ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

# Automotive Kit Demand Forecasting Using Advanced Forecasting Models: A Data-Driven Approach for Optimal Demand Forecasting

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**Abstract:- This study addresses the major challenges of forecasting automotive kit items(parts of vehicles) by enhancing the delivery of the products and managing the inventory. The kit items vary as per customers and it is unique on its own, where the uniqueness determines the vehicle parts. Customers are the major role players who provide the business hence, this study highlights various factors contributing to the customer's choice of kit items with features consisting of vehicle name, original equipment manufacturer (OEM), Item Description (collection of vehicle parts) type of product (brand of vehicle) and monthly allotment of each kit item as per customer starting from 2021 April to 2024 January.**

**We conducted an extensive analysis to assess a range of time series analysis techniques for predicting kit demand within the automotive industry, the methods we investigated encompassed Autoregressive (AR), Autoregressive Moving Average (ARMA) ,Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Simple Exponential Smoothing (SES), Holt's Linear Trend Method - Double Exponential Smoothing, Triple Exponential Smoothing - Holt Winters, Long Short-Term Memory (LSTM) and advanced forecasting models such as prophet in evaluating the accuracy of these models, we employed key metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), this study aims to drive significant progress in the automotive industry by optimising inventory management reducing storage costs and improving delivery efficiency to ensure smooth business operations moreover the integration of visually engaging dashboards for real-time analysis of projected values plays a pivotal role in identifying crucial monthly demand trends this integration not only enhances operational efficiency but also fosters enriched customer engagement thereby facilitating sustained advancement within the automotive sector.**

***Keywords:-*** *Time Series Analysis, Demand Forecasting, Inventory Management, Deep Learning, Prophet, Supply Chain.*

## I. INTRODUCTION

Within the intensely manufacturers in competitive automobile industry must prioritise efficient handling of inventories and the majority in effective distribution of automotive kit items as a result of customer choices shift quickly as supply networks are increasing in complex forecasting predicting market trends and choosing a kit allocation have become critical challenges retaining profitability and providing outstanding client experiences need precise demand forecasts and clever allocation tactics.

This research paper focuses on developing a system to forecast the required availability of kit items, enabling effective stock management and ensuring a steady business flow in the automotive sector. The automotive industry is characterised by constant change, with a vast array of new items being continuously introduced. To capture this dynamic nature, a comprehensive dataset spanning from April 2021 to January 2024 has been analysed, providing insights into industry trends and requirements.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

An innovative intelligent system is proposed to revolutionise the automotive industry's approach to kit item allotment through the use of cutting-edge algorithms for machine learning and forecasting analytics, this platform grants producers an exceptional capacity to forecast future demand trends and enhance the distribution of kit items with unmatched precision. The proposed intelligent system follows the Cross Industry Standard Procedure for high-quality Machine Learning Assurance(CRISP-ML(Q)) methodology[11] which is publicly available on the 360 digitmg website[1] [Fig. 1]..

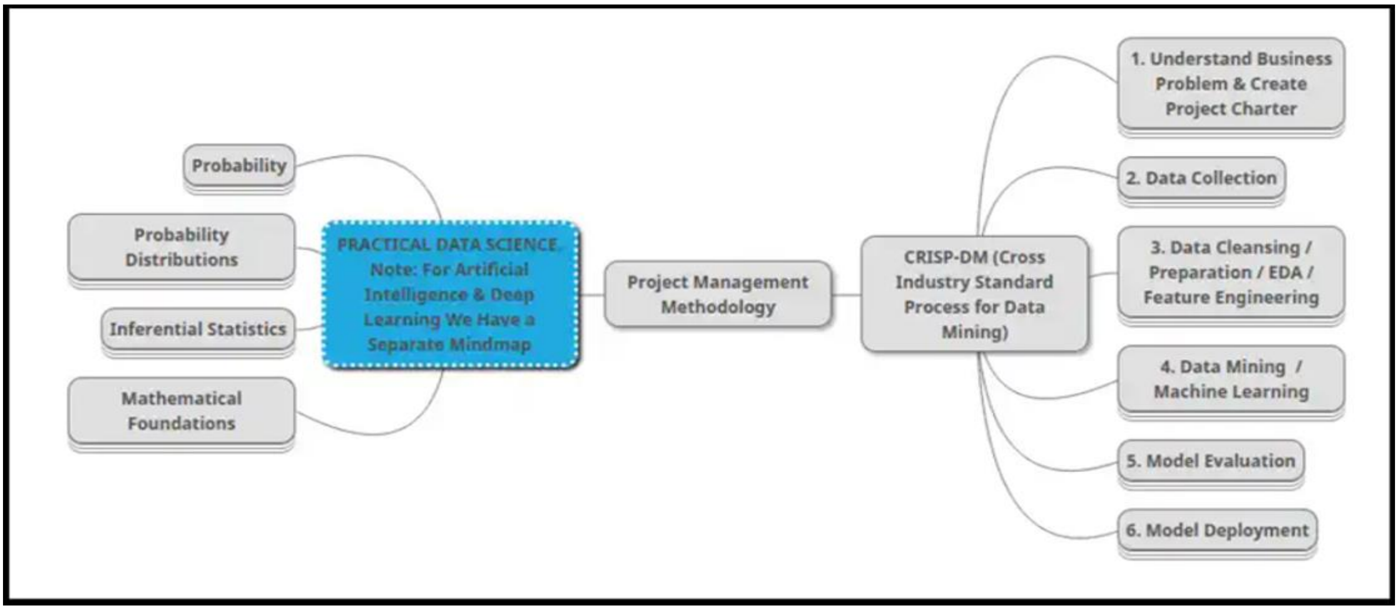


Fig 1 The CRISP-ML (Q) Methodological Framework.
(Source: Mind Map - 360digitmg)

This basic flow represents the consecutive phases in the ml workflow starting with collecting the data and inputs via multiple sources then data is wrangled before being go over feature engineering[13] entails identifying and developing appropriate characteristics for training the models which are then trained on factual data and tested for correctness the next stage is for these models to anticipate automotive kit asks based on each customer and forecast future allotments in the hope of to manage supply chain effectively.

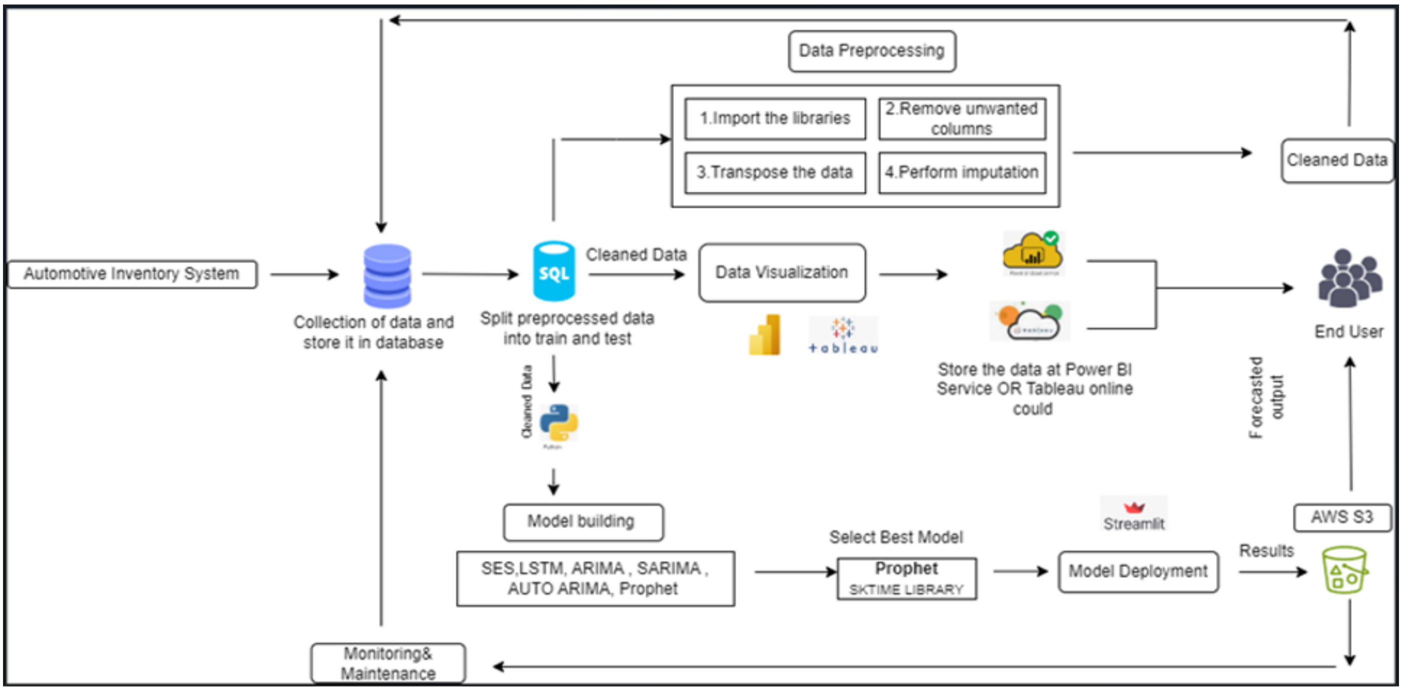


Fig 2 Architecture Diagram Showing the Flow of the Entire Project with Detailed Information
(Source: Https://360digitmg.Com/Ml-Workflow)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

The preceding figure represents the general architectural design workflow of the automotive kit industry beginning with the data getting collected from the clients SAP database then followed by splitting the entire dataset into test and train then perform the model building, later the cleaning of this dataset is done by applying various preprocessing techniques such as imputation techniques and removing irrelevant features finally the model is built on and deployed using the streamlit framework which can now be accessed from on cloud AWS instance. [Fig.2]

## II. METHODS AND METHODOLOGY

➢ *Data Collection*

The client furnished an Excel sheet extracted from their SAP system, as denoted in [Fig.2]. This Excel sheet encompasses kit allot data ranging from 1 April 2021 to 1 January 2024. The dataset comprises 306 rows and 42 columns, offering a comprehensive depiction of the allotment. This structured collection of data provides valuable insights into various allotments of each kit item, which is serving as the primary source for the analysis.

Table 1 Data Description of all the Features in the Dataset.

| SI. No | Descriptor | Description | Type | Units | Count | Unique Values | Missing Values |
|---|---|---|---|---|---|---|---|
| 1 | Customer Code | Customer ID | String | N/A | 306 | 76 | No |
| | Date | Transaction date | Date | DD/MM/YYYY | 306 | 34 | No |
| 2 | Customer Name | Name of the customer | String | N/A | 306 | 76 | No |
| 3 | KIT ITEM | Kits required for each customer | String | N/A | 306 | 292 | No |
| 4 | OEM | Original Manufacturer of kit | String | N/A | 306 | 95 | No |
| 5 | Item Description | Various part of kit | String | N/A | 306 | 254 | No |
| 6 | Product type | Type of product as per kit | String | N/A | 306 | 35 | No |
| 7 | Vehicle 1 | Brand name | String | N/A | 306 | 53 | No |
| 8 | QTY | • Presence of value indicates ongoing business<br>• Absence of value indicates no business | Integer | Pieces/Units | 306 | 97 | Yes |
| 9 | Total | Total allot of kits | Integer | Pieces/Units | 34 | 34 | No |

➢ *Data Preprocessing*

This research article emphasises the intricate relationships between automotive parts within each kit, the clients acquiring these kits, and the specific automotive models these kits are destined for. The dataset, covering transactions from April 2021 to January 2024, offered a comprehensive view into customer preferences and kit item utilisation. Each kit item consists of various automotive parts, tailored to meet the needs of specific automotive models. This customization is central to the analysis, emphasising the uniqueness of each kit. Customers have the flexibility to purchase between one to seven or eight distinct kit items, with each kit being unique to the buyer to ensure no overlap of kit usage among customers.

The data does not contain duplicates, instead multiple purchases from the same customer are observed, this allows us to focus on analysing customer preferences and the applicability of different kit items. For each kit, the dataset includes the Kit Number, providing a unique identifier for tracking and analysis. The Customer Code and Customer Name [Table 1] fields ensure that we accurately attribute kit items to the correct buyer, facilitating a deeper understanding of customer buying behaviours. Adding another layer to the analysis, the Product Type field indicates the kit's area of application within the automotive industry, offering insights into market demands and product distribution. The Item Description encompasses the various automotive parts included in the kit, shedding light on the composition and potential applications of each package.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

Significantly, the inclusion of Vehicle Information in the dataset allows us to link each kit item to specific vehicle models. This connection is crucial for tailoring the products to fulfil the exact requirements of the automobile sector and enhancing the understanding of which kit configurations are most sought after for different vehicle types.

We positioned ourselves to get important insights on the patterns of kit item purchases the variety of client preferences and the targeted uses of the items by carefully structuring the dataset this phase of preparing data was crucial in establishing the foundation for a thorough investigation of the market for automotive kit items emphasising the connections between kit compositions consumer preferences and automobile model specifications.

➢ *Exploratory Data Analysis*

A country's several states are represented in this dataset with the allocation of automobile kit components. The dataset reveals that certain customers manage multiple units across different locales. In the case of Original Equipment Manufacturers (OEMs), it's not uncommon to find a single OEM with operations at one or more locations, mirroring the pattern observed with customers who may have the same company name but operate in different areas. Each OEM is tasked with allocating the appropriate automotive kits.

Using Loess, a seasonal and trend decomposition analysis[3] was executed to examine the allotment patterns, which brought to light evident trends, seasonality, and residuals. This analysis confirmed the presence of clear seasonal fluctuations and variances[Fig.3, Fig.4] Below two plots represent seasonal decomposition[3] between two kits among the entire kits.

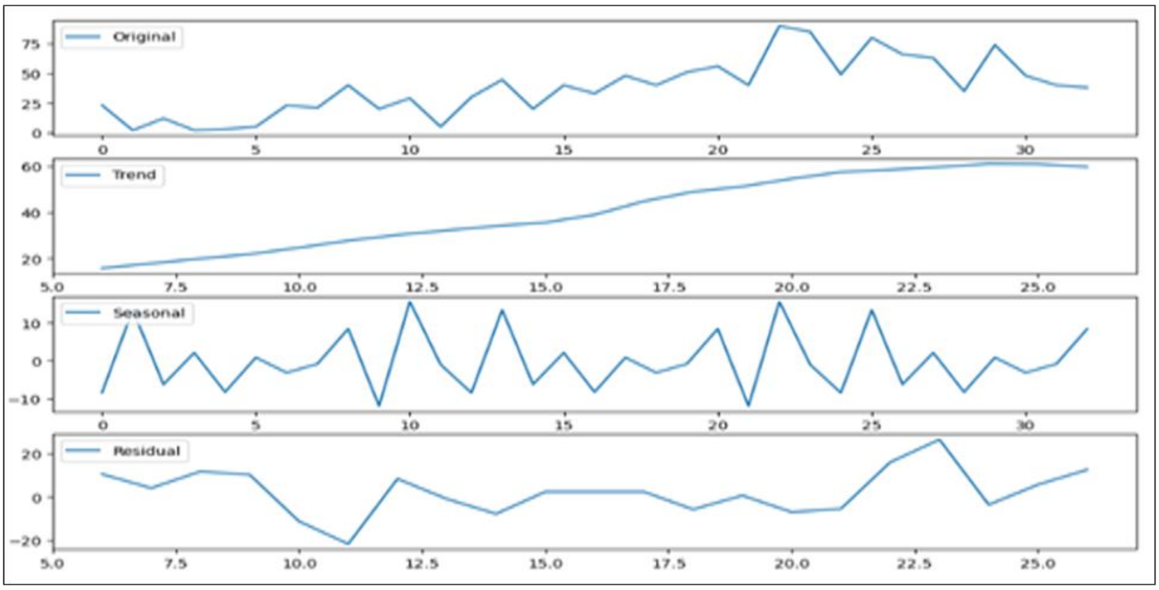


Fig 3 Trend, Seasonal, Residual Values Through (Seasonal and Trend Decomposition Using Loess) S T L [3] of KIT_35

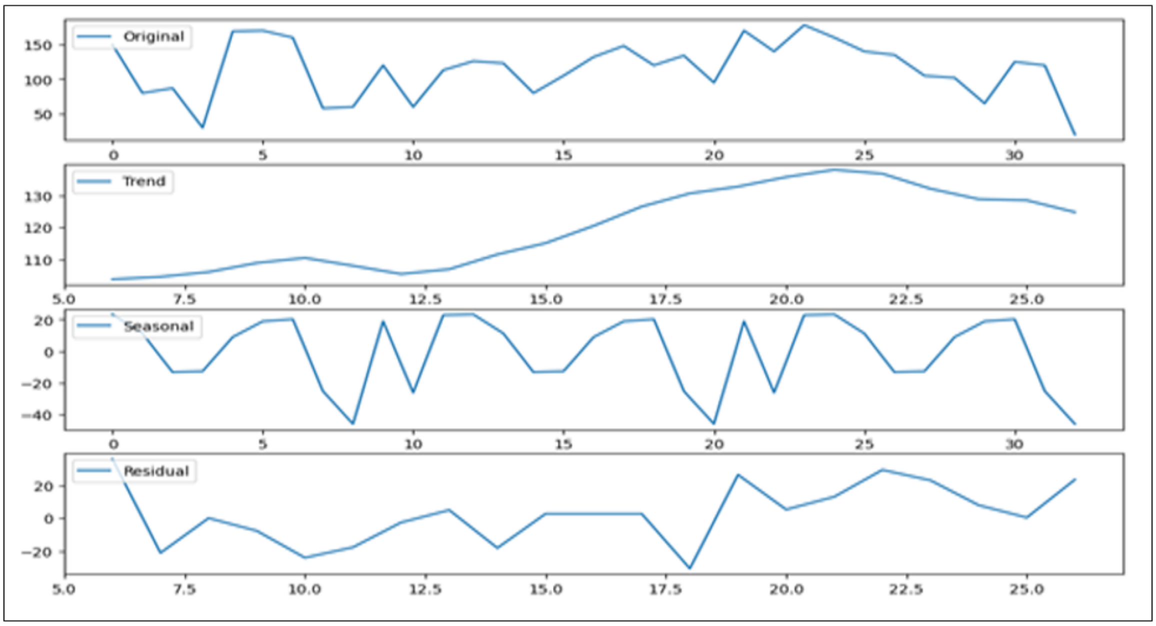


Fig 4 Trend, Seasonal, Residual Values Through (Seasonal and Trend Decomposition Using Loess) S T L[3] of KIT_06

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

To further scrutinise the dataset this study utilised a methodical approach to examine the characteristics of the automotive kit items dataset within the Python environment. By integrating the pandas library for data handling, with statsmodels and arch libraries for advanced statistical analysis, we executed a series of tests to discern the presence of Random Walk and Stationarity.

For random walk detection, our custom function check_random_walk evaluated each time using the Augmented Dickey-Fuller (ADF)[4], Variance Ratio (VR), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests[10]. The ADF test assessed the null hypothesis of a unit root indicative of a random walk, the VR tested for the variance of the series, and the KPSS test checked for stationarity around a deterministic trend. A series was considered to exhibit a random walk if all three tests aligned, factoring in a significance level (alpha) set to 0.05.

Table 2 Random Walk Check Using Check_Random_ Walk () Custom Method

| | KIT ITEM | Indicates Random Walk |
|---|---|---|
| 0 | KIT_01 | False |
| 1 | KIT_02 | False |
| 2 | KIT_03 | False |
| 3 | KIT_04 | False |
| 4 | KIT_05 | False |
| 5 | KIT_06 | False |
| 6 | KIT_07 | False |
| 7 | KIT_08 | False |
| 8 | KIT_09 | False |
| 9 | KIT_10 | False |
| 10 | KIT_11 | False |
| 11 | KIT_12 | False |
| 12 | KIT_13 | False |
| 13 | KIT_14 | False |
| 14 | KIT_15 | False |

To comprehensively evaluate the stationary behaviour of the dataset we employed a multi-faceted analytical strategy we utilised a specialised function named check stationarity to systematically apply the augmented dickey-fuller, kwiatkowski-phillips-schmidt-shin, and phillips-perron statistical tests while adf and pp tests shared the same null hypothesis. The kpss test was predicated on the assumption of stationarity to ensure a robust consensus on the stationarity characteristics of the dataset we required agreement across all three tests with their corresponding p-values serving as the decisive metric the results from these comprehensive tests were meticulously compiled into organised data frames providing a clear and thorough indication of whether each individual series within the dataset displayed characteristics of a random walk table[Table.2] or stationary behaviour[Table.3] this dual-pronged proceed towards involving both rigorous stationary behaviour tests and structured data frame compilation was a critical component of our analytical strategy it enabled us to thoroughly validate the underlying assumptions of our models ensuring a solid foundation for our subsequent analysis and forecasting efforts.

Table 3 Stationary Check Using Check Stationarity () Custom Method

| | Column | ADF P-Value | KPSS P-Value | PP P-Value | Is Stationary? |
|---|---|---|---|---|---|
| 0 | KIT_01 | 3.640592e-03 | 0.100000 | 5.533406e-03 | True |
| 1 | KIT_02 | 3.804515e-03 | 0.100000 | 1.979874e-03 | True |
| 2 | KIT_03 | 9.067878e-03 | 0.100000 | 4.692767e-03 | True |
| 3 | KIT_04 | 7.979786e-01 | 0.010000 | 4.913388e-02 | False |
| 4 | KIT_05 | 8.015911e-03 | 0.014526 | 1.694666e-03 | False |
| 5 | KIT_06 | 5.995047e-01 | 0.016820 | 3.592443e-05 | False |
| 6 | KIT_07 | 2.679413e-03 | 0.041597 | 3.373645e-04 | False |
| 7 | KIT_08 | 2.545830e-01 | 0.100000 | 1.866563e-05 | False |
| 8 | KIT_09 | 2.582832e-01 | 0.025454 | 7.098626e-04 | False |
| 9 | KIT_10 | 2.982905e-01 | 0.053156 | 4.039502e-06 | False |
| 10 | KIT_11 | 1.543179e-01 | 0.090062 | 1.134009e-04 | False |
| 11 | KIT_12 | 1.715137e-02 | 0.100000 | 3.756857e-02 | True |
| 12 | KIT_13 | 1.189276e-01 | 0.067324 | 1.179446e-01 | False |
| 13 | KIT_14 | 1.549395e-02 | 0.100000 | 2.291284e-02 | True |
| 14 | KIT_15 | 2.074462e-01 | 0.100000 | 8.147432e-06 | False |

The procedure also involved pinpointing anomalies within the data however due to relatively small data size comprising only 34 data points the decision was made not to remove these outliers eliminating them could adversely impact the dependability and precision of the projections made later.

➢ *Feature Engineering*

From a feature engineering perspective ,the importance of kit items is matched by the significance of customer relationships, as the continuity of business varies greatly. This dataset, which is pivotal for insights , contained 307 initial records of customer transactions, on which 292 were of unique and it included newly onboarded clients and longer-term partners.

Given the cyclical and sometimes short-term nature of the engagements—ranging from three to six months–our approach to forecasting necessitated the exclusion of customers with less than nine months of activity, post-April 2021. This exclusion criterion was vital as it allowed us to focus on stable, historical patterns that lend themselves to more accurate predictive analysis.The monthly data, which naturally reflects the transactional patterns within the industry, posed challenges when extrapolating it to an annual scale. This difficulty stemmed from the unique timing of business operations within the industry.

After applying our defined criteria to refine the dataset, we narrowed down the information to encompass 97 kit items for 54 customers, specifically targeting those who consistently engage on a monthly basis. The distribution volumes for these kit items revealed significant variation, reflecting the diverse needs for various parts and configurations of kits.

In dealing with automotive datasets, a frequent issue encountered is the occurrence of absent data, particularly in continuous sequences. To tackle this problem, we adopted a strategy known as mean imputation. This approach was

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

selected over alternative interpolation techniques due to its greater appropriateness for automotive datasets, where gaps in data are likely to appear as contiguous segments [14].

The presence of entire data points is instrumental in signifying active business periods while their absence marks intervals without transactions by meticulously refining our dataset and employing strategic feature engineering[13] practices we established a solid foundation for robust and reliable forecasting within the automotive kit item sector a domain where precision and foresight are invaluable.

- *Model Building*

This study harnessed the capabilities of the sktime library's [5] implementation of the Prophet forecasting model. sktime's Prophet feature integrates a range of intuitive functionalities designed to handle the unique challenges of time series data. It excels in capturing seasonality patterns and events that could influence allot trends. Moreover, it allows for adding custom seasonality to account for external variables.The decision to utilise the Prophet model in sktime uses a forecasting horizon logic[5] which has to be set with is_relative=False parameter to forecast the allot demand of the kit.

After experimenting with an array of advanced models, such as Auto-Regressor (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA)[1], auto_arima, Simple Exponential Smoothing(SES)[8], Double Exponential Smoothing, Holt-Winters, and Long Short-Term Memory Networks(LSTM)[2], all of which are renowned for their effectiveness in time series forecasting, they consistently generated negative forecasts for the specific dataset under examination. In contrast, the Prophet model yielded forecasts that aligned more closely with the actual allot trends observed in the automotive kit item sector.

- *Model Chosen*

Initially numerous models were tested with appropriate data preprocessing at first AutoRegressive model was performed to determine the correlation between past time periods, later Moving Average was performed to identify the noise fluctuation present in the dataset, later ARIMA was built based on the (P,D,Q)[10] results, where P is AutoRegressive term(AR), D is Differencing value , Q is Moving Average value(MA) got through the observation of ACF and PACF [9]plots , though ARIMA model gave some what good prediction , the negative forecast was prevalent. Then SARIMA was conducted to compare the seasonality along side the original dataset where only few kit items out of 97 were giving results and same negative forecast impact was present.Since Smoothing, Holts model and Holts Winter model gave prediction results near but the MAPE score was not accurate and over the period of forecast the values are changing and upper and lower bound values had negative results. After conducting many tests the sktime library had a Prophet model with additional features like grown_cap, growth_floor which was very useful in capping the negative values. Hence we resorted to the Prophet model.

When deploying the prophet model[3] within our automotive kit item allot analysis we carefully considered the hyper-parameters that would reflect the time series data characteristics. Prophet offers a range of hyper-parameters that can be fine-tuned to optimise the model's execution for particular forecasting tasks. For our automobile dataset we recognized the importance of yearly seasonality due to the industry's annual cycles were no consistent pattern is followed and the company requires the allotment of automobile kits with different range of quantity even though the weekly and daily seasonality is not contributing much, we enabled yearly seasonality while setting weekly and daily seasonality to ‘auto’[5] allowing the model to determine the relevance of these frequencies based on the data this decision acknowledges that while daily and weekly patterns might not be as pronounced or consistent in the automobile industry they could still play a function in the overall allot trends hence these hyper-parameters was executed with the intention of creating a model that can effectively interpret an automotive allot data taking into account the two of them industries cyclic patterns and potential irregularities the fine-tuning process strived to strike a balance between model responsiveness and stability, ensuring precise and trustworthy forecasts that can be used to inform business plans for the automobile industry.

- *Hyper Parameter (Fine Tuning)*

Sktime library provides a comprehensive strategy for automotive kits to fine tune the model based on solely focusing on fine-tuning parameters specific to the seasonal pattern including kit seasonality and trend enables us to optimise our forecasting model this meticulous adjustment process allows us to better capture and interpret the cyclical variations in demand for the kits code below shows the parameter tuning applied for one kit item as the kits are both seasonal and non seasonal the below parameter varies

(freq=’MS’, add_seasonality=None, add_country holidays= None, growth='linear', growth_floor=0, growth_ cap=8000, changepoints=None, yearly_seasonality=True, weekly_seasonality='auto', daily_seasonality='auto', holidays =None, seasonality_mode='additive')[5]

By applying the above fine tuning along with the forecasting horizon given by the sktime which is available under zktime forecasting base class the effective allotment of the automotive vehicle parts kits are predicted along with 95 percent confidence and 85% accuracy.

- *Model Fitting*

Once the prototype is fitted to the spotless and processed data it produces projections for the next half-year along with accompanying 95% confidence intervals[9] these confidence intervals quantify the uncertainty associated the projections allowing interested parties to create informed decisions and plan accordingly within the automotive kit items the confidence interval is aligned within the prophet model itself.To evaluate the accuracy of the forecasts the research employs the MAPE metric rather than RMSE where both are taken but accuracy of the forecast was considered only on MAPE[7]

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} 100\left(\frac{|y_i - \hat{y}_i|}{y_i}\right)$$

A typical statistic called MAPE determines the absolute mean deviation in between the entries that are anticipated and the real entries indicated as a percent of the real entries. This measurement gives an intuitive comprehension of the performance of the forecasts allowing for comparisons across distinct time periods or product categories. By leveraging the prophet prototypes robust predicting capabilities and evaluating the precision through MAPE the scholarly article equips businesses along with valuable perceptions of the future demand for automobiles kit items.

- *Model Deployment*

Initially the model was implemented using the streamlit framework which facilitated rapid prototyping and easy testing of its performance this agile approach allowed the team to validate the model swiftly before proceeding to the next phase after refining and validating the model it was deployed off-premises on an aws cloud instance this shift to cloud deployment offered enhanced scalability and security enabling the model to handle larger datasets and user traffic moreover it simplified customer access to future predictions through the cloud infrastructure.

- *Software and Tools*

In this study the python language was utilised for data cleaning and data preprocessing as well as for selecting and deploying the model the packages employed included pandas and matplotlib for visualising the demand for automotive parts seaborn an advanced visualisation tool was also used to identify outlier anomalies the arch package was used to detect variance influence while statsmodels aided in checking for stationarity using the autocorrelation function acf and partial autocorrelation function pacf the kwiatkowski-phillips-schmidt-shin kpss kpss and augmented dickey-fuller adf tests were conducted additionally smoothing models and holts winter method were employed to construct the model the sktime library was utilised for forecasting using the prophet approach which requires python version 38 or higher furthermore the all extras package necessary for avoiding dependency issues was installed in the anaconda environment via pip install time-all extras.

The Prophet (sktime) model[3, 6], which demonstrated approximately 85% accuracy for most of the kits during the model development phase, was deployed on AWS for practical forecasting. The deployment[11] covered a 6-month horizon, forecasting from Feb 2024 to Jul 2024. By leveraging AWS, we ensured that the model could efficiently handle the forecasting workload, making real-time or batch predictions as needed.

Finally, they can push the refined data into the sktime Library for a 6-month forecast . List of library versions we used in this research articles are as follows, Streamlit (1.29.0), SKTIME( 0.26.0), ,Matplotlib (3.7.2), seaborn,( 0.13.2) ,streamlit( 1.31.1), arch( 6.3.0), pmdarima(2.0.4), Pandas (2.0.3),keras(3.0.4).

## III. RESULTS AND DISCUSSION

Table 4 Accuracy of Prophet Model for Customer_68 and Customer_35 with Kit Item KIT_56 and KIT_24 [12]

| Customer Name | KIT ITEM | Model | Train_MAPE | Test_MAPE |
|---|---|---|---|---|
| Customer_35 | KIT_24 | ARIMA | 28.55236438 | 14.41112643 |
| Customer_35 | KIT_24 | LSTM | 36.54809475 | 21.11443346 |
| Customer_35 | KIT_24 | Prophet(SKTIME) | 6.386150828 | 21.45862378 |
| Customer_35 | KIT_24 | AUTO ARIMA | 28.07309768 | 13.46851718 |
| Customer_35 | KIT_24 | Exponential Smoothing (additive) | 25.27997229 | 8.587870927 |
| Customer_35 | KIT_24 | Exponential Smoothing(multiplicative) | 27.51364276 | 8.070846965 |
| Customer_35 | KIT_24 | Exponential Smoothing(Additive_Damped) | 26.57126012 | 8.286806225 |
| Customer_35 | KIT_24 | Exponential Smoothing(Multiplicative_Damped) | 27.53912621 | 8.746633093 |
| Customer_68 | KIT_56 | ARIMA | 16.38890851 | 14.81065636 |
| Customer_68 | KIT_56 | LSTM | 20.11378984 | 16.90795389 |
| Customer_68 | KIT_56 | Prophet(SKTIME) | 7.077416715 | 22.2850002 |
| Customer_68 | KIT_56 | AUTO ARIMA | 16.41133429 | 15.30287829 |
| Customer_68 | KIT_56 | Exponential Smoothing (additive) | 10.13459986 | 8.917048576 |
| Customer_68 | KIT_56 | Exponential Smoothing(multiplicative) | 10.03834094 | 8.470161423 |
| Customer_68 | KIT_56 | Exponential Smoothing(Additive_Damped) | 10.17675761 | 9.171870236 |
| Customer_68 | KIT_56 | Exponential Smoothing(Multiplicative_Damped) | 10.07683366 | 8.661917181 |

The table [Table.4] beyond depicts different models and the corresponding MAPE score for the full training entries is taken here it is clearly visible that the prophet model is giving good results and that was chosen as the primary strategy which was taken from sktime[6] library later the model was meticulously configured with a collection of hyper-parameters tailored on to the specific characteristics of the automotive demand data.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939

Remarkably the model attained an 85 precision rate which is an important achievement considering the intricate and dynamic nature the correctness of the models for the automobile industry a single kit item among the 97 things along along with its good precision and MAPE score is depicted in the diagram below

This exceptional level of precision exceeded as well as fulfilled the stringent business criteria set by stakeholders highlighting the models robustness and its capability to capture the nuances and complexities inherent in automotive demand patterns one outstanding characteristic of the prototype is its flexibility and expandability .Along with the availability of new data it seamlessly integrates into the existing dataset enabling continuous learning and refinement of its forecasting capabilities. This recursive procedure guarantees the model's continuous applicability and precision even when market circumstances and customer preferences alter.

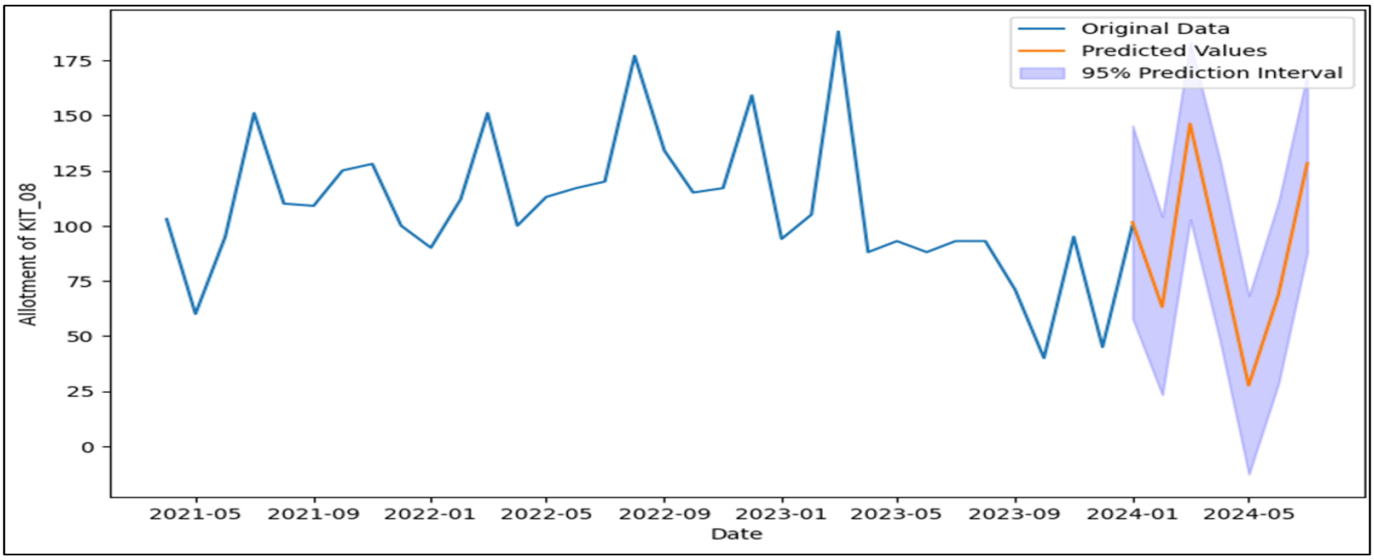

Fig 5 Automotive Demand Forecasting of KIT_56 for Customer_68 with Accurate Prediction [7, 9]

Additionally, due to the models integration with sophisticated data visualisation technologies the prediction process now heavily relies on visual aids. This makes it possible for stakeholders to make data-driven choices confidently gaining a thorough understanding of the predicted demand through interactive and user-friendly dashboards. Besides enhancing user engagement this visual representation facilitates a deeper understanding of the numerous intricacies inherent in the automotive industry.

The outcomes of this study have paved the way for the automotive sector to embrace an innovative approach to demand planning. The model serves as a valuable tool for companies aiming to enhance client contentment, streamline stock management and improve operational efficiency. Its capacity in order to produce precise projections and evolve continuously makes its a great option for companies looking for reliable prediction methods.

## IV. CONCLUSION

This study investigates how demand for automotive parts fluctuates in a dynamic supply chain environment it proposes a novel approach that combines CRISP_ML(Q) methodology with advanced forecasting techniques to conduct exploratory data analysis the approach involves designing data pre-processing models that align with traditional automotive principles the goal is to summarise strategies that can be optimise inventory levels through improved the supply chain management this includes a real-time monitoring using cloud platforms like AWS to address demand variations in the pallet manufacturing industry the emphasis on data quality throughout this comprehensive strategy aims to build a robust and adaptable supply chain ultimately ensuring greater profitability and long-term growth for clients

## REFERENCES

[1]. JOHN A. MILLER, MOHAMMED ALDOSARI, FARAH SAEED, NASID HABIB BARNA, SUBAS RANA, I. BUDAK ARPINAR, and NINGHAO LIU A Survey of Deep Learning and Foundation Models for Time Series Forecasting https://arxiv.org/abs/2401.13912
[2]. P.E. Naill M. Momani King Abdul Aziz University, Jeddah, Kingdom of Saudi Arabia, Financial Time Series Forecasting with the Deep Learning Ensemble Model https://www.mdpi.com/2227-7390/11/4/1054
[3]. Serdar Arslan Computer Engineering Department, Cankaya University, Ankara, Turkey A hybrid forecasting model using LSTM and Prophet for energy consumption with decomposition of time series data https://peerj.com/articles/cs-1001/
[4]. Yun Yang1 & ChongJun Fan1 & HongLin Xiong1 A novel general-purpose hybrid model for time series forecasting, https://link.springer.com/article/10.1007/s10489-021-02442-y

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1939


[5]. Vinay Kumar Reddy Chimmula∗ , Lei Zhang Faculty of Engineering and Applied Science, University of Regina, Regina, Saskatchewan, S4S0A2 Canada Time series forecasting of COVID-19 transmission in Canada using LSTM networks https://www.sciencedirect.com/science/article/pii/S0960077920302642

[6]. Löning, M., & Király, F. (2020). Forecasting with sktime: Designing sktime's new forecasting api and applying it to replicate and extend the m4 study. arXiv preprint arXiv:2005.08067.

[7]. Christophorus Beneditto Aditya Satrio, William Darmawan, Bellatasya Unrica Nadia, Novita Hanafiah, Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET, Procedia Computer Science, Volume 179, 2021, Pages 524-532, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2021.01.036.

[8]. Emir Žunić1,2, Kemal Korjenić1 , Kerim Hodžić2,1 and Dženana Đonko2 1 Info Studio d.o.o. Sarajevo, Bosnia and Herzegovina 2Faculty of Electrical Engineering, University of Sarajevo, Bosnia and Herzegovina APPLICATION OF FACEBOOK'S PROPHET ALGORITHM FOR SUCCESSFUL SALES FORECASTING BASED ON REAL-WORLD DATA https://arxiv.org/abs/2005.07575

[9]. Sourabh Shastri1 , Amardeep Sharma2 , Vibhakar Mansotra3 , Anand Sharma4 , Arun Singh Bhadwal5 , Monika Kumari6, A Study on Exponential Smoothing Method for Forecasting https://www.researchgate.net/profile/Sourabh-Shastri/publication/325814694_A_Study_on_Exponential_Smoothing_Method_for_Forecasting/links/5b509b450f7e9b240ff05579/A-Study-on-Exponential-Smoothing-Method-for-Forecasting.pdf

[10]. Jamal Fattah1 , Latifa Ezzine1 , Zineb Aman2 , Haj El Moussami2 , and Abdeslam Lachhab1 Forecasting of demand using ARIMA model https://journals.sagepub.com/doi/pdf/10.1177/1847979018808673

[11]. Caryl Vivien C. Capiral, Ruth Jane T. Lotrinia, Romie C. Mabborang, Josephine R. Macasieb , Cracking the Code of Crop Growth: Illuminating the Future of Philippines' Onion Production for a Resilient Filipino Diet with the ARMA ForecastingModel,https://eajournals.org/ejcsit/wp-content/uploads/sites/21/2023/06/Cracking-the-Code.pdf

[12]. Stefan Studer 1,* , Thanh Binh Bui 2,*, Christian Drescher 1 , Alexander Hanuschkin 1,3 , Ludwig Winkler 2 , Steven Peters 1 and Klaus-Robert Müller 2,4,5,6 ,Towards CRISP-ML(Q): A Machine Learning Process Model with Quality Assurance , Methodology, https://www.mdpi.com/2504-4990/3/2/20

[13]. Lorenzo Menculini 1,* , Andrea Marini 1, Massimiliano Proietti 1, Alberto Garinei 1,2, Alessio Bozza 3, Cecilia Moretti 4 and Marcello Marconi 1,2 , Comparing Prophet and Deep Learning to ARIMA in Forecasting Wholesale Food Prices https://www.mdpi.com/2571-9394/3/3/40.

[14]. Irfan Pratama1, Adhistya Erna Permanasari2, Igi Ardiyanto3, Rini Indrayani4, A review of missing values handling methods on time-series data,https://www.researchgate.net/publication/313867740_A_review_of_missing_values_handling_methods_on_time-series_data