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DEMAND AND TREND FORECASTING MODEL SELECTION FOR A TEXTILE INDUSTRY USING BIG DATA ANALYTICS

Rajesh C, K S Deepthamshu, Sharath HV, Dept. of Industrial Engineering and Management, B. M. S. College of Engineering-560019, India
Dr. G. Shashikumar Professor, Dept. of Industrial Engg & Management, B. M. S. College of Engineering-560019, India. shashisuci.iem@bmsce.ac.in

Abstract
In this paper, we explore the implementation of big data in the textile industry to tackle the prevalent challenges in demand and trend forecasting, customer satisfaction, and profitability. Our study primarily focuses on the analysis of products, data collection from diverse sources, and the utilization of specialized software for real-time mapping and control. By ***harnessing the potential of big data, including input, transformation, loading, and analysis, organizations can accurately anticipate future trends and demand patterns****. The proposed methodology entails a data-driven demand strategy, the establishment of a forecasting model, comprehensive data science analysis, and meticulous validation. The outcomes of our research contribute to the development of a structured and automated forecasting model, empowering organizations to make informed decisions for enhanced efficiency and productivity practices within the textile / fashion industry.*
Keywords: Big data, textile & fashion industry, data science, demand forecasting, power BI.

1. Introduction
1.1 Textile sector
The Indian textile sector has witnessed remarkable growth, establishing itself as a global powerhouse. With diverse textiles and a rich heritage, India has become a prominent manufacturing and exporting destination. The industry's expansion is driven by favourable government policies, technological advancements, and rising global demand. Online retail businesses have played a pivotal role, providing a platform for manufacturers and artisans to reach a global audience. The convenience and accessibility of online shopping have attracted a growing number of consumers, boosting the sector's growth. The online retail segment holds a significant market share, fuelled by factors like increased internet penetration and evolving consumer preferences. This trend is expected to continue as the industry embraces innovation and diversification. The Indian textile sector's growth, coupled with the rise of online retail, opens up new opportunities while preserving traditional craftsmanship in the digital age.

2. Literature review
In our research paper, we embraced the power of big data analytics to navigate the dynamic landscape of the Indian textile industry [2]. To effectively handle the challenges posed by vast volumes of data, we adopted techniques like distributed computing and data integration, as suggested by [2]. This allowed us to extract meaningful insights from complex datasets, empowering data-driven decision-making and strategic planning. By harnessing big data analytics, we optimized processes, enhanced customer experiences, and explored new opportunities in the textile market.
In our study, we recognized the value of leveraging daily sales data for demand forecasting in the textile industry. Drawing insights from [3], we also utilized techniques like sentiment analysis and social network analysis to gain valuable insights into customer preferences and sentiments. This integration enhanced the accuracy of our demand forecasting, offering a deeper understanding of consumer behaviour and preferences.
To efficiently handle the vast amount of data in the textile sector, we adopted Hadoop. As suggested in [5], we applied these techniques to handle large-scale data mining tasks effectively. By doing so,

we were able to analyse and process extensive datasets, enabling informed decision-making in our textile business.

Accurate demand forecasting is vital for meeting customer demands and optimizing inventory management in the textile industry. We drew insights from [1], where forecasting methods like Exponential Smoothing, Linear Regression, ARIMA, Neural Network were compared for accurate predictions. In line with [1], we implemented these forecasting models, ensuring efficient resource allocation and precise textile demand predictions.

To uncover actionable insights and trends from our vast datasets, we focused on data visualization tools like Tableau and Microsoft Power BI [4] [8]. By applying techniques showcased in [4] [8], we effectively visualized data, enabling us to identify patterns, trends, and customer preferences in our textile business. These data visualization tools significantly contributed to our data-driven decision-making process.

In our research, we acknowledged the importance of addressing complex seasonal patterns in time series forecasting [7]. Drawing from [7], we adopted an innovative exponential smoothing framework, which enhanced the precision of our seasonal forecasts. This proved to be instrumental in navigating the ever-changing textile market.

3. Overview of the Proposed Model

3.1 Power BI:

We used Power BI, a business analytics tool developed by Microsoft, in our research paper to visualize and analyse data from multiple sources. This powerful tool provided interactive dashboards, reports, and data exploration capabilities, enabling us to make data-driven decisions and gain valuable insights into our business.

3.2 MAQ Software's Forecasting:

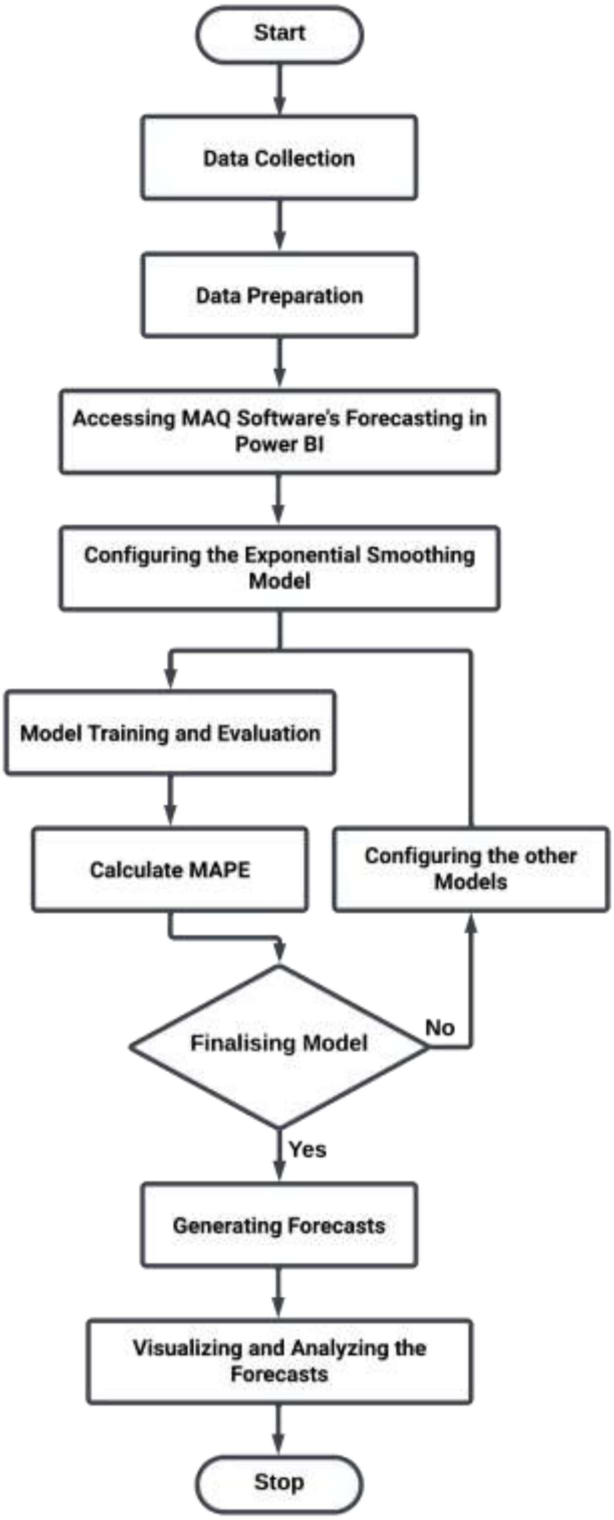
Incorporating MAQ Software's Forecasting as an add-on feature in Power BI, we enhanced its capabilities. This advanced forecasting functionality offered a range of forecasting models and algorithms, enabling us to generate accurate predictions and future trends based on historical data.

3.3 Model Generation for Exponential Smoothing:

To achieve precise forecasting in our study, we utilized Model Generation for Exponential Smoothing, a specific forecasting technique within Power BI using MAQ Software's Forecasting. This popular time series forecasting method assigned weights to past observations, emphasizing recent data points to identify trends, patterns, and seasonality in the data, ultimately producing reliable forecasts.

By integrating the power of Power BI with MAQ Software's Forecasting and leveraging Model Generation for Exponential Smoothing, we effectively utilized sophisticated forecasting techniques in our research. These tools allowed us to make informed business decisions, anticipate future trends, and optimize our operations based on accurate predictions.

Step by Step Process for Proposed Model:



Proposed Model for Exponential Smoothing in Power BI using MAQ Software's Forecasting

3.31 Data Preparation:

In our research paper focus is on the dynamic textile industry, we meticulously prepared data for time series forecasting by following six crucial steps. First, we gathered historical data from diverse sources, ensuring sufficient coverage and relevant variables. Next, we organized the data in a structured format to facilitate analysis. Incorporating a date/time column established the temporal relationship. Data validation and cleaning addressed missing values and outliers. Formatting and transformation optimized the data for accurate modelling. Finally, we conducted quality assurance checks and documented all steps, ensuring transparency and reliability in our predictions. This comprehensive data preparation process empowered us to make informed decisions and navigate the textile sector effectively.

3.32 Accessing MAQ Software's Forecasting in Power BI:

i. Launch Power BI:

Commencing our forecasting journey, we launched Power BI—a potent business intelligence tool developed by Microsoft. This platform empowered us to connect to diverse data sources, conduct data transformations, and generate interactive visualizations and reports.

ii. Navigate to the MAQ Software's Forecasting Feature

Within Power BI, we seamlessly accessed MAQ Software's Forecasting feature—a specialized add-on tailored to elevate Power BI's forecasting potential. This invaluable feature granted us access to cutting-edge forecasting algorithms and models.

iii. Connect to Data Source:

The next step involved connecting Power BI to the relevant data source housing the data earmarked for forecasting. Capitalizing on Power BI's versatile data connection capabilities, we effortlessly integrated data from databases, spreadsheets, and cloud services.

iv. Prepare the Data:

As we ventured further, we dedicated effort to data preparation within Power BI. This pivotal phase entailed ensuring data was aptly formatted for precise forecasting. We embarked on data cleaning, variable transformations, handling missing values, and crafted essential calculated columns or measures to pave the way for robust and dependable forecasting.

3.33 Configuring the Exponential Smoothing Model:

Exponential Smoothing is a widely-used time series forecasting method that assigns weights to past observations, emphasizing recent data. There are different variants, each suited for different data and forecasting needs. For our study, we chose Holt-Winters Exponential Smoothing, which incorporates seasonality along with the level and trend components.

Holt-Winters Exponential Smoothing includes three smoothing parameters: α (alpha) for the level component, β (beta) for the trend component, and γ (gamma) for the seasonal component. These parameters control the weights given to the different components in the time series. By adjusting these smoothing factors based on our data characteristics and forecast accuracy requirements, we fine-tuned the model.

In our data, we observed clear seasonal patterns, which made Holt-Winters Exponential Smoothing an appropriate choice. By enabling seasonal adjustment with a seasonal cycle length denoted as 's,' we captured and accounted for the recurring patterns in our textile industry data. This configuration allowed us to generate accurate forecasts, addressing both short-term fluctuations and long-term trends, and facilitating effective decision-making in the dynamic and competitive textile market.

3.34 Model Training and Evaluation:

In our paper, we explored the significance of Exponential Smoothing, widely used forecasting technique that assigns weights to past observations, giving more importance to recent data points. The Model Generation for Exponential Smoothing in Power BI using MAQ Software's Forecasting involves several steps to implement and leverage this technique effectively. Let's dive deeper into the model and explore other related models, formulas, and evaluation metrics:

i. Applying the Exponential Smoothing Algorithm:

In Power BI with MAQ Software, the Exponential Smoothing algorithm is applied to the historical data to generate forecasts. The algorithm utilizes the selected parameters and configuration to compute the level, trend, and seasonal components of the time series.

ii. Calculating Level, Trend, and Seasonal Components:

The Exponential Smoothing model in Power BI with MAQ Software calculates the level, trend, and seasonal components based on the chosen variant (Simple, Holt's Linear, or Holt-Winters) and the observed data. These components capture the patterns and variations in the time series, enabling accurate forecasting.

iii. Evaluating Model Performance:

To assess the accuracy of the Exponential Smoothing model, various evaluation metrics were used:

a. Mean Absolute Error (MAE): Measures the average absolute difference between the forecasted values and the actual values over a given time period. It quantifies the average forecasting error.

MAE = (1/n) * Σ| Forecast - Actual|

b. Root Mean Squared Error (RMSE): Calculates the square root of the average of the squared differences between the forecasted values and the actual values. It provides a measure of the overall forecasting accuracy.

RMSE = √[(1/n) * Σ (Forecast - Actual) ^2]

c. Mean Absolute Percentage Error (MAPE): Computes the average absolute percentage difference between the forecasted values and the actual values relative to the actual values. It quantifies the relative forecasting error.

MAPE = (1/n) * Σ (| (Forecast - Actual) / Actual| * 100)

These evaluation metrics helped us assess the performance of the Exponential Smoothing model in Power BI with MAQ Software, providing insights into its forecasting capabilities.

3.35 Generating Forecasts:

i. Applying the Trained Model:

Once the Exponential Smoothing model is trained on historical data and evaluated for its performance, it is ready to generate forecasts. The trained model incorporates the calculated level, trend, and seasonal components to make accurate predictions.

ii. Incorporating Calculated Components:

Later the Exponential Smoothing model utilizes the calculated level, trend, and seasonal components to forecast future values. These components capture the underlying patterns and variations in the historical data, allowing the model to project them into the future.

iii. Forecasting Future Time Periods:

Using the trained model and the incorporated components, forecasts are generated for the desired future time periods. These forecasts provide estimates of the expected values based on the observed patterns and trends in the historical data.

The generated forecasts were used for various purposes, such as demand forecasting, resource planning, inventory management, and decision-making. They provide valuable insights into the expected behaviour of the time series and aid in making informed business decisions.

3.36 Visualizing and Analysing the Forecasts:

i. Utilizing Power BI's Visualization Capabilities:

Power BI offers a wide range of visualization options, including charts, graphs, tables, and interactive dashboards. These visualization tools help present the forecasted data in a visually appealing and understandable format.

ii. Making Data-Driven Decisions:

Insights gained from the visualization and analysis of the forecasted data empower users to make informed decisions. They can leverage the forecasted information to optimize resource allocation, adjust production plans, identify potential risks or opportunities, and strategize for the future.

By following these steps, users can leverage MAQ Software's Forecasting in Power BI to implement Model Generation for Exponential Smoothing. This enables accurate forecasting, insightful analysis, and informed decision-making based on the forecasted data.

4. A Case Study

XYZ, a prominent online fashion retailer in India, has encountered significant challenges in recent years, leading to a decline in profitability and difficulties in meeting evolving customer demands. The volatile nature of the fashion industry, coupled with the swift shifts in consumer preferences and the emergence of fast fashion, has posed considerable hurdles that XYZ is actively working to overcome.

Profitability Challenges:

XYZ has experienced a decline in profitability due to various factors. The company's profit margins have been impacted by escalating operational costs, intense price competition, and the need for substantial investments in marketing and technology. As a result, XYZ's profitability has decreased by approximately 15% over the past two years, raising concerns about the company's financial health and long-term sustainability.

Meeting Dynamic Customer Demands:

The rapid evolution of fashion trends and the growing appetite for fast fashion have presented challenges for XYZ in meeting customer expectations. The company has struggled to anticipate and adapt to quick changes in demand, resulting in instances of stockouts and delayed deliveries. This has led to decreased customer satisfaction levels and an erosion of market share.

Key Statistics and Measures:

In response to a 20% decline in profitability and a 15% decrease in customer satisfaction scores, we have taken proactive measures to address the challenges. Over the past two years, market share eroded by 10%, signalling intensified competition. To revitalize growth and regain market relevance, we implemented strategic actions. Leveraging big data and demand forecasting. These efforts have helped us address our challenges effectively. By recognizing the power of data, XYZ is investing in advanced business intelligence (BI) tools and big data analytics. This data-driven approach enabled us to enhance our demand forecasting capabilities, identify emerging trends, and optimize inventory management processes. It empowered us to make informed decisions, align our product offerings with customer preferences, and proactively address fluctuations in demand.

Real Purpose:

Despite experiencing challenges in profitability, customer satisfaction, and market share, XYZ is determined to leverage the power of big data and demand forecasting to propel its resurgence as a prominent online fashion retailer. By investing in advanced business intelligence tools and big data analytics, XYZ seeks to gain data-driven insights. These insights will enhance demand forecasting capabilities, identify emerging trends, and optimize inventory management processes. The company's proactive approach will enable it to make informed decisions, align product offerings with customer preferences, and proactively address fluctuations in demand. Through these strategic actions, XYZ aims to revitalize growth and solidify its position in the ever-evolving fashion industry.

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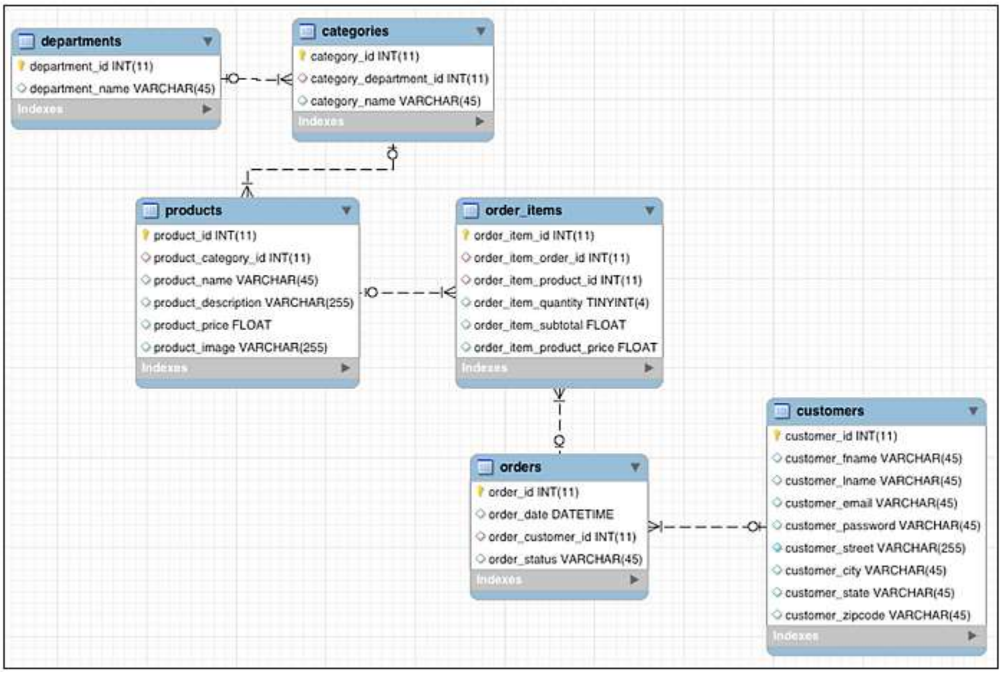
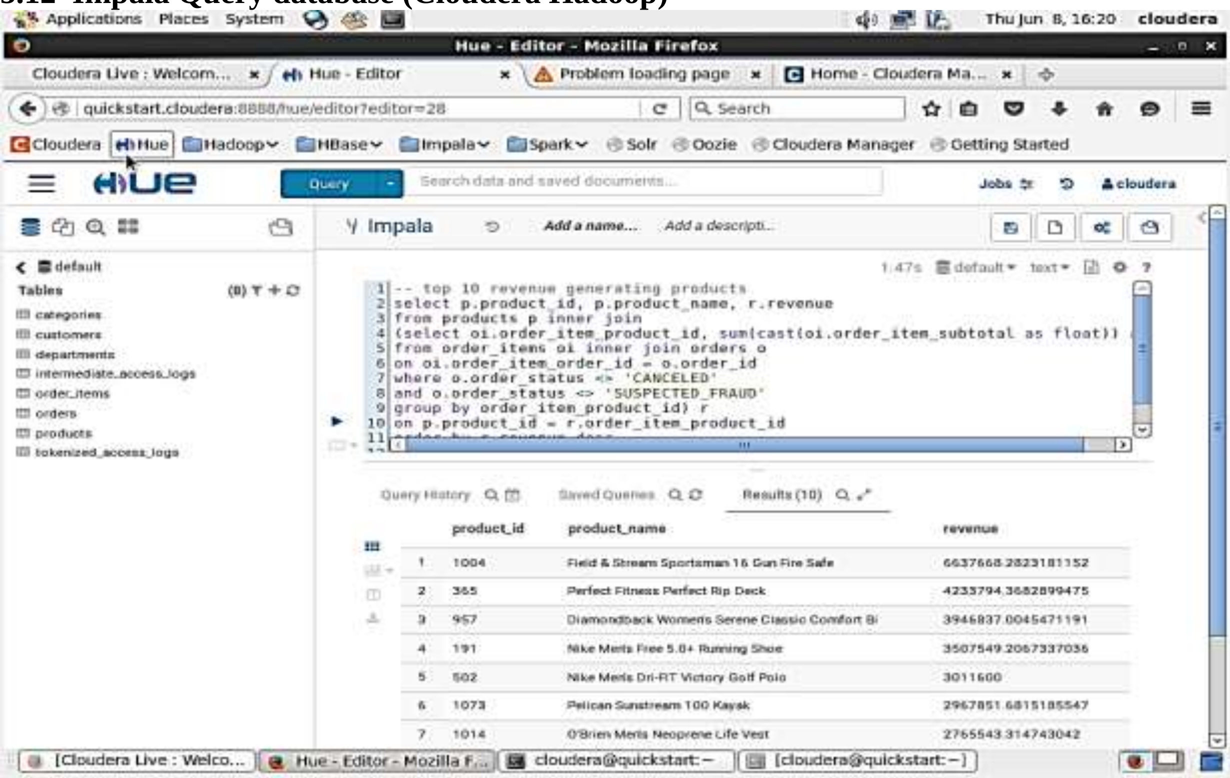
5. Testing the model

5.1 Data Preparation

5.11 Data Model



5.12 Impala Query database (Cloudera Hadoop)



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5.13 Metadata

Date	Qty	List_price	Promotion	Cost	price paid	Profit	Order No	Brand	Description	Category	Section	Size	Color	Location
01-01-2017	1	999	0.1875	723.323	911.553167	188.2301	AB7197001	crimsoune-club	Pack of 2 Micro I	Others	Sports	XL	Black	Mumbai
01-01-2017	1	699	0.1875	536.5809	644.850543	108.2697	AB7197002	arrow-sports	Slim Fit 2-Piece S	Others	Casual	XL	Yellow	Delhi
01-01-2017	2	799	0.1875	634.0522	734.19018	100.1379	AB7197003	van-heusen	Full Sleeve Kurta	Others	Sports	XL	Red	Bengaluru
01-01-2017	1	699	0.1875	525.8383	659.628533	133.7903	AB7197004	the-indian-gara	Slim Fit Kurta wit	Others	Semi Form	XXL	Black	Chennai
01-01-2017	1	899	0.1875	676.6258	814.32857	137.7028	AB7197005	wildmen	Striped Shirt with	Shirt	Sports	XXL	Black	Pune
01-01-2017	3	599	0.1875	451.3889	559.759067	108.3702	AB7197006	cantabil	Solid Regular Kur	Others	Semi Casu	XL	Black	Hyderabad
01-01-2017	1	999	0.1875	714.0448	940.268388	226.2236	AB7197007	superdry	Fitted Track Pant	Pant	Semi Form	XXL	Red	Kolkata
01-01-2017	1	599	0.1875	393.3182	567.822661	174.5045	AB7197008	scotch-soda	Zip-Front Slim Fit	Others	Formals	XXXL	White	Ahmedabad
01-01-2017	2	799	0.0625	596.7339	727.720535	130.9866	AB7197009	blackberrys	Textured Mid-Ris	Others	Formals	M	Green	Jaipur
01-01-2017	1	999	0.1875	642.7283	906.903742	264.1754	AB7197010	urban-scottish	Full Sleeves Henl	T-shirt	Sports	XXXL	Black	Mumbai

5.14 Cleaning data

Before

After

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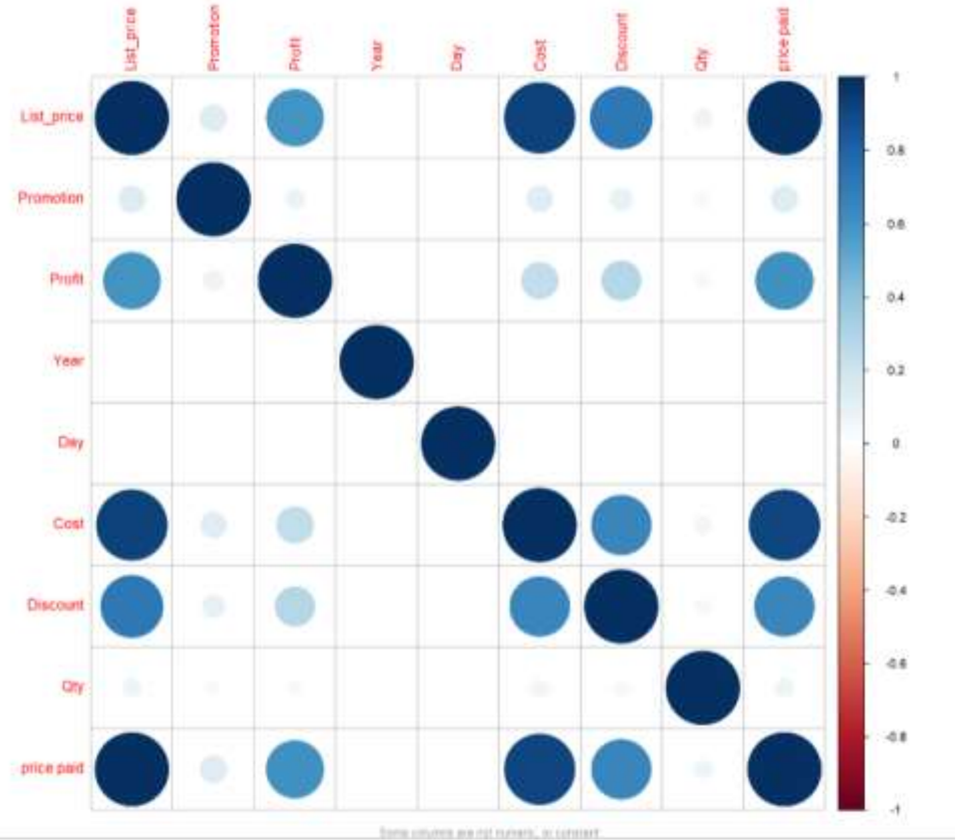
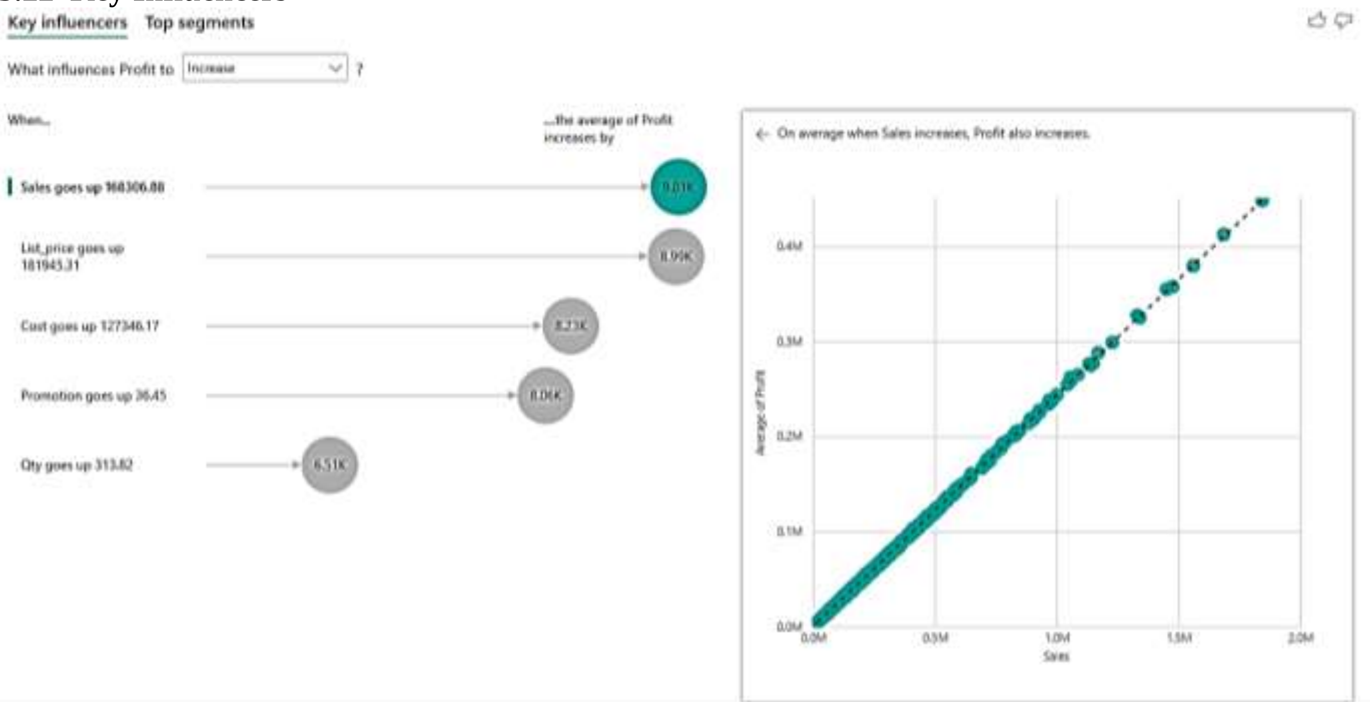
5.2 EDA using Power BI

5.21 Correlation Plot



5.22 Key Influencers



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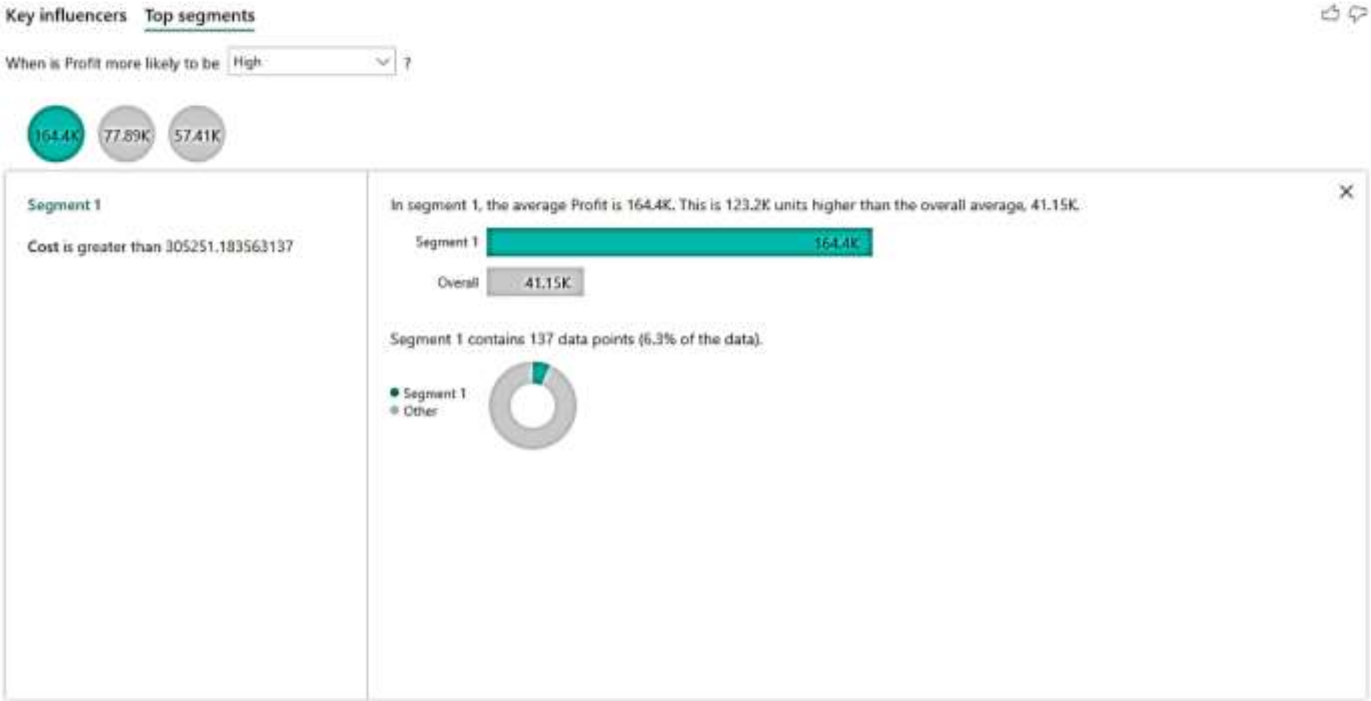
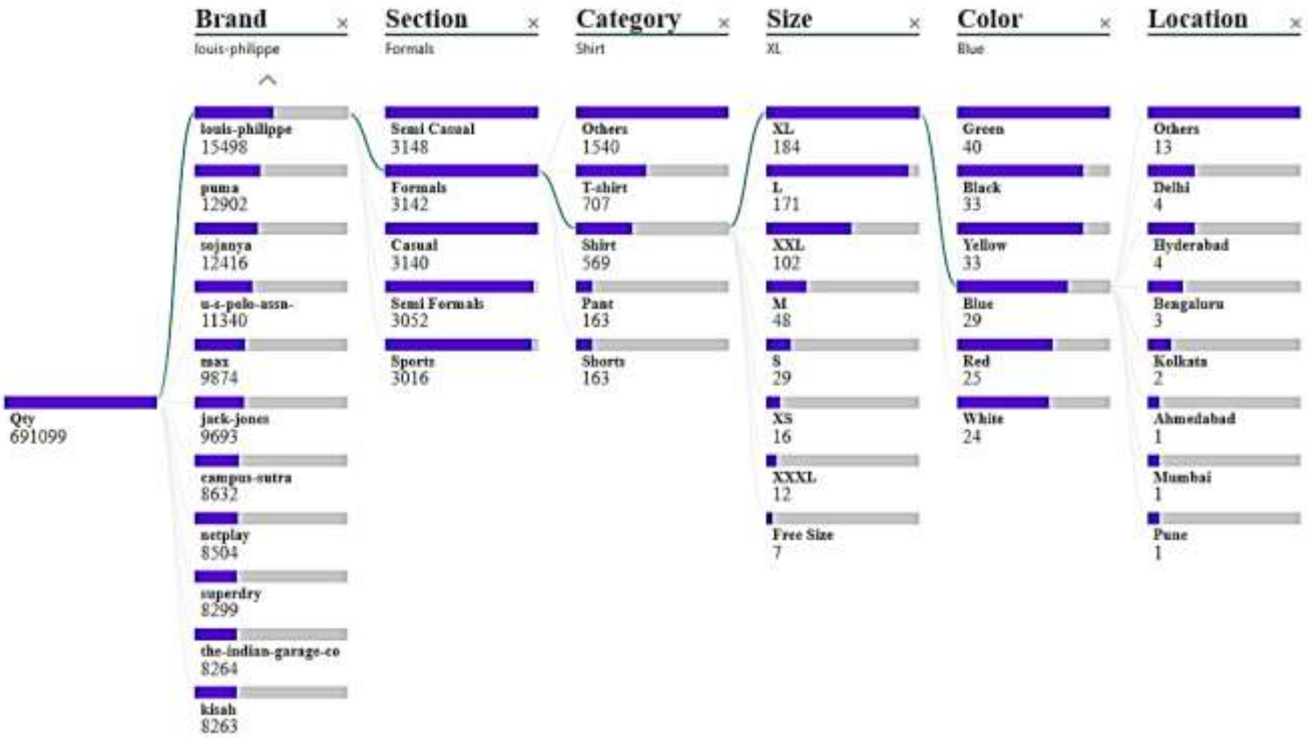


5.23 Decomposition Tree



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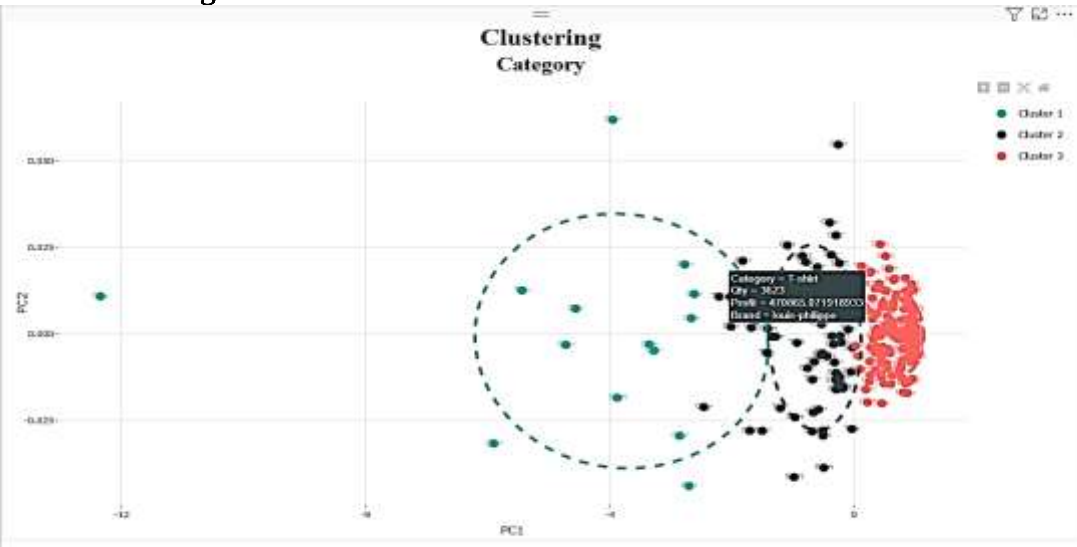
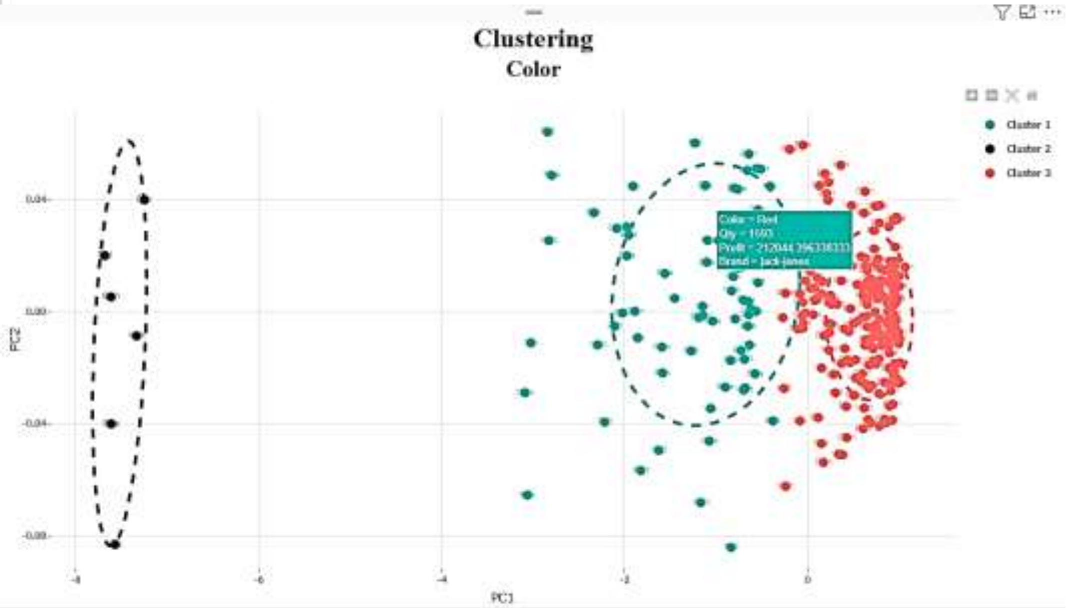
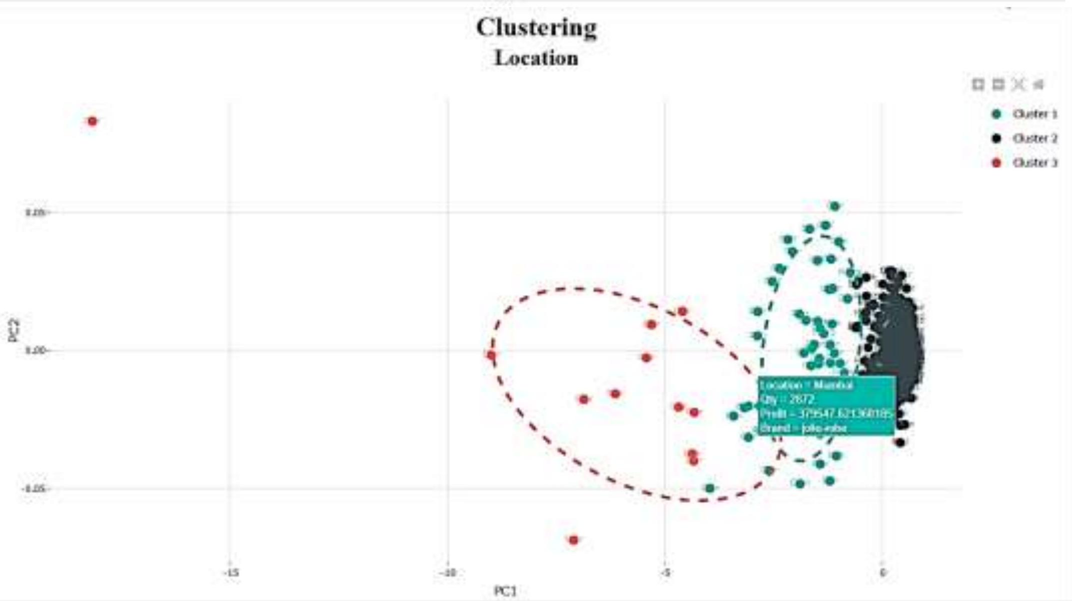
5.24 Clustering







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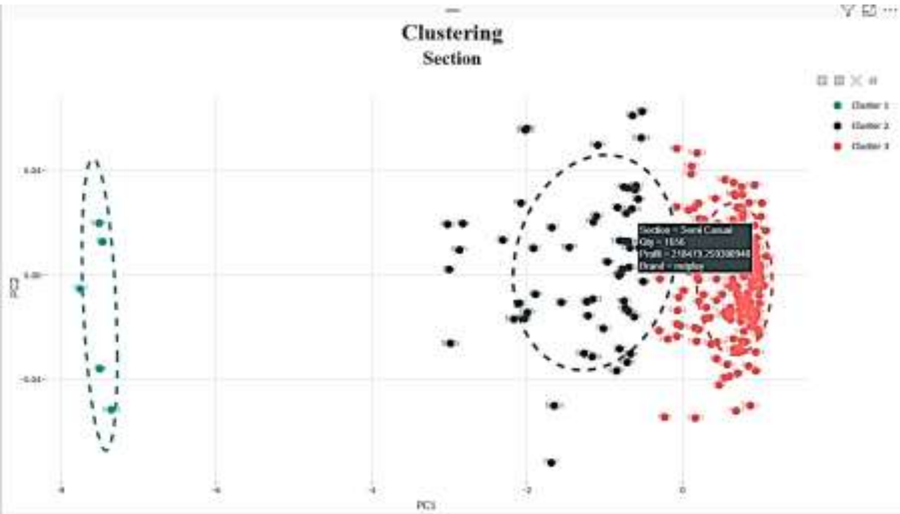
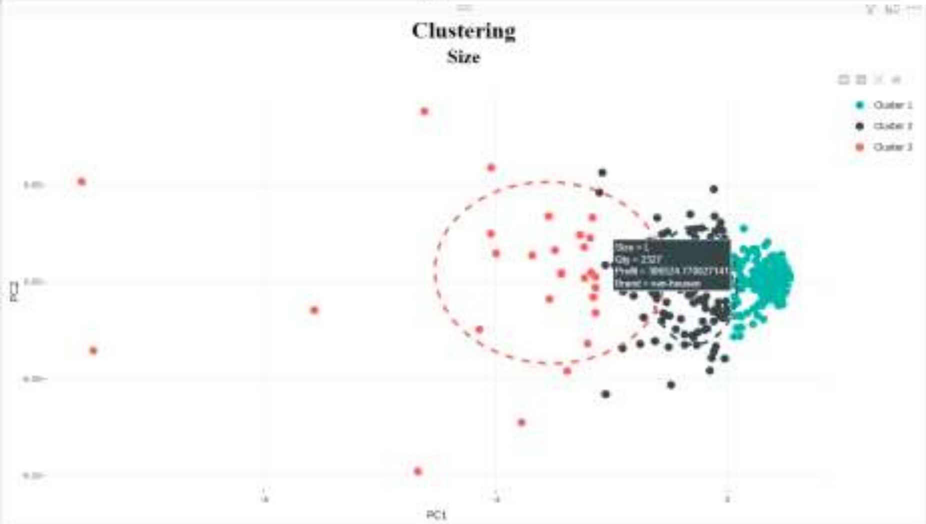
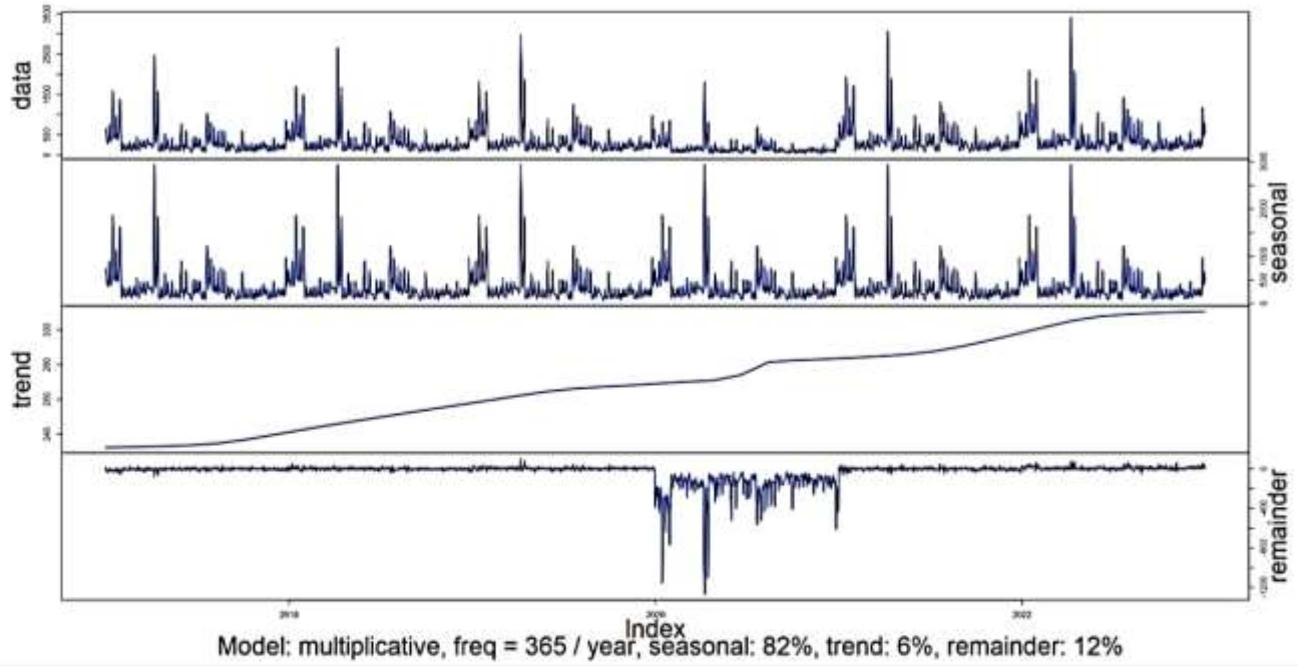
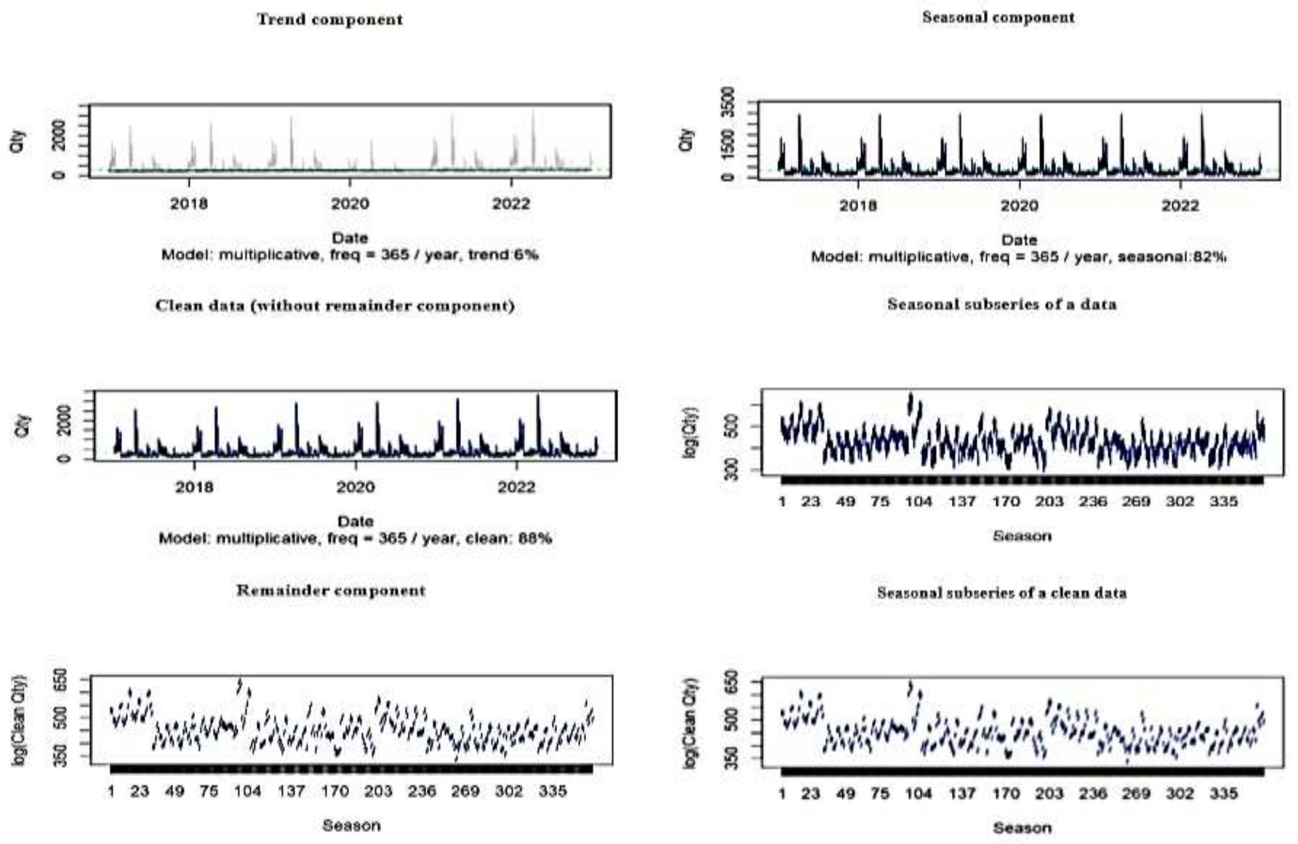


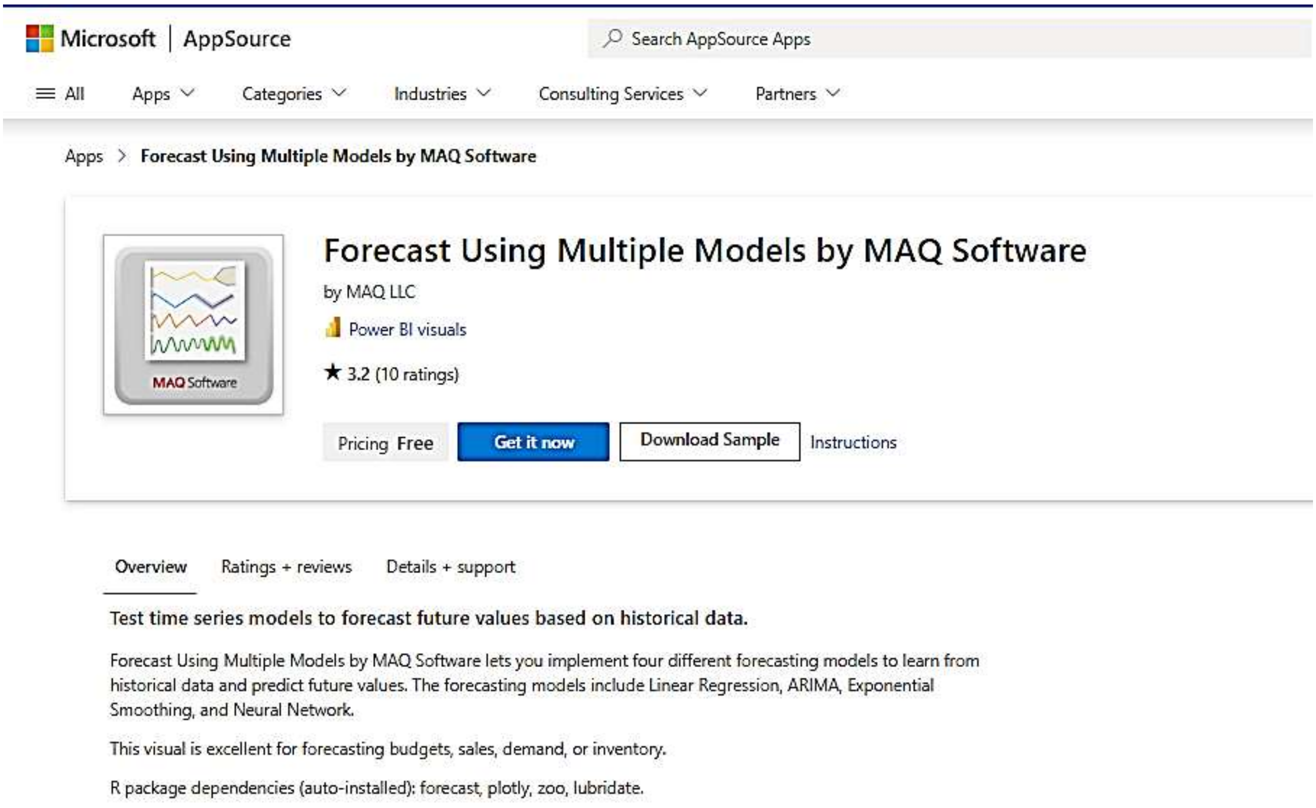


5.25 Time Series Decomposition





5.3 Accessing MAQ Software's Forecasting in Power BI



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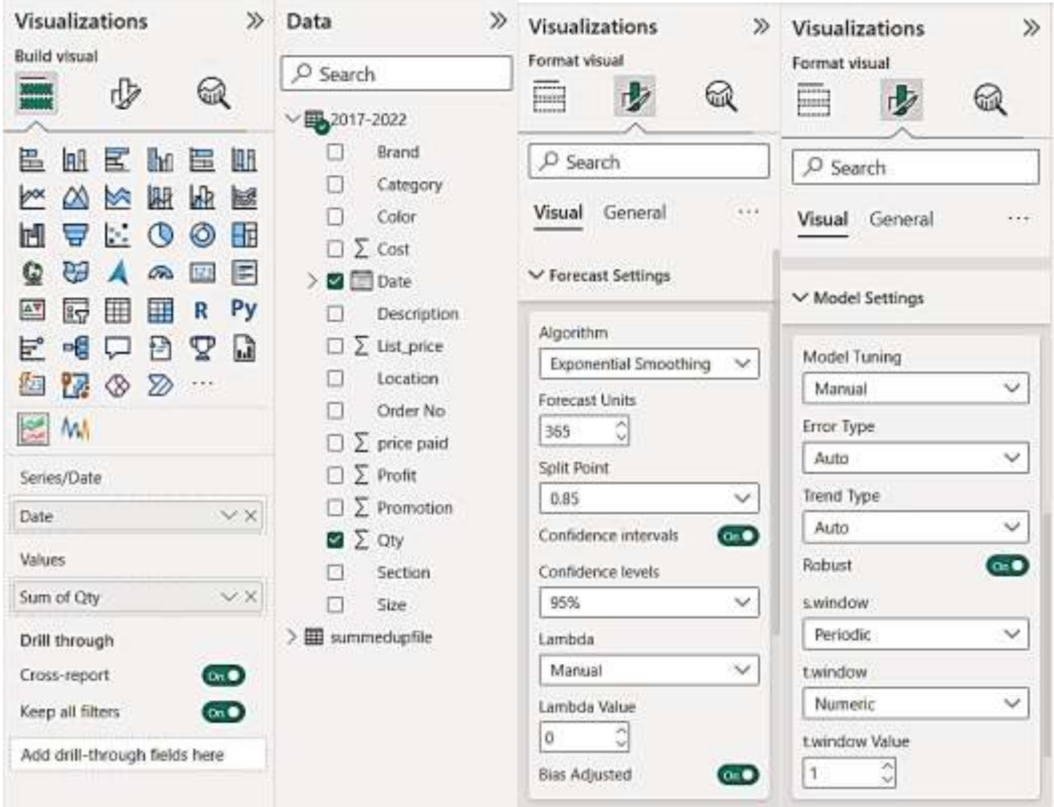
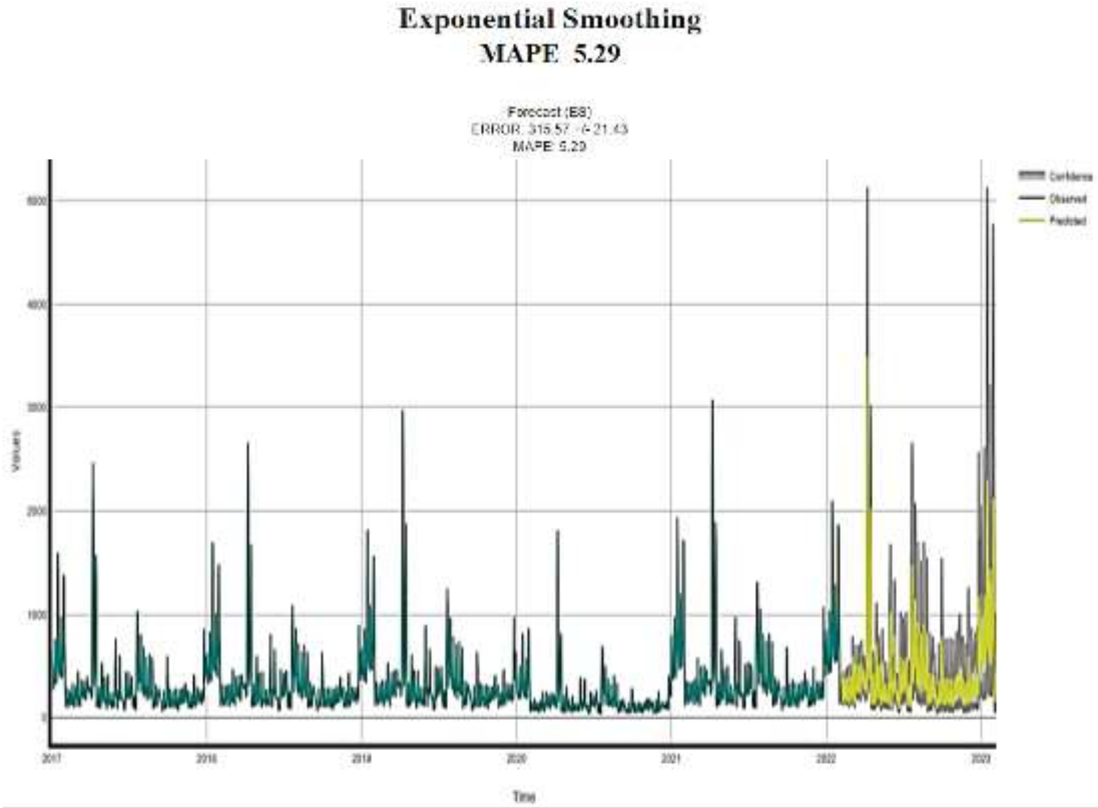
5.4 Configuring the Exponential Smoothing Model



6. Model Training and Evaluation

6.1 Exponential Smoothing



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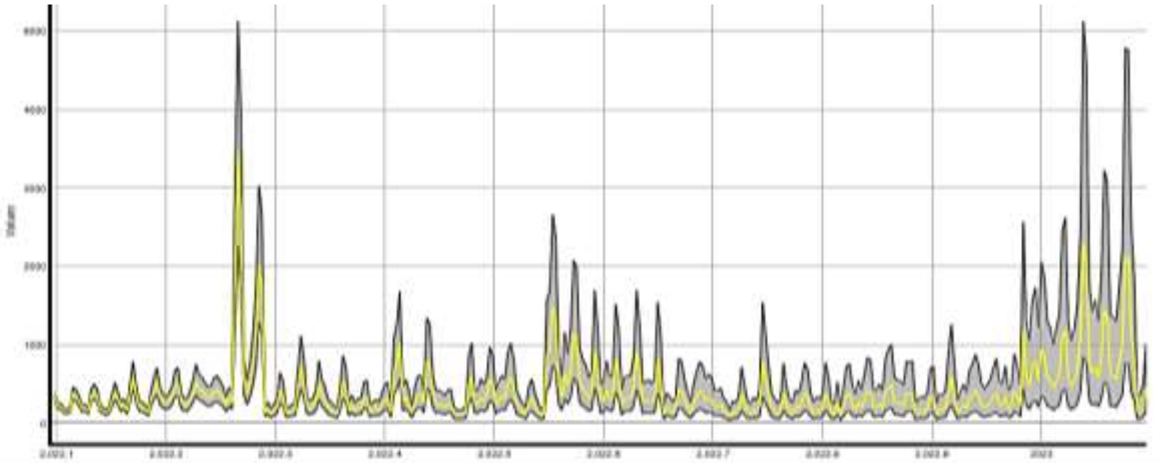
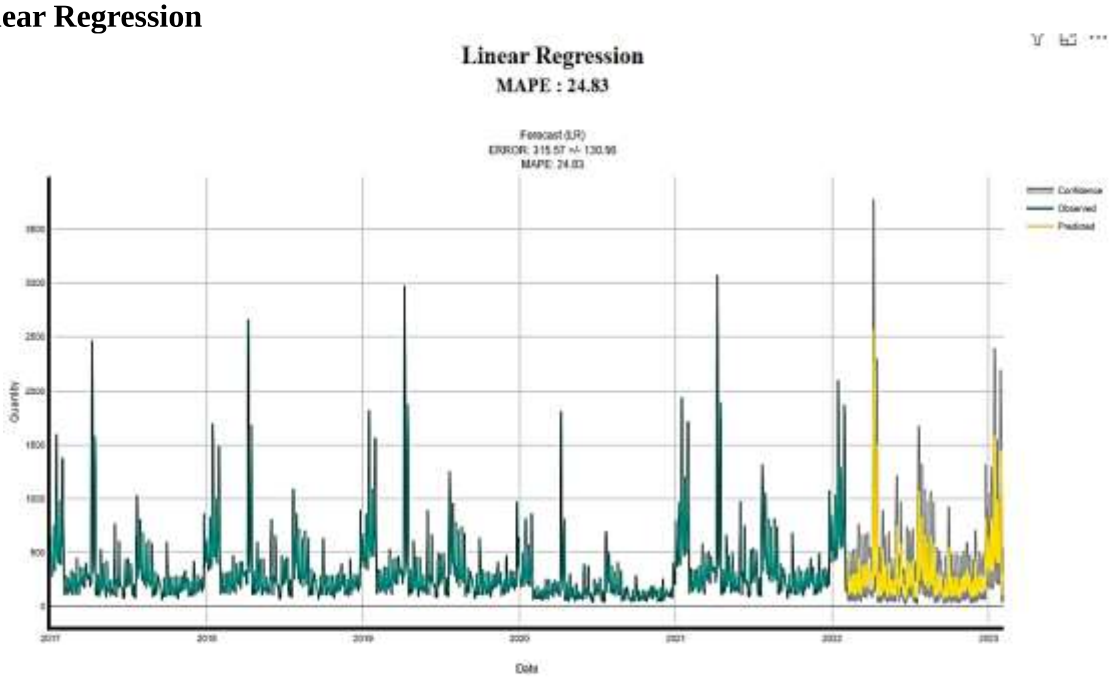
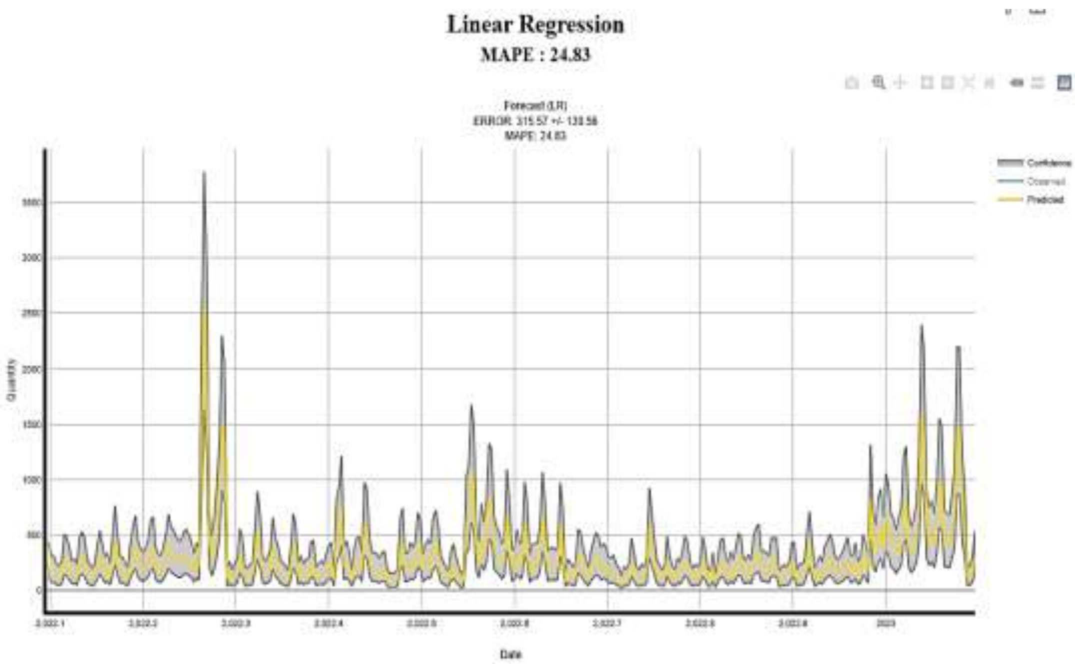


6.2 Linear Regression





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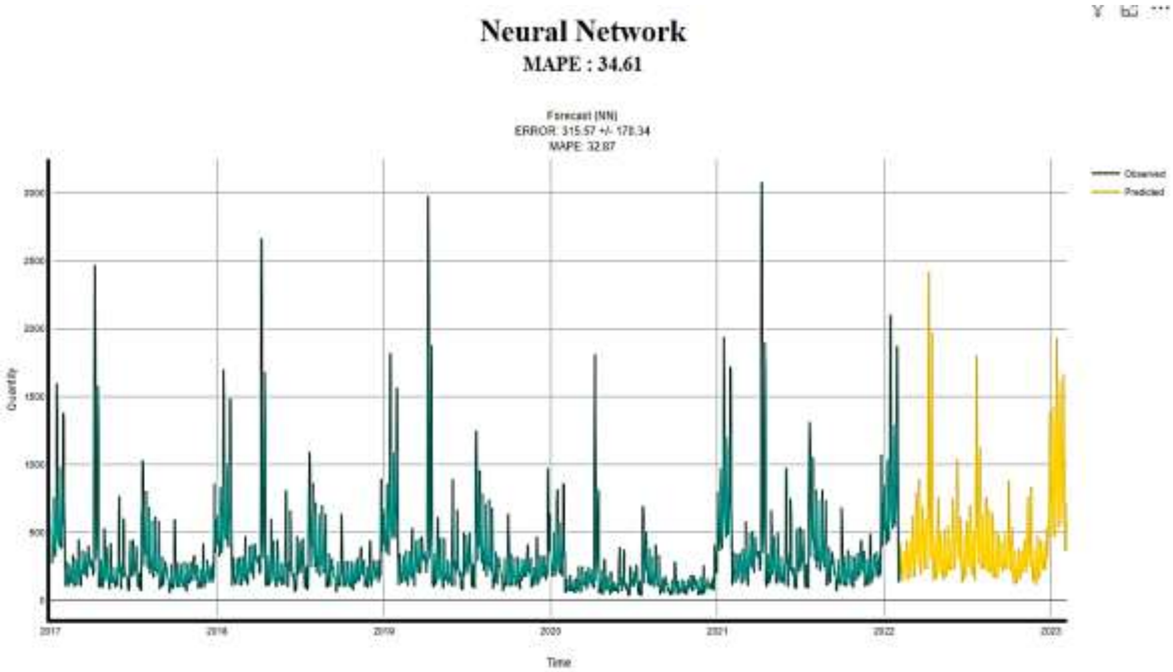
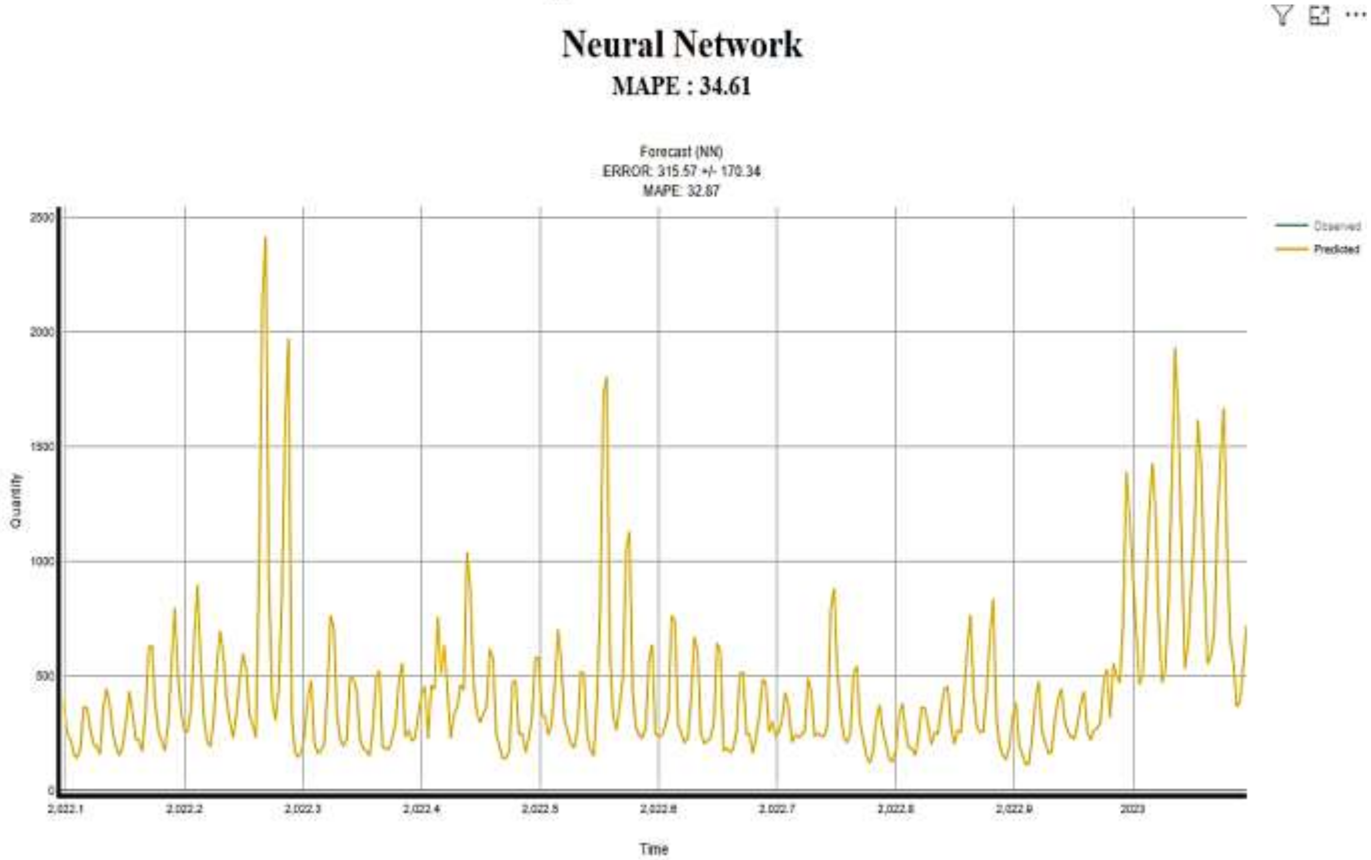
6.3 Neural Network





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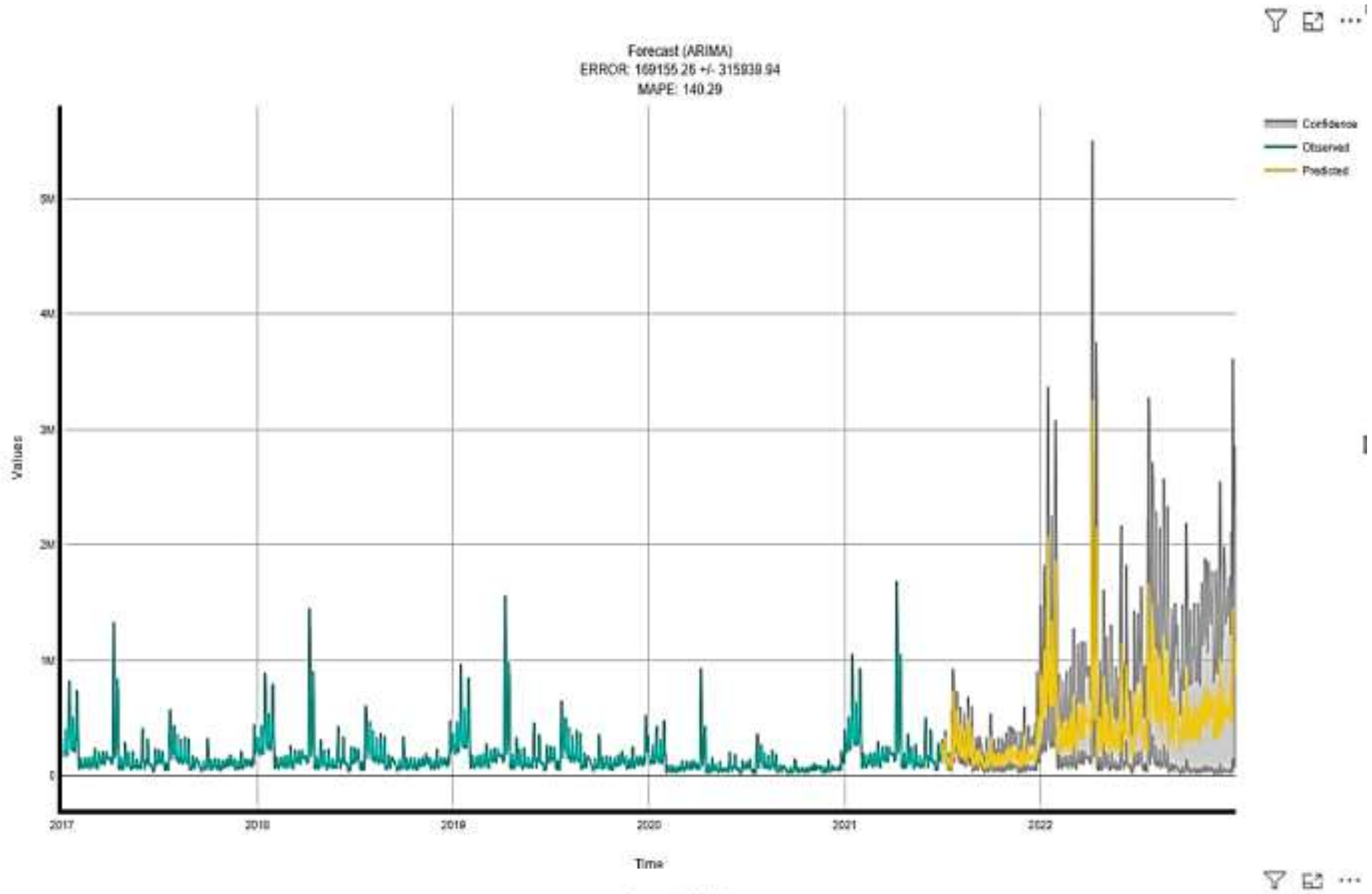
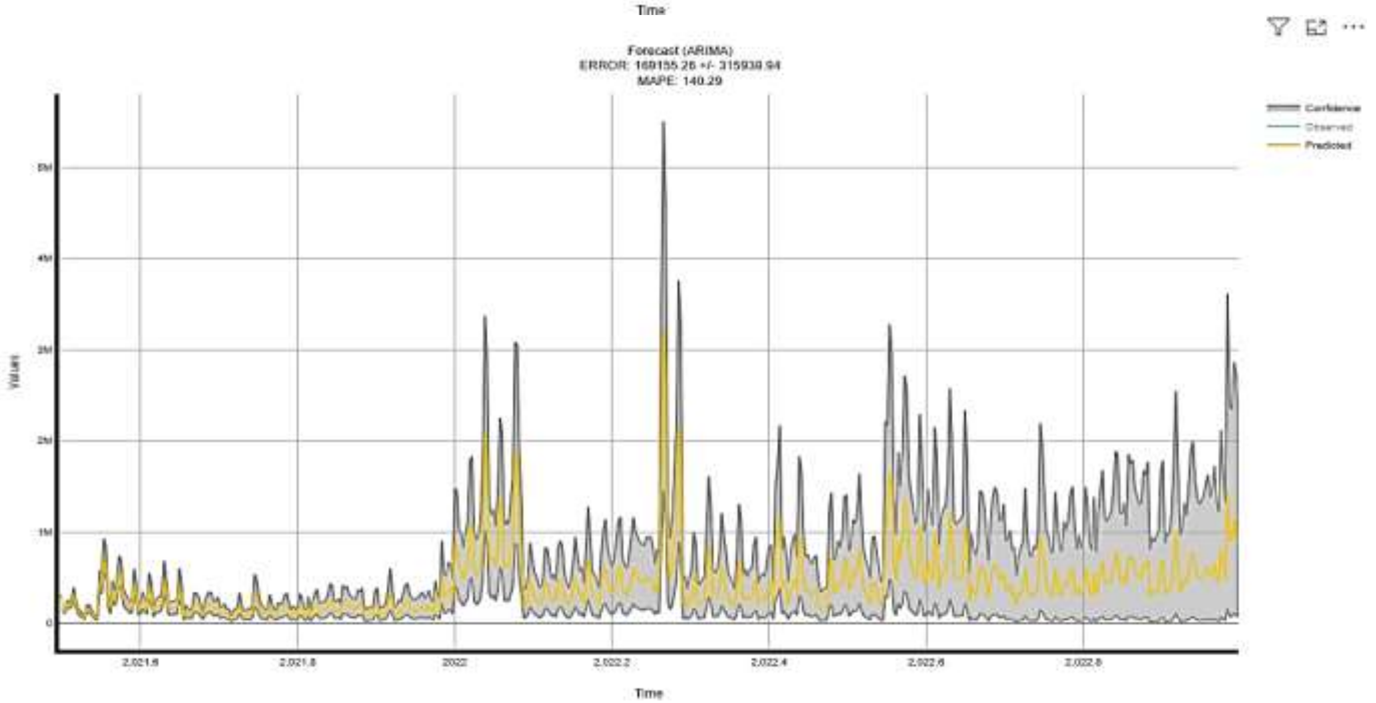
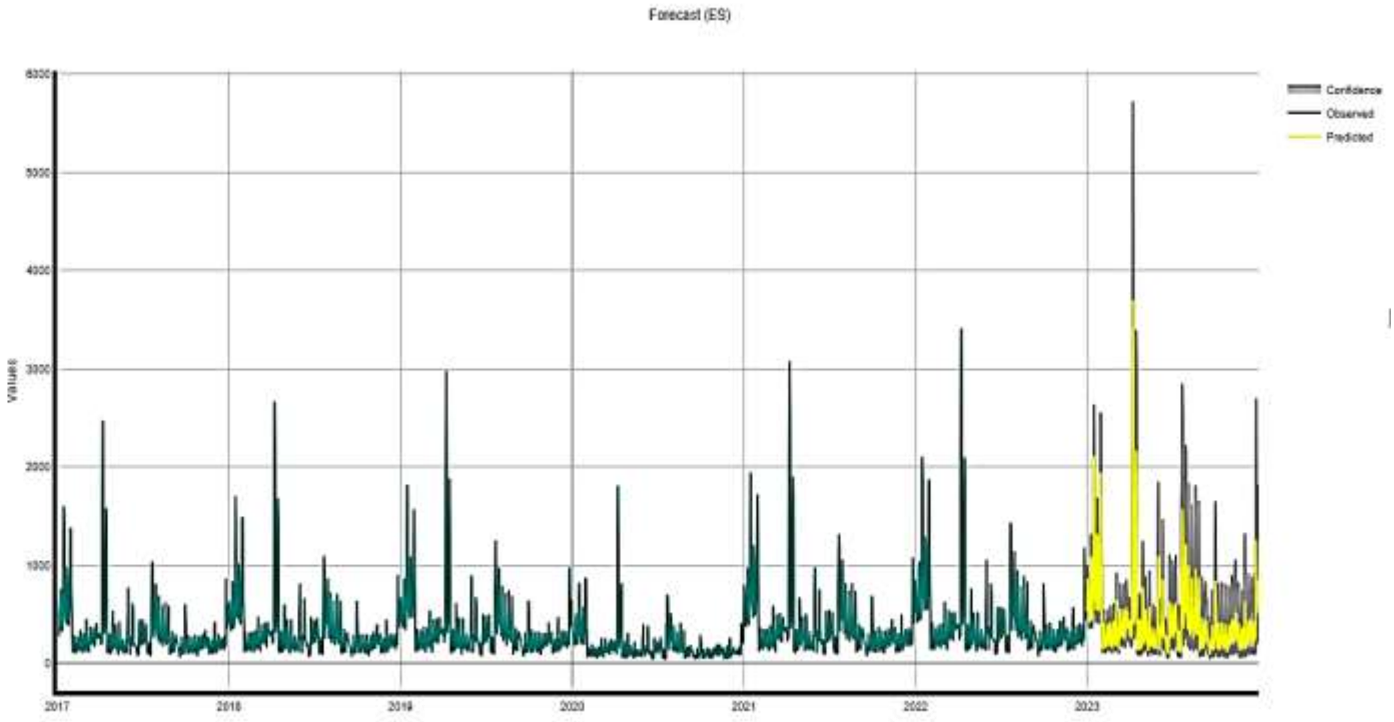
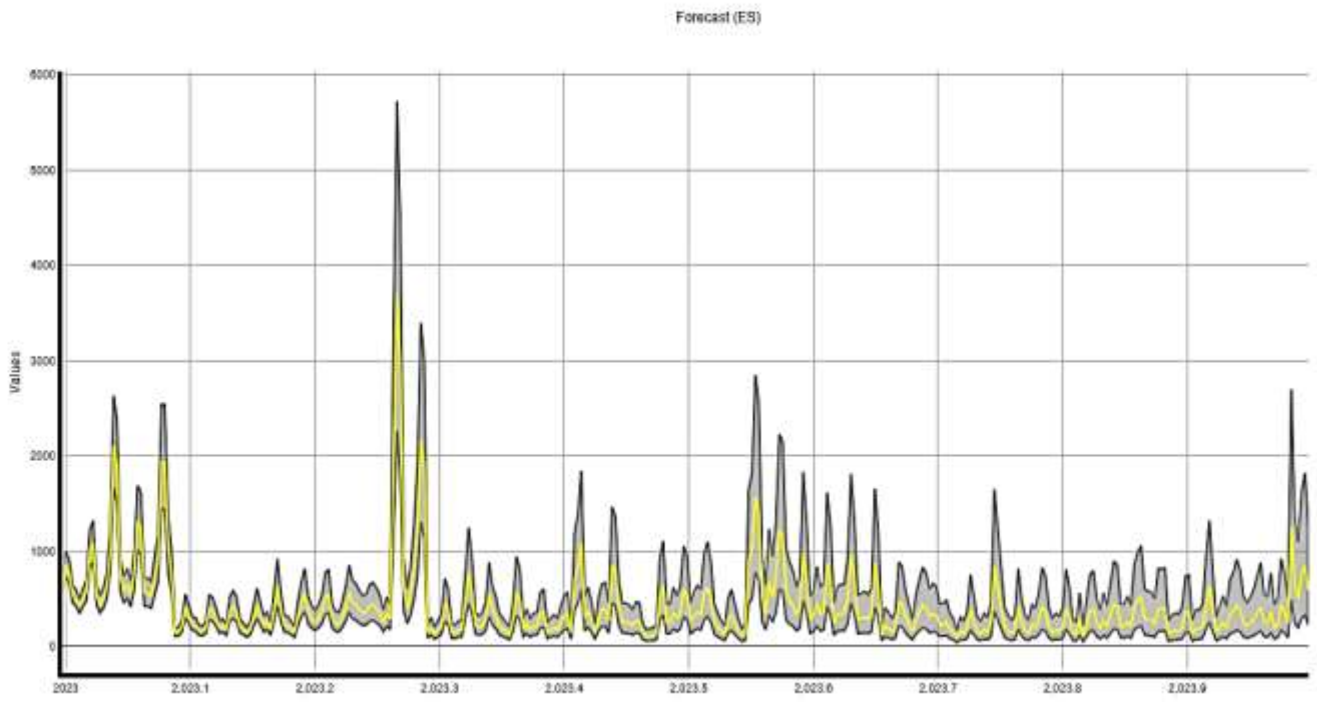
6.4 ARIMA





7. Generating Forecasts using Exponential Smoothing





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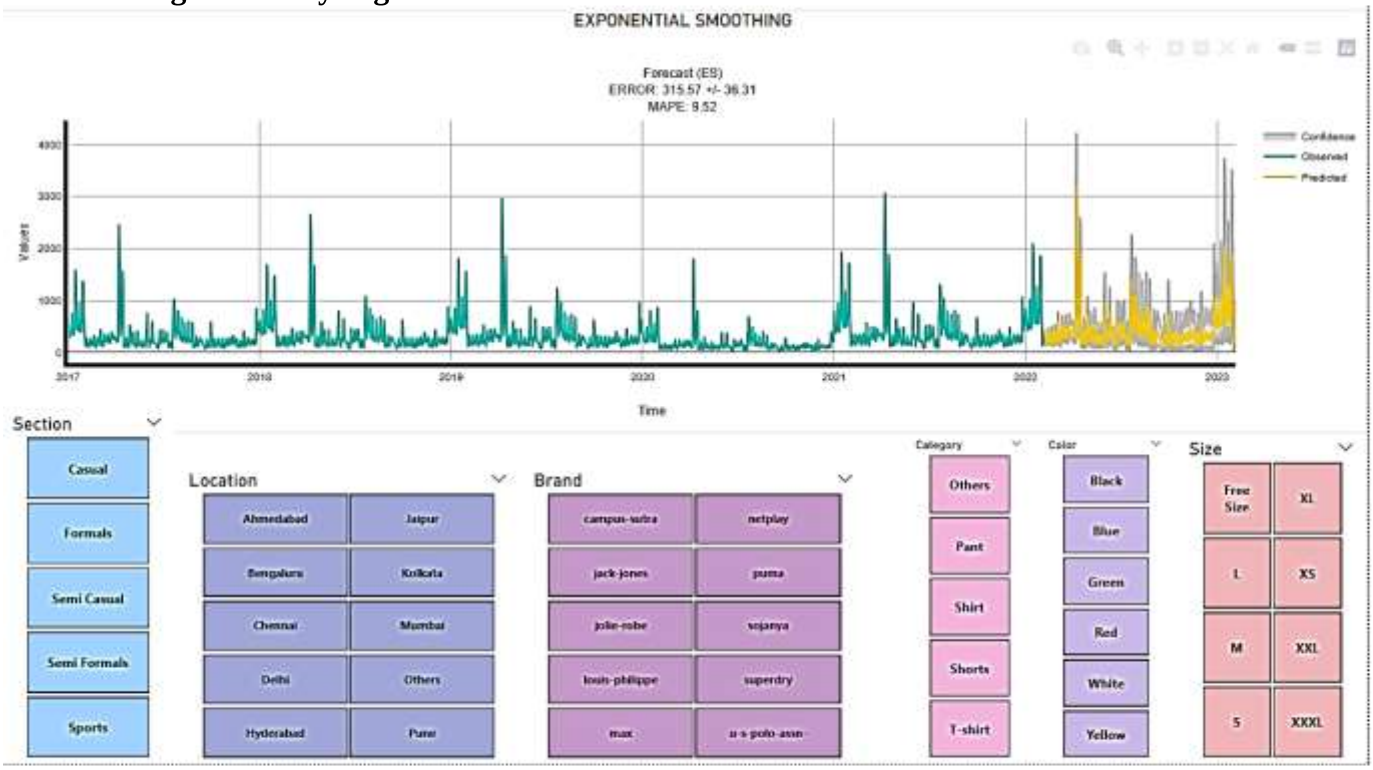
8. Visualizing and Analysing the Forecasts



9. Results and Conclusion

Based on the demand forecasting analysis of the XYZ transaction sales dataset using four different models (exponential smoothing, linear regression, neural network, and ARIMA), the following conclusions were drawn:

➢ Exponential Smoothing: The model achieved a MAPE (Mean Absolute Percentage Error) value of 5.29. It performed the best among all the models, demonstrating a high level of accuracy in predicting demand for XYZ transaction sales.

➢ Linear Regression: The model yielded a MAPE value of 24.83. indicating slightly less accuracy in demand forecasting.

➢ Neural Network: The model resulted a MAPE value of 32.87. indicating a lower level of accuracy in forecasting XYZ transaction sales demand.

➢ ARIMA: The model performed the least accurately among all the models, with a MAPE value of 140.29 suggesting that it may not be suitable for forecasting demand in the XYZ transaction sales dataset.

Based on the analysis, Exponential Smoothing was considered the best model for demand forecasting in the XYZ transaction sales dataset, as it achieved the lowest MAPE value. This model can be relied upon to provide more accurate predictions. Studying workflows and how the generated data behave over the product development life cycle is one of the issues faced by the industrial sector. Accordingly, the objective of this applied research is to create a demand and trend forecasting model for XYZ which focuses on Big Data and decision-making analysis.

Through this paper the demand and trend forecasting models as well as the existing business processes of the textile industry were studied using the current technology.

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