work in real world scenarios and sheds light on their strengths and weaknesses. For example, Kayyali El Alem (2023) did a study that looked at the effectiveness of four models, ARIMA, SARIMA, Prophet, and LSTM for predicting sales in a multinational retail company. The study discovered that although traditional time series methods, like ARIMA and SARIMA showed outcomes in addressing linearity and seasonality patterns; the Prophet model excelled in managing occurrences and holiday impacts with greater effectiveness. Conversely, LSTM demonstrated performance compared to other models in managing complex and nonlinear datasets, especially over extended timeframes due to its specialized design for historical data analysis.

Taylor & Letham (2018) provided a major study that illustrated the use of Prophet in the retail industry and evaluated the model's effectiveness in comparison with other models. The research was made on a large e-commerce retail company whose sales were highly variable due to promotional and flash sales. The analysis showed that Prophet had certain advantages over the standard models, including ARIMA, in terms of its usability and adaptability to multiple changes and/or several types of recurring patterns in sales. The features such as an option to adjust domainspecific holidays and events to be considered as part of the forecasting procedure were also noted as a major advantage since they enable Prophet to provide better forecasts, which in turn makes it more valuable for the retailer.

A research conducted by Makridakis et al., (2018) examined how well the Random Forest and Gradient Boosting models performed compared to neural networks in predicting retail demand. Using a sales dataset from a global retail company as the basis for comparison against traditional statistical methods; the study found that machine learning and deep learning methods such as Random Forest and Gradient Boosting generally surpassed older models by uncovering intricate connections and patterns in the data. Ziegler (2020) conducted research using neural networks, like LSTM and found that they can effectively adapt to changing trends in retail settings by learning from sequential information and accounting for variability to make precise predictions. Nonetheless, the study highlighted that modern machine learning techniques are computationally demanding and necessitate thorough preprocessing of vast amounts of information.

Altogether, the cases surveyed in this paper highlight the importance of selecting the right model elements to predict retail data and meet forecasting needs. SARIMA and ARIMA are standard models that are effective for handling linear trends; however, when dealing with non-linear trends, advanced models such as Prophet, Random Forest, Gradient Boosting, and LSTM are more effective. The comparative analysis gives an idea of the effectiveness of using a hybrid model, which combines the strengths of different models, typically delivers the best performance, providing retailers with the necessary tools to manage the complex nature of contemporary inventory management.

2. 7 Research Gaps

Even though there has been significant progress in the area of predictive analytics, there are still gaps in the literature, particularly regarding its application in retail inventory management. Therefore, addressing these gaps is essential for the field’s development and for achieving the goals of this research.

It is imperative to note several major gaps. One involves assessing the feasibility and accuracy of using historical sales data for quantitative sales forecasts across multiple retail product categories. Prior empirical studies often focus on specific types of products or a small set of categories, which limits the universality of predictive models. To address this, the research aims to assess the applicability and accuracy of these models by extending the benchmark study to a wider variety of retail product categories.

Another crucial gap in existing sales forecast models is the failure to utilize data patterns to improve model efficacy. While much work focuses on basic patterns, few studies emphasize the application of complex patterns within model-based approaches. This includes working with diverse variables such as market seasonality and consumer habits. The objective of this research is to refine the models to better forecast these complex and diverse patterns and to enhance the depth of the analysis.

Furthermore, the efficiency of these predictive models during periods of higher traffic, such as holidays or sales campaigns, is often not examined. Most researchers measure actual demand while overlooking the unique circumstances experienced during peak periods. This research addresses this gap by assessing the performance of models specifically during high-demand times, utilizing predictive analytics to optimize inventory management.

Lastly, there is a scarcity of studies on the quantifiable benefits that organizations can derive from managing inventory holding costs in their stores or warehouses, as well as its impact on customer satisfaction levels. This study aims to fill that gap by not only creating models but also evaluating them, which helps improve customer satisfaction and provides heuristic value to retailers.

2.8 Challenges and Limitations of Predictive Analysis in Retail

The application of predictive analytics has been instrumental in improving the efficiency of retail inventory management by allowing greater accuracy in demand forecasting and aiding decision-making. However, studies on the use of predictive analytics in retail businesses indicate key issues and limitations.

Challenges and Limitations

One of the main issues that arises when adopting PA solutions in retailing is data quality and accessibility. Business forecasting relies on detailed historical data to build its predictive models, and therefore, quality data is essential for accuracy. Often, retail data may be weak, inconsistent, or outdated, leading to poor predictions of the future. Additionally, data silos within organizations hinder the aggregation of data collected from different departments, resulting in an incomplete view of the business as a whole (Bradlow et al., 2017).

The second notable difficulty is that many models are predictive, which means their construction entails certain complications. Neural networks and other ensemble methods are somewhat more complicated to implement and consume a lot of computational power, even for simple applications (Chawla et al., 2002). Additionally, the implementation of these models often suffers from a lack of adequate support infrastructure and qualified human resources within retailers' organizations. This can lead to the use of third-party solutions that are not always an exact fit for the business's specific needs.

Another challenge in integrating current systems and processes is the use of outdated technology platforms, which may not be capable of integrating with updated analytical solutions. This can result in expensive and time-consuming conversions. Additionally, resistance to change within the organization's upper echelons can block the introduction of newer technologies. The workforce may also lack confidence in new approaches, such as predictive analytics, and may prefer to rely on more conventional methods they are familiar with (McAfee & Brynjolfsson, 2012).

2.9 Ethical Considerations

While researching the use of predictive analytics in managing retail inventory, there are several important aspects of ethical concern to consider. In our study, we strictly follow appropriate measures of data privacy and security. The approaches used in carrying out the studies are described in detail with the view to ensuring that the results can be replicated. Also, the study focuses on the equitable, ethically sound, and legally proper use of algorithms and related systems to reduce ethnic unpredictable consequences that could affect inventory management systems. By maintaining the egregious ethical standard, we aim to make responsible use of predictive analytics in the improvement of retail functioning and minimization of consumer rights violations to increase trust in the industry.

Chapter 3: Methodology

This chapter describes the methods used in this research to develop a strategy for inventory management in the retail industry. It explains the methods employed for data exploration and preparation, mainly related to the daily sales data of the Superstores dataset from 2014 to 2017, and reviews the process of data cleaning to enhance its quality. The chapter also describes the methodologies used to improve the quality of the features used in the models and continues this by describing the processes involved in the selection, construction, and assessment of different machine learning models.

3.1 Model Design

The approach to model design in this study involves using structured methodologies to generate and test the models used for predicting inventory management in the retail industry, as shown in Figure 1.

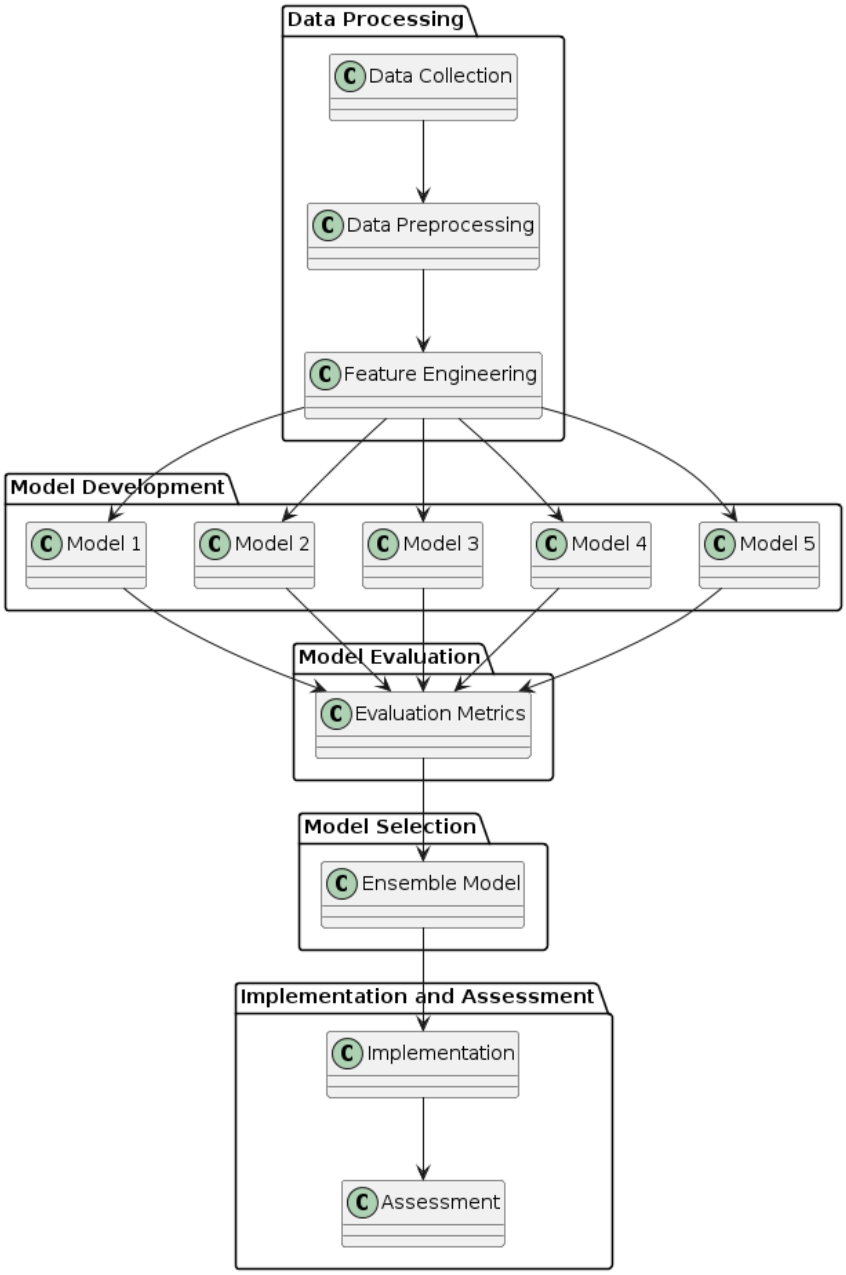

Figure 1, Model design

Source: Own representation

The above model is structured in the following way:

Data Collection: Based on the sales data of Superstores from the year 2014 up to 2017 obtained from Kaggle.

Data Preprocessing: Sub-processes that comprise data cleaning, handling missing data, duplicate records removal, and handling outliers to improve data quality.

Feature Engineering: It includes handling seasonal variables, building lag variables, and converting the categorical variables for analysis.

Model Development: Consists of the design and assessment of five different models including ARIMA, SARIMA, Prophet, Random Forest, and Gradient Boosting for future demand prediction.

Model Evaluation: Strictly evaluate the model employing measures of accuracy such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Coefficient of determination R2.

Model Selection: Selecting the most accurate models out of all the models for evaluation to increase the chances of getting more accurate predictions.

Implementation and Assessment: Deploy the chosen model into a live environment and employ an informative and user-friendly interface that will assist the stakeholders in making the right inventory decision.

3.2 Data Collection

The data used in this study originated from the Superstores' daily sales dataset comprising a time series ranging from the year 2014 to 2017. Superstores Inc. is a retail chain with stores located across the United States, dealing in various sectors including furniture, technology, and office supplies, among others. Serving both consumers and business clients, Superstores Inc. is a broad company that targets different population segments, which makes it possible to use it for examining inventory management (Superstore, 2024). This dataset was sourced from Kaggle, a very reputable platform known for its quality datasets and contributions from the data science community. The dataset has a total of 21 columns and 9999 rows that recorded elaborate sales transactions.

Given the fact that this dataset is relatively large and encompasses a range of variables, it can be used for the creation of a predictive inventory model. This information helps to understand various characteristics of the retail processes, including fluctuations throughout the year, repeated customer demographics, and the distribution of sales across regions. The detailed records of customer transactions facilitate the analysis of purchasing behavior and the trends that exist in the market. Furthermore, the time horizon of the dataset guarantees that it is sensitive to short-term seasonal variations and long term trends, which are both important in demand forecasting. To achieve high accuracy in the management of inventory in the retail sector, this study proposes to improve on the existing and advanced models of inventory management by utilizing this rich dataset.

3.3 Data Analysis

Python will be the primary programming language for the analysis and application of machine learning algorithms in this research, as it is an optimal, all-purpose language with a multitude of libraries designed for data science. Python offers rich built-in data types and libraries, including NumPy for intensive mathematical computations, Pandas for data analysis and manipulation, and Matplotlib for graphical data illustration. These tools are highly useful for investigating, transforming, and manipulating the Superstores' sales data for use in machine learning.

Python for Machine Learning: Python has gained the upper hand in machine learning due to its simplicity, clear syntax, and the support of powerful libraries like Scikit-Learn, TensorFlow, and PyTorch (Liu, 2017). It contains libraries that support various algorithms, such as regression, classification, and time series models, among others. The language is rich with diverse libraries and can be effortlessly integrated, making it highly efficient for handling complex data analysis tasks.

Exploratory Data Analysis (EDA): Before building the final predictive model, analytical and associative exploration will be performed using Python and its relevant libraries. The goal of exploratory data analysis is to provide a numerical and graphical description of the data to understand the patterns and structures within the compiled information.

Model Evaluation: Python's libraries, such as the Scikit-learn framework, offer a wide array of methods for evaluating the performance of regression and classification models, including MAE, MSE, and R-squared. In addition to model evaluation, there are opportunities for learning and improving the models through hyperparameter tuning, which allows for continuous enhancement of the model's performance.

3.4 Feature Engineering

Feature engineering is a critical process of constructing features from raw data because it enhances the input variables in machine learning (Yun et al., 2021). In the context of the learning process and feature engineering for the Superstores' sales dataset, the focus is on generating new features or modifying existing ones to increase predictive accuracy and uncover valuable patterns in the dataset.

Feature Selection: This refers to the ability to identify the most relevant features that have a significant impact on the performance of the models. This includes selecting the most important features that have close relations to the target element, such as sales, without including other characteristics that do not have such relations (Guyon & Elisseeff, 2003).

Temporal Features: This approach involves incorporating time-related information into the dataset. Since the data is periodical with sales, features like day of the week, month, quarter, and year can help in understanding seasonality and trends that exist. Similarly, the features that are lagged such as past values of sales or other variables help the model capture historical dependencies and auto-correlations which are very important when it comes to forecasting (Hyndman & Athanasopoulos, 2018).

Encoding Categorical Variables: This is an important step in machine learning that involves converting categorical variables into binary values that can be easily analyzed. Examples of categorical variables include product type, customer segments, and geographical location; these need to be transformed into numerical types for compatibility with the model. Nominal data can be transformed into ordinal data using techniques such as one-hot encoding, label encoding, or target encoding, which help preserve meaningful relationships and hierarchies (Geron, 2019).

Transformation and Scaling: There can be situations in the dataset in which there may be continuous variables that have skewed distributions or great variability in the values. Operations such as log transformations or Min-Max scaling can be used to bring the data to uniformity and receive better interpretable and generalizable models (Geron, 2019).

3.5 Model Development

The models selected for this study, guided by the research question, include ARIMA, SARIMA, Prophet, Random Forest Regression, and Gradient Boosting Regression. The ultimate aim is to establish models that can capture past sales data, identify patterns and trends, perform well during peak sale periods, and help reduce inventory management costs, ultimately leading to better customer satisfaction. Each model has its unique applications, making them appropriate for specific areas of sales forecasting.

3.5.1 Models

ARIMA

The basic ARIMA method is a very effective statistical tool used in analyzing time series data and making forecasts. The model is most suited for datasets that exhibit temporal characteristics but not so much seasonal variation. The general form of the ARIMA model is given as ARIMA(p, d, q). The equation is given as (Shumway & Stoffer, 2017):

Equation 3, ARIMA

$$Y_t = c + \sum_{i=1}^{p} \phi_i \, Y_{t-i} + \sum_{j=1}^{q} \theta_j \, \epsilon_{t-j} + \epsilon_t$$

Where:

Y_t is the value at time t.

ϕ_i are the parameters of the autoregressive part.

θ_j are the parameters of the moving average part.

ϵ_t is the error term.

ARIMA models help to deal with linear trends and past values of sales to determine future values.

SARIMA

SARIMA is just an extension of ARIMA used on the datasets that have seasonal or repeatable patterns. The SARIMA model is represented as ARIMA$(p, d, q)(P, D, Q, s)$, where (P, D, Q) are the seasonal components and s is the length of the seasonal cycle. The equation is given as (Khashei et al., 2012):

Equation 4, SARIMA

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{P} \Phi_k Y_{t-sk} + \sum_{l=1}^{Q} \Theta_l \epsilon_{t-sl} + \epsilon_t$$

Where:

Φ_k is the seasonal autoregressive parameter.

Θ_l is the seasonal moving average parameter.

S is the period of seasonality.

The use of SARIMA is most effective in the retail industry, where sales fluctuations are typically cyclical, driven by factors such as holidays, special offers, and other seasonal events.

Prophet

Prophet is a popular modeling tool created by Facebook that allows for high-level adjustments to model predictions for data with daily frequency and multiple seasonalities, including holidays. The equation is given as (Rafferty, 2021):

Equation 5, Prophet

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

Where:

$g(t)$ is the trend component.

$s(t)$ is the seasonal component.

$h(t)$ represents holiday effects.

ϵ_t is the error term.

Due to the nature of Prophet's methodology, it can handle missing data, outliers, and change points with ease, making it well-suited for the fluctuations and irregularities of retail data.

Random Forest Regression

Random Forest Regression is an ensemble method that builds a large number of decision trees during the training of the model, with the final forecast being the average of the individual trees. The equation is given as (Breiman, 2001):

Equation 6, Random Forest

$$\hat{f}(X) = \frac{1}{N}\sum_{i=1}^{N} T_i\,(X)$$

Where:

T_i represents individual decision trees.

N is the number of trees.

Random Forest is resistant to overfitting and is well-suited for capturing non-linear and interaction effects among variables, making it appropriate for diverse and prevailing sales data.

Gradient Boosting Regression

Gradient Boosting Regression forms a tree model step by step, and each tree learns from the mistakes of the previous tree. The equation is given as (Friedman, 2001):

Equation 7, Gradient Boosting

$$\hat{f}(x) = \sum_{m=1}^{M} \gamma_m\, h_m(x)$$

Where:

M is the number of trees.

$h_m(x)$ are individual regression trees.

γ_m is the learning rate.

The need for Gradient Boosting stems from its efficiency in handling datasets with unique trends, and working in gradient units enhances the overall prediction capacity by enabling learning in stages

3.5.2 Process of Model Development

Training the Models

To train each of the predictive models using the historical sales data from the dataset, the process starts with data preprocessing, in which preliminary operations are carried out to solve issues associated with the data, such as missing values, handling outliers, and data inconsistencies. The preprocessed data is then partitioned into a training and a validation set; the train-test split ratio is maintained at 80:20 to ensure consistency in model evaluation.

The use of historical sales data to make predictions:

ARIMA and SARIMA: These models use historical sales data to integrate and model linear trends, building on previous sales records with the goal of accurately predicting future sales volume. The training process involves feeding the models with training data to learn from past patterns, while validation sets are used to test the models' generalization capabilities (Hyndman & Athanasopoulos, 2018).

Prophet: The prophet model uses historical sales data to estimate the changes in trends, weekly and monthly fluctuations, and impact of holidays. The training process involves adjusting some of the parameters to account for the flexibility of trends, seasonality, and the effects that holidays have on sales to enhance the forecast based on past trends in the sales data (Hyndman & Athanasopoulos, 2018).

Random Forest and Gradient Boosting: Both these methods of ensemble learning create multiple decision trees iteratively utlizing historical sales data. Random Forest ensures that the results obtained from different trees are combined to achieve a low level of bias and a high level of accuracy on the different sales patterns (Breiman, 2001). In Gradient Boosting, trees are built sequentially, with each tree correcting the errors of the previous ones, which aims at reducing residuals (Friedman, 2001). Both methods require historical data to establish a complex correlation of features and sales results, which makes predictions more accurate.

Tuning Model Parameters

Hyper-tuning of parameters is fundamental to advancing the performance of every model. Various approaches, like grid search or random search, are used for searching that specific combination of hyperparameters that can help minimize the forecast errors and improve the predictive ability.

Enhancing the Performance of the Forecasting Models

ARIMA and SARIMA: Tuning involves the process of selecting and finalizing the forecast values which are expressed by the model parameters. The goal is to identify the appropriate values for lags, differences, and moving averages (for ARIMA) and seasonal components (for SARIMA) that best capture the patterns in the sales data (Hyndman & Athanasopoulos, 2018).

Prophet: The seasonal and trend factors are adjusted by the model to gain higher forecast accuracy when it comes to trend flexibility and holiday effects. By tuning these parameters, the model seeks to improve its capacity to identify multiple seasonalities and specific events observed in the sales data that are not apparent in a basic sales graph (Hyndman & Athanasopoulos, 2018).

Random Forest: Tuning parameters in a Random Forest model include the number of trees, maximum tree depth, minimum samples required to split a node, and the number of features considered for splitting at each node. Optimizing these parameters helps the model capture nonlinearity and interactions between features in the sales dataset, thereby improving its accuracy in predicting sales patterns (Breiman, 2001).

Gradient Boosting: In this model the number of trees, learning rate, and the maximum depth of the tree can be tuned to optimize the performance. This tuning process involves adjusting these parameters to enhance the model’s ability to minimize prediction errors, thereby improving its capacity to generalize and make accurate forecasts (Friedman, 2001).

3.5.3 Model Evaluation

To analyze and select suitable models for use in inventory management in the retail sector, it is necessary to evaluate the predictive models created for such a purpose. This includes coming up with an evaluation plan for the models whereby the models are thoroughly tested and compared against historical data before being permitted to operate on new data that has not been used in the training phase.

Evaluating Prediction Accuracy

Metrics used: In the assessment of this work's sales forecast accuracy, the metrics MAE, MSE, RMSE and R^2 are selected as evaluation measures. These metrics are suitable for this purpose as they measure how accurately the model predictions match the actual sales data, indicating the model's capability to capture patterns and trends (Hyndman & Athanasopoulos, 2018). Using these metrics ensures a robust assessment of the models predictive power, aligning with the goals of this study.

Selection of Evaluation Metrics (Hyndman & Athanasopoulos, 2018):

Mean Absolute Error (MAE) is a widely utilized assessment measure that assesses the overall size of inaccuracies in a set of forecasts without taking into account their directionality. It is determined by averaging the absolute disparities between anticipated values and real values. In this context, MAE proves to be valuable due to its straightforward interpretation of prediction accuracy, capturing the mean error in the same units as the data. This makes it intuitive for evaluating the accuracy of sales predictions by the model.

Mean Squared Error (MSE) is commonly used to calculate the average of the squared differences between predicted and real values. In this work, MSE is particularly valuable as it penalizes larger errors more severely, making it effective for evaluating the precision of the model's sales forecasts. By focusing on the squared differences, MSE emphasizes the impact of significant deviations, helping to refine the model for better predictive accuracy.

Root Mean Squared Error (RMSE) is commonly utilized as an evaluation measure for predictive models. It is defined as the square root of the average of the squared differences between predicted values and actual values. In this work, RMSE is crucial because it provides a clear measure of model accuracy by penalizing larger errors more heavily, making it particularly effective for identifying and correcting significant discrepancies in sales forecasts.

In this study, **R^2 (coefficient of determination)** serves as a statistical measure that evaluates how accurately the model forecasts match with the real data points. Adding to its significance R^2 helps to quantify the proportion of variability in sales data explained by the model. Therefore, it can give clues about how the model fits and captures the underlying trends within the data set.

Evaluating the Results of the Models

Ranking Models: After training and testing, the models with the best test scores are identified. The models with low MAE, MSE, RMSE, and high R^2 are recognized as having the desired accuracy for predicting sales quantities. This combination of metrics provides a comprehensive assessment, ensuring that the selected models not only minimize errors but also explain the maximum variance in the sales data. Consequently, these models are deemed the most suitable for implementation.

Visualization: To visualize the performance of the models, time series plots showing the comparison between the predicted and the actual sales data are used. These visualizations are beneficial to stakeholders because they can give them an understanding of the areas of strength and weakness of the respective models to allow for appropriate decision making.

3.6 Implementation and Assessment

In the implementation phase, the chosen predictive model is applied for the actual use in organizing stock in the retail store depending on the comprehensive analysis outcome. One of the important aspects of this phase is to design an effective communication system that presents inventory and sales information in a form comprehensible for stakeholders. This can be achieved using a web-based application, such as Streamlit, a popular library for developing apps with interactive graphical interfaces. Streamlit transforms data scripts into interactive web applications, all using pure Python (Streamlit, 2021).

Visualization of Inventory Levels

A detailed dashboard can be constructed using Streamlit to present the current state of inventory for products and stores. This dashboard provides real-time graphical reports, depicting the current stock status, inventory trends, and forecasted inventory demands. This enables tactical decisions such as adjusting reorder points, redistributing stock, and preventing a backlog of items.

Visualization of Sales Trends

For sales visualization, the dashboard can include time series plots, bar charts, and heat maps to highlight changes and trends. Time series plots illustrate past performance alongside projected future trends, allowing stakeholders to compare performance. Bar charts can be used to represent sales distribution by area, or product, offering a general view of sales density. Heat maps can quickly highlight high and low sales areas, helping retailers adjust marketing and promotional strategies accordingly.

Interactive Features and Insights

Streamlit adds interactivity to the dashboard, allowing users to filter data, modify inputs, and view specific cases of inventory and sales analytics. End users can select time periods or product types for a detailed view of the data. Additionally, future stock and demand forecasts from the predictive analytics engine can be incorporated into the dashboard, enhancing inventory decision-making. The Streamlit dashboard provides management with a comprehensive and detailed view of inventory and sales, enabling informed, actionable decisions and improving sales and operational outcomes in the retail industry.

An example of a few bar charts displayed within the Streamlit interface is shown below. The data represented in these graphs comes from the product subcategories in the Superstore dataset:

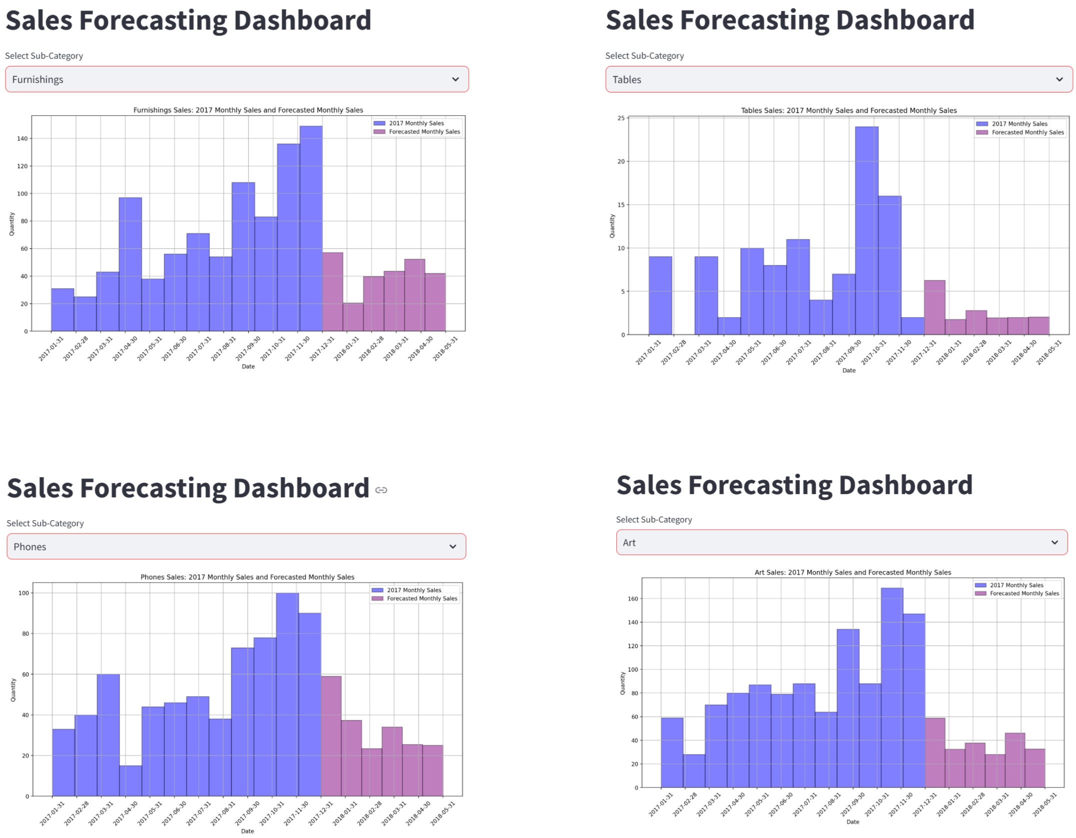

Figure 2, Example bar charts of sales forecast by product subcategories using hybrid models

Source: Own representation

Chapter 4: Results and Findings

This chapter presents the results of the predictive inventory management research to propose a inventory management strategy for the retail sector. It contains details regarding the results of data pre-processing, feature engineering, model building, and performance assessment steps. As performance measures, the accuracy of the trained models (ARIMA, SARIMA, Prophet, and Random Forest & Gradient Boosting) was evaluated. Furthermore, this chapter contains the outcome of applying the selected models and presents graphics that help to analyze sales and store inventory.

4.1 Data Preprocessing

Loading the Dataset

The first step in data preprocessing involves loading the Superstore sales dataset from 2014 to 2017. This step facilitates an exploration of the dataset's structure and variables, allowing for the identification of relevant features and data types to focus on.

The features of the Superstore sales dataset are shown in the table below:

Table 1, Superstores Dataset Features

Columns	Description
Row ID	Unique identifier
Order ID	Unique identifier
Order Date	Date of order placement
Ship Date	Date of order shipment
Ship Mode	Shipping mode
Customer ID	Customer identifier
Customer Name	Customer name
Segment	Customer segment
Country	Country of customer
City	City of customer
State	State of customer
Postal Code	Postal code of the customer
Region	Geographic region
Product ID	Product identifier
Category	Product category
Sub-Category	Product sub-category
Product Name	Name of the product
Sales	Sales amount
Quantity	Quantity purchased
Discount	Discount applied
Profit	Profit from the transaction

Source: Kaggle (2022)

Data Cleaning

Before feeding data into analytical models, it undergoes preparation to eliminate or reduce inconsistencies. This process encompasses the following key steps:

Handling missing values: Missing data can skew analysis results and degrade model performance. Therefore, identifying and addressing this issue is crucial. After checking the features, no missing values were found, so imputation was not required.

Removing duplicates: Duplicate records can complicate analyses by causing incorrect calculations and biased results. The dataset was checked for duplicates, and none were found.

Outlier detection and removal: Outliers can distort data analysis. The Interquartile Range (IQR) method was used to identify and remove outliers in the 'Quantity' column, minimizing their impact on analytical results.

Ensuring data consistency: Normalizing data format is essential for consistency in analysis. This was achieved by properly formatting date fields, ensuring consistent functionality across different features.

4. 2 Historical Sales Data: Forecasting Sales Quantities

This section presents the results of forecasting sales quantities across various retail product categories using ARIMA, SARIMA, Prophet, Random Forest, and Gradient Boosting models.

4.2.1 Data Compilation and Aggregation

The initial step in the analysis involved accumulating sales data and grouping it weekly. This aggregation helps smooth out daily sales fluctuations and provides a clearer indication of sales trends over time. All models were trained on the sales quantity data, and their results were analyzed by comparing the forecasted quantities with the actual quantities. The performance of the models can be observed in the respective graphs in this section, where the data is split into train and test sets, and predictions are shown for the test values across each product category.

4.2.2 Model Results

ARIMA

The performance of the ARIMA model on the weekly sales data for each product category is visualized as shown below:

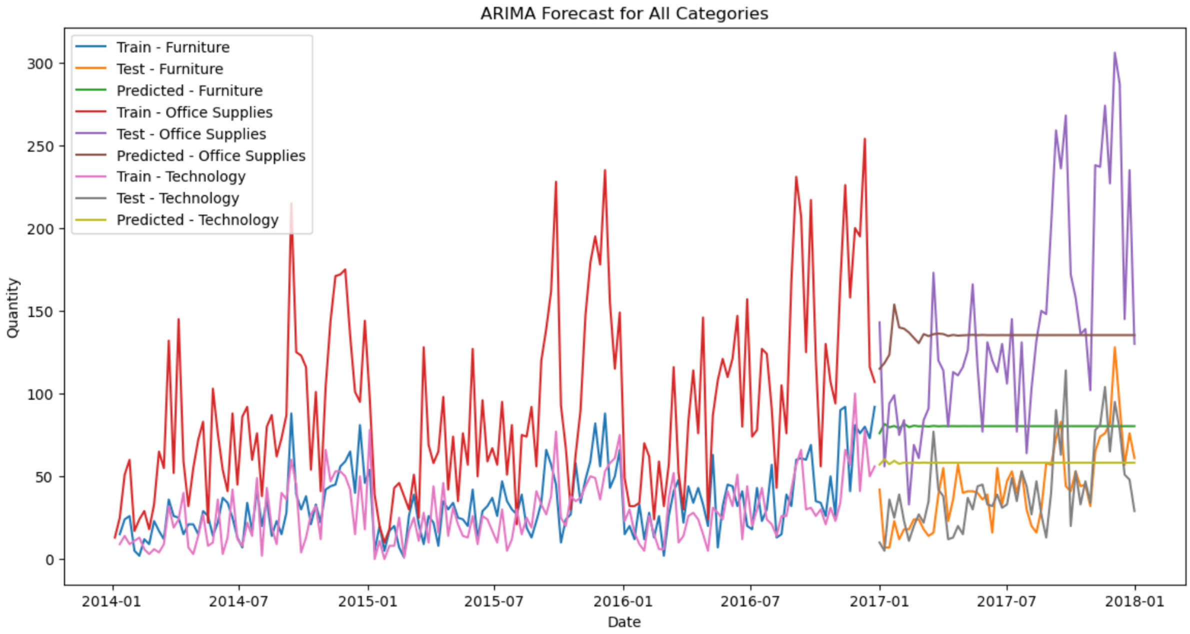

Figure 3, ARIMA forecasted sales vs actual sales

Source: Own representation

SARIMA

The performance of the SARIMA model on the weekly sales data for each product category is visualized as shown below:

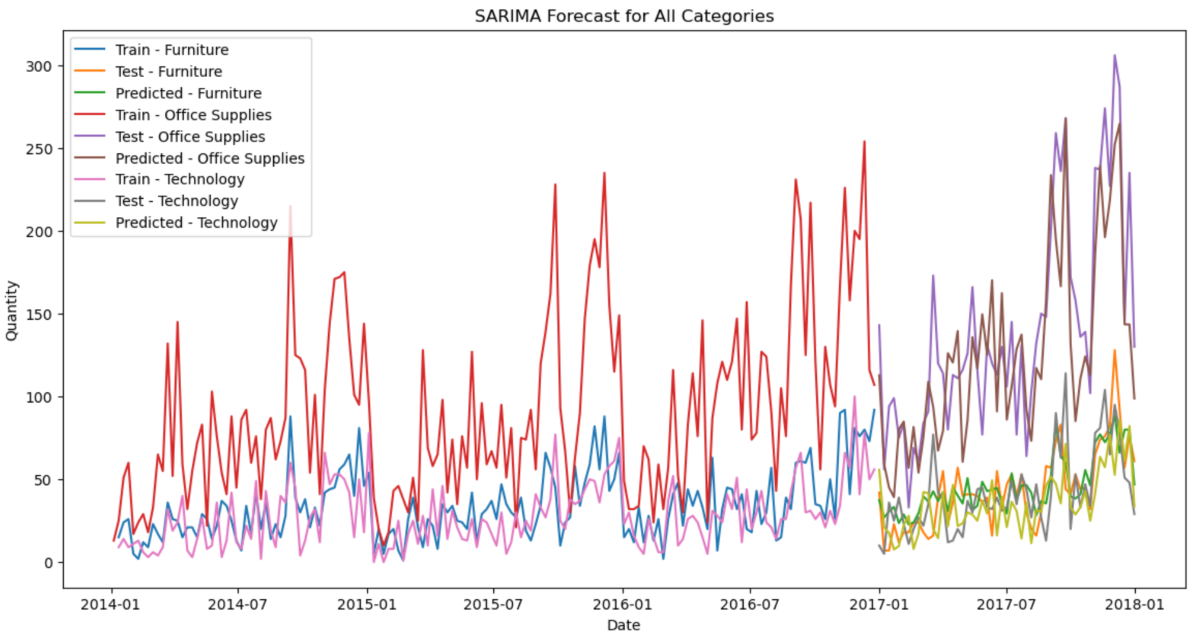

Figure 4, SARIMA forecasted sales vs actual sales

Source: Own representation

Prophet

The performance of the Prophet model on the weekly sales data for each product category is visualized as shown below:

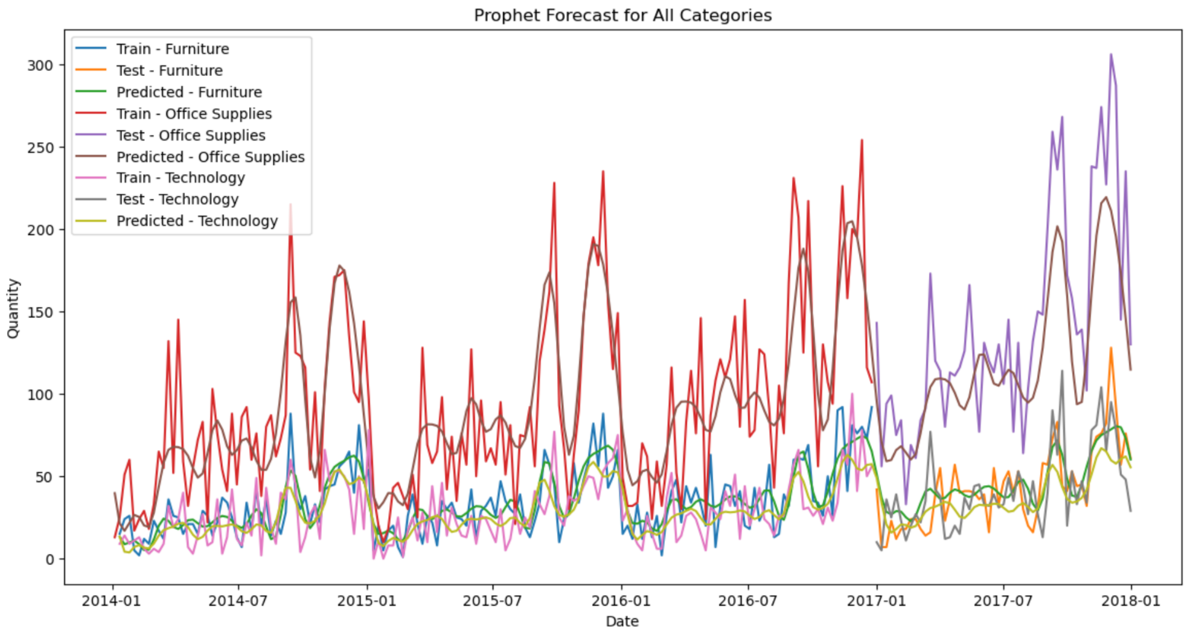

Figure 5, Prophet forecasted sales vs actual sales

Source: Own representation

Random Forest Model

The performance of the Random Forest model on the weekly sales data for each product category is visualized as shown below:

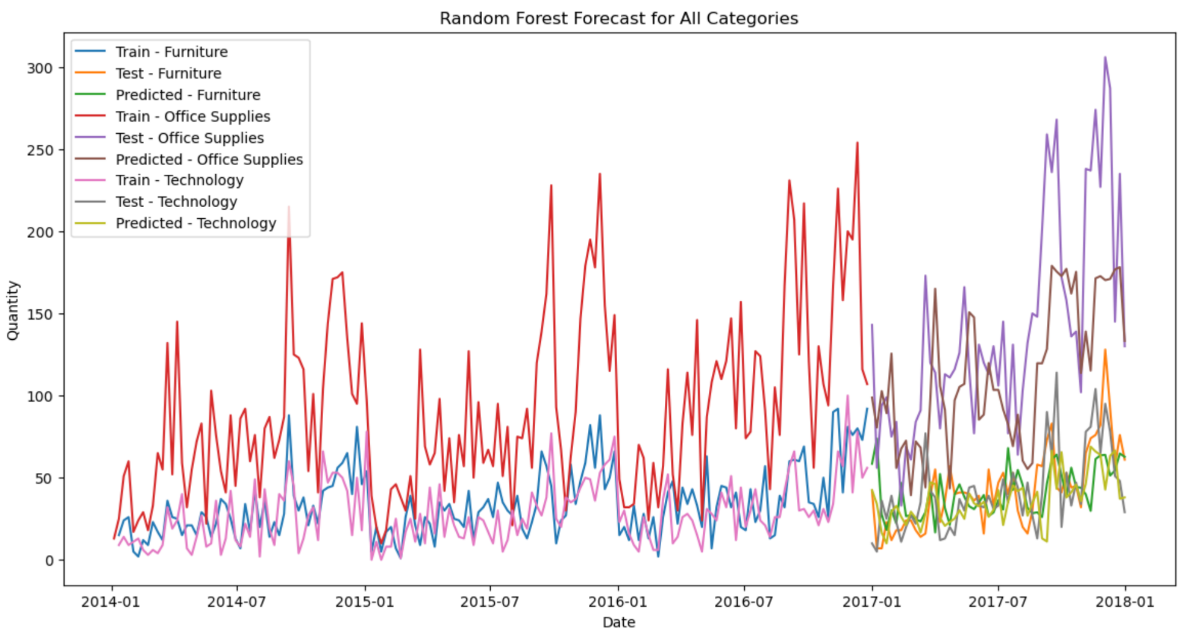

Figure 6, Random Forest forecasted sales vs actual sales

Source: Own representation

Gradient Boosting

The performance of the Gradient Boosting model on the weekly sales data for each product category is visualized as shown below:

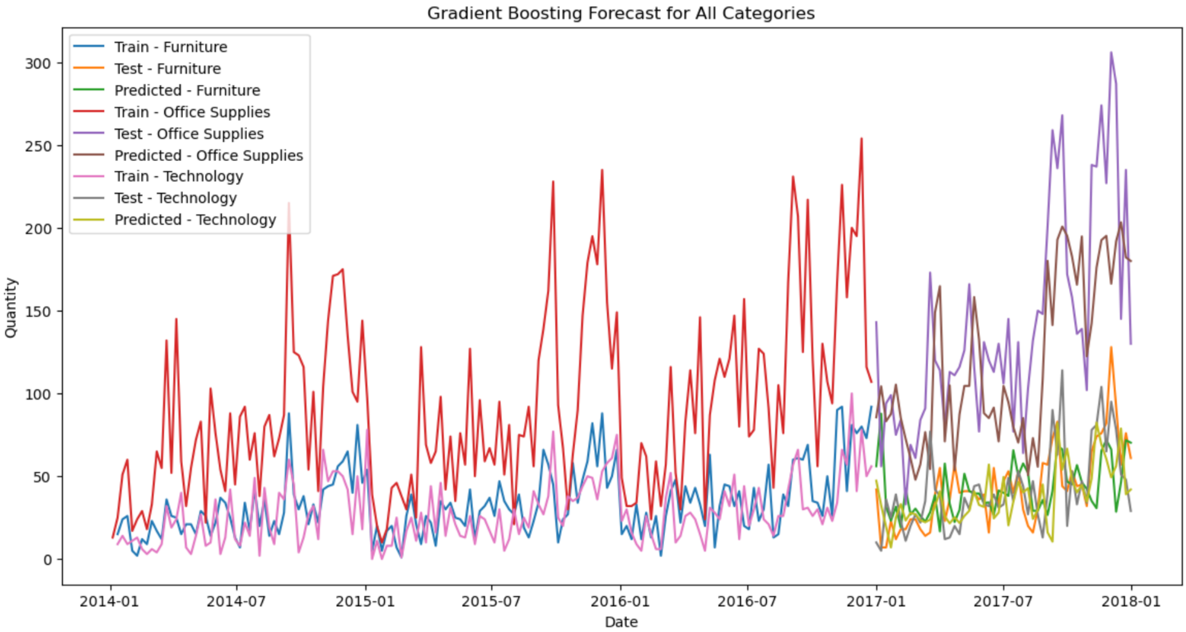

Figure 7, Gradient boosting forecasted sales vs actual sales

Source: Own representation

4.2.3 Model's Performance by Metrics

Table 2, Models Performance on Sales Forecasts

Category	Model	MAE	MSE	RMSE	R^2
Furniture	ARIMA	39.17	1922.95	43.85	-2.37
	SARIMA	11.79	210.36	14.50	0.63
	Prophet	11.15	225.58	15.02	0.60
	Random Forest	17.50	525.77	22.93	0.08
	Gradient Boosting	17.45	593.18	24.36	-0.04
Office Supplies	ARIMA	49.37	4232.27	65.06	-0.01
	SARIMA	31.84	1585.79	39.82	0.62
	Prophet	31.82	1637.06	40.46	0.61
	Random Forest	46.33	3481.32	59.00	0.17
	Gradient Boosting	44.37	2918.47	54.02	0.31
Technology	ARIMA	26.42	874.42	29.57	-0.46
	SARIMA	17.99	519.55	22.79	0.13
	Prophet	15.08	407.30	20.18	0.32
	Random Forest	16.11	553.57	23.53	0.08
	Gradient Boosting	16.81	558.17	23.63	0.07

Source: Own representation

A summary and comparison of all the model performances across each category, as per the results of this table, will be discussed in the upcoming sections.

4.3 Estimating Patterns and Trends within Sales Data

In this section, we delve into the identification of underlying patterns and trends within the daily sales data across each product category. We evaluate how well different predictive models are able to capture these patterns and trends, utilizing both visualizations and quantitative evaluation metrics. Through this comprehensive analysis, we assess the models' effectiveness in forecasting sales and highlight which models are most successful in leveraging the detected patterns to enhance prediction accuracy.

4.3.1 Analyzing Seasonal Trends

Seasonal trends are systematic variations that occur in cycles, typically aligned with seasons due to their seasonal impacts. These trends are particularly noticeable in retail sales, as sales volumes fluctuate throughout the year, especially during festive seasons (Ehrenthal et al., 2014). To account for these seasonal variations, the daily sales data was split into its seasonal, trend, and random components using the STL (Seasonal and Trend decomposition using Loess) technique, as shown below.

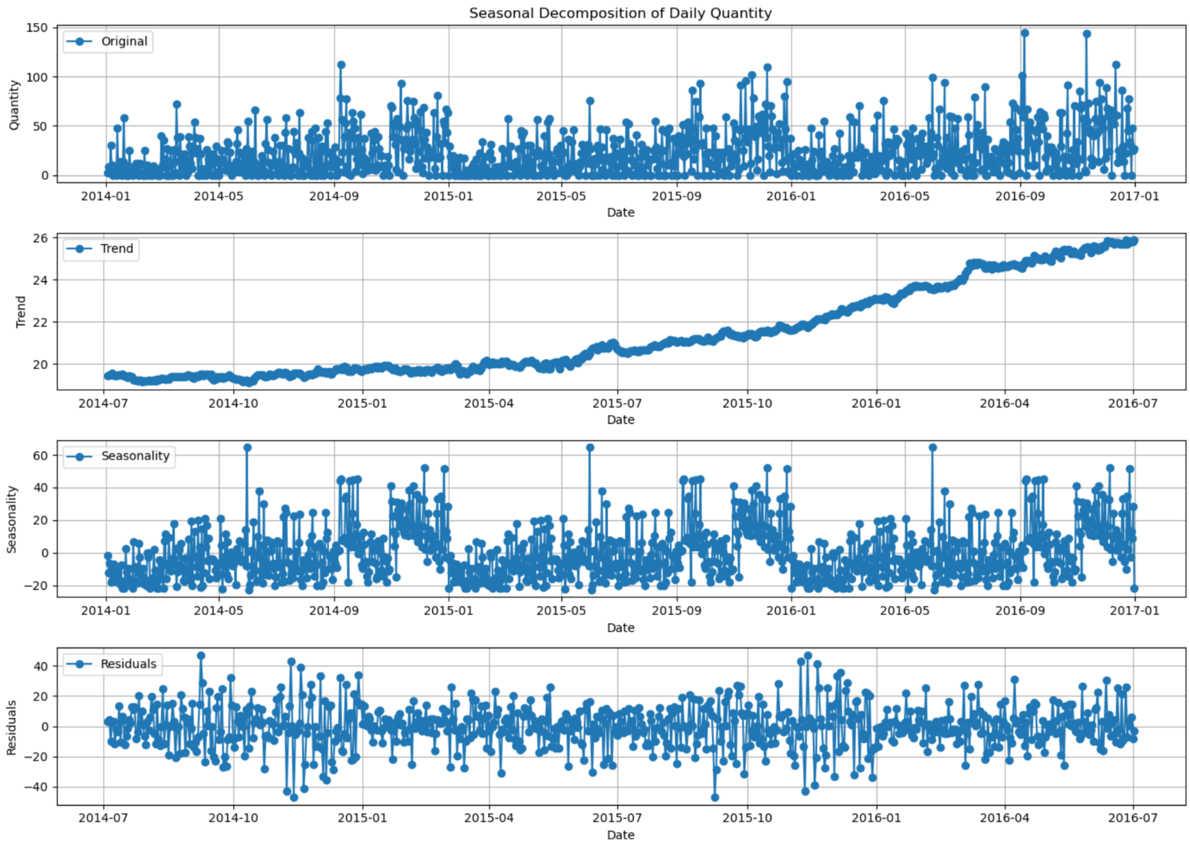

Figure 8, Seasonal Decomposition Chart

Source: Own representation

The trend component from the Decomposition chart shows a clear upward trajectory over time. Starting from a stable level in 2014, there's a gradual and consistent increase in sales, particularly noticeable from early 2015 onward, with a sharper rise by mid-2016. This indicates a strong positive trend, suggesting that sales quantities are growing due to factors like increased demand or market expansion.

The seasonality component from the Decomposition chart reveals distinct annual patterns, with consistent fluctuations in sales during certain months. Peaks are commonly observed in May and December, likely due to the impact of spring and winter seasons, while dips typically occur in January, July, and August. These recurring trends underscore the significant influence of seasonal factors on sales volumes.

Capturing these trends and seasonal patterns is crucial for accurate sales forecasting. Therefore, this work evaluates how well the selected models perform on this data, focusing on their ability to account for these underlying patterns. Although the decomposition chart represents the entire dataset rather than individual product categories, the purpose was to demonstrate the presence of patterns and trends within the sales data. The following section will focus on predicting sales for each product category separately, rather than analyzing the entire dataset.

4.3.2 Model Results

ARIMA

The performance of the ARIMA model on the daily sales data for each product category is visualized as shown below:

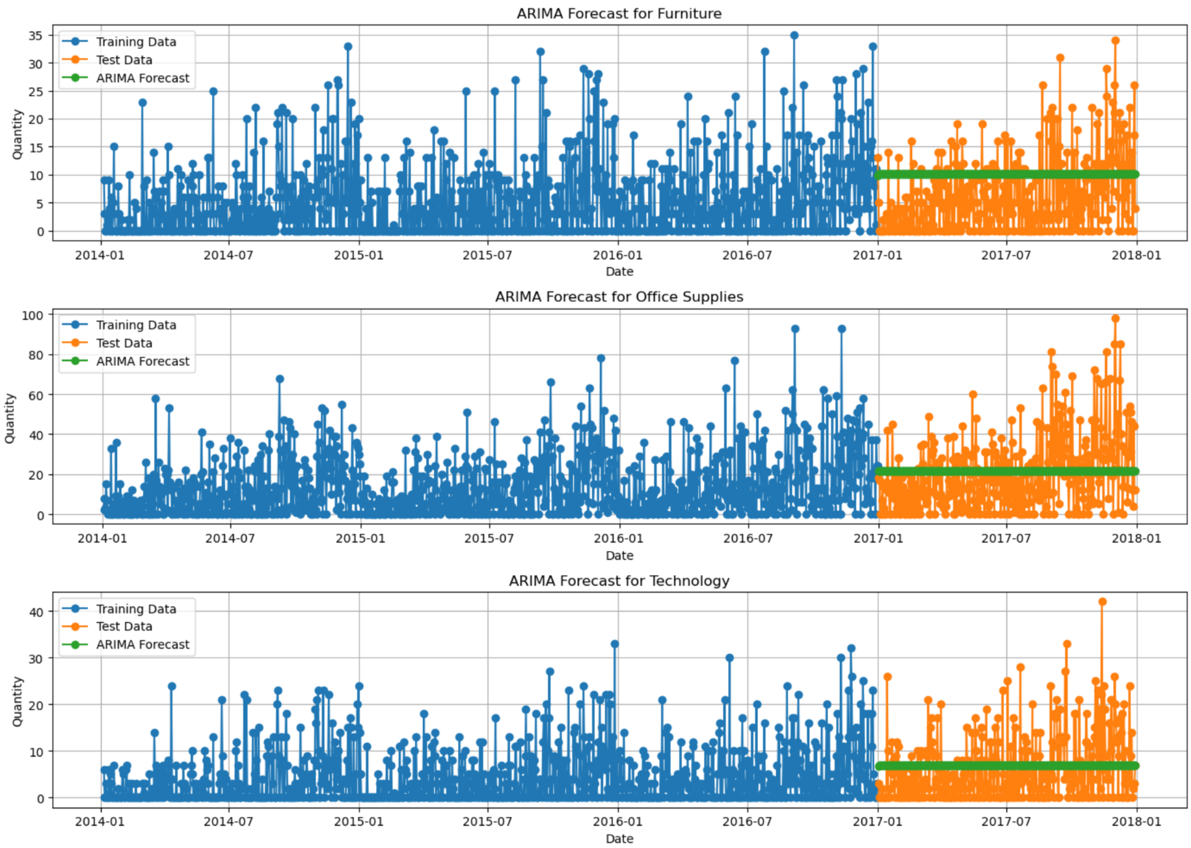

Figure 9, ARIMA Seasonal Forecasts

Source: Own representation

SARIMA

The performance of the SARIMA model on the daily sales data for each product category is visualized as shown below:

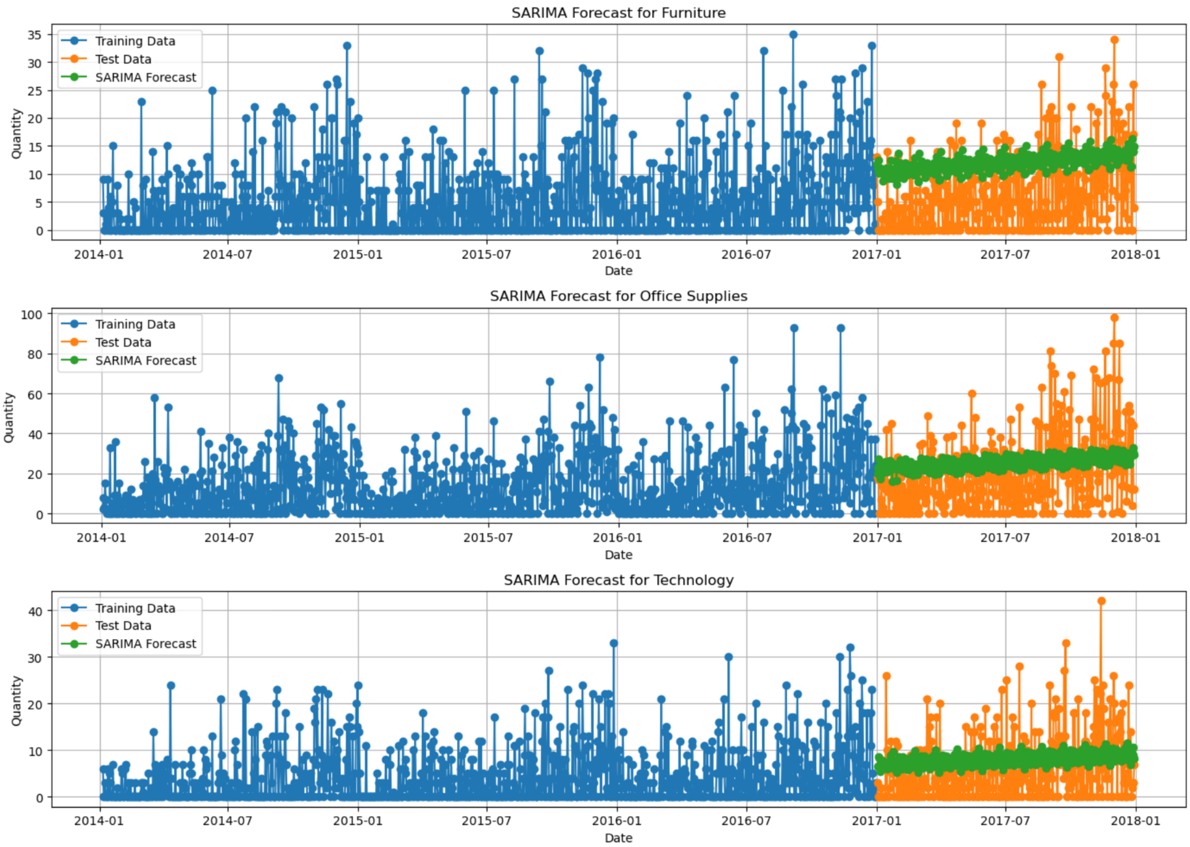

Figure 10, SARIMA Seasonal Forecasts

Source: Own representation

Prophet

The performance of the Prophet model on the daily sales data for each product category is visualized as shown below:

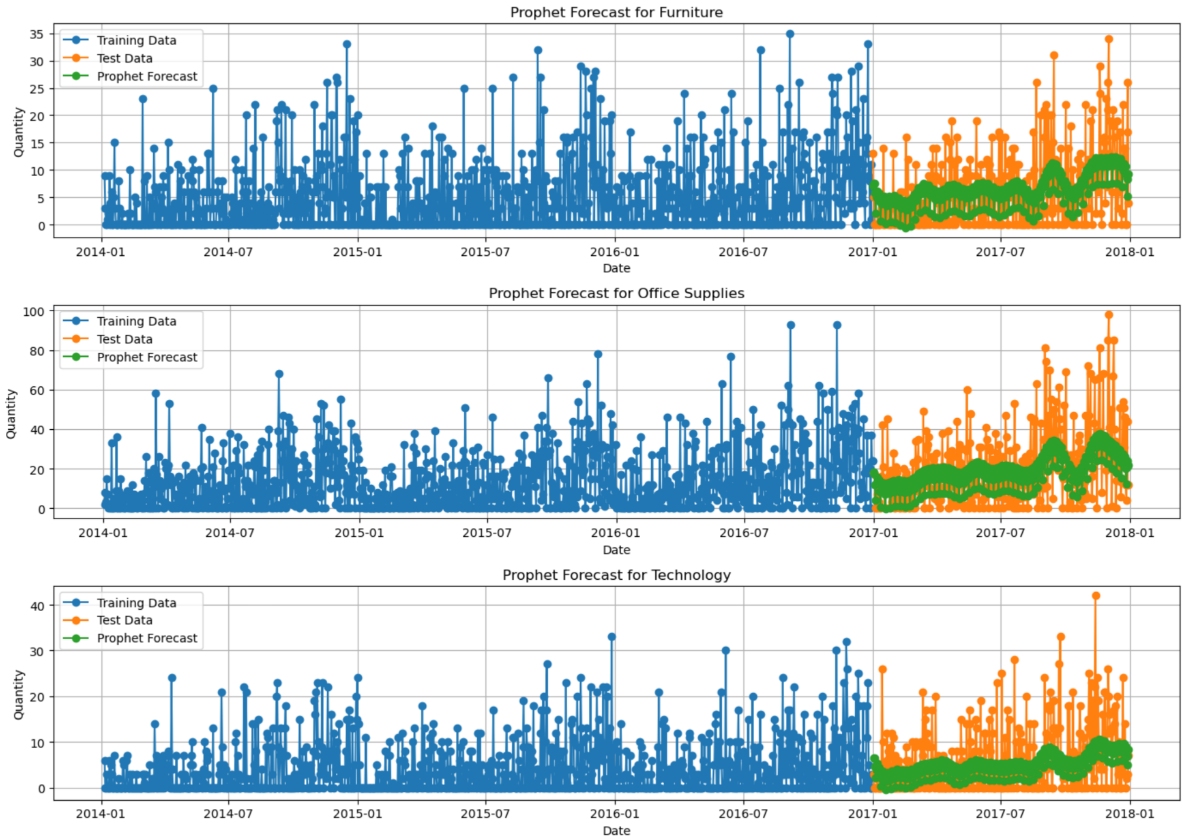

Figure 11, Prophet Seasonal Forecasts

Source: Own representation

Random Forest

The performance of the Random Forest model on the daily sales data for each product category is visualized as shown below:

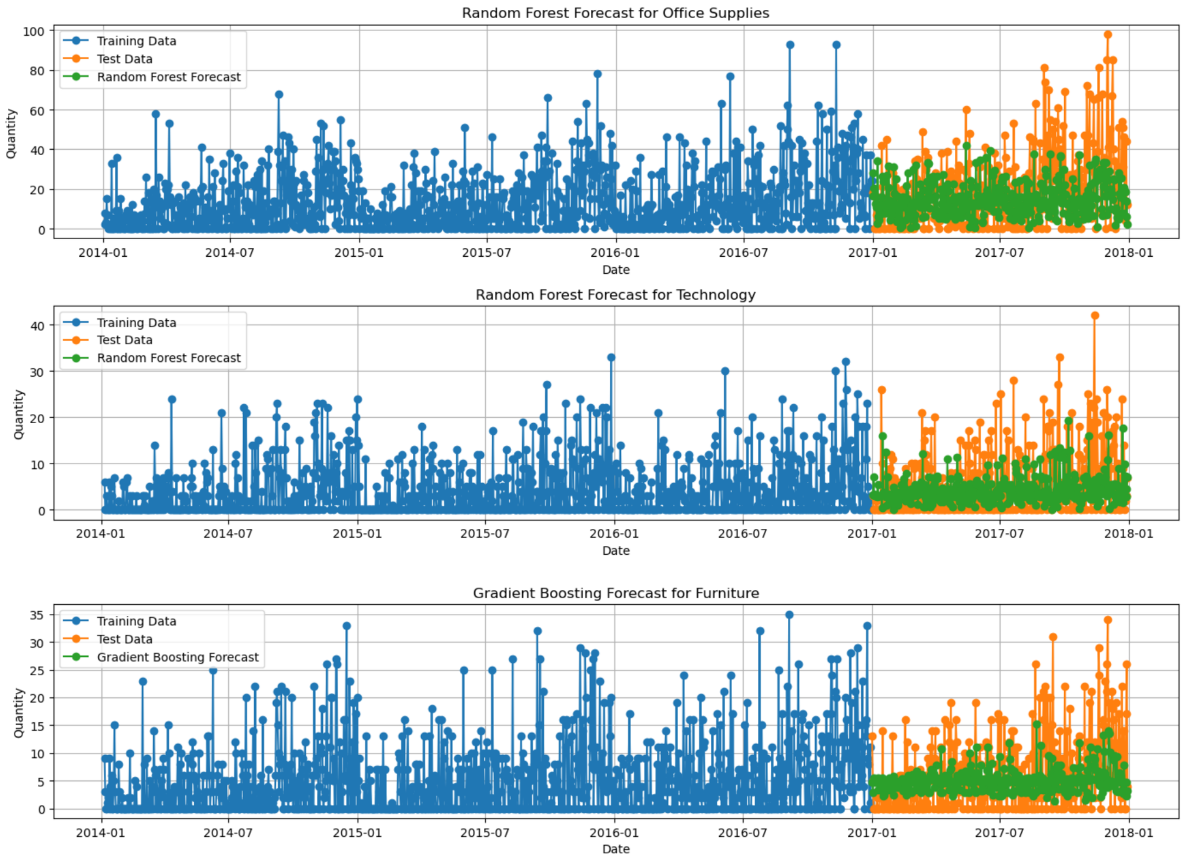

Figure 12, Random Forest Seasonal Forecasts

Source: Own representation

Gradient Boosting

The performance of the Gradient Boosting model on the daily sales data for each product category is visualized as shown below:

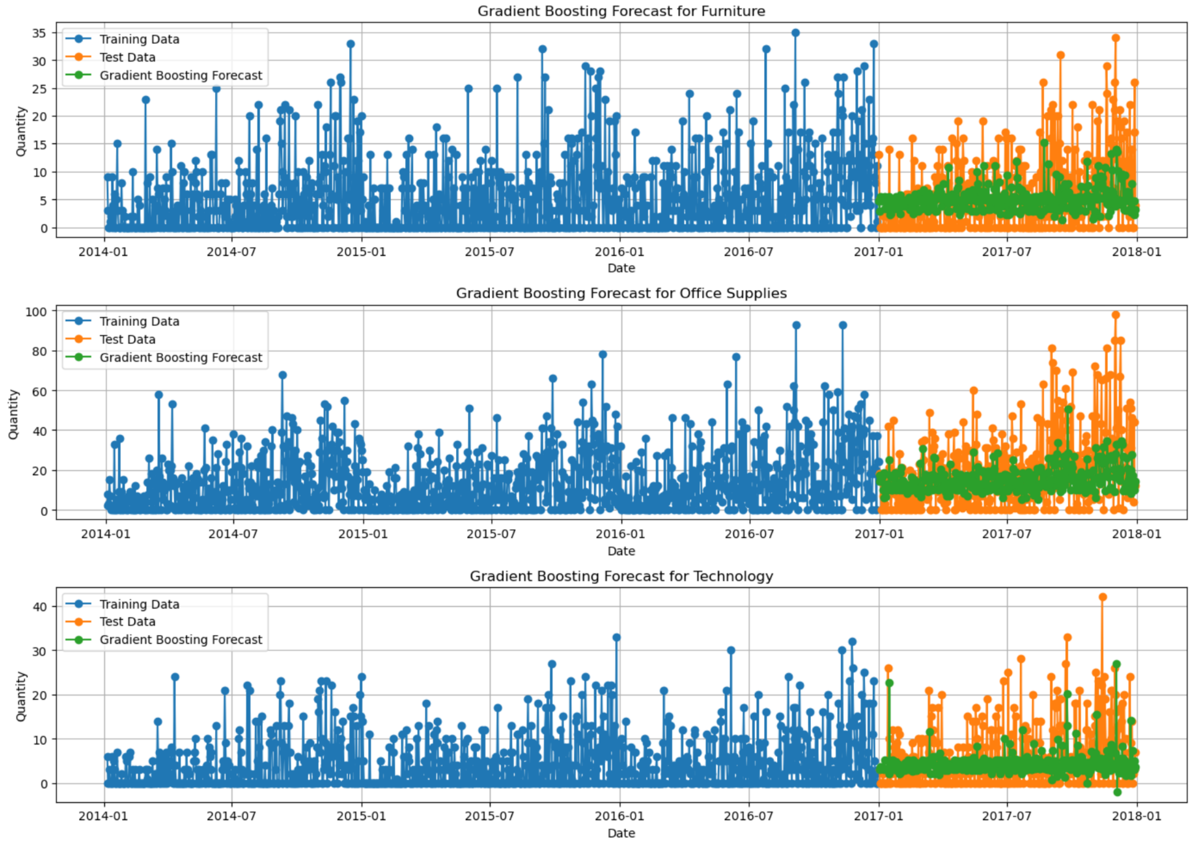

Figure 13, Gradient Boosting Seasonal Forecasts

Source: Own representation

4.3.3 Model's Performance by Metrics

Table 3, Models Performance on Seasonality Metrics

Category	Model	MAE	MSE	RMSE	R^2
Furniture	ARIMA	6.69	58.84	7.67	-0.34
	SARIMA	7.63	75.28	8.68	-0.71
	Prophet	5.11	40.42	6.36	0.08
	Random Forest	5.60	55.49	7.45	-0.26
	Gradient Boosting	5.29	49.00	7.00	-0.11
Office Supplies	ARIMA	14.13	329.61	18.16	-0.00
	SARIMA	15.06	344.78	18.57	-0.05
	Prophet	10.88	216.82	14.72	0.34
	Random Forest	14.19	379.84	19.49	-0.16
	Gradient Boosting	13.37	340.78	18.46	-0.04
Technology	ARIMA	5.87	51.36	7.17	-0.01
	SARIMA	6.24	54.11	7.36	-0.07
	Prophet	5.29	48.54	6.97	0.04
	Random Forest	5.55	59.56	7.72	-0.18
	Gradient Boosting	5.46	56.16	7.49	-0.11

Source: Own representation

A summary and comparison of all the model performances across each category, as per the results of this table, will be discussed in the upcoming sections.

4. 4 Evaluation of Predictive Model Performance during Holidays and Promotions

In this section, we focus on assessing the performance of the models specifically during holidays and promotional periods, and how these results compare to their performance during regular periods. Capturing the details of sales patterns during holidays and promotions can be crucial for effective retail inventory management. Therefore, in this work, the models make predictions on the data and their performances are evaluated to understand their effectiveness.

4.4.1 Data Filtering

The sales data has been narrowed down to only include periods that correspond with holidays or promotional events, excluding regular sales periods. Further details is explained in the following table.

Table 4, Periodic Holidays with Expected High Sales

Period Type	**Criteria**	**Details**
Holidays	Major holidays in the USA	• New Year's Day (01/01). • Independence Day (07/04). • Thanksgiving (Fourth Thursday of November). • Christmas Day (12/25)
Promotions	Orders with a discount greater than 0.5	Any order where the discount has a value > 0.5
Regular	All other dates not falling under Holidays or Promotions	Normal sales days with no significant discounts or a holiday

Source: Own representation

Forecasts were generated to demonstrate the capability of predictive models to estimate sales quantities across different retail product categories. The analysis features subplots showing both actual sales and predictions from models like ARIMA, SARIMA, Prophet, Random Forest, and Gradient Boosting. Additionally, a line representing the average sales value for each category is included for a side-by-side comparison of sales data, both filtered and unfiltered.

4.4.2 Model Results

The performance of each of the models on the filtered sales data for Furniture category is visualized as shown below:

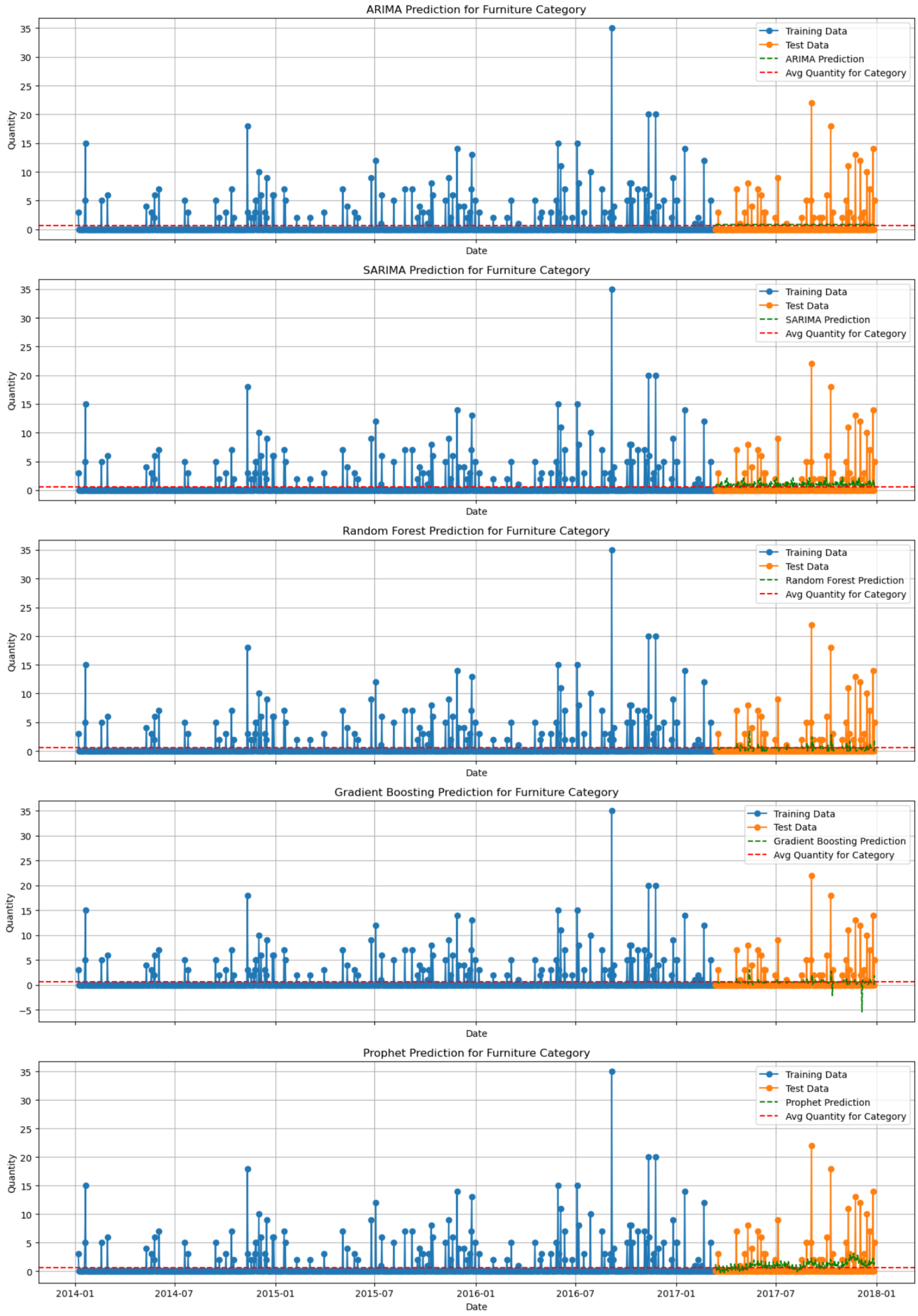

Figure 14, Plotting model forecasts on major sales for the Furniture category (Holidays and discounts)

Source: Own representation

The performance of each of the models on the filtered sales data for Office Supplies category is visualized as shown below:

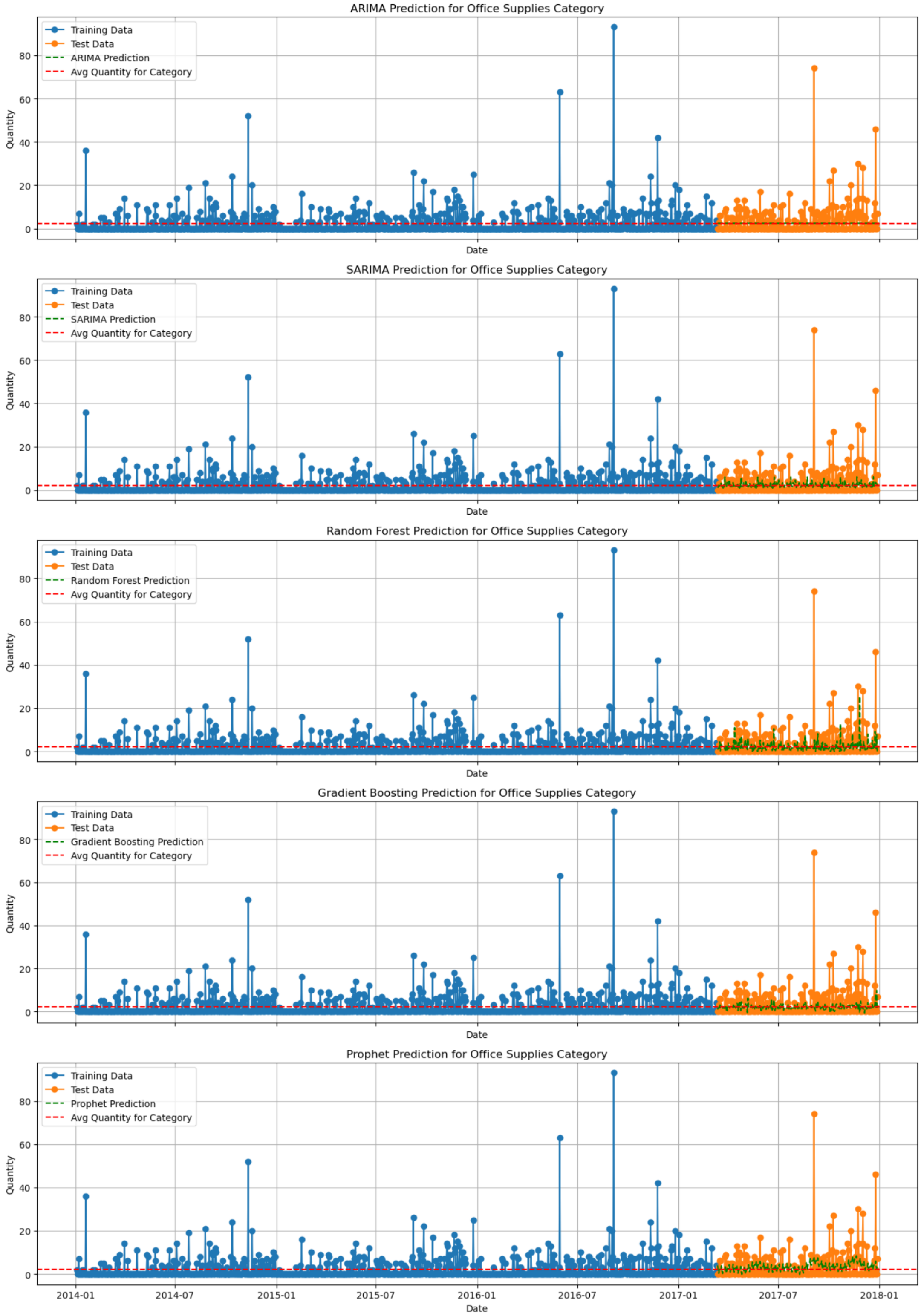

Figure 15, Plotting models forecast on major sales for the Office Supplies category (Holidays and discounts)

Source: Own representation

The performance of each of the models on the filtered sales data for furniture category is visualized as shown below:

Figure 16, Plotting models forecast on major sales for the Technology category (Holidays and discounts)

Source: Own representation

4.4.3 Model's Performance by Metrics

Table 5, Holidays and Promotions Metrics Table

Category	Model	MAE	MSE	RMSE	R^2
Furniture	ARIMA	1.35	6.74	2.60	-0.00
	SARIMA	1.49	7.01	2.65	-0.04
	Prophet	1.46	6.37	2.52	0.05
	Random Forest	1.13	6.76	2.60	-0.00
	Gradient Boosting	1.17	6.87	2.62	-0.02
Office Supplies	ARIMA	3.77	47.21	6.87	-0.01
	SARIMA	3.81	48.87	6.99	-0.05
	Prophet	3.80	42.23	6.50	0.09
	Random Forest	3.83	50.99	7.14	-0.09
	Gradient Boosting	3.66	47.76	6.91	-0.03
Technology	ARIMA	0.57	3.62	1.90	0.00
	SARIMA	0.69	3.69	1.92	-0.02
	Prophet	0.72	3.36	1.83	0.07
	Random Forest	0.51	4.42	2.10	-0.22
	Gradient Boosting	0.50	4.51	2.12	-0.25

Source: Own representation

A summary and comparison of all the model performances across each category, as per the results of this table, will be discussed in the upcoming sections.

4.5 Comparison of Model Performances

In this section, we evaluate and compare the performances of the five predictive models across various product categories. Each model is assessed using four evaluation metrics. These metrics enable the determination of each model's ability to predict future sales quantities, identify seasonal patterns, and react to changes during holiday and promotional periods.

4.5.1 Overall Model's Performance by Metrics

Table 6, Overall Model Performance Metrics Comparison

Category	**Model**	**Weekly Sales**				**Seasonal Sales**				**Holiday and Promo**			
		MAE	MSE	RMSE	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE	R^2
Furniture	ARIMA	39.17	1922.95	43.85	-2.37	6.69	58.84	7.67	-0.34	1.35	6.74	2.60	-0.00
	SARIMA	11.79	210.36	14.50	0.63	7.63	75.28	8.68	-0.71	1.49	7.01	2.65	-0.04
	Prophet	11.15	225.58	15.02	0.60	5.11	40.42	6.36	0.08	1.46	6.37	2.52	0.05
	Random Forest	17.50	525.77	22.93	0.08	5.60	55.49	7.45	-0.26	1.13	6.76	2.60	-0.00
	Gradient Boosting	17.45	593.18	24.36	-0.04	5.29	49.00	7.00	-0.11	1.17	6.87	2.62	-0.02
Office Supplies	ARIMA	49.37	4232.27	65.06	-0.01	14.13	329.61	18.16	-0.00	3.77	47.21	6.87	-0.01
	SARIMA	31.84	1585.79	39.82	0.62	15.06	344.78	18.57	-0.05	3.81	48.87	6.99	-0.05
	Prophet	31.82	1637.06	40.46	0.61	10.88	216.82	14.72	0.34	3.80	42.23	6.50	0.09
	Random Forest	46.33	3481.32	59.00	0.17	14.19	379.84	19.49	-0.16	3.83	50.99	7.14	-0.09
	Gradient Boosting	44.37	2918.47	54.02	0.31	13.37	340.78	18.46	-0.04	3.66	47.76	6.91	-0.03
Technology	ARIMA	26.42	874.42	29.57	-0.46	5.87	51.36	7.17	-0.01	0.57	3.62	1.90	0.00
	SARIMA	17.99	519.55	22.79	0.13	6.24	54.11	7.36	-0.07	0.69	3.69	1.92	-0.02
	Prophet	15.08	407.30	20.18	0.32	5.29	48.54	6.97	0.04	0.72	3.36	1.83	0.07
	Random Forest	16.11	553.57	23.53	0.08	5.55	59.56	7.72	-0.18	0.51	4.42	2.10	-0.22
	Gradient Boosting	16.81	558.17	23.63	0.07	5.46	56.16	7.49	-0.11	0.50	4.51	2.12	-0.25

4.5.2 Understanding of Model Performances

ARIMA

The results of the ARIMA models were mixed for the product categories in the data. In the Furniture category, the RMSE of ARIMA was 43.85, a Mean Absolute Error (MAE) of 39.17, a Mean

Squared Error (MSE) of 1922.95, and an R^2 score of -2.37, which places it at the lower end of model effectiveness. Similarly, in the Office Supplies category, the RMSE of ARIMA was 65.06, an MAE of 49.37, an MSE of 4232.27, and an R^2 score of -0.01, reflecting relatively low performance compared to other models. In the Technology category, ARIMA had an RMSE of 29.57, an MAE of 26.42, an MSE of 874.42, and an R^2 score of -0.46, indicating that its performance was also on the lower end. These findings suggest that ARIMA may not provide the most precise predictions, particularly for categories with higher sales fluctuations and demand variation.

When examining performance during promotional and discount periods, ARIMA had an RMSE of 1.35 for Furniture, 3.77 for Office Supplies, and 0.57 for Technology. The MAE values were 0.86 for Furniture, 3.31 for Office Supplies, and 0.38 for Technology, with R^2 scores of -0.00, -0.01, and 0.00, respectively. These figures indicate that ARIMA was not highly effective in predicting sales during promotional periods, performing worse than other models such as SARIMA and Prophet, which showed slightly better R^2 scores and lower RMSEs. This suggests that ARIMA may not be as sensitive to promotional effects as models like SARIMA or Prophet.

Additionally, during high-demand periods, ARIMA's performance was subpar. In the Furniture category, ARIMA's performance was relatively poor compared to other models, showing high error rates. Similarly, during periods of high demand in the Office Supplies and Technology categories, ARIMA's performance lagged, with higher RMSE and MAE values than the Prophet and SARIMA models. This implies that ARIMA may struggle to capture demand variations during peak periods, leading to less accurate forecasts.

SARIMA

The SARIMA model performed significantly better than ARIMA across most product categories in the data. In the Furniture category, SARIMA achieved an RMSE of 14.50, a Mean Absolute Error (MAE) of 11.79, a Mean Squared Error (MSE) of 210.36, and an R^2 score of 0.63, indicating a more accurate and reliable performance compared to ARIMA. Similarly, in the Office Supplies category, SARIMA produced an RMSE of 39.82, an MAE of 31.84, an MSE of 1585.79, and an R^2 score of 0.62, demonstrating solid forecasting ability. In the Technology category, SARIMA had an RMSE of 22.79, an MAE of 17.99, an MSE of 519.55, and an R^2 score of 0.13, showing better performance compared to ARIMA, although with room for improvement.

During promotional and discount periods, SARIMA demonstrated moderate sensitivity to fluctuations. The RMSE values were 1.49 for Furniture, 3.81 for Office Supplies, and 0.69 for Technology. The MAE values were 1.49 for Furniture, 3.81 for Office Supplies, and 0.69 for Technology, with corresponding R^2 scores of -0.04, -0.05, and -0.02. While SARIMA did not achieve the highest accuracy during these periods, it still performed better than ARIMA and exhibited greater sensitivity to sales variations during promotions.

During high-demand periods, SARIMA continued to outperform ARIMA in all categories. For Furniture, the model's performance was relatively strong, with lower error rates compared to ARIMA. Similarly, in Office Supplies and Technology, SARIMA delivered more accurate predictions, capturing demand variations more effectively, which is reflected in the lower RMSE and MAE values. These results suggest that SARIMA is a more robust model for forecasting during peak demand periods, although further improvements could be made in its sensitivity to holiday and promotional influences.

Random Forest

The performance of the Random Forest model in the data showed varied results across the different product categories. In the Furniture category, Random Forest produced an RMSE of 22.93, a Mean Absolute Error (MAE) of 17.50, a Mean Squared Error (MSE) of 525.77, and an R^2 score of 0.08. While this performance is better than ARIMA, it still lags behind SARIMA and Prophet in terms of accuracy. In the Office Supplies category, Random Forest showed an RMSE of 59.00, an MAE of 46.33, an MSE of 3481.32, and an R^2 score of 0.17, indicating moderate performance but not significantly better than other models in this category. In the Technology category, the RMSE was 23.53, the MAE was 16.11, the MSE was 553.57, and the R^2 score was 0.08, showing that while Random Forest performs better than ARIMA, it is still not as effective as SARIMA or Prophet.

During promotional and discount periods, Random Forest demonstrated relatively low sensitivity to variations. The RMSE values were 1.13 for Furniture, 3.83 for Office Supplies, and 0.51 for Technology. The MAE values were 1.13 for Furniture, 3.83 for Office Supplies, and 0.51 for Technology, with corresponding R^2 scores of -0.00, -0.09, and -0.22, respectively. These results suggest that Random Forest struggles to capture promotional effects as effectively as models like SARIMA or Prophet.

In periods of high demand, the performance of Random Forest was again mixed. In the Furniture category, the model delivered better accuracy than ARIMA, but still fell short compared to SARIMA and Prophet. In Office Supplies and Technology, Random Forest produced forecasts with higher error rates, as reflected in the higher RMSE and MAE values. This suggests that the Random Forest model may not be well-suited for capturing demand fluctuations in categories with significant volatility. While Random Forest provides a good balance between accuracy and computational efficiency, it may require further tuning or integration with other models for better results during high-demand and promotional periods.

Gradient Boosting

The Gradient Boosting model demonstrated mixed performance across the different product categories in the data. In the Furniture category, Gradient Boosting had an RMSE of 24.36, a Mean Absolute Error (MAE) of 17.45, a Mean Squared Error (MSE) of 593.18, and an R^2 score of -0.04.

These results indicate that Gradient Boosting, while comparable to Random Forest in error metrics, did not perform as well as SARIMA or Prophet in this category. In the Office Supplies category, Gradient Boosting produced an RMSE of 54.02, an MAE of 44.37, an MSE of 2918.47, and an R^2 score of 0.31, placing it slightly ahead of Random Forest but still behind Prophet and SARIMA in terms of accuracy. For the Technology category, Gradient Boosting showed an RMSE of 23.63, an MAE of 16.81, an MSE of 558.17, and an R^2 score of 0.07, again indicating that while it performs reasonably well, it is not as effective as other models like SARIMA and Prophet.

During promotional and discount periods, Gradient Boosting struggled to capture the effects of promotions effectively. The RMSE values were 1.17 for Furniture, 3.66 for Office Supplies, and 0.50 for Technology. The MAE values were 1.17 for Furniture, 3.66 for Office Supplies, and 0.50 for Technology, with corresponding R^2 scores of -0.02, -0.03, and -0.25, respectively. This shows that Gradient Boosting, similar to Random Forest, had difficulty modeling the impact of promotional periods and performed worse than SARIMA and Prophet in these contexts.

In periods of high demand, Gradient Boosting showed moderate performance but did not excel compared to other models. In the Furniture category, it delivered forecasts with a slightly higher error rate than Random Forest, while in Office Supplies, the performance was marginally better. In the Technology category, however, Gradient Boosting struggled, with higher error rates and lower R^2 scores than the other models. These results suggest that while Gradient Boosting can provide reasonable predictions in steady conditions, it may not be the best model for capturing volatile demand or responding to promotions effectively. Overall, Gradient Boosting offers competitive accuracy but may require further optimization for use in more dynamic sales environments.

Prophet

The Prophet model demonstrated solid performance across the product categories in the data, often outperforming ARIMA and Random Forest. In the Furniture category, Prophet produced an RMSE of 15.02, a Mean Absolute Error (MAE) of 11.15, a Mean Squared Error (MSE) of 225.58, and an R^2 score of 0.60. These results indicate that Prophet performed comparably to SARIMA, delivering accurate predictions. In the Office Supplies category, Prophet showed an RMSE of 40.46, an MAE of 31.82, an MSE of 1637.06, and an R^2 score of 0.61, again closely matching SARIMA's performance and outperforming ARIMA and Random Forest. For the Technology category, Prophet achieved an RMSE of 20.18, an MAE of 15.08, an MSE of 407.30, and an R^2 score of 0.32, outperforming ARIMA and Random Forest, while remaining competitive with SARIMA.

During promotional and discount periods, Prophet was effective in capturing sales fluctuations, showing relatively strong performance. The RMSE values were 1.46 for Furniture, 3.80 for Office Supplies, and 0.72 for Technology. The MAE values were 1.46 for Furniture, 3.80 for Office Supplies, and 0.72 for Technology, with corresponding R^2 scores of 0.05, 0.09, and 0.07, respectively. Prophet's ability to capture sales trends during promotions was superior to ARIMA and Random Forest, and in some cases, it rivaled SARIMA's performance.

In periods of high demand, Prophet continued to show strong results across all categories. In the Furniture category, the model's RMSE and MAE were lower than those of ARIMA and Random Forest, suggesting it is better suited to capture high-demand periods. Similarly, in Office Supplies, Prophet delivered more accurate forecasts, closely matching the performance of SARIMA. In the Technology category, Prophet's lower error rates and higher R^2 scores compared to ARIMA and Random Forest demonstrate its ability to better capture demand fluctuations. Overall, Prophet proved to be a reliable model for both regular and high-demand periods, providing balanced performance across all categories and outperforming many of the other models tested in this study.

4.5.3 Model Ranking and Selection

A comparative analysis of five predictive models was conducted across three product categories. Each model was evaluated using four key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). These metrics gauge the models' accuracy and effectiveness in forecasting sales, where lower MAE, MSE, and RMSE values indicate higher accuracy, and higher R^2 values suggest a better fit to the data. From this analysis, the top three performing models have been identified and will be used as inputs for the hybrid model in the upcoming section.

Selection of Top Performing Models

1. Prophet

Prophet demonstrates strong performance, particularly in the Technology and Office Supplies categories, where it achieves positive R^2 values in both weekly and seasonal sales predictions. It consistently shows lower error metrics (MAE, MSE, RMSE) compared to other models, indicating a good predictive accuracy and model fit across different scenarios. In holiday and promotional periods, Prophet also maintains a competitive edge with relatively low error rates and positive R^2 values, suggesting its effectiveness in handling irregular sales patterns during these times. Its overall stability across weekly, seasonal, and holiday sales makes it a versatile and reliable choice for forecasting.

2. SARIMA

SARIMA excels in the Furniture category, particularly in weekly sales predictions, where it achieves the highest R^2 value among the models, showcasing its ability to capture seasonal trends effectively. However, its performance varies across other categories, with mixed results in seasonal and holiday sales predictions, particularly evident in the Technology category where R^2 values drop below zero. Despite these variations, SARIMA's strength lies in its robust modeling of seasonality, making it particularly valuable in markets with pronounced seasonal patterns, although it may struggle during irregular periods like holidays and promotions.

3. Random Forest

Random Forest exhibits moderate accuracy, with mid-range error values and slightly positive R^2 values, reflecting decent performance though with less consistency compared to Prophet and SARIMA. Its ensemble approach is robust and effective in handling diverse data patterns, offering reliable predictions, but it generally underperforms relative to the other two models, making it a secondary choice in scenarios where Prophet and SARIMA may not fully meet forecasting needs.

These models are chosen based on their ability to perform across different metrics and categories, reflecting their utility in real-world forecasting tasks.

4.6 Hybrid Model

In this section, a Hybrid model is developed based on the predictions of the top 3 performing models Prophet, SARIMA, and Random Forest using Multiple Linear Regression.

Multiple Linear Regression (MLR) is a statistical technique that models the relationship between one dependent variable and two or more independent variables. In the context of the hybrid model, the independent variables are the predictions from Prophet, SARIMA, and Random Forest, while the dependent variable is the actual sales data. MLR works by fitting a linear equation to the observed data, determining the optimal coefficients that minimize the difference between the predicted and actual values (Tranmer & Elliot, 2008).

By using Multiple Linear Regression, the hybrid model can effectively combine the strengths of each individual model. Each model may excel in capturing different aspects of the data such as seasonality, trends, or complex patterns and MLR allows these different predictions to be weighted appropriately. This combination helps to reduce the overall error and improve the accuracy of the forecasts. The result is a more robust and reliable prediction, as the hybrid model leverages the best features of each model, compensating for their individual weaknesses and capitalizing on their strengths. This approach ensures that the final forecast is more accurate than any single model could achieve on its own (Adhikari & Agrawal, 2013).

4.6.1 Model Results

The performance of the Hybrid model on the daily sales data for Furniture category is visualized as shown below:

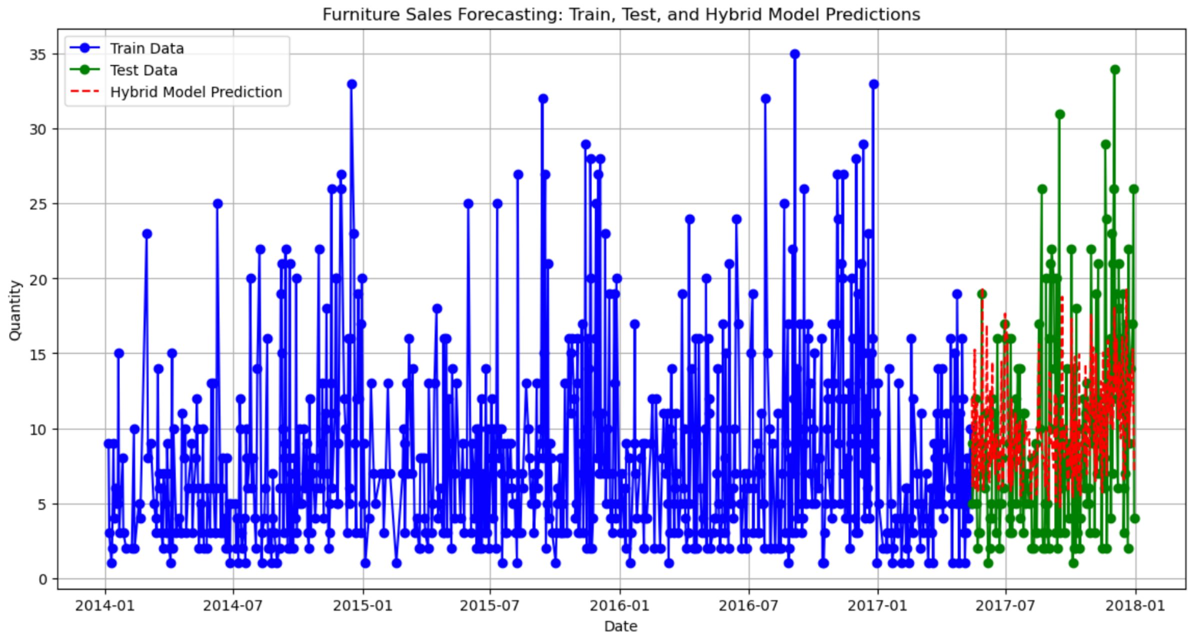

Figure 17, Hybrid model performance in Furniture category

Source: Own representation

The performance of the Hybrid model on the daily sales data for Office Supplies category is visualized as shown below:

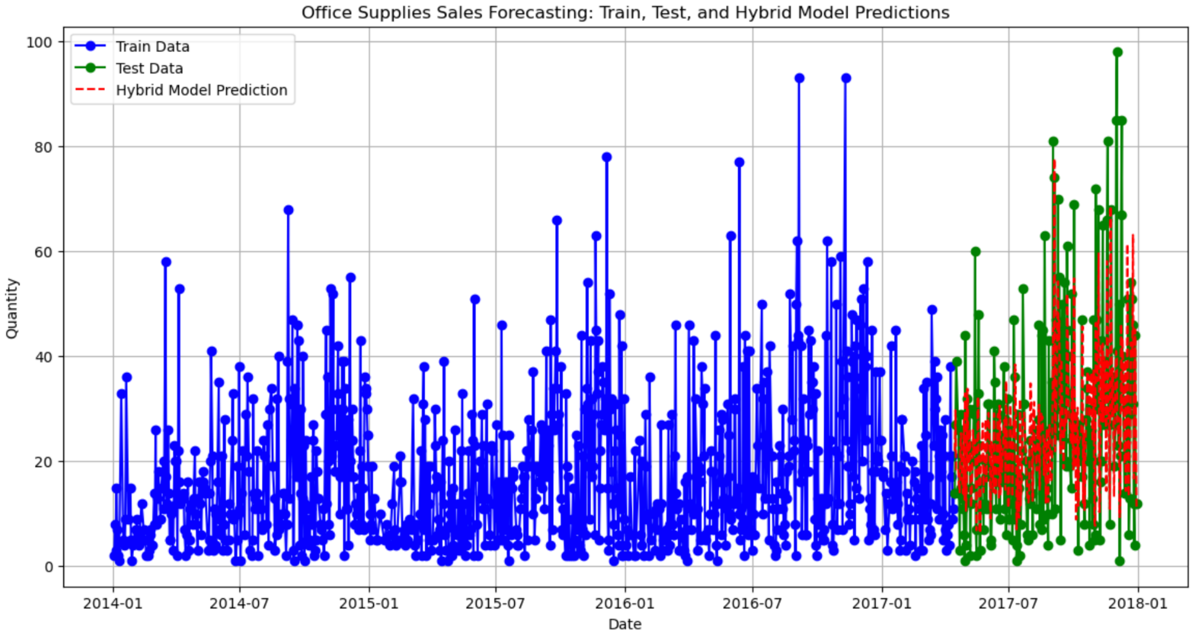

Figure 18, Hybrid model performance in Office Supplies category

Source: Own representation

The performance of the Hybrid model on the daily sales data for Technology category is visualized as shown below:

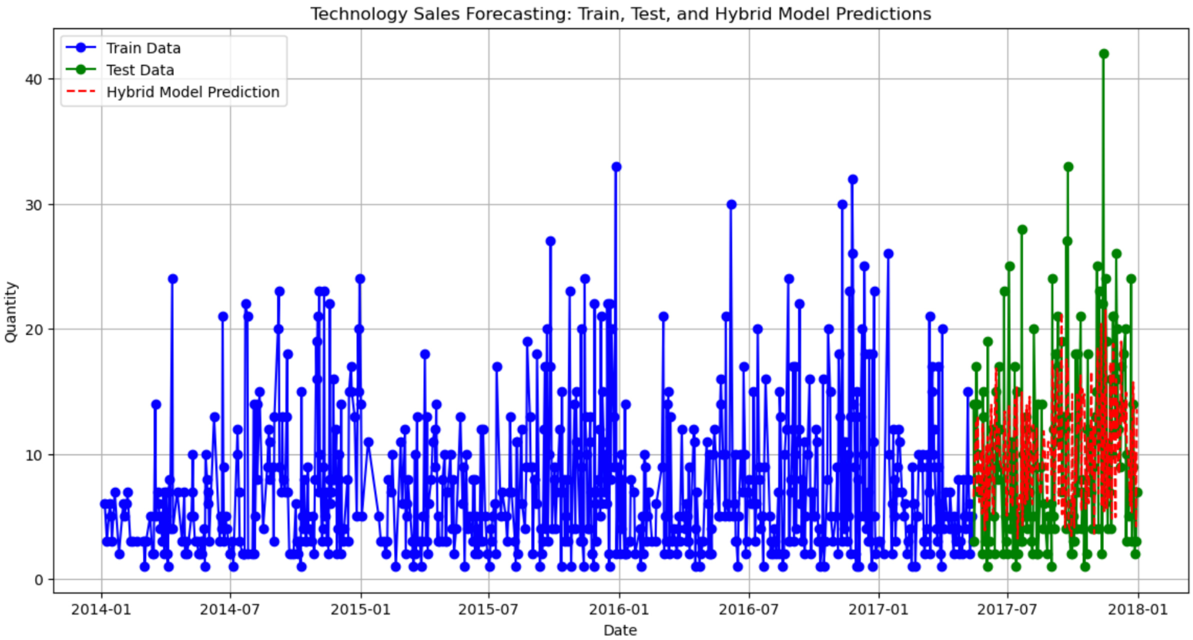

Figure 19, Hybrid model performance in Technology category

Source: Own representation

4.6.2 Evaluation of the Hybrid Model

To ensure consistency, the same evaluation metrics used in the previous models are applied to assess the performance of the hybrid model. Additionally, learning curves are also utilized in the evaluation process.

Learning curves graphically show how a machine learning model's performance changes as the training dataset grows. They plot training and validation errors (or scores) against the number of training samples, helping diagnose overfitting (good training performance, poor validation) or underfitting (poor performance on both). By analyzing these curves, practitioners can assess model generalization, determine if more data improves accuracy, and identify if the model needs further tuning (Raschka, 2020).

The evaluation metric results are shown in the following table:

Table 7, Hybrid Model Performance Metrics

Category	**MAE**	**MSE**	**RMSE**	**R^2**
Furniture	4.42	33.33	5.77	0.26
Office Supplies	10.48	196.44	14.02	0.43
Technology	4.82	37.62	6.13	0.32

The learning curves for each category is visualized in following figures:

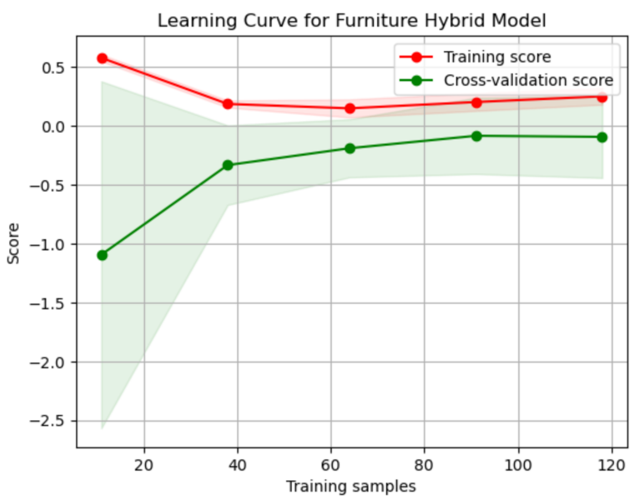

Figure 20, Hybrid models learning Curve in Furniture category

Source: Own representation

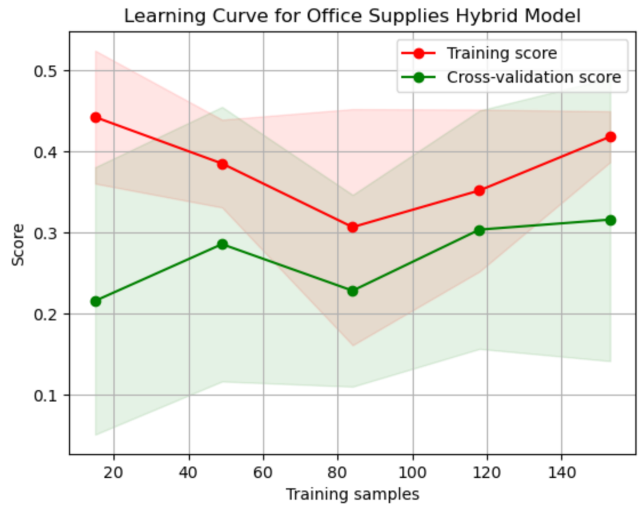

Figure 21, Hybrid models learning Curve in Office Supplies category

Source: Own representation

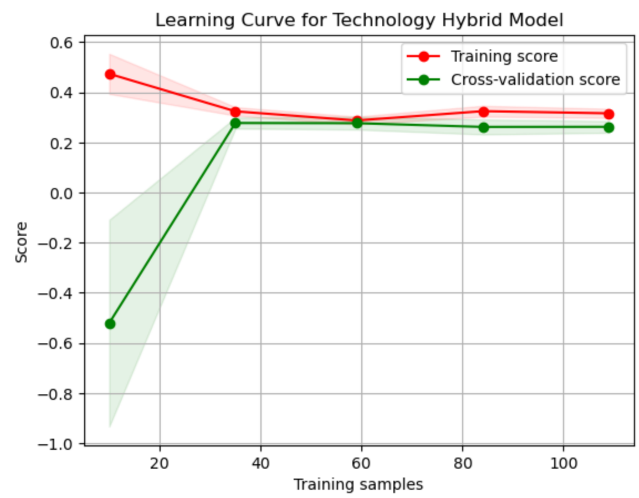

Figure 22, Hybrid models learning Curve in Technology category

Source: Own representation

The results obtained from the combined model (Hybrid model) show a better fitness measure compared to the base models without combination. For Furniture, with the hybrid model, the RMSE is 5.77 and the R^2 score is 0.26. When compared to the individual models, such as ARIMA with an RMSE of 43.85 and R^2 of -2.37, or SARIMA with an RMSE of 14.50 and R^2 of 0.63, the hybrid model shows a balanced performance, although it doesn't outperform SARIMA in R^2, it still provides more stable results across various metrics. In the Office Supplies category, the hybrid model achieves an RMSE of 14.02 and an R^2 of 0.43, closely matching Prophet's performance (RMSE of 14.72 and R^2 of 0.34 in weekly sales). However, the hybrid model demonstrates better accuracy and consistency across metrics when compared to other models like ARIMA (RMSE of 65.06, R^2 of -0.01) or Random Forest (RMSE of 59.00, R^2 of 0.17). This indicates that the hybrid model provides improved predictive power by combining the strengths of individual models. In the Technology category, the hybrid model results in an RMSE of 6.13 and R^2 of 0.32. This outperforms ARIMA, which has an RMSE of 29.57 and R^2 of -0.46, and also provides better performance than Prophet with an RMSE of 20.18 and R^2 of 0.32. Although Prophet performs similarly in terms of R^2, the hybrid model offers more consistency across different data patterns, including seasonal and holiday promotions.

The results suggest that the hybrid model enhances general reliability by effectively capturing different aspects of the data, although it doesn't always achieve the highest scores in every individual category. However, it shows significant improvement in overall stability and predictive accuracy across multiple data points. Despite this, lower R^2 scores and relatively higher error rates may indicate several challenges. Firstly, the time series data might not be long enough to capture richer variance, which could impact the model's ability to identify complex patterns. Additionally, sales volatility across different product categories, along with outliers, seasonal influences, and promotions, might reduce the model's predictive flexibility.

Additionally, the learning curves provide further insights into these observations. In Furniture learning curve, while the training score starts high, the cross-validation score improves with more training samples, indicating better generalization, though the gap suggests some overfitting. In Office Supplies learning curve, the training and cross-validation scores converge, reflecting a well-trained and stable model, aligning with the higher R^2 score for this category. However, in Technology learning curve, both scores converge at a lower level, suggesting the model struggles to capture complex patterns, potentially due to sales volatility or insufficient feature representation. However, the chosen features and model parameters could be further optimized to improve performance, as indicated by the learning curves in all categories. Learning curve for Technology in particular suggests that while the model is stable, additional tuning or feature engineering could be necessary to achieve better performance. Finally, unpredictable random fluctuations in sales data could limit the model's accuracy. Nevertheless, the learning curves suggest that the models are well-trained, with training and validation loss getting closer, indicating improved stability and a better fit to the data.

Therefore, these findings reveal that the hybrid model approach, which incorporates several forecasting methods, is highly effective across categories. These results highlight the importance of using different forecasting methods to minimize their respective limitations. A study by Xiao et al., (2012) further confirms the efficiency of hybrid models in improving forecast accuracy by leveraging several models to capture different elements of a time series.

4.7 Impact on Inventory Levels

This section addresses the development and application of a hybrid predictive model used to forecast future inventory quantities. The predictions cover the subsequent six months, utilizing the complete training dataset. Each category is plotted separately, showing the historical sales of products from 2014 to 2018, as well as the predicted sales quantities for the next six months. By leveraging past sales data and machine learning algorithms, the proposed model forecasts the necessary stock for each category.

The performance of the Hybrid Model on predicting the future sales for Furniture category is visualized as shown below:

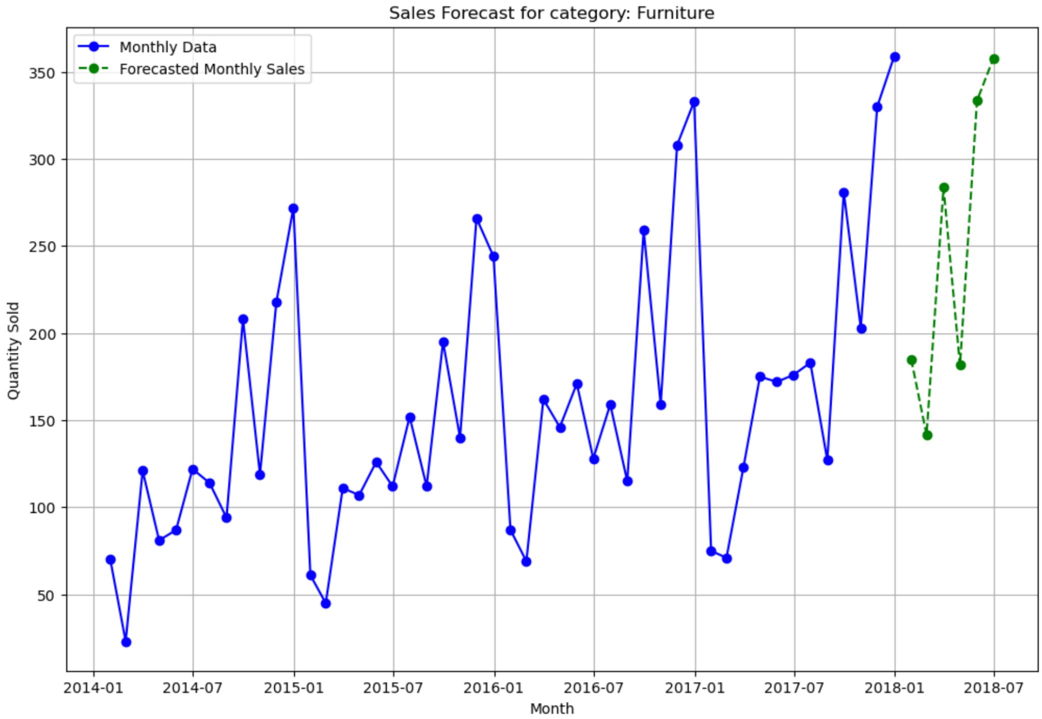

Figure 23, Graph of Furniture category sales forecast using the hybrid model

Source: Own representation

The performance of the Hybrid Model on predicting the future sales for Office Supplies category is visualized as shown below:

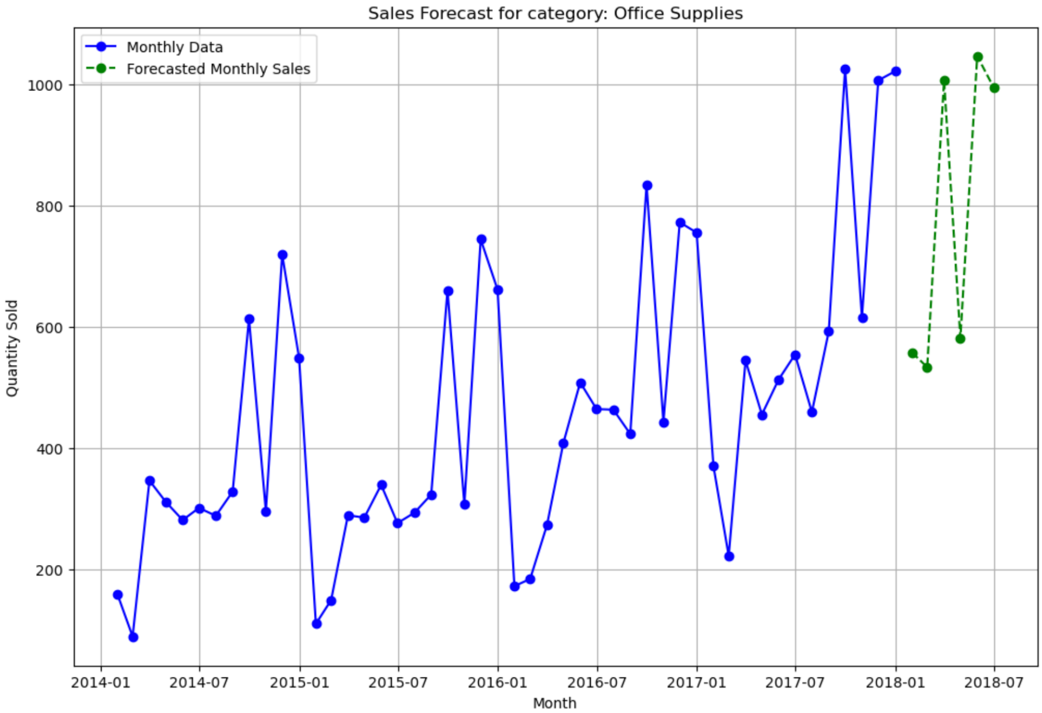

Figure 24, Graph showing Office Supplies category sales forecast using hybrid model

Source: Own representation

The performance of the Hybrid Model on predicting the future sales for Technology category is visualized as shown below:

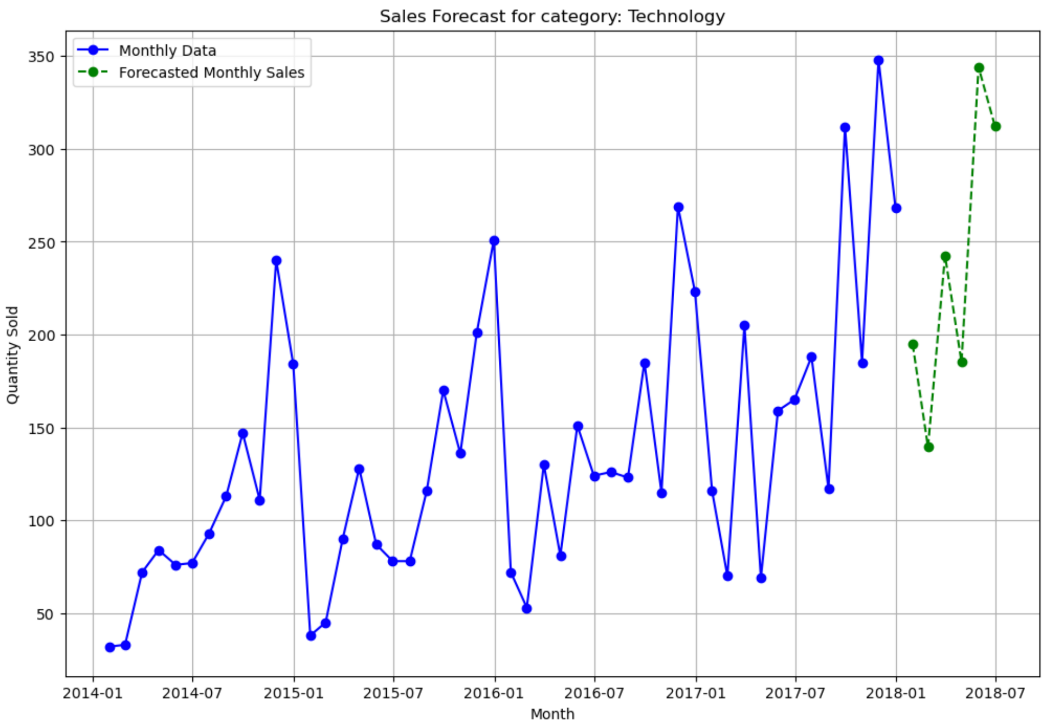

Figure 25, Graph of Technology category sales forecast using hybrid model

Source: Own representation

The above graphs show the sales forecasts for the Furniture, Office Supplies, and Technology categories over time, with historical monthly sales data (blue) and forecasted sales for the next six months (green). In all three categories, the forecasts suggest an upward trend in sales, although fluctuations are noticeable, especially in Office Supplies and Technology, where sales have more volatility compared to Furniture. These predictions can be used to optimize inventory management by ensuring adequate stock levels to meet anticipated demand while minimizing holding costs. Additionally, they help businesses prepare for peak sales periods and promotional events, allowing for better resource allocation and improved customer satisfaction by avoiding stockouts or overstocking. The forecasts also guide strategic planning for procurement and sales promotion efforts based on predicted demand trends in each product category.

The approach that has been taken to make predictions at the category level can be extended to more granular levels, such as sub-categories or individual products. By applying the same predictive modeling techniques, businesses can forecast sales not only for broader product categories but also for specific sub-categories or individual items. This deeper level of forecasting can provide even more precise insights, allowing for more effective inventory management, targeted marketing strategies, and resource allocation. By understanding demand patterns at a sub-category or product level, businesses can tailor their stock levels and promotional activities to meet specific customer needs, leading to improved operational efficiency and profitability.

4.8 Alignment and Comparison of Findings with Existing Literature

Sales forecasting

The outcomes of the models, as shown in the table 2, demonstrate its ability to predict demand levels effectively. The models' predictions, reflected in the individual graphs, showcase their capacity to forecast varying product quantities. Lower MAE, MSE, RMSE, and higher R^2 scores indicate lesser variability and greater accuracy in demand forecasting, thereby reducing uncertainty. This precision in forecasting enables organizations to manage their inventory more effectively by ordering the right stock, thereby avoiding both stockouts and overstocking, which can be costly. When integrated into inventory management systems, these models ensure that informed decisions are made based on accurate demand forecasts, helping businesses optimize stock levels to meet customer needs while minimizing inventory utilization.

Our research supports existing theories on sales forecasting, particularly regarding the use of past sales data to predict future sales in various retail product categories. For example, Bhatia (2008) also highlighted that sales forecasting plays a crucial role in managing inventory and budgeting for retail events and strategic developments. Our findings corroborate these observations, demonstrating that properly preprocessed and modeled historical sales data serves as a reliable basis for forecasting future sales quantities.

Seasonality

Examining the sales data as depicted in the seasonal decomposition chart in Figure 7, it is clear that the dataset contains important patterns and trends. The upward trend shown in the figure indicates that, over time, Superstore has recorded an average increase in daily sales quantity. This trend can be used to adjust future projections by factoring in market expansion or contraction. The seasonality graph shows cyclical oscillations, proving the presence of seasonal trends in the sales data. These patterns are crucial for guiding inventory management and should be integrated into forecasting models to help businesses anticipate variations during peak and low sales periods. As a result, forecasting models that can capture these seasonal patterns, such as Prophet and SARIMA models, tend to perform better. These insights can inform inventory management strategies, helping to determine the optimal stock levels to meet fluctuating customer demand.

Seasonality features are widely used in retail sales forecasting, as highlighted by Franses (1998) and Taylor & Letham (2018). These studies align with our findings from the seasonal decomposition chart, which revealed similar peaks and lows across various months. Incorporating seasonal patterns into models, particularly when sales exhibit strong seasonality, enhances the accuracy of sales forecasting. This is consistent with the literature, where seasonality is recognized as essential for producing reliable forecasts.

Promotional Impacts

By analyzing data during periods of high demand, such as holidays or when products are on promotion, the differences in predictive model performance across various categories become evident. These models can effectively manage seasonal fluctuations and temporary spikes in demand for certain products, making them suitable for forecasting during promotions and across different holiday periods for various types of goods.

Promotions and holidays have a significant impact on the retail business, as highlighted by Blattberg et al. (1995). This is evident in our study, where the models showed improved performance. For instance, the Prophet and Random Forest models captured these variations, highlighting the capability of machine learning in managing the complexities of promotional impacts. This aligns with the literature, which emphasizes the superiority of advanced models when demand is highly variable.

Integration with Hybrid Model

This work demonstrates the effectiveness of the hybrid model in predicting and forecasting sales quantities, contributing to the literature by combining multiple models to enhance forecast accuracy in the retail industry. The integration of different components from these models into the hybrid approach improves overall prediction precision. This application also show that the proposed hybrid approach can result in higher accuracy, reducing forecast errors and improving inventory control for organizations.

This strategy aligns with recent studies that highlight the advantages of hybrid models in increasing forecast accuracy. For instance, Zhang (2003) highlights the importance of incorporating hybrid models in time series forecasting to increase prediction accuracy. The application of hybrid models in inventory management systems is particularly practical, enabling retailers to make better demand forecasts, which leads to improved stock positions, reduced markdowns, and overall better financial outcomes. The key advantage of a hybrid inventory management system is its flexibility in responding to demand patterns, allowing for high service levels during promotions, irregular demand periods, and seasonal fluctuations.

4.9 Measurable Impacts of Adopting Predictive Inventory Management

The use of predictive inventory management in retail, by leveraging advanced forecasting models, greatly helps optimize stock levels by predicting future customer demand, thereby avoiding excess stock that may not be sold. In this study, the hybrid model allows to forecast sales for the next six months in the Office Supplies, Furniture, and Electronics categories. This approach has demonstrated several measurable benefits for Superstore, as outlined as follows:

Decrease in Holding Cost of Inventory

The integrated predictive system minimizes inventory holding costs by aligning procurement levels with expected demand. For instance, by forecasting sales for the next six months, it becomes easier to order the appropriate and timely inventory, preventing both overstocking and understocking. Overstocking leads to high storage costs for unsold products, while understocking results in lost sales due to stock-outs. According to Anderson (2021), efficient demand forecasting can reduce holding costs by 20-30%. Our findings support this, as proper inventory management effectively reduces carrying costs when implemented correctly.

Improved Cash Flow Management

Sales forecasting is directly related to cash flow management in any company, as it helps determine the right timing and quantity for ordering stock. Forecasting models enable retailers to decide how frequently and in what amounts to order inventory, preventing situations where business capital is tied up in unsellable stock. As a result, forecasts for various categories contribute to better financial planning and more efficient use of funds, ultimately improving cash flow. This is supported by Panagiota et al., (2020), who highlight that demand forecasting aids in managing current assets, shaping a company’s liquidity and financial future.

Improved customer satisfaction and customer loyalty

Research shows that customer satisfaction is closely tied to product availability. By adopting predictive inventory management, retailers can restock popular products to meet customer demand, avoiding costly stockouts that lead to lost sales and customer churn. These models help maintain high service levels in product categories by accurately forecasting demand for the next six months. This strategic approach to inventory management enhances the customer experience, increasing their loyalty. Similarly, as Corsten & Gruen (2005) highlighted, inventory availability and customer satisfaction significantly influence repeat purchasing behavior.

Cutting expenses on Markdowns and Clearance

Having excess stock poses a significant problem, as products often have to be sold at discounted prices to clear inventory, which cuts into the profit that could have been made. Predictive inventory management reduces these costs by anticipating customer demand and adjusting inventory levels accordingly. This paper highlights that accurate forecasting of product categories was effective in reducing overstock situations, leading to fewer markdowns. This finding aligns with Tadayonrad & Ndiaye (2023), who assert that avoiding markdowns through accurate demand forecasting and optimal stocking of products leads to financial gain.

Better Strategic Decision-Making

The use of predictive models in managing inventory generates valuable insights to support managers' decision-making processes. When demand is understood, firms can make informed decisions about their merchandise mix, advertising, marketing, and distribution channels (Tadayonrad & Ndiaye, 2023). By using a hybrid model, the factors influencing future demand can be identified, allowing contingency plans for inventory management and marketing activities to be developed. This alignment is crucial for maintaining competitive advantage and adjusting supply chain performance in response to market influences.

Chapter 5: Conclusion and Recommendations

5.1 Conclusion

This paper reveals how the latest advancements in machine learning have the potential to revolutionize inventory management, a major operational challenge in the retail industry. Retail enterprises often need to strike a balance between maintaining sufficient ready inventory and a flexible stock level to meet immediate customer demands. Our study contributes to this effort by demonstrating that, for sales forecasting of future quantities, the SARIMA, Prophet, and Random Forest models show good predictive capabilities across different product categories.

Historical sales data is an essential source for forecasting future sales quantities for various retail products. Sales history reveals patterns and seasonal volatility that are crucial for creating accurate forecasts. For example, models like SARIMA and Prophet can incorporate time-related factors, allowing for the forecasting of high and low sales periods throughout the year. These models are particularly useful when analyzing historical data, as they can capture the effects of holidays, back-to-school seasons, and other promotional influences. Additionally, advanced machine learning methods such as Random Forest and Gradient Boosting leverage historical records to capture non-linear interactions among various contributing factors and sales outcomes. This enables retailers to predict demand more accurately and make necessary adjustments to inventory levels, avoiding both stockouts and overstocking. As a result, this approach not only enhances sales forecast accuracy but also supports strategic management in marketing, supply chain operations, and overall business planning, thereby improving efficiency and revenue generation in the retail industry.

The patterns and trends present in sales data, such as seasonality, promotions, holiday effects, and product category-specific behaviors, can be discovered and applied to enhance predictive models. Sales fluctuations within a calendar year, such as during the holiday or back-to-school seasons, are particularly useful and can be leveraged by models like SARIMA and Prophet. Promotions and discount events create distinct peaks within specific periods, and when accurately captured, these models can adjust forecasts to reflect the impact of such promotions. Recognizing these promotional effects and incorporating them into the models improves forecast accuracy. Additionally, product category-specific behaviors must be differentiated. For instance, Technology is less seasonal compared to Office Supplies and Furniture, so different models may be required for these product types. By segmenting data according to categories, models can better capture the nature and patterns of sales. Furthermore, identifying long-term dynamics such as growth or decline helps models adapt to changes in consumer behavior over time. This not only increases model accuracy but also supports the application of more strategic approaches to inventory management and marketing schedules.

It is common for the performance of predictive models during high-demand periods, such as the holiday season or sales events, to differ significantly from usual periods. During these times of high variation, models like SARIMA and Prophet perform well by providing accurate forecasts for patterns influenced by seasonality and promotions. For instance, in the dataset, product categories experience a sales spike during the holiday season, and models that incorporate seasonality are likely to produce more accurate predictions. Prophet, which can account for holiday effects, often outperforms other methods in replicating such increases. However, non-linear models like Random Forest and Gradient Boosting can analyze complex patterns of variables and better adapt to fluctuations in sales caused by promotions. Nevertheless, they can sometimes be more erratic, as their estimates are sudden, with promotional effects often being impulsive or unexpected. In contrast, during normal periods, these models tend to provide steadier and more reliable forecasts, as they are less affected by spikes in demand. A key success factor for these models is their ability to respond to sales fluctuations in high-traffic areas, as supply is directly related to sales. At the same time, inventory must be well-stocked to meet customer needs without overstocking, which would increase inefficiencies, or understocking, which would fail to meet high consumer demand.

This study also highlights that the SARIMA, Prophet, and Random Forest models can help achieve optimal stock levels for inventory, thereby minimizing holding costs. By managing inventory to align closely with changes in demand, the models reduce the likelihood of accumulating unsellable stock while also preventing stockouts, which can hinder business operations. At the product-specific level, the same model assessment and selection methods can be applied. The models can be fine-tuned and trained with more specific data when focusing on individual products or inventory categories. This includes the ability to adjust the forecasting models to account for the unique patterns, promotional effects, and demand variations at a more detailed level, ultimately improving inventory management. Additionally, using feature engineering to capture product-specific attributes and applying ensemble methods to enhance prediction accuracy can further improve inventory management. Better stock control also ensures that customers' needs are met promptly, enhancing their satisfaction. These outcomes not only underscore the importance of this research in addressing key industry challenges but also emphasize the transformative role of advanced machine learning methodologies in making retail operations more dynamic and profitable.

In relating the results to prior theoretical guidelines and assumptions about retail inventory management, this work supports the emerging literature emphasizing the growing importance of advanced machine learning in improving business performance. The demonstrated ability of SARIMA, Prophet, and Random Forest models to address issues related to seasonal changes, promotions, and consumer behavior makes them well-suited for modern retail environments. These findings also reinforce theoretical premises on how advanced predictive modeling methods can enhance organizational decision-making regarding inventory management. Thus, this study not only supports existing theories but also encourages further research on hybrid models for improving the performance of retail inventory management.

Despite its contributions, this study has several limitations worth noting. Firstly, the implications of our findings are limited by the nature of the sample and the specific retail industry examined. It is important to consider that changes in market structure, customer expectations, and product types may affect the efficacy of forecasting models in various ways. Secondly, on the methodological front, while the hybrid approach appears promising, model selection and optimization require attention to factors such as available computational resources, model interpretability, and implementation complexity. Thirdly, some of the metrics used are common in predictive modeling but may lack detailed insights into retail performance, such as stock turnover rates or specific measures of customer satisfaction. Finally, given the dynamic nature of the retail environment, some models may require frequent updates to ensure their interpretations remain accurate over time.

Therefore, future research should aim to address these limitations to improve the robustness and generalizability of hybrid retail inventory management models.

5.2 Recommendations

Based on the findings that contribute to solving retail inventory management problems, several recommendations emerge to inform future studies and practices in the field of retail, including:

Integration of Real-Time Data Streams

Emphasizing the integration of real-time data plays a crucial role in improving the precision and timeliness of predictions used for inventory control in the retail sector. Future research should also focus on tracking daily sales and customer interactions with products, while incorporating factors such as weather conditions and stock exchange rates, which influence sales and enhance forecast accuracy. The data is often heterogeneous and massive, so the integration and processing of such data can be improved through the use of proper data pipelines and reliable cloud computing resources.

Enhancement of Hybrid Model Selection and Optimization

The features of hybrid models like SARIMA, Random Forest, and Prophet suggest that this field can still be fine-tuned and enhanced for optimal results. In future studies, more focus should be placed on developing methods to automate the selection of the best models based on specific retail contexts and goals. Promising approaches such as ensemble learning and meta-learning could be employed to update model weights and parameters, improving accuracy and providing a competitive advantage in new markets.

Incorporation of Customer Behavior Analytics

Various customer behavior analytics collected from different sources can be integrated with inventory management systems to help identify variations and trends. This could serve as the basis for future research exploring how customer segmentation models, social media perceptions, and recommendation systems can provide a clearer picture of demand trends. To increase customer satisfaction, reduce stockouts, and maintain more relevant inventory levels, retailers need to gain a deeper understanding of customer behavior.

Implementation of Agile Inventory Strategies

The implementation of a flexible inventory management system, incorporating just-in-time inventory, dynamic pricing strategies, and adaptable inventory policies, can help retailers effectively respond to the dynamic nature of demand and the market. Future studies should explore best practices from the manufacturing and logistics industries that can be applied to retail stock control using agile methodologies. This includes investigating replenishment strategies that enhance flexibility while controlling costs and minimizing inventory holding, without compromising service levels.

Continuous Monitoring and Model Updating

As store environments constantly change over time, it is essential to monitor these changes and frequently update predictive models. Future researchers should focus on developing monitoring systems that can instantly identify discrepancies between expected and actual sales numbers. Incorporating feedback mechanisms and enabling models to learn from changes in trends or seasonality can make them self-adaptive, ensuring they remain relevant and effective over time.

Investment in Training and Skill Development

As the use of data science becomes more prevalent in retail planning, training and retraining retail personnel should become a priority. Future empirical studies and industry actions should focus on developing retailers' awareness, critical thinking, and specific skills in data, statistics, and machine learning. By equipping decision-makers with the appropriate analytical competencies, this methodology can contribute to fostering innovation and evidence-based retail strategies within the organization.

Ethical Considerations and Transparency

Finally, as the use of predictive analytics (PA) and advanced machine learning algorithms grows in the retail context, it is essential to focus on ethical issues and ensure clarity in the models' creation and utilization processes. More research is needed on the ethical dimensions of AI in the retail industry, including fairness, accountability, and transparency. The following recommendations can provide guidance on implementing ethical principles, helping to establish strong customer relationships and promote ethical consumerism.

Appendix

The GitHub repository for the Python code implementation of the above research work can be accessed at the following link:

GitHub Repository: https://github.com/Ajaychandra123/Predictive-Inventory-Management-for-Retail-Using-Advanced-Machine-Learning-Techniques-

Bibliography

Adhikari, R., & Agrawal, R. K. (2013). *An Introductory Study on Time Series Modeling and Forecasting* (arXiv:1302.6613). arXiv. https://doi.org/10.48550/arXiv.1302.6613

Aljohani, A. (2023). Predictive Analytics and Machine Learning for Real-Time Supply Chain Risk Mitigation and Agility. *Sustainability*, *15*(20), Article 20. https://doi.org/10.3390/su152015088

Allen, R. C. (2017). *The Industrial Revolution: A Very Short Introduction*. Oxford University Press.

Alsharif, M. H., Kelechi, A. H., Yahya, K., & Chaudhry, S. A. (2020). Machine Learning Algorithms for Smart Data Analysis in Internet of Things Environment: Taxonomies and Research Trends. *Symmetry*, *12*(1), Article 1. https://doi.org/10.3390/sym12010088

Anderson, C. J. (2021). *Forecasting Demand for Optimal Inventory with Long Lead Times: An Automotive Aftermarket Case Study - ProQuest*. https://www.proquest.com/openview/78c0cea77da6f24659d9ca1c8d2d9140/1.pdf?pq-origsite=gscholar&cbl=18750&diss=y

Andriolo, A., Battini, D., Grubbström, R. W., Persona, A., & Sgarbossa, F. (2014). A century of evolution from Harris′s basic lot size model: Survey and research agenda. *International Journal of Production Economics*, *155*, 16–38. https://doi.org/10.1016/j.ijpe.2014.01.013

Artun, O., & Levin, D. (2015). *Predictive Marketing: Easy Ways Every Marketer Can Use Customer Analytics and Big Data*. John Wiley & Sons.

Atasever, S., Öztürk, B., & Bilgiç, G. (2022). A new approach to short-term wind speed prediction: The prophet model. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *44*(4), 8826–8841. https://doi.org/10.1080/15567036.2022.2126035

Bhatia, S. C. (2008). *Retail Management*. Atlantic Publishers & Dist.

Blattberg, R. C., Briesch, R., & Fox, E. J. (1995). How Promotions Work. *Marketing Science*, *14*(3), G122–G132.

Bonney, M., & Jaber, M. Y. (2011). Environmentally responsible inventory models: Non-classical models for a non-classical era. *International Journal of Production Economics*, *133*(1), 43–53. https://doi.org/10.1016/j.ijpe.2009.10.033

Bradlow, E. T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The Role of Big Data and Predictive Analytics in Retailing. *Journal of Retailing*, *93*(1), 79–95. https://doi.org/10.1016/j.jretai.2016.12.004

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Cai, J., Xu, K., Zhu, Y., Hu, F., & Li, L. (2020). Prediction and analysis of net ecosystem carbon exchange based on gradient boosting regression and random forest. *Applied Energy*, *262*, 114566. https://doi.org/10.1016/j.apenergy.2020.114566

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*, *16*, 321–357. https://doi.org/10.1613/jair.953

Corsten, D., & Gruen, T. (2005). On Shelf Availability: An Examination of the Extent, the Causes, and the Efforts to Address Retail Out-of-Stocks. In G. J. Doukidis & A. P. Vrechopoulos (Eds.), *Consumer Driven Electronic Transformation* (pp. 131–149). Springer. https://doi.org/10.1007/3-540-27059-0_9

Ehrenthal, J. C. F., Honhon, D., & Van Woensel, T. (2014). Demand seasonality in retail inventory management. *European Journal of Operational Research*, *238*(2), 527–539. https://doi.org/10.1016/j.ejor.2014.03.030

Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. *International Journal of Forecasting*, *38*(4), 1283–1318. https://doi.org/10.1016/j.ijforecast.2019.06.004

Flores, B. E., & Clay Whybark, D. (1986). Multiple Criteria ABC Analysis. *International Journal of Operations & Production Management*, *6*(3), 38–46. https://doi.org/10.1108/eb054765

Franses, P. H. (1998). *Time Series Models for Business and Economic Forecasting*. Cambridge University Press.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics*, *29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Geron, A. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems* (2nd ed.). O'Reilly Media, Inc.

Green, K. W., Inman, R. A., Birou, L. M., & Whitten, D. (2014). Total JIT (T-JIT) and its impact on supply chain competency and organizational performance. *International Journal of Production Economics*, *147*, 125–135. https://doi.org/10.1016/j.ijpe.2013.08.026

Gurtu, A. (2021). Optimization of Inventory Holding Cost Due to Price, Weight, and Volume of Items. *Journal of Risk and Financial Management*, *14*(2), Article 2. https://doi.org/10.3390/jrfm14020065

Guyon, I., & Elisseeff, A. (2003). An Introduction of Variable and Feature Selection. *J. Machine Learning Research Special Issue on Variable and Feature Selection*, *3*, 1157–1182. https://doi.org/10.1162/153244303322753616

Hegelich, S. (2016). Decision Trees and Random Forests: Machine Learning Techniques to Classify Rare Events. *European Policy Analysis*, *2*(1), 98–120. https://doi.org/10.18278/epa.2.1.7

Herold, D. M., & Marzantowicz, Ł. (2023). Supply chain responses to global disruptions and its ripple effects: An institutional complexity perspective. *Operations Management Research*, *16*(4), 2213–2224. https://doi.org/10.1007/s12063-023-00404-w

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice*. OTexts.

Jr, R. B. E., & Hébert, R. F. (2013). *A History of Economic Theory and Method: Sixth Edition*. Waveland Press.

Kaggle. (2022). *Superstore Dataset*. https://www.kaggle.com/datasets/vivek468/superstore-dataset-final

Kayyali El Alem, Y. (2023). *Optimizing Sales Forecasting, Inventory, Pricing and Sourcing Decisions* [EPFL]. https://doi.org/10.5075/epfl-thesis-10040

Khashei, M., Bijari, M., & Hejazi, S. R. (2012). Combining seasonal ARIMA models with computational intelligence techniques for time series forecasting. *Soft Computing*, *16*(6), 1091–1105. https://doi.org/10.1007/s00500-012-0805-9

Liu, Y. (Hayden). (2017). *Python Machine Learning By Example*. Packt Publishing Ltd.

Lukinskiy, V., Lukinskiy, V., & Sokolov, B. (2020). Control of inventory dynamics: A survey of special cases for products with low demand. *Annual Reviews in Control*, *49*, 306–320. https://doi.org/10.1016/j.arcontrol.2020.04.005

McAfee, & Brynjolfsson. (2012). *Big data: The management revolution | Request PDF*. https://www.researchgate.net/publication/304535150_Big_data_The_management_revolution

Mitchell, T. M. (1997). *Machine learning* (Nachdr.). McGraw-Hill.

Nemtajela. (2016). *Inventory Management under Demand Uncertainty in the Fast Moving Consumer Goods Organisation in Gauteng—ProQuest*. https://www.proquest.com/openview/52d9bf8e938f22a90e2146f245512f39/1?pq-origsite=gscholar&cbl=2026366&diss=y

Nemtajela, N., & Mbohwa, C. (2017). Relationship between Inventory Management and Uncertain Demand for Fast Moving Consumer Goods Organisations. *Procedia Manufacturing*, *8*, 699–706. https://doi.org/10.1016/j.promfg.2017.02.090

Panagiota, L., T, P. S., & K, E. O. (2020). Demand Forecasting of Retail Sales Using Data Analytics and Statistical Programming. *Management & Marketing*, *15*(2), 186–202.

Punia, S., & Shankar, S. (2022). Predictive analytics for demand forecasting: A deep learning-based decision support system. *Knowledge-Based Systems*, *258*, 109956. https://doi.org/10.1016/j.knosys.2022.109956

Rafferty. (2021). *Forecasting Time Series Data with Facebook Prophet[Book]*. https://www.oreilly.com/library/view/forecasting-time-series/9781800568532/

Raschka, S. (2020). *Model Evaluation, Model Selection, and Algorithm Selection in Machine Learning* (arXiv:1811.12808). arXiv. https://doi.org/10.48550/arXiv.1811.12808

Ren, F., Tian, C., Zhang, G., Li, C., & Zhai, Y. (2022). A hybrid method for power demand prediction of electric vehicles based on SARIMA and deep learning with integration of periodic features. *Energy*, *250*, 123738. https://doi.org/10.1016/j.energy.2022.123738

Sen, P. C., Hajra, M., & Ghosh, M. (2020). Supervised Classification Algorithms in Machine Learning: A Survey and Review. In J. K. Mandal & D. Bhattacharya (Eds.), *Emerging Technology in Modelling and Graphics* (pp. 99–111). Springer. https://doi.org/10.1007/978-981-13-7403-6_11

Shumway, R. H., & Stoffer, D. S. (2017). *Time Series Analysis and Its Applications: With R Examples*. Springer International Publishing AG. http://ebookcentral.proquest.com/lib/badhonnef/detail.action?docID=6312856

Siami-Namini, S., Tavakoli, N., & Siami Namin, A. (2018). A Comparison of ARIMA and LSTM in Forecasting Time Series. *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 1394–1401. https://doi.org/10.1109/ICMLA.2018.00227

Streamlit. (2021, January 14). *Streamlit • A faster way to build and share data apps*. https://streamlit.io/

Superstore. (2024, August 26). *Superstore Inc—Company Profile and News*. Bloomberg.Com. https://www.bloomberg.com/profile/company/7959678Z:JP

Tadayonrad, Y., & Ndiaye, A. B. (2023). A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. *Supply Chain Analytics*, *3*, 100026. https://doi.org/10.1016/j.sca.2023.100026

Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. *The American Statistician*, *72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021). Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. *Mathematical Problems in Engineering*, *2021*(1), 1476043. https://doi.org/10.1155/2021/1476043

Tranmer, M., & Elliot, M. (2008). Multiple linear regression. *The Cathie Marsh Centre for Census and Survey Research (CCSR)*, *5*(5), 1–5.

Turk. (2012). *The Impact of Stockouts on Customer Loyalty to Lean Retailers—ProQuest*. https://www.proquest.com/openview/7e26965882e4edd1f5c63f77cb2a671d/1?pq-origsite=gscholar&cbl=18750

Udousoro, I. C. (2020). Machine Learning: A Review. *Semiconductor Science and Information Devices*, *2*(2), Article 2. https://doi.org/10.30564/ssid.v2i2.1931

Wagner, G., Schramm-Klein, H., & Steinmann, S. (2020). Online retailing across e-channels and e-channel touchpoints: Empirical studies of consumer behavior in the multichannel e-commerce environment. *Journal of Business Research*, *107*, 256–270. https://doi.org/10.1016/j.jbusres.2018.10.048

Wrigley, N., & Lowe, M. (2010). *The globalization of trade in retail services—Report commissioned by OECD trade policy linkages and services division for the OECD experts meeting on distribution services*.

Xiao, Y., Xiao, J., & Wang, S. (2012). A hybrid model for time series forecasting. *Human Systems Management*, *31*(2), 133–143. https://doi.org/10.3233/HSM-2012-0763

Yun, K. K., Yoon, S. W., & Won, D. (2021). Prediction of stock price direction using a hybrid GA-XGBoost algorithm with a three-stage feature engineering process. *Expert Systems with Applications*, *186*, 115716. https://doi.org/10.1016/j.eswa.2021.115716

Zai, A., & Brown, B. (2020). *Deep Reinforcement Learning in Action*. Simon and Schuster.

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, *50*, 159–175. https://doi.org/10.1016/S0925-2312(01)00702-0

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