Comparative Analysis of Time Series Forecasting Using Classical Statistical Methods and Advanced Machine Learning Models

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(Submitted 18 December 2024)

Abstract: This study conducts a comprehensive comparative analysis of classical statistical techniques and modern machine learning models for time series forecasting, focusing specifically on the significance of choosing the appropriate model for a compact data series. The traditional models evaluated include Seasonal Autoregressive Integrated Moving Average (SARIMA) and Triple Exponential Smoothing, both known for their robustness in handling linear trends and seasonality. These are compared against advanced machine learning methods such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM), which are increasingly popular for their ability to capture complex, nonlinear patterns. Key performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), are employed to assess both accuracy and computational efficiency. The analysis reveals that classical statistical models, despite their simplicity, often outperform advanced machine learning models on smaller datasets, particularly in their ability to effectively capture trends and seasonal components with limited data. The findings emphasize the importance of aligning model selection with the specific characteristics of the dataset and the forecasting objectives. This study concludes by offering practical recommendations for practitioners, detailing scenarios where traditional models may be preferable over complex machine learning approaches and vice versa. Ultimately, this research highlights the complex trade-offs between model complexity, data size, and forecasting performance, offering a guide for effective model selection in time-sensitive decision-making contexts.

Keywords: Time Series Forecasting, SARIMA; Support Vector Machine; Triple Exponential Smoothing; Recurrent Neural Network; Long Short-term Memory

Acknowledgments

I would like to express my deepest gratitude to Dr. Alei Duan for his invaluable guidance, consistent feedback, and unwavering support throughout the course of this project. His expertise and encouragement were instrumental in shaping the direction and success of this research, titled *Comparative Analysis of Time Series Forecasting Using Classical Statistical Methods and Advanced Machine Learning Models*.

I would also like to extend my sincere thanks to both Dr. Alei Duan and Dr. Konstantinos Skindilias for their willingness to oversee the project demonstration, scheduled on 13 December 2024. Their input and constructive evaluation have been greatly appreciated.

Finally, I wish to thank my peers and the faculty of the Computing & Mathematical Sciences department at the University of Greenwich for fostering an environment conducive to learning and collaboration, which greatly enriched this experience.

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1. Introduction

Time series forecasting is a critical component of predictive analytics, providing organizations with the ability to anticipate future trends and patterns based on historical data. These time series forecasts are essential for businesses across various sectors, including finance, retail, healthcare, and logistics, as they enable organizations to optimize operations, allocate resources effectively, and make data-driven strategic decisions. By predicting demand, managing inventory, forecasting revenue trends, and streamlining supply chains, these forecasts play a critical role in improving efficiency. Specifically, daily sales data is a key metric in industries like retail, e-commerce, and supply chain management, where understanding fluctuations in demand is crucial for maintaining smooth operations. (Falatouri, et al., 2022).

Although crucial, predicting future outcomes using historical data is a complex task. Time series data poses specific challenges because of its inherent features, such as trends, seasonality, and noise. One major obstacle is that not all time series data display clear and consistent trends or seasonal patterns. This issue becomes more pronounced when working with short datasets, where the limited observations make it hard to identify significant relationships and predict future values accurately. Additionally, many datasets do not follow a consistent trend over time. External factors like market conditions, holidays, or unforeseen events can cause fluctuations, complicating the task for both traditional and advanced models in capturing these variations correctly.

The task becomes even more complex when time series data exhibits seasonality, as periodic fluctuations can introduce significant variability in the dataset. Seasonality typically appears in recurring cycles—daily, weekly, monthly, or yearly—and can significantly impact the accuracy of predictive models. Therefore, a model's ability to account for seasonality is vital to producing reliable forecasts. The effectiveness of forecasting models is often determined by factors such as the dataset's complexity, its length, and the presence of seasonality or irregular events, all of which require tailored-modeling approaches for accurate predictions.

The dataset used in this research consists of 2,439 daily sales records collected over several years, from 2010 to 2018. This extensive dataset offers a valuable opportunity to explore forecasting strategies. However, the concentrated nature of daily data presents distinct challenges, such as the need to address seasonality, trends, and irregular fluctuations within a relatively limited historical timeframe. In total, the dataset covers 97 months. Since this dataset comes from one of the largest retail companies in Bosnia and Herzegovina, there is a significant possibility of seasonality affecting the sales patterns (Žunić, 2019).

This research shifts its focus from the traditional evaluation of retail store performance to a more innovative approach that leverages historical time series data for accurate forecasting. By utilizing this data-driven methodology, this study aims to explore the effectiveness of classical statistical models, such as SARIMA and Triple Exponential Smoothing, as well as advanced techniques like neural networks, specifically designed to handle short datasets. In addition to identifying the performance of each forecasting model, performance metrics have been conducted, including mean absolute percentage error, mean square error, and root mean square error, to provide a comprehensive analysis of their predictive capabilities.

The findings of this analysis will provide valuable insights into the field of time series forecasting, particularly in industries where precise sales trend predictions are essential. By comparing classical methods with advanced machine learning models, this research highlighted the strengths and limitations of each approach, help to make more informed decisions when choosing forecasting tools. Additionally, the results will offer practical guidance for organizations seeking to optimize their forecasting capabilities and enhance operational efficiency.

Ultimately, this study aims to demonstrate the importance of selecting the right forecasting model. By offering a detailed comparison of traditional and modern forecasting methods, the research will contribute to improved decision-making, better outcomes, and assist organizations in navigating the complexities of data forecasting. Whether addressing challenges related to seasonality, irregular trends, or resource allocation, the insights from this study will play a crucial role in refining forecasting practices and supporting sustainable growth across various sectors.

2. Literature Review

Prediction accuracy is a crucial factor in determining the effectiveness of any forecasting model. Since future data is unavailable at the time of prediction, it is vital to ensure that predictive models are reliable and generate results with minimal errors. To accomplish this, models need to be validated by comparing their predictions against a well-defined validation dataset (Ahmad & Dias, 2021). The available data series acts as a benchmark for evaluating the model's performance, ensuring that its predictions align closely with actual outcomes. By minimizing errors during validation, the model's credibility is enhanced, which increases its potential for accurate future forecasting.

However, not all models are suitable for every type of dataset. Model performance varies based on the characteristics of the dataset (Singh, et al., 2017). In this study, I explore which models yield the most accurate predictions for medium size with seasonality and less complex time series datasets by evaluating their performance using statistical metrics such as RMSE (Root Mean Square Error), MAPE (Mean Absolute Percentage Error), and MSE (Mean Squared Error).

2.1. Classical Statistical Methods

There are many statistical methods available to forecast time series data, each with its own strengths and limitations. Among these, the more straightforward techniques, Auto-Regressive (AR) and Moving-Average (MA) models are normally used for time series projections. However, these methods often struggle to effectively capture the pattern of seasonal data, as they primarily focus on the direct relationship between past values and the current forecast. This limitation has led to the development of more advanced models (Arumugam & Natarajan, 2023).

One such advanced model is the SARIMA model, which is widely considered a solution to the challenges encountered by AR and MA models. According to (Arumugam & Natarajan, 2023) "SARIMA combines AR and MA components with additional seasonal elements, making it more suitable for data series that exhibit seasonal patterns." This enhanced model not only accounts for the temporal dependencies in the data but also adjusts for seasonal oscillations, significantly enhancing forecasting accuracy. SARIMA models have proven to be effective in forecasting variables such as rainfall, temperature, and energy consumption, where seasonal patterns play a crucial role. In meteorology, for instance, these models excel at predicting monthly precipitation by capturing seasonal components while also managing the non-stationary nature of time series data. Additionally, SARIMA has the advantage of handling non-stationary datasets—those where statistical properties like the mean and variance change over time. By incorporating differencing (the "I" in SARIMA), it converts a non-stationary series into a stationary one, enabling more reliable predictions. As highlighted in the book Forecasting: Principles and Practice (Rob J Hyndman & Athanasopoulos, 2023), the SARIMA model has proven effective in addressing both the seasonality and non-stationarity issues that often hinder forecasting with simpler models. Therefore, SARIMA offers a robust solution for time series forecasting, especially when dealing with data that exhibits seasonal trends or non-stationarity. However, determining the optimal parameters for a SARIMA model can be challenging, as it requires iterative testing of various seasonal and non-seasonal components to achieve the right balance between model complexity and forecasting accuracy (Arumugam & Natarajan, 2023).

Another well-known classical technique is Triple Exponential Smoothing, also referred to as the Holt-Winters method. This method extends simple exponential smoothing by adding extra smoothing equations to capture trends and seasonal variations. Its flexibility in handling both additive and multiplicative seasonal components make it suitable for a wide range of time series forecasting applications (Makatjane & Moroke, 2016). The triple exponential smoothing approach is especially useful for datasets with clear seasonal patterns, such as monthly sales, tourism data, or weather trends. One of the main advantages of the triple exponential smoothing method is its simplicity and computational efficiency. Unlike more complex machine learning models, it uses a recursive process to consistently update forecasts in real time as new data becomes available. This characteristic makes it especially useful for situations that require quick and efficient forecasting (Atmojo, et al., 2022).

2.2. Advanced Machine Learning Methods

Machine learning models are especially effective for time series forecasting, especially when traditional statistical techniques have difficulty handling the complex and nonlinear nature of the data (Ricardo, et al., 2021). Notably, methods like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVMs) are particularly good at identifying intricate patterns and relationships within time series datasets.

RNNs model is a specialized type of neural network designed for processing sequential data, making them particularly effective for tasks such as time series forecasting. Unlike conventional feedforward neural networks, RNNs have feedback loops that allow them to retain information from previous time steps. This capability is crucial for capturing temporal dependencies in time series data (Pascanu, et al., 2015). However, traditional RNNs encounter challenges like vanishing or exploding gradients during training, which can impede their ability to learn long-term dependencies effectively. Despite their limitations, recurrent neural networks (RNNs) have been effective in capturing short-term dependencies in time series data. For instance, they have been successfully used in financial forecasting to predict stock prices and currency exchange rates, where understanding short-term trends is essential. However, RNN performance often declines when handling longer sequences or datasets that display complex seasonality and trends (Pascanu, et al., 2015).

Long Short-Term Memory (LSTMs) networks are an advanced type of Recurrent Neural Network (RNNs) designed to overcome the limitations of traditional RNNs, especially their struggle to learn long-term dependencies. LSTMs accomplish this by incorporating a memory cell and gating mechanisms that regulate the flow of information. These mechanisms enable LSTMs to retain crucial information over extended periods while discarding irrelevant data, making them highly effective for tasks that require an understanding of extended temporal contexts (Saxena, 2023). LSTMs are commonly utilized in time series forecasting due to their capacity to handle complex, nonlinear patterns. Their main advantage is their ability to manage long-term dependencies, which makes them especially effective for applications such as energy demand forecasting and weather prediction. In these cases, the relationships between past and future data points often span multiple time steps. LSTMs have a higher computational complexity compared to traditional statistical models, which can be a disadvantage, especially when working with smaller datasets. Additionally, to achieve optimal performance with LSTMs, careful tuning of hyperparameters is necessary, including the learning rate, the number of layers, and the size of the memory cell. Despite these challenges, LSTMs are invaluable for time series forecasting due to their ability to capture nonlinear dependencies, making them particularly suitable for scenarios that require high accuracy and adaptability (Saxena, 2023).

Support Vector Machines (SVMs) is a supervised learning approach that has shown considerable success in time series forecasting. It is especially effective for datasets exhibiting nonlinear trends and patterns that can be challenging for traditional modeling techniques. For example, SVMs have been applied to demand forecasting in retail and energy consumption, where irregularities and external influences add significant complexity to the data. Their straightforward implementation and low risk of overfitting, particularly with smaller datasets, enhance their attractiveness for time series forecasting (Sapankevych, et al., 2009). However, a key limitation of SVMs is their computational inefficiency during training, which can make them less suitable for large datasets.

3. Research Contribution

The primary research contributions of this study are outlined below:

- The dataset is authentic and was obtained from one of the largest retail companies in Bosnia and Herzegovina. It was published by the 4TU. Centre for Research Data, and the organizer is the University of Sarajevo, Faculty of Electrical Engineering (Žunić, 2019).
- This study contrasts with previous research that focused on a specific approach by incorporating various methodologies. It includes statistical techniques such as Triple Exponential Smoothing and SARIMA, as well as advanced machine learning models

like Support Vector Machines (SVM), Recurrent Neural Networks (RNN), and Long Short-Term Memory Networks (LSTM).

- The main objective is to conduct a comprehensive analysis and compare the outcomes derived from these models to determine the most effective forecasting method. Statistical accuracy measurement techniques, such as Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), are used to evaluate the accuracy of these models.
- The results are analyzed and compared, and the best method is selected for forecasting the short dataset.

4. Exploratory Data Analysis (EDA)

The dataset used in this research comes from the largest retail company in Bosnia and Herzegovina and covers the period from 2010 to 2018, consisting of a total of 2,611 data points. Each entry in the dataset contains two columns: one for the transaction date and the other for the corresponding sales value. Notably, the dataset is free of missing values, making it clean and suitable for time series forecasting tasks. Since this analysis involves time series forecasting, the first crucial step is to convert the "Date" column into a datetime index format. This conversion is essential for efficient time-based indexing and manipulation within the DataFrame. By transforming the date column to a datetime format, it becomes easier to perform various time-based operations, such as resampling and aggregation.

Once the date column has been converted, a complete index for the DataFrame is created, ensuring that every date within the defined period (from 2010 to 2018) is represented in the dataset. In instances where specific dates were initially missing from the raw data, these gaps are filled by assigning a sales value of zero for those particular dates. This process ensures that the dataset reflects a continuous time series without any missing dates, which is crucial for time series analysis and modeling. As a result, the number of data points increases from the initial 2,611 entries to a total of 3,192.

Since the primary objective of the analysis is to forecast sales on a monthly basis, the next step involves resampling the data to a monthly frequency. This is achieved by aggregating the daily sales data into monthly sums. The rationale behind this resampling approach is that sales data often experiences short-term fluctuations. Aggregating the data into monthly totals provides a clearer view of long-term trends and seasonal patterns. In this process, daily sales values for each month are summed, effectively smoothing out any noise or outliers present in the daily data. After resampling, the dataset is transformed into monthly data, which allows for the application of time series forecasting techniques to predict future sales values. The aggregated monthly data is more manageable for modeling and enables the identification of seasonal trends, long-term patterns, and other important temporal factors that might affect sales. This approach is well-suited for forecasting, as monthly data offers an adequate level of granularity while reducing the impact of daily volatility.

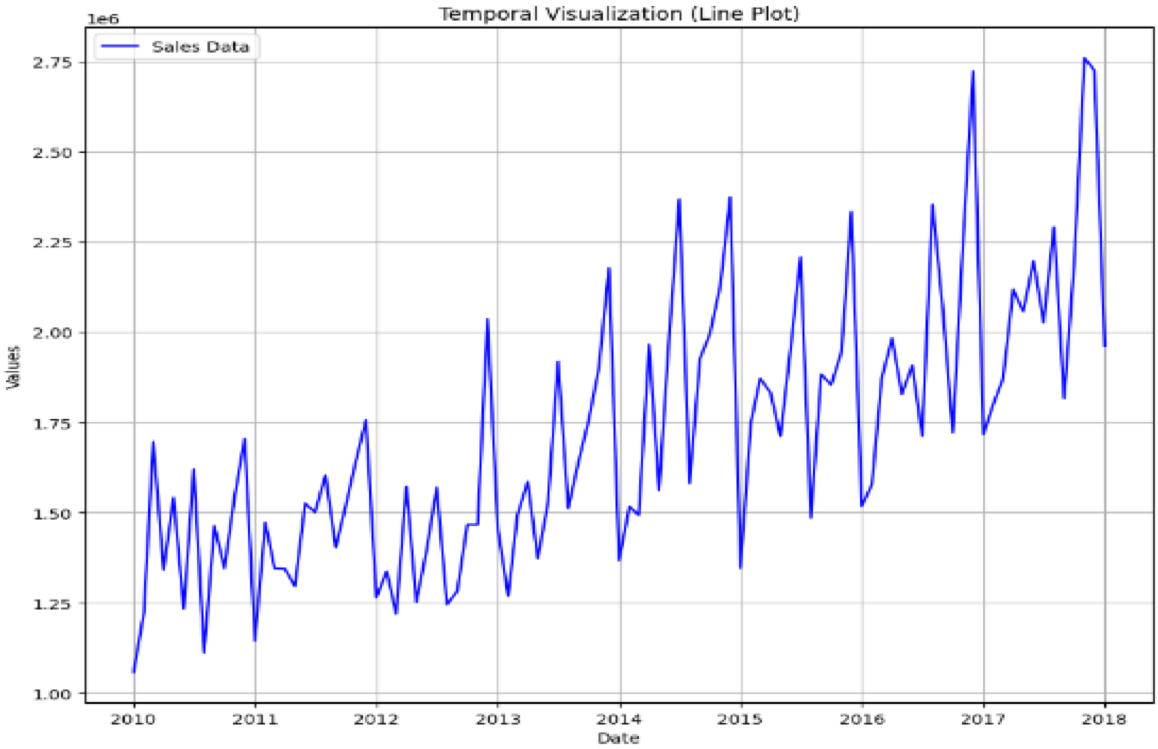

Figure 1. *Data Series*

Figure 1 presents the sales graph, which serves as the basis for making predictions. The graph shows that sales fluctuate over the observed time period, indicating a certain degree of variability. Although the data does not display a clear or strong seasonal pattern, noticeable fluctuations occur throughout the period. These variations may result from several factors, including marketing campaigns, economic conditions, or other external variables that influence consumer behaviour. This variability suggests that the data may contain noise, making it challenging to identify any distinct seasonal or cyclical trends.

Despite these fluctuations, the graph indicates a gradual upward trend in sales over time. This suggests that sales have generally increased throughout the entire period. Such a gradual increase may reflect long-term growth, potentially due to factors like an expanding customer base, enhanced product offerings, or greater market reach. This upward trend is significant for forecasting, as it provides insight into the overall direction of sales. However, the presence of noise and the lack of a strong, predictable seasonal pattern indicate that forecasting models will need to account for these fluctuations when predicting future sales.

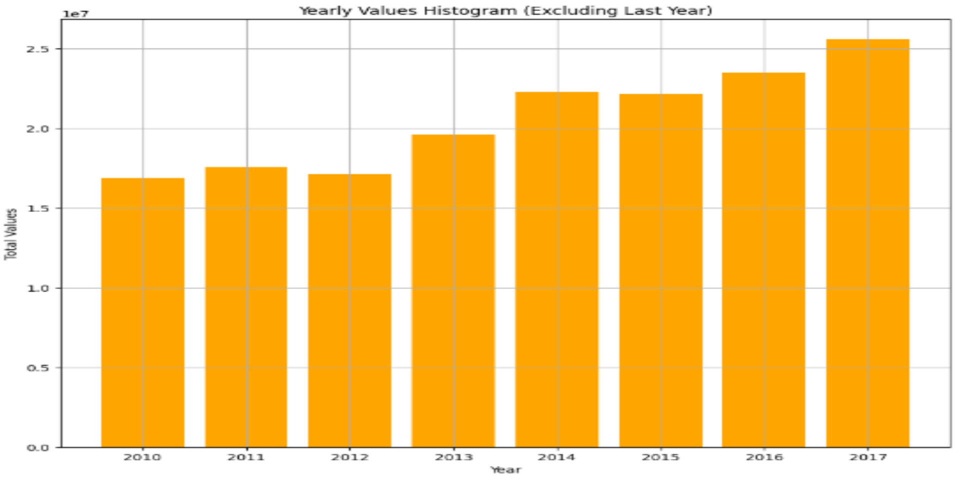

Figure 2. *Yearly Sales*

Figure 2. The "Yearly Values Histogram" illustrates the total annual sales data from 2010 to 2017, providing a clear overview of sales performance during this period. The bar chart shows a consistent upward trend in yearly sales, with total values gradually increasing each year. Notable peaks occur in 2016 and 2017, marking the highest recorded sales figures. This visualization effectively illustrates the overall growth trajectory, as the rising bar heights clearly indicate sustained sales improvement. The steady increase aligns with previous analyses that have highlighted a broader pattern of rising sales over time. This consistent growth may be attributed to several factors, including effective marketing strategies, improved product offerings, stronger customer engagement, and favorable market conditions. The chart also allows for year-to-year comparisons, showcasing the gradual and stable pace of growth without major fluctuations. This stability suggests a predictable growth environment, enabling businesses to analyze the underlying drivers and apply successful strategies for future planning.

In summary, the histogram provides a concise yet informative depiction of sales performance over the observed years. By emphasizing the upward trend in total yearly sales, it highlights the company's potential for sustained growth and sets the stage for further investigation into the factors contributing to this success.

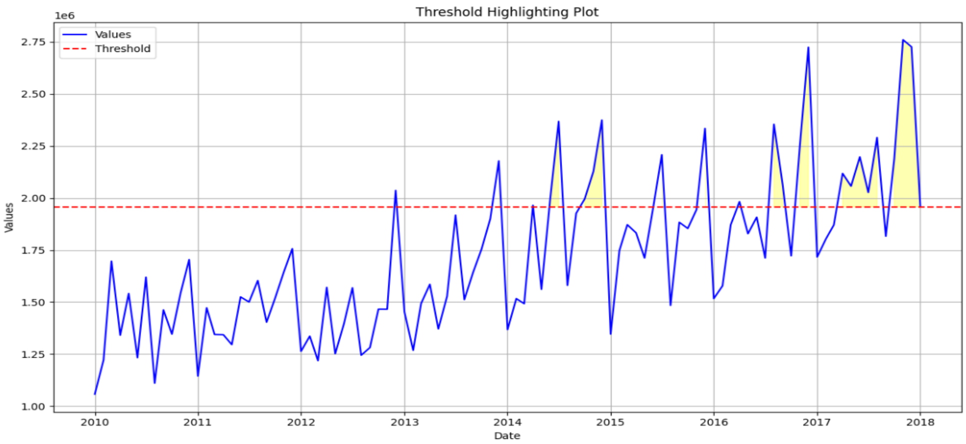

Figure 3. *Threshold Highlighting Plot*

The "Threshold Highlighting Plot" illustrates the sales performance from 2010 to 2018, highlighting periods when sales exceeded a defined threshold, specifically the third quartile (75th percentile). The sales trajectory is represented by a blue line, while a red dashed line indicates the threshold level. Instances where sales surpass this threshold are highlighted in yellow, providing a clear view of exceptional performance periods. The plot shows an overall upward trend in sales during the observed years, indicating sustained growth. Between 2010 and 2013, sales were relatively modest, with few instances of exceeding the threshold. This phase reflects stable yet lower performance. Starting in 2014, there is a significant increase in both the frequency and magnitude of sales spikes, suggesting enhanced performance potentially driven by external factors such as improved marketing efforts, economic growth, or increased customer engagement.

From 2016 onward, the yellow-highlighted regions become more prominent, signalling a period of significant growth and increased variability. Frequent threshold-surpassing spikes during this time suggest that the company may have expanded its market presence, launched new products, or effectively capitalized on seasonal opportunities. The most notable sales peaks occur in late 2017 and early 2018, representing the highest performance levels within the dataset. These exceptional spikes may correspond to key promotional campaigns, major holidays, or other significant drivers of consumer behaviour. While the plot demonstrates a consistent upward trend, it also reveals substantial variability in sales performance. The fluctuating blue line highlights the presence of both strong and weak sales periods, emphasizing the importance of considering external factors and inherent data variability in business planning and forecasting. Additionally, the periodic nature of these sales spikes suggests an underlying seasonality, which could be leveraged for more accurate predictions and tailored strategies to optimize performance.

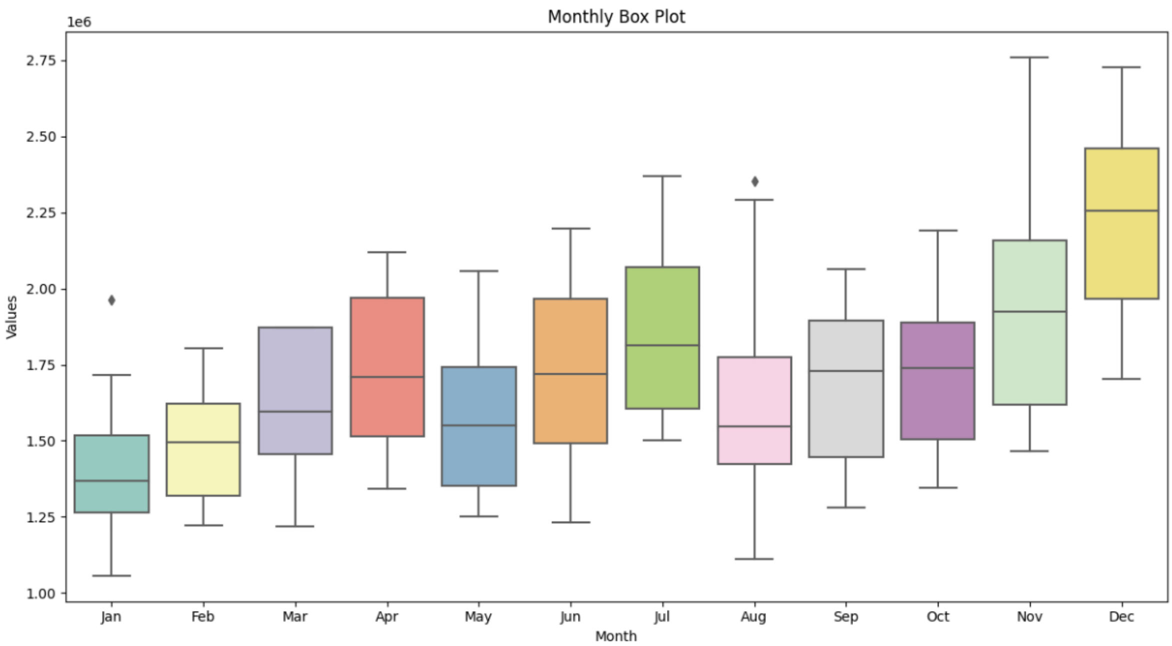

Figure 4. *Monthly Box Plot*

The "Monthly Box Plot" provides valuable insights into the distribution and seasonal patterns of sales performance throughout the year. December emerges as the highest-performing month, showing the greatest median sales along with significant variability. This wide range highlights the influence of increased consumer activity during the holiday season, where both regular shopping and exceptional peak days contribute to sales. November also reflects elevated sales levels, likely driven by pre-holiday shopping events, promotional campaigns, and consumer anticipation for upcoming celebrations.

In contrast, January and February consistently report the lowest median sales, indicating a typical decline in consumer spending following the holiday season. These months exhibit narrower ranges in sales data, suggesting less variability and a more stable, though subdued, level of sales activity compared to the rest of the year. Such trends underscore the challenges businesses face in maintaining momentum during the post-holiday slump. Some months, like August, show notable variability, with a wide range of sales values and prominent outliers exceeding the upper whisker. These outliers may be attributed to targeted promotions, seasonal events, or unforeseen external factors that temporarily boost sales. Similar variability is observed in June and December, where high performance combined with noticeable fluctuations suggests a mix of predictable trends and sporadic sales spikes, potentially linked to specific campaigns or shopping behaviours. A clear seasonal pattern emerges from the data, marked by a gradual increase in sales from mid-year, peaking in December, followed by a steady decline from January through March. Outliers in months such as January and August represent isolated high-performing days that may correspond with significant campaigns, sales events, or external influences. These anomalies highlight the importance of identifying and capitalizing on such opportunities to enhance revenue.

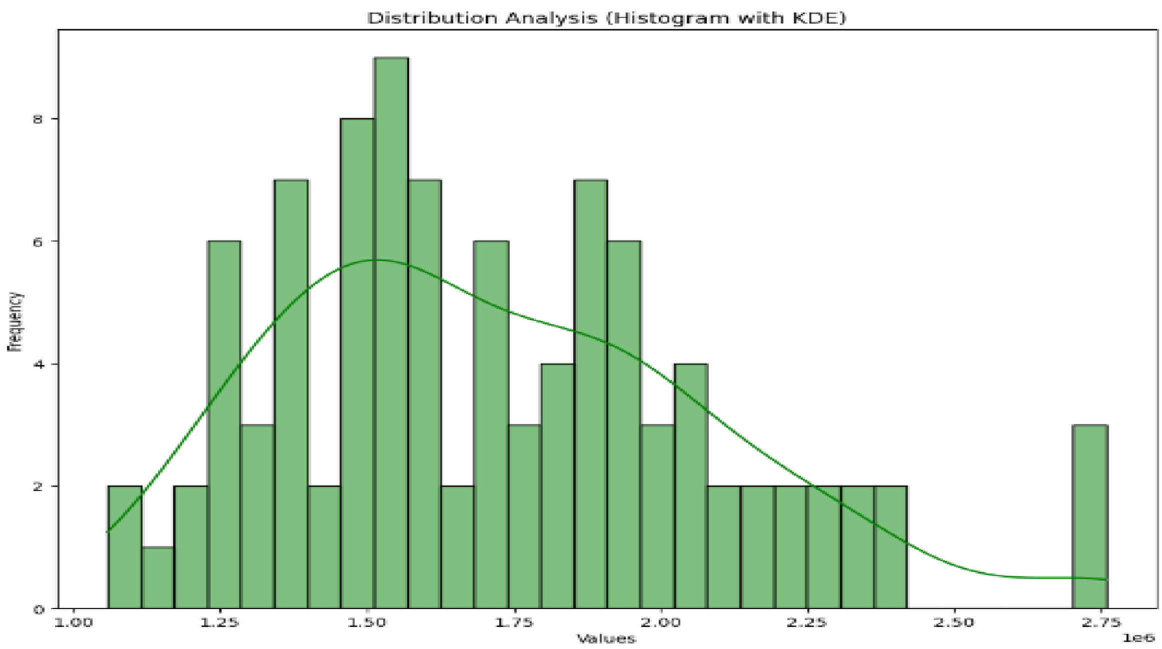

Figure 5. *Distributed Analysis*

Figure 5, titled "Distribution Analysis (Histogram with KDE)," provides a clear overview of the distribution of sales values over the entire period. This dual representation, which includes both a histogram and a Kernel Density Estimate (KDE) curve, offers valuable insights into the underlying sales patterns and their variability. The histogram shows a distribution that is positively skewed, with most sales values concentrated at the lower end. This indicates that a significant portion of daily sales falls within modest ranges, while occasional spikes in sales contribute to a longer right tail. These spikes may occur during promotional periods, holiday sales, or other special events, highlighting the influence of external factors on sales performance. The KDE curve enhances this analysis by smoothing the data to reveal density trends. The curve peaks around 1.5, indicating that this is the most common range for daily sales. The rightward tail of the curve emphasizes the effect of high-value outliers, which correspond to exceptional sales days. Together, the histogram and KDE provide a comprehensive understanding of the sales distribution, illustrating both typical behaviour and remarkable deviations.

A key concerning thing in time series data is non-stationarity, which occurs when the data shows trends, seasonality, or cyclic patterns. Non-stationary data presents challenges for accurate modeling and prediction because these patterns introduce variability over time. This variability makes it difficult for models to identify consistent relationships. To address non-stationarity, techniques such as detrending or differencing are often required. It can be checked by decomposition plot and Augmented Dickey Fuller (ADF) test.

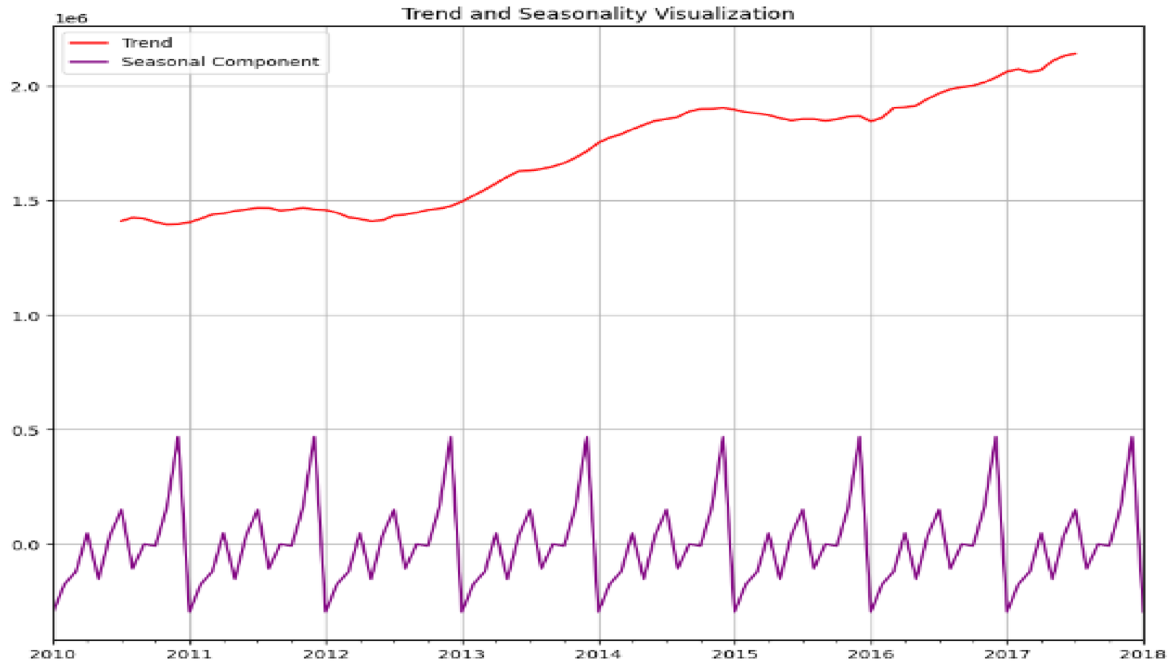

Figure 6. *Trend and Seasonality Visualization*

Figure 6, titled "Trend and Seasonality Visualization," offers valuable insights by breaking down the time series data into its fundamental components: trend and seasonality. This decomposition enhances our understanding of sales patterns over time. The trend, represented by the red line, shows a consistent upward movement, confirming previous observations of positive long-term growth in sales. The purple line illustrates the seasonal component, which features recurring fluctuations that follow an annual cycle. These regular peaks and troughs indicate the presence of seasonality in the sales data, a common characteristic in the retail industry. Identifying these seasonal patterns highlights the importance of incorporating seasonality into predictive models. So, these features indicate that the data is non-stationary.

The Augmented Dickey-Fuller (ADF) test is a statistical method used to determine whether a time series is stationary or non-stationary by assessing the presence of a unit root (Paparoditis & Politis, 2016). This test analyses the relationship between the value of a time series and its mean. Specifically, if the current value is above the mean, the test predicts a downward movement in the next step. Conversely, if the value is below the mean, it anticipates an upward movement. By examining these deviations, the ADF test evaluates whether the series exhibits consistent statistical properties over time, which is a key characteristic of stationarity. If the p-value from the ADF test is less than 0.05, the series is considered stationary. However, if the p-value is greater than 0.05, it indicates that the series is non-stationary. To achieve better results with the SARIMA model, the dataset must be converted to a stationary series (Paparoditis & Politis, 2016).

In this study, I leveraged Python's auto-SARIMA functionality. This powerful tool automates the transformation of data to meet stationarity requirements, ensuring that the time series is ready for accurate forecasting. By eliminating the need for manual intervention, auto-SARIMA streamlines the modeling process, making it more accessible and efficient for users.

5. Methodology and Experimental Framework

5.1. Overview of the Forecasting Process

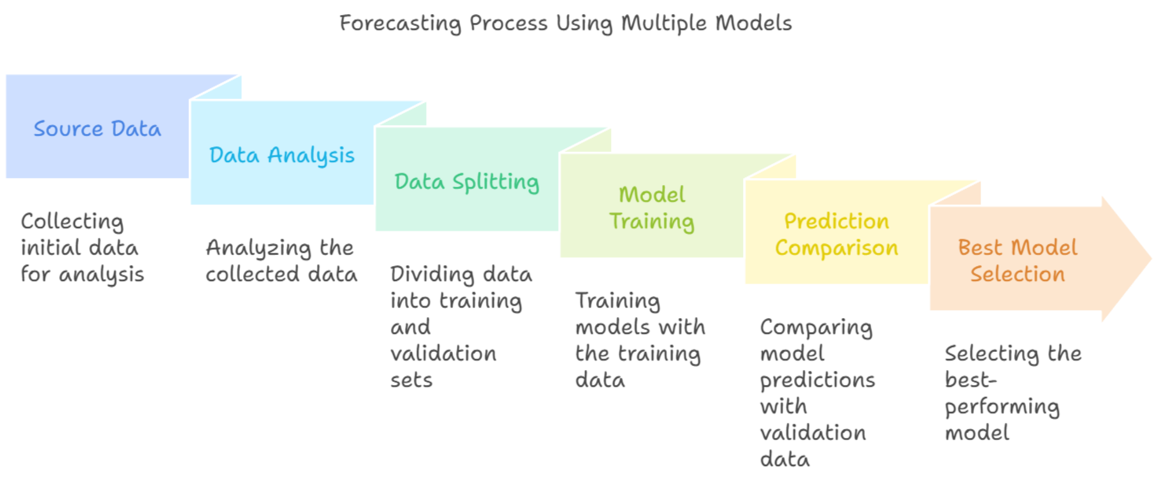

Figure 7. *Workflow for the forecasting process*

Time series data is initially collected from the data source (Žunić, 2019), and the data series is comprehensive and relevant to the problem domain. Once the data has been collected, it is thoroughly analyzed to uncover its underlying characteristics, such as trends, seasonality, and potential anomalies. This analysis provides essential insights that guide the subsequent preprocessing steps.

The data series is then standardized by applying scaling techniques to confirm uniformity and to enhance the performance of the models. Following this, the data is split into training and validation sets. The training set is used for model development, while the validation set is reserved for evaluating the performance of the trained models. Using the training data, multiple models are developed and trained to capture the patterns within the time series. Each model generates predictions, which are subsequently compared against the actual values in the validation set. Performance metrics, such as MSE, RMSE and MAPE are calculated to assess the accuracy and effectiveness of the predictions.

Based on these evaluations, the best-performing model is identified and selected. This systematic procedure ensures that the most appropriate model is chosen for the assigned time series dataset, optimizing its predictive capabilities.

5.2. Objective of the Study

The primary goal of this study is to thoroughly evaluate the effectiveness of different models for time series forecasting, specifically focusing on short seasonal datasets. To achieve this, two types of methods are explored: classical statistical techniques, which have long been used in forecasting, and advanced machine learning models that leverage modern computational power and algorithms. In total five unique models are assessed. Recognizing that the performance of forecasting models can significantly differ based on the characteristics of the data series used, this study emphasizes the importance of experimenting with a variety of models. This multifaceted approach enhances the ability to adapt and respond to the unique challenges each data series presents, ultimately leading to more reliable and precise forecasting outcomes.

5.3. Dataset Source

Selecting and identifying a suitable dataset can be challenging, as it requires careful consideration of various factors such as availability, scale, reliability, and relevance. This challenge is heightened for time series data due to the limited availability of comprehensive datasets online. However, after extensive research, I have secured a trustworthy and well-suited data series for my study. This time series data is particularly valuable because it includes essential features like seasonality and trends, making it highly applicable to my research objectives. Published by the 4TU Centre for Research Data and organized by the University of Sarajevo's Faculty of Electrical Engineering, this dataset is credible and meticulously curated.

A key advantage of this data series is its quality and completeness; it contains no null values, ensuring data integrity and simplifying the preprocessing efforts. The data spans an extensive period from 2010 to 2018, providing a robust temporal scope for analysis. This comprehensive timeframe enhances the potential for uncovering meaningful patterns and insights. The dataset's reliability, rich features, and temporal range make it an ideal choice for my study, allowing for a rigorous and insightful analysis of time series phenomena.

5.4. Data Cleaning and Transformation

In this study of forecasting, data is forecasted on a monthly basis. To achieve this, it is essential to convert the date index into a monthly format. Since the collected dataset is in a daily format, it is converted into a monthly frequency by aggregating the daily sales data into monthly sums. This conversion ensures consistency with the forecasting objectives, as the analysis is focused on predicting monthly values.

Five different models are applied to make predictions, so it is crucial to evaluate their accuracy in terms of forecasting performance and compare their results. To assess model effectiveness, short-term predictions are made using all five models, focusing on a time period where complete data is available. This approach allows the performance of each model to be assessed by comparing the predicted outcomes with the real, existing data.

For this process, the dataset is split into two subsets: a training dataset and a validation dataset. The validation dataset consists of the last 12 months of data, while the remaining data is included in the training dataset. For the RNN, LSTM, and SVM models, the data processing steps are slightly different when preparing the dataset for time series forecasting. The first step involves scaling the data to transform the original sales figures into a range that is more suitable for machine learning models to identify patterns. This transformation is carried out using the MinMaxScaler. Before applying the scaler, the sales data is reshaped into a column vector. Next, the scaled data is divided into sequences of a fixed length of 12. These sequences are crucial for the time series models, as each one consists of consecutive data points from the past. The target variable for each sequence is the following data point, which represents the next value in the time series. Finally, the dataset is split into two parts: the training dataset, which includes all but the last 12 time steps, and the validation dataset, which contains the last 12 data points (last 12 months).

The training dataset is used for model learning, where the models are trained on historical data to identify patterns and relationships within the dataset. After training, the models forecast the next 12 months of data. These forecasted values are then compared with the validation dataset, which contains the actual data for those months. The error of the forecast is calculated by comparing the predicted values with the actual values in the validation dataset. This allows for an evaluation of how well the models perform in forecasting future data.

5.5 Methods for Calculating Forecast Errors

There are several methods available for assessing the performance of forecasting models, most of which involve comparing predicted results to actual outcomes. In this study, various evaluation metrics are used to determine model accuracy and effectiveness.

The Mean Squared Error (MSE) measures the average of the squared differences between predicted and actual values. It gives an overall indication of error magnitude, with larger errors being penalized more heavily due to the squaring operation. The Root Mean Squared Error (RMSE), which is derived from the MSE, represents the standard deviation of the prediction errors. As a scale-dependent metric, RMSE is influenced by the units of the data, making it unsuitable for comparing forecasts across datasets with different scales. However, it offers a more interpretable measure of error magnitude, expressed in the same unit as the original data. The Mean Absolute Percentage Error (MAPE) calculates the average of the absolute percentage differences between predicted and actual values. This metric expresses forecast errors as a percentage, making it especially useful for evaluating models on datasets with varying scales or units. MAPE is widely used due to its intuitive interpretation and flexibility in comparing model performance across different datasets. By employing these metrics, the study ensures a comprehensive evaluation of the forecasting models, focusing on the magnitude and relative accuracy of prediction errors. This approach allows for a robust comparison of model performance across diverse scenarios and datasets.

5.5. Classical Statistical Methods

5.5.1. Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

Seasonal Auto-Regressive Integrated Moving Average (SARIMA) is an advanced statistical method developed for modeling and forecasting seasonal time series data. It is created from the Auto Regressive Moving Average (ARMA) model by counting seasonal components, making it mainly suitable for data series with recurring seasonal patterns. The SARIMA model is expressed as SARIMA(p, d, q)(P, D, Q)m, where (p, d, q) are the non-seasonal parameters, and (P, D, Q)m represent the seasonal parameters. Each of these parameters plays a distinct role in the modeling process.

In the non-seasonal features, p signifies the autoregressive (AR) order, capturing the influence of previous observations on the present value through partial autocorrelation. The q parameter corresponds to the moving average (MA) component, reflecting the relationship between the current observation and the residual errors from past observations. Meanwhile, d exhibits the degree of differencing needed to transform non-stationary data into a stationary form, which is crucial since SARIMA assumes that the time series is stationary. This capability to stabilize non-stationary data makes SARIMA particularly useful for forecasting time series that display trends or changing variance over time.

The seasonal terms (P, D, Q)m enhance SARIMA's utility for datasets with periodic fluctuations. Here, P represents the seasonal autoregressive component, Q denotes the seasonal moving average, and D signifies the seasonal differencing. The parameter m indicates the cycle or length of seasonality (for example, 12 for monthly data exhibiting yearly seasonality).

One of the most critical steps in applying the SARIMA model is identifying these parameters, as their values depend on the specific dataset. Traditionally, selecting parameters involved a trial-and-error process or relied on the expertise of the analyst, which could be time-consuming and complex. To address this challenge, modern computational tools offer automated methods for parameter selection. In this study, Python programming language has been utilized, which has the auto_sarima function. This function efficiently identifies optimal values for the SARIMA parameters based on the given dataset, eliminating the need for manual tuning. Automating the parameter assignment process streamlines the model development workflow, making SARIMA more accessible to users with varying levels of expertise in time series analysis.

SARIMA is an effective tool for forecasting seasonal time series due to its ability to address non-stationarity and seasonality. The inclusion of automated parameter selection, such as through Python's auto_sarima function, simplifies its application and allows users to focus on interpreting outcomes rather than getting bogged down in model configuration intricacies. This study demonstrates the practical benefits of combining statistical methodologies with computational tools to achieve accurate and efficient forecasting.

5.5.2. Triple Exponential Smoothing

Triple Exponential Smoothing, commonly referred to as the Holt-Winters method, is a widely recognized approach for forecasting time series data, particularly in contexts where trends and seasonality are significant. This method enhances basic exponential smoothing by integrating three essential components: level, trend, and seasonality.

The level represents the smoothed average of the data at any point, and it is adjusted to reflect both trends and seasonal patterns. The trend component identifies the direction and rate of change in the data, which enables the model to forecast consistent upward or downward movements. The seasonal component addresses recurring patterns, such as those observed on a monthly or yearly basis, rendering this method particularly effective for periodic time series analysis. The methodology employs recursive updates of these three components. The level is modified through a weighted combination of the observed value and the previous estimates of both level and trend. The trend component is updated based on changes in the smoothed level, while the seasonality adjusts to account for recurring variations. This model can accommodate both additive seasonality—where fluctuations are consistent over time—and multiplicative seasonality—where the seasonal effects vary in proportion to the series level.

A key strength of Triple Exponential Smoothing lies in its adaptability to new data as it becomes available, ensuring that forecasts remain relevant and accurate. However, the precision of these predictions is contingent upon selecting optimal smoothing parameters for the level, trend, and seasonality components, as well as on effectively initializing these components.

In comparison to the SARIMA method, which utilizes differencing and autoregressive techniques to manage seasonality and trends, Triple Exponential Smoothing achieves similar results through smoothing and decomposition. Generally, SARIMA is preferred for data series that necessitate stationarity transformations, whereas Triple Exponential Smoothing is better suited for direct modeling of trends and seasonality. Both methodologies leverage computational tools to facilitate efficient and accurate implementation. Overall, Triple Exponential Smoothing is a versatile and intuitive forecasting technique. Its ability to dynamically adjust to evolving trends and seasonal behaviours, coupled with automated parameter selection, establishes it as a robust option for time series analysis across a wide range of datasets.

5.6. Machine Learning Models

5.6.1. Recurrent Neural Networks

Recurrent Neural Networks (RNNs) represent a sophisticated and effective methodology for forecasting time series data by adeptly capturing sequential patterns and temporal dependencies. Unlike conventional statistical techniques, RNNs are specifically architected to process and learn from sequential data, rendering them particularly suitable for forecasting applications where the interrelations between past and future data points are critical. The utilization of RNNs spans a multitude of fields.

A prominent advantage of RNNs is their capacity to retain information over time through recurrent connections, thereby facilitating the analysis of relationships between historical inputs and current forecasts. Distinct from feedforward neural networks, which evaluate inputs in isolation, RNNs consider the sequential structure of time series data, allowing for the learning of complex temporal relationships. The RNN model presented in this context enhances this capability through a multi-layer architecture combined with regularization techniques, ensuring high efficacy in time series forecasting.

The RNN model is constructed utilizing Keras and adheres to a sequential architecture. The initial layer comprises a SimpleRNN with 50 units, employing the hyperbolic tangent activation function. This choice of activation function promotes efficient learning by ensuring a smooth gradient flow, which is vital for the training of deep networks. To mitigate the risk of overfitting, the architecture incorporates a dropout layer with a 20% dropout rate. An additional SimpleRNN layer further processes the sequential data, followed by a second dropout layer to enhance generalization. The culmination of the model is a Dense layer with a single output unit, designed specifically to yield the forecasted value. To prepare the dataset for training, the time series is transformed into input-output sequences. This procedure organizes the data into a supervised learning format, where historical observations serve as inputs, and the corresponding future values constitute the targets. The model is trained on these sequences utilizing the Adam optimizer, which dynamically adjusts learning rates to ensure efficient convergence. The selected loss function is mean squared error (MSE), which penalizes significant deviations between predicted and actual values. Training is carried out over 50 epochs with a batch size of 32, during which the model iteratively updates its weights to minimize prediction errors. Post-training, the model is evaluated using validation data to assess its forecasting performance. Predictions for the validation set are subsequently rescaled to their original scale via an inverse transformation, ensuring that the forecasts are interpretable within the context of the original dataset.

RNNs excel in their proficiency to learn from time-dependent data, attributed to their unique architecture which employs recurrent connections for memory retention. The implementation discussed herein, which includes multiple RNN layers, dropout regularization, and a dense output layer, guarantees that the model remains both versatile and robust. While traditional forecasting methods often depend on pre-established statistical relationships or assumptions, RNNs learn these patterns directly from the data itself, showcasing remarkable adaptability to intricate temporal structures.

The aim of using the RNN model is that model offers an effective framework for time series forecasting by harnessing its ability to learn sequential patterns and temporal relationships. Its architecture, augmented by regularization techniques and adaptive optimization strategies, positions it as a powerful instrument for capturing the nuances inherent in time-dependent data. Through the application of contemporary deep learning methodologies, RNNs outperform many conventional approaches, particularly in scenarios characterized by intricate temporal dynamics. This adaptability underscores the inherent strengths of RNNs in addressing a diverse array of forecasting challenges.

5.6.2. Long Short-Term Memory Networks (LSTM)

The Long Short-Term Memory (LSTM) model described here is a robust deep-learning approach for forecasting time series data. LSTMs are especially adept at capturing long-term dependencies because they are designed to remember important information across extended sequences. This makes them ideal for time series problems where past data points influence future predictions.

This specific LSTM model features a deep architecture with three LSTM layers, each followed by a dropout layer to reduce the risk of overfitting. The first LSTM layer consists of 100 units and uses the tanh activation function. The second LSTM layer also contains 100 units and is followed by a dropout layer that randomly deactivates 20% of the units to enhance generalization. The third LSTM layer has 50 units, processing the extracted features further, followed by another dropout layer. The model concludes with a Dense layer that produces a single value representing the forecasted result.

The model is compiled with the Adam optimizer, recognized for its effectiveness in adjusting learning rates. The learning rate is set to 0.0005, ensuring gradual updates to the model's weights during training. The loss function selected is mean squared error (MSE), a common choice for regression problems like time series forecasting. MSE minimizes the discrepancy between predicted and actual values, guiding the model toward more accurate forecasts. The model is trained for 100 epochs with a batch size of 32, meaning it processes the entire dataset 100 times, updating weights after every 32 samples. Before training, the time series data is reshaped into input-output pairs. This sequence creation is a crucial preprocessing step, allowing the LSTM model to utilize past observations to predict future outcomes.

LSTMs are favoured for time series forecasting due to their ability to model complex patterns and long-term dependencies. Unlike traditional statistical models such as ARIMA or SARIMA, which require manual transformations and specific assumptions, LSTMs learn patterns directly from the data. This is particularly advantageous in situations where data relationships are non-linear or span long intervals, which traditional models may struggle to capture. By incorporating multiple LSTM layers, the model can progressively extract more intricate features from the data. The dropout layers serve an essential role in regularization, helping prevent overfitting by randomly deactivating a portion of the neurons during training. Additionally, the relatively low learning rate used with the Adam optimizer supports smooth and stable weight updates, improving the model's ability to generalize to unseen data.

Overall, this LSTM model offers an effective and adaptable solution for time series forecasting. Its deep architecture, combined with dropout regularization and the Adam optimizer, enables the model to learn complex temporal relationships and deliver accurate forecasts. LSTMs are particularly powerful when applied to data with long-term dependencies, making this model well-suited for a wide range of forecasting tasks. By capturing underlying patterns in the data, LSTM networks provide a significant advantage over traditional statistical methods in time series prediction.

5.6.3. Support Vector Machine

Support Vector Machine (SVM), particularly in the form of Support Vector Regression (SVR), is widely used in machine learning for tasks involving continuous prediction, such as time series forecasting. SVR aims to fit a function to the data that minimizes errors within a specified tolerance margin. The core strength of SVR lies in its ability to capture intricate, non-linear patterns in the data, thanks to its use of kernel functions. The SVR model is implemented with a radial basis function (RBF) kernel, which is highly effective for identifying complex, non-linear trends often present in time series datasets.

The model's performance is greatly influenced by key hyperparameters: C, epsilon, and gamma. The C parameter regulates the trade-off between fitting the data too closely (which may lead to overfitting) and generalizing the model to new data (reducing overfitting risk). A higher value of C forces the model to fit the training data more precisely, while a lower value encourages smoother, more generalized predictions. Epsilon determines the width of the margin where no penalty is applied for deviations. A larger epsilon allows for more flexibility in how closely the model follows the data, while a smaller epsilon produces a tighter fit. Finally, gamma controls how much influence each data point has on the decision boundary, with a larger gamma making the model more sensitive to individual points, which could lead to overfitting, while a smaller gamma helps prevent this by reducing the influence of any single point.

To find the optimal values for these hyperparameters, Grid Search is used. This method systematically tests a range of combinations of hyperparameter values using cross-validation to identify the best configuration that minimizes the model's mean squared error (MSE) on the validation set. After this process, the model with the best parameters is selected and used to make predictions on unseen data. The model is trained on flattened versions of the input and output data to ensure compatibility with the SVR algorithm. After training, it generates predictions for the validation dataset, providing a forecast based on the learned patterns. One of the key advantages of SVR for time series forecasting is its ability to handle non-linear relationships in data, which is often seen in real-world time series datasets where the patterns are not strictly linear. Additionally, SVR models tend to be more resistant to overfitting, especially when proper regularization is applied through the C parameter.

Overall, Support Vector Regression is an excellent choice for time series forecasting tasks due to its ability to model complex non-linear patterns, its robustness to overfitting, and its computational efficiency. By leveraging Grid Search for hyperparameter optimization, the model is fine-tuned to deliver accurate predictions tailored to the specific characteristics of the dataset. This makes SVR a valuable tool, particularly when forecasting data that involves intricate relationships not easily captured by simpler, linear models.

6. Results and Discussion

6.1. Triple Exponential Smoothing

Triple Exponential Smoothing is a statistical method employed in this study to forecast data and evaluate its effectiveness on a small time series dataset. The forecasted data is compared to actual data through a plot, and prediction errors are calculated. The plot illustrates that the model successfully captured the underlying trends and seasonality; however, it struggled to predict the rapid growth observed in the final phase, which is a common limitation of smoothing-based approaches when faced with quick changes.

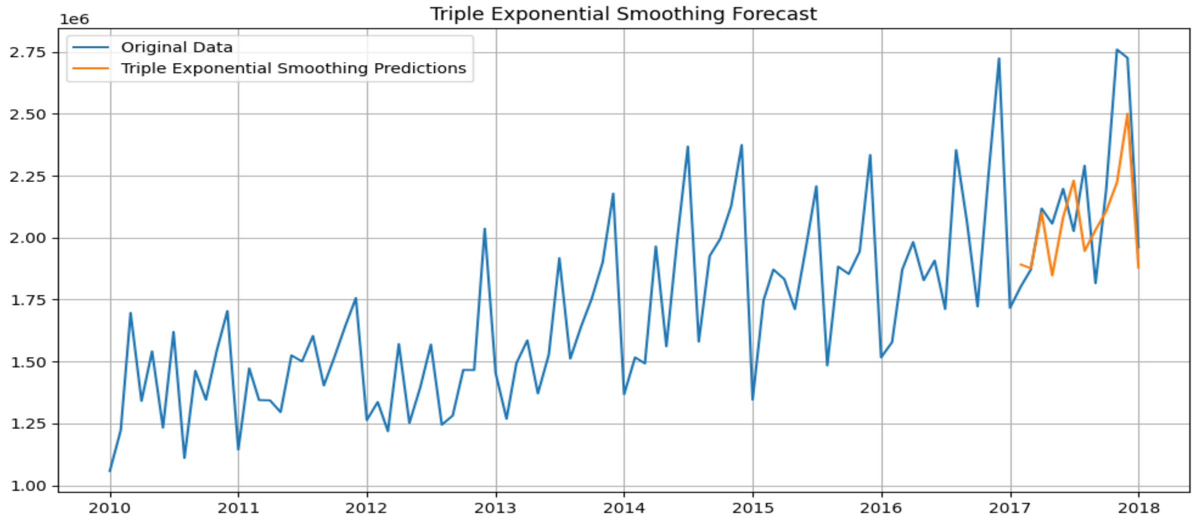

Figure 8. *Triple Exponential Smoothing Forecasting*

The performance metrics offer valuable insights into the model's accuracy. The Mean Squared Error is 51905384433.76, and the Root Mean Squared Error is 227827.53. While the MSE and RMSE are important metrics reflecting the large scale and variability of the data, the Mean Absolute Percentage Error presents a more positive outlook. With a MAPE of 7.84%, the model demonstrates reasonably strong accuracy, as its predictions deviate from the actual values by less than 10% on average. This highlights the model's effectiveness in capturing overall trends and patterns, despite its challenges in providing precise forecasts during periods of significant volatility.

6.2. Seasonal Auto Regressive Moving Average

The Seasonal Auto Regressive Integrated Moving Average (SARIMA) model has proven to be effective in generating forecasts by effectively capturing both seasonal patterns and overall trends in the data. The forecasts produced by this method align closely with observed data during the projection period, demonstrating its capability to handle time series with seasonality and trends.

Additionally, the confidence interval provides important context by indicating the range within which future values are expected to fall, taking into account possible uncertainties. However, while SARIMA adeptly manages seasonal cycles, it may struggle to fully capture sudden spikes or irregular fluctuations, which could impact its accuracy in highly dynamic situations.

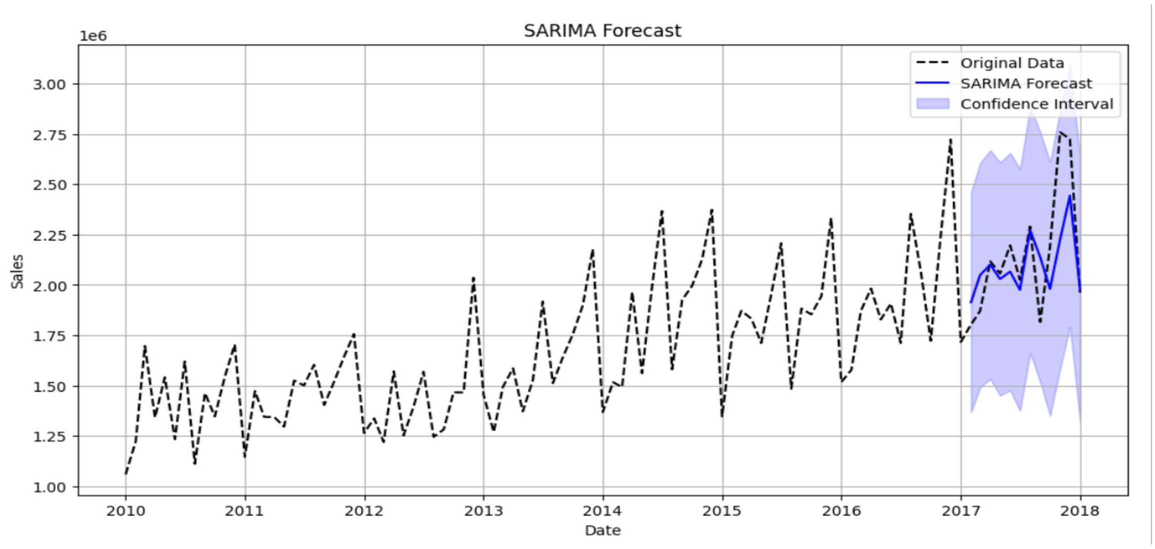

Figure 9. *SARIME model forecasting*

In terms of performance metrics, SARIMA exhibits a Mean Squared Error of 47,924,428,130.36 and a Root Mean Squared Error of 218,916.49. These figures indicate that SARIMA has slightly better accuracy compared to the Triple Exponential Smoothing method, highlighting its ability to more effectively capture the variability in the data. Furthermore, the Mean Absolute Percentage Error stands at 7.06%, which means that the predictions deviate by just over 7% on average from the actual values. This represents an improvement over the TES model, which recorded a MAPE of 7.84%. Overall, SARIMA presents a reliable fit for this dataset, achieving lower error rates and more precise forecasts.

6.3. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a commonly used machine learning model for data forecasting. In this study, SVM was applied for data forecasting but demonstrated notable limitations when dealing with the short dataset used. For instance, the model struggled to accurately capture subtle changes in the data. Specifically, when there is a slight dip in the data, SVM tends to predict a sharp decline, leading to an overestimation of the downward trend. Additionally, in the final periods of forecasting, SVM projected rapid growth; however, the predicted increase is usually smaller than what is actually observed.

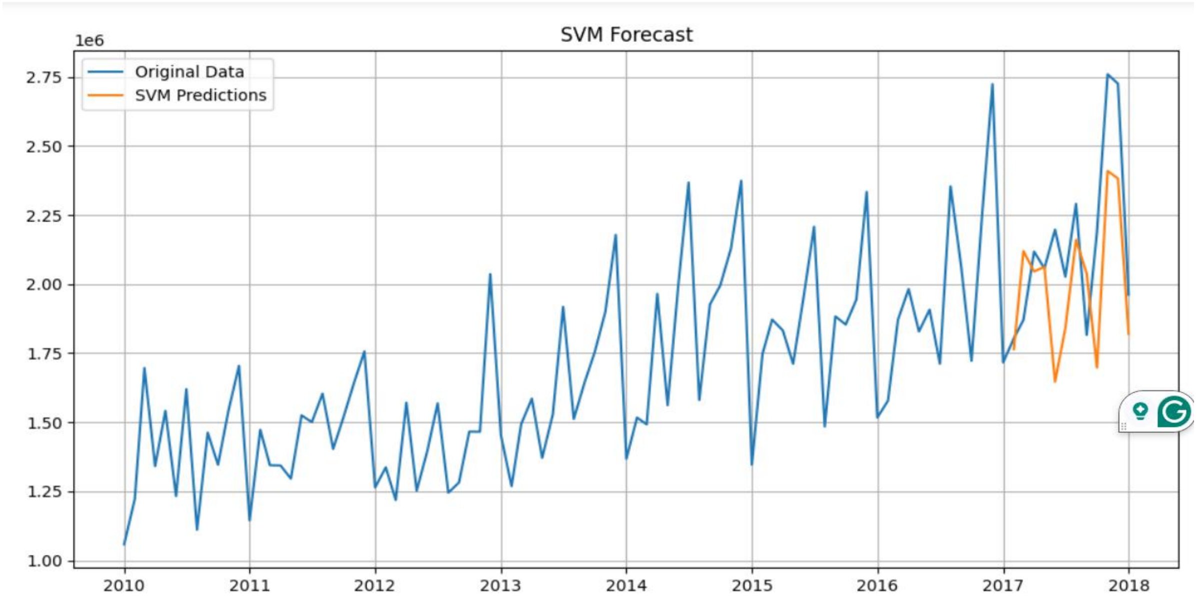

Figure 10. *SVM model forecasting*

The performance metrics further highlight these inaccuracies. The Mean Squared Error was 81,217,454,824.65, indicating significant discrepancies between predicted and actual values. The Root Mean Squared Error was 284,986.76, reflecting large prediction errors in the same units as the target variable. Moreover, the Mean Absolute Percentage Error was 10.52%, suggesting that on average, the predictions deviated by 10.52% from the actual values. These errors underscore the SVM's inability to provide reliable forecasts in this scenario.

6.4. Recurrent Neural Networks (RNNs)

The Recurrent Neural Network (RNN) is an advanced machine learning model commonly used for sequential and time-series data due to its ability to learn temporal dependencies. However, in this research, the RNN demonstrated limitations in its predictive accuracy when applied to a short dataset. While the model can forecast data patterns, it struggled to accurately capture the initial trends during the forecast period, particularly when the actual data showed a decreasing pattern, as the predictions instead exhibited an inverse trend.

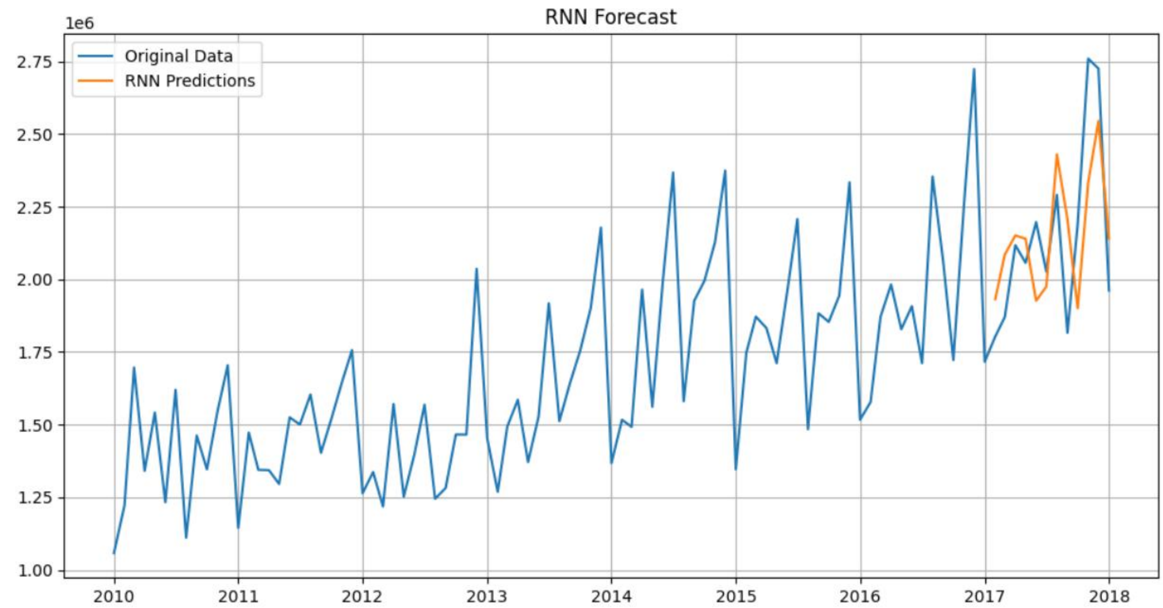

Figure 11. *RNN model forecasting*

The RNN struggles to make accurate predictions on this short dataset, which is evident from its poor performance metrics. The Mean Squared Error is exceptionally high at 53,817,918,260.03, indicating significant discrepancies in the predictions. The Root Mean Squared Error of 231,986.89 further underscores the large prediction errors. Although the Mean Absolute Percentage Error is relatively modest at 8.23%, the overall results show that the RNN is not suitable for reliable forecasting on this limited dataset.

6.5. Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory (LSTM) networks are a powerful tool for modeling time series data. However, in this case, the LSTM model fails to effectively capture the intricate patterns present in the dataset. The results highlight this limitation, as the forecasted data series appears almost as a straight line, showing only minimal fluctuations. This is in stark contrast to the original dataset, which demonstrates a clear seasonal pattern characterized by significant variations over time. Such discrepancies suggest that the LSTM model struggles to account for the underlying complexity and periodic nature of the data.

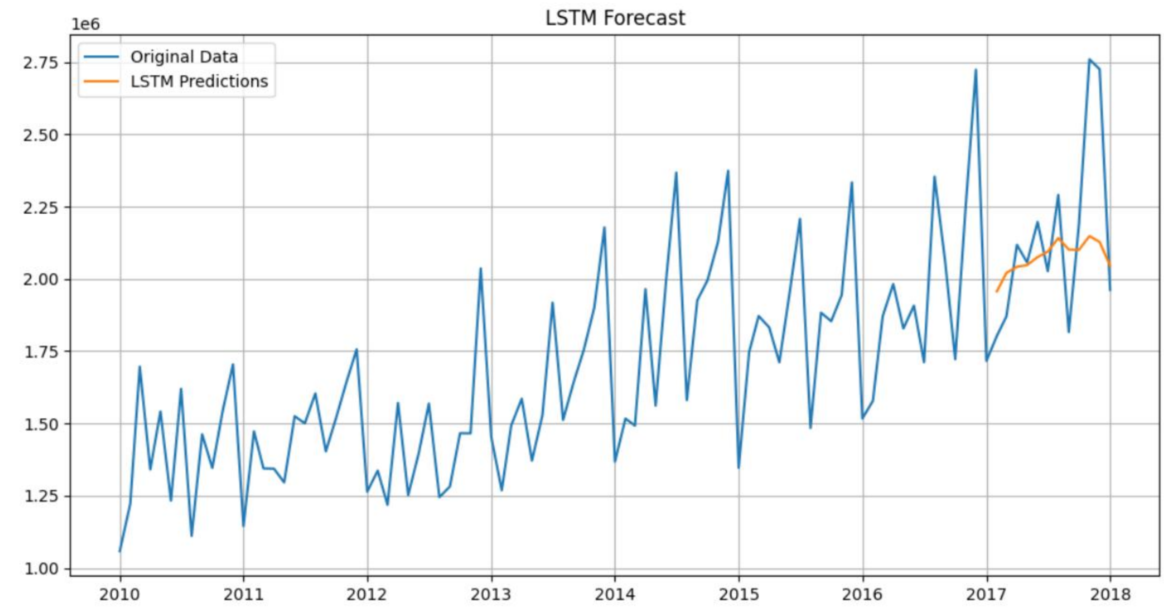

Figure 12. *LSTM model forecasting*

The performance metrics of the LSTM model highlight its limitations in accurately predicting patterns in the dataset. The Mean Squared Error is extremely high at 80,469,526,185.08, indicating significant deviations between the predicted and actual values. The Root Mean Squared Error, calculated at 283,671.51, further emphasizes the model's inability to closely follow the true data trends.

Despite these high error measures, the Mean Absolute Percentage Error is relatively low at 8.82%. This suggests that while the percentage differences may appear modest, the overall magnitude of the errors is still substantial due to the scale of the dataset.

These results indicate that the model struggles to generalize effectively and fails to learn the dataset's inherent seasonal and nonlinear patterns.

6.6. Discussions

In this study, five effective methods are used to forecast time series data. The performance of these models is compared using plots and metrics, including MSE, RMSE, and MAPE. These metrics provide valuable insights into the capabilities of the models for the given dataset.

	Original Data	Triple ExponentialSmoothing	SARIMA	RNN	LSTM	SVM
2017-02-01	1803187.17	1891410.20	1913657.06	1832716.50	1949793.88	1764175.33
2017-03-01	1870286.06	1876602.90	2049314.85	2099245.00	2008838.88	2119249.80
2017-04-01	2117629.03	2100053.51	2100963.14	2146760.00	2028665.75	2045190.08
2017-05-01	2056550.76	1847654.85	2029593.56	2072873.00	2033995.12	2062440.12
2017-06-01	2196984.86	2081767.01	2066266.65	1888166.50	2059964.25	1646369.45
2017-07-01	2026293.22	2230209.17	1975605.14	1898612.38	2077302.62	1841139.20
2017-08-01	2290105.04	1946148.58	2273016.86	2437541.25	2120967.25	2159918.84
2017-09-01	1816028.11	2030945.45	2138067.31	2067482.50	2084124.75	2038153.45
2017-10-01	2189198.58	2105971.49	1980407.99	1799272.38	2083350.12	1697647.18
2017-11-01	2759163.58	2222935.67	2226665.47	2309004.50	2127548.25	2409186.93
2017-12-01	2724997.55	2500276.47	2444350.26	2525108.00	2109365.25	2381729.70
2018-01-01	1961436.31	1879120.21	1977726.04	1950193.00	2035704.25	1819535.64

Table 1. *Comparing original data and forecasting data of all models*

Figures 12 and 13 present a comprehensive comparison between the forecasted data and the actual data. Upon examining these figures, it becomes apparent that the majority of the models successfully capture the underlying pattern of the data series. Among them, the SARIMA model stands out as the most effective, with its predicted values closely mirroring the actual values throughout the observed period. The Triple Exponential Smoothing model also shows commendable performance, outperforming the other three machine learning models in terms of accurately depicting the data's trend. In stark contrast, the LSTM model fails to deliver reliable predictions, as it struggles to recognize and replicate the intricate patterns present in the data. This assessment highlights the varying degrees of effectiveness among the forecasting models, underscoring the SARIMA model's superiority in accuracy.

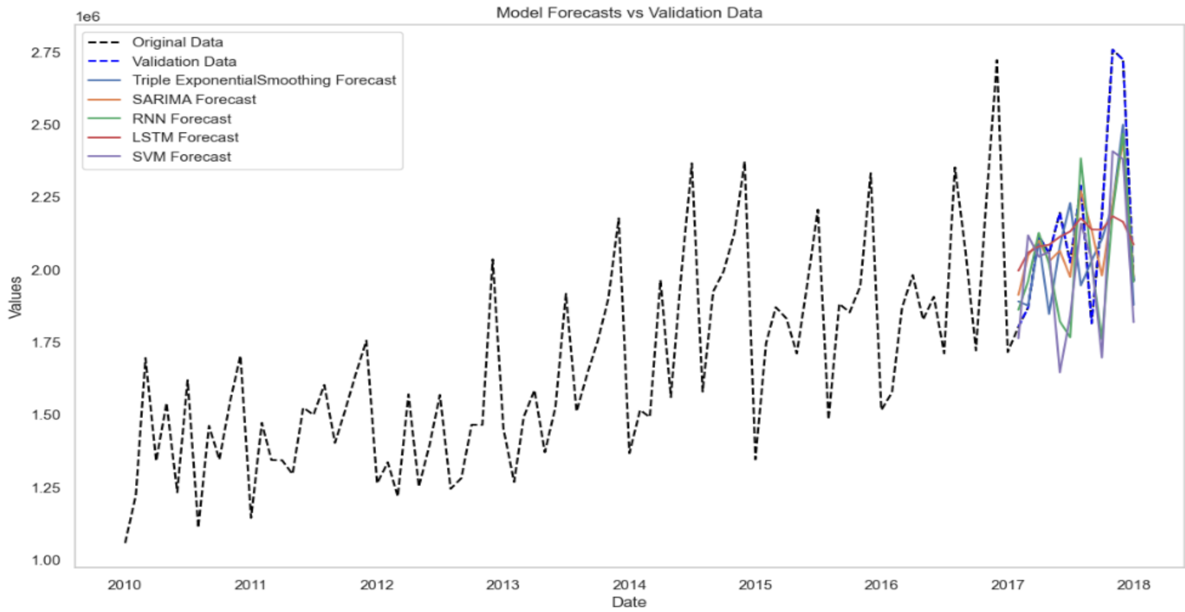

Figure 13. *Comparison of Forecasting Models*

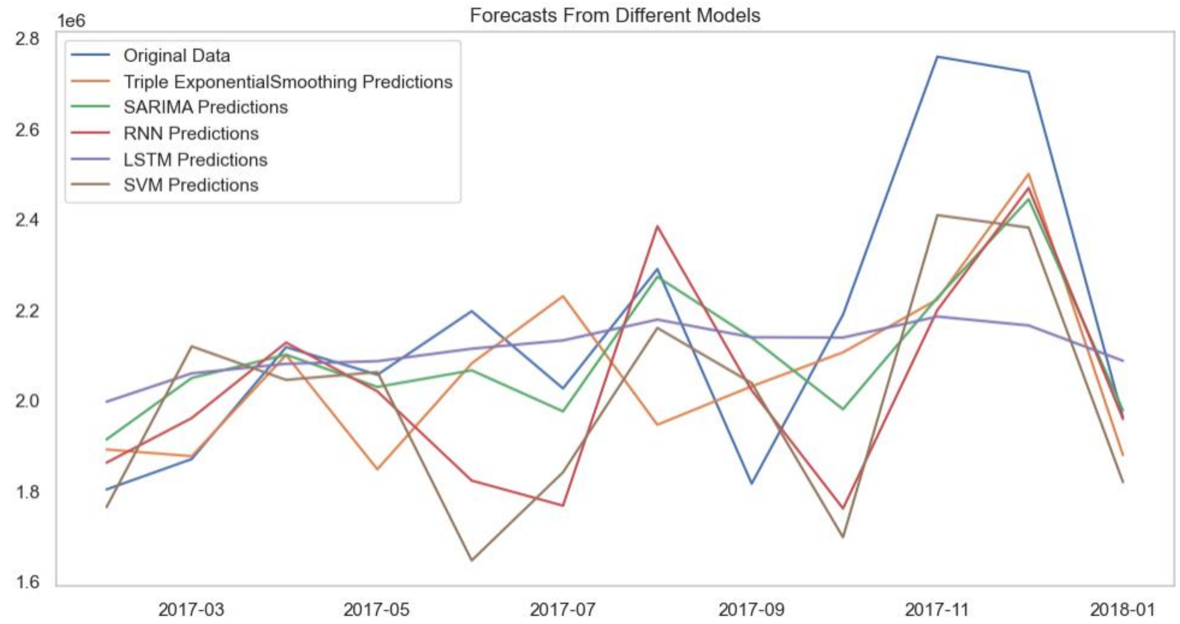

Figure 14. *Comparison of Forecasting Models (only forecasted period)*

Model	MSE	RMSE	MAPE
Triple Exponential Smoothing	51905384433.76	227827 53	7.84
SARIMA	47924428130.36	218916 49	7.06
RNN	53817918260.03	231986.89	8.23
LSTM	80469526185.08	283671.51	8.82
SVM	81217454824.65	284986.76	10.52

Table 2. *Performance matrices of all models*

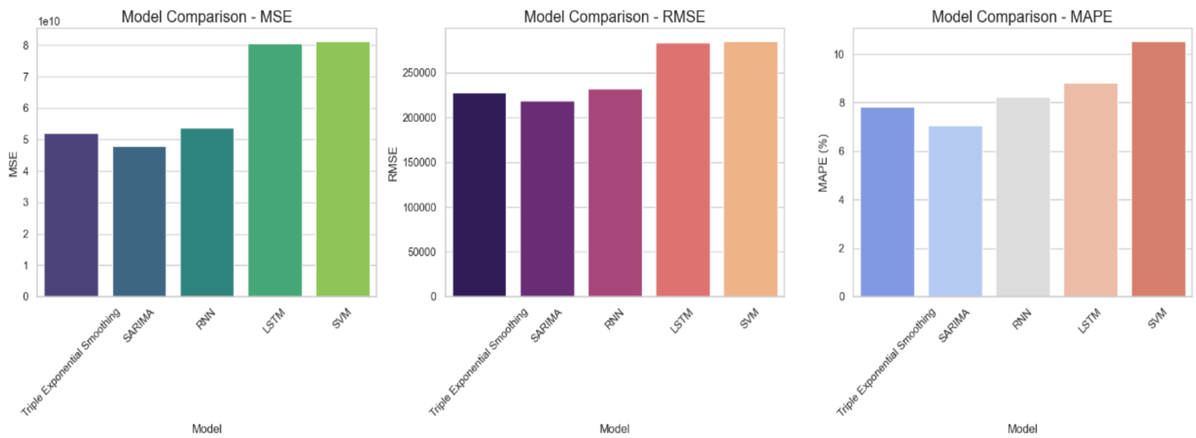

Figure 15. *Performance comparison of all models*

Figure15. and Table 2. compare the performance of five models: Triple Exponential Smoothing, SARIMA, RNN, LSTM, and SVM. The evaluation of these models is grounded in three key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). In the context of predictive performance, lower values for these metrics are indicative of superior accuracy, and the accompanying bar charts visually illustrate the comparative effectiveness of each model. In the analysis of MSE, SARIMA stands out with the lowest recorded value of 47924428130.36, suggesting its exceptional capability in minimizing the squared differences between the predicted and actual values. Hot on its heels, Triple Exponential Smoothing demonstrates commendable performance with an MSE of 51905384433.76. On the contrary, SVM exhibits the highest MSE at 81217454824.65, highlighting its relatively weaker predictive performance. RNN and LSTM demonstrate intermediate results, with MSE values of 69476274520.40 and 72655545932.24, respectively, indicating a moderate level of accuracy in their predictions.

The RMSE comparison further corroborates the findings from the MSE analysis. SARIMA again achieves the lowest RMSE, recorded at 218,916, reinforcing its strong capability in reducing prediction errors. Following closely, Triple Exponential Smoothing ranks second with an RMSE of 227,827, showcasing its reliability. In contrast, RNN (263,583) and LSTM (269,546) present higher error levels, indicating their challenges in precision, while SVM, with the highest RMSE of 284,986, emphasizes its limitations within this evaluation framework.

Lastly, the MAPE comparison assesses the models based on their percentage errors, providing a clear perspective on their accuracy. Leading the pack once again is SARIMA, boasting a MAPE of 7.06%, affirming its status as the most accurate forecasting model. Following its performance, Triple Exponential Smoothing shows a MAPE of 7.84%. Both RNN (8.75%) and LSTM (8.82%) exhibit similar yet less precise results, whereas SVM lags behind with a MAPE of 10.52%, marking it as the least effective model in this comparative analysis.

6.7. Insights

The SARIMA model consistently demonstrates superior performance compared to other forecasting models across all evaluation metrics. Its ability to accurately predict the underlying patterns in the data series establishes it as the most reliable option for precise forecasts. In comparison, Triple Exponential Smoothing serves as a strong alternative, albeit with slightly diminished performance relative to SARIMA.

When considering RNN (Recurrent Neural Networks) and LSTM (Long Short-Term Memory networks), they exhibit moderate effectiveness in handling time-series data. Conversely, Support Vector Machine (SVM) shows a significant deficiency, performing poorly across all measured metrics, which suggests that it is not well-suited for this particular forecasting task.

Overall, this analysis underscores SARIMA's robust capabilities in time-series forecasting, further confirming its practical utility and effectiveness in real-world applications.

7. Conclusion

In today's fast-paced and data-driven world, time series forecasting has become an essential tool across various industries. It not only minimizes risks but also provides deeper insights that are crucial for effective planning and decision-making. However, the accuracy of these forecasts is paramount; if the predictions are off the mark, the consequences can lead to significant setbacks. This highlights the importance of carefully selecting the appropriate forecasting method.

In this study, I explore five different forecasting models tailored to a particular data series, with the goal of evaluating their accuracy and effectiveness. I focused on a dataset characterized by less complex and have and have seasonal patterns. After applying all models to this data series, the results demonstrated that different models yield divergent outcomes. It became evident that not all forecasting methods can deliver equally high performance under specific data series. Among all the models tested, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model stood out, showcasing remarkable robustness in capturing intricate data patterns and seasonality. Its superior accuracy was further validated through various performance metrics. Following the SARIMA model, Triple Exponential Smoothing emerged as the next best performer, indicating its effectiveness in forecasting for similar types of data. These findings suggest that for short to medium-range data series with seasonal trends, traditional forecasting models often outperform more advanced machine learning approaches. This indicates that, for short to medium-range data series with less complexity and seasonal patterns, classical models are more effective than advanced machine learning models.

In summary, it is important to recognize that advanced machine learning techniques do not always produce the most accurate results. There is a common belief that neural networks are inherently superior to other modeling approaches for every task, but this assumption is not supported by the findings of this study. For instance, while neural networks can excel with large and intricate datasets, there are specific scenarios where they may not be the best choice. In particular, when dealing with time series data that is of moderate length, relatively simple, and exhibits seasonal patterns—such as the data utilized in this research—the SARIMA (Seasonal Autoregressive Integrated Moving Average) model proves to be more effective for generating precise forecasts. This indicates that choosing the right model is crucial, and sometimes traditional statistical methods can outperform complex machine learning algorithms in certain contexts.

8. References

Ahmad, N. & Dias, K., 2021. What is Data Validation? *Computer,* [Online]. 54(10), pp. 129-132. Available at: https://ieeexplore.ieee.org/document/9548110 [Accessed 05 December 2024]

Arumugam, V. & Natarajan, V., 2023. Time Series Modeling and Forecasting Using Autoregressive Integrated Moving Average and Seasonal Autoregressive Integrated Moving Average Models. *International Journal of Modeling and Optimization (I2M),* [Online]. 22(04), pp. 161-168. Available at: https://iieta.org/Journals/I2M [Accessed 02 November 2024]

Atmojo, Y. P. et al., 2022. *Performance Analysis of the Triple Exponential Smoothing Method During the Covid-19 Pandemic on Tourist Visit Data.* [Online] Available at: https://ieeexplore.ieee.org/document/9872863 [Accessed 24 November 2024].

Falatouri, T., Darbanian, F., Brandtner, P. & U., C., 2022. Predictive analytics for demand forecasting – A comparison of SARIMA and LSTM in retail SCM. *Procedia Computer Science,* [Online]. 200, p. 754–763. Available at: https://www.sciencedirect.com/science/article/pii/S1877050922003076 [Accesed 05 November 2024]

Pascanu, R., Mikolov, T., & Bengio, Y. (2015). A critical review of recurrent neural networks for sequence learning. *arXiv preprint* arXiv:1506.00019.[Online]. Available at: https://arxiv.org/abs/1506.00019 [Acceded 27 October 2024]

Makatjane, K. D. & Moroke, N. D., 2016. Comparative Study of Holt-Winters Triple Exponential Smoothing and Seasonal ARIMA: Forecasting Short-Term Seasonal Car Sales in South Africa. *Risk Governance & Control: Financial Markets & Institutions,* [Online]. 6(1), p. 71. Available at: https://virtusinterpress.org/IMG/pdf/10-22495_rgcv6i1art8.pdf [Accessed 01 December 2024]

Ricardo, et al., 2021. Machine learning advances for time series forecasting. *Journal of Economic Surveys,* [Online]. 37(1), pp. 76-111. Available at: https://onlinelibrary.wiley.com/doi/10.1111/joes.12429 [Accessed 04 December 2024].

Rob J Hyndman & Athanasopoulos, G., 2023. *Forecasting: Principles and Practice.*[e-book]. 3rd ed. OTexts. Available at: https://otexts.com/fpp3/ [Accessed 24 August 2024].

Sapankevych, I., N., Sankar & Ravi, 2009. Time Series Prediction Using Support Vector Machines: A Survey. *IEEE Computational Intelligence Magazine,* 24 April, 4(2), pp. 24-38. Available at: https://ieeexplore.ieee.org/abstract/document/4840324 [Accessed 05 July 2024].

Saxena, A., 2023. *Introduction to Long Short-Term Memory (LSTM).* [Online] Available at: https://medium.com/analytics-vidhya/introduction-to-long-short-term-memory-lstm-a8052cd0d4cd#:~:text=LSTMs%20come%20to%20the%20rescue,inputs%20(prior%20sentence%20words) [Accessed 24 September 2024].

Singh, A., Halgamuge, M. N. & Lakshmiganthan, R., 2017. Impact of Different Data Types on Classifier Performance of Random Forest, Naïve Bayes, and K-Nearest Neighbors Algorithms. *International Journal of Advanced Computer Science and Applications,* [Online] 8(12). Available at:

https://thesai.org/Publications/ViewPaper?Volume=8&Issue=12&Code=IJACSA&SerialNo=1 [Accessed 05 December 2024].

Paparoditis, E., & Politis, D. N. (2016). The asymptotic size and power of the augmented Dickey-Fuller test for a unit root. *Communications in Statistics - Theory and Methods,* [Online] 46(19), pp. 9603-3616. Available at: https://doi.org/10.1080/00927872.2016.1178887 [Accessed 05 July 2024].

Žunić, E., 2019. *Real-world sales forecasting benchmark data.* [Online] Available at: https://data.4tu.nl/datasets/8f5339ce-4b89-43e3-92cc-40adcb565a9a/1 [Accessed 06 June 2024].