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Demand Forecasting for Inventory Optimization

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Abstract: - Any supply chain management must control manufacturing, storage, transportation, sales, and services in a way to meet all business demands within time. An optimum goal is to produce and store just enough to meet current needs with certain par reserves. With adequate data, we can forecast consumer behavior and demands for a specific product or service. With the help of time series analysis, we can recognize patterns and check for any correlation between storage and consumption. It incorporates seasonal fluctuations, consumer habits, and trends. Thus, if modeled adequately, it can predict future behavior from the correlation observed and thus help find its causation, which will help management teams avoid excess stockings and reduce capital investment on standing assets and reserves.

I. INTRODUCTION

1.1 Overview

Forecasting the inventory supplies and probable future demands is a necessary part of efficiently managing stocks and capital. In this competitive ecosystem, the philosophy of just-in-time manufacturing and deliveries is crucial.

This not only helps customers get products on time, saves in wasteful stocking, and saves capital to invest in areas that could be more beneficial.

Thus, an inventory management system can be deemed useful if it could generate insights to properly estimate the demands from current trends. If we could model the generation of results within a particular tolerance band. It will lead to effectively managing supplies and thus keep the system running at optimal operational efficiency also raising confidence in clients. Day by day the use of ML algorithms[14-22] in the different applications are being applied scrupulously.

1.2 Problem Definition and Objectives

1.2.1 Problem Definition

To build an end-to-end product for demand forecasting for inventory optimization with Time series forecasting model at its core, along with user interface, database, file connectors, and various charting options and to determine a suitable buying function (what, when, and how much to buy at a given point of time using a machine learning engine.)

1.2.2 Objectives

1. Demand Forecasting
2. Inventory Optimization
3. Budget Optimization

1.3 Methodologies of Problem Solving

- Effective analysis of the various components of time-series data of sales of the product.
- Use different machine learning and statistical algorithms to build a model capable of predicting demands as desired.
- Provide accuracy of the built models for the desired product.
- Allow the user to choose a suitable model according to requirements.

II. SPECIFICATIONS

2.1 Assumptions

The outcome of the research carried by the Machine Learning Engine will be used for service personalization of corporate firms.

Access to the required datasets of stocks and sales of the firm will be provided timely.

Necessary software and hardware requirements would be met on time as per the requirements of the business.

2.2 Dependencies

Dataset access

Access to the dataset of the firm should be available for proper analysis and predictions based on time-series analysis. The datasets are also required for the verification of the predictions made.

Table1: Data access

Data	Type	Feature
Sales Data	Sales History	Demand Forecasting and Planning; unit-based analysis
	Prices of products	Revenue Forecasting
	Revenue History	Revenue Generation Analysis
Inventory data	Basic Information	Stock out and overstock analysis
	In transition Information	Inventory Planning
	Pending Orders	Inventory Optimization
Locations	Locations	Demand Forecasting by location
	Channels	Demand Forecasting by channel
Bill of Materials	Cost incurred for Material	Material Requirements Planning
Product Shelf Life	Life Span of products	Inventory Optimization in accordance with shelf life of products

2.3 Functional Requirements

2.3.1 Determining the most profitable products

The most profitable products are determined using time series analysis on the given sales dataset. The various factors considered are the time required for manufacturing the product, investment amounts, and corresponding returns.

2.3.2 Maximize the ROI of inventory investments

The system should help the user to buy the most profitable products within the given fixed budget and help increase margins and sales. The replenishments are planned with multi-scenario simulation and predict the achievable ROI with the next purchasing budget.

2.3.3 Estimate future sales of the products

A solution based on Machine learning to forecast and predict the accurate demand is developed to derive business growth with better estimates of future sales.

2.3.4 Optimizing the stocks

The timing makes the difference when it comes to managing the firm's inventory. Real-time purchase order suggestions enable managers to prevent lost sales and make the customers happy. It tells the quantity of the stock needed by the firm at any point in time.

2.3.5 Making intelligent business decisions

The system helps the firm improve stock availability and raise service levels by reducing inventory costs and freeing up capital locked by excess stock. It also involves identifying items in overstock and estimating the stockout risk. The demands of customers are eventually met with lower inventory investments.

2.4 System Requirements

2.4.1 Software Requirements

1. Operating System: Linux Ubuntu 16.04
2. Programming Language: Python (3+)
3. Machine Learning/ Deep Learning libraries: sklearn, NumPy, pandas, etc.
4. IDE: Jupyter Notebook/ Sublime Text
5. SQLite Server (For system administrator only)
6. Application Server: Flask
7. Analytic toolkit: bokeh, matplotlib.

2.4.2 Hardware Requirements

1. Processor: Intel Core i5
2. HDD: 100 GB
3.RAM: 8 GB

III. SYSTEM DESIGN

3.1 System Architecture

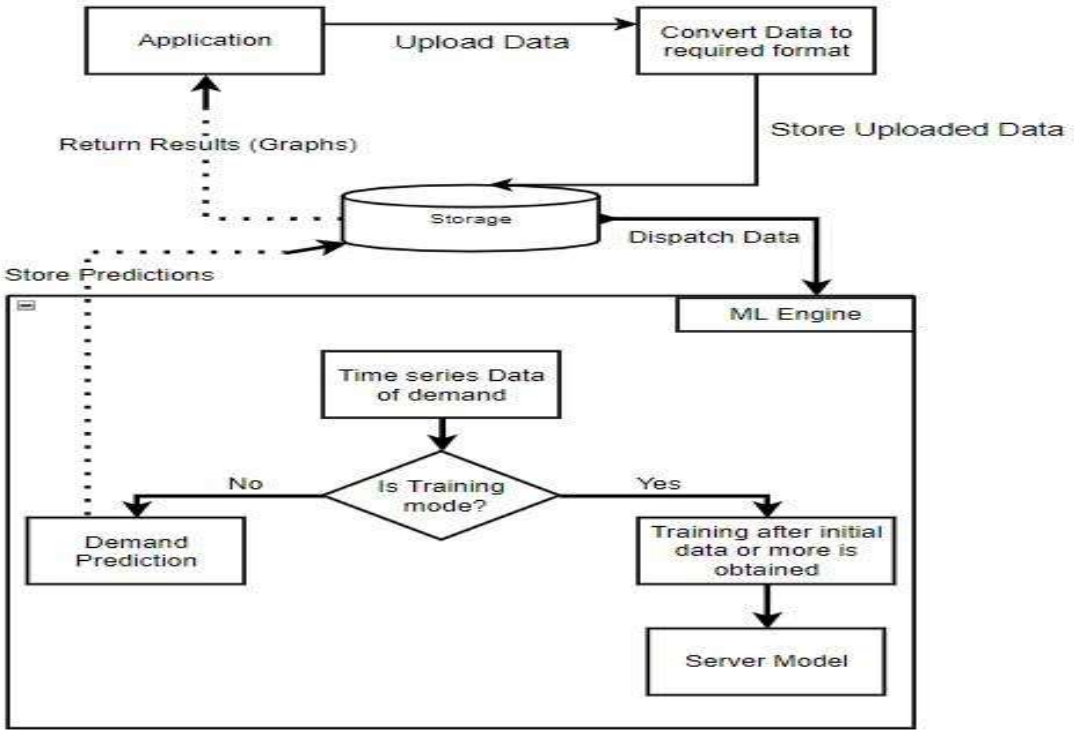

Figure 3.1: System Architecture

3.2 Time-Series Analysis

Definition of Time Series: Time Series Analysis [5][6][9] is composed of methods and tools for analyzing sequential time-based datasets which mine meaningful and valuable characteristics of underline data. Time series forecasting is achieved by modeling the data to render future probabilities. Actively used non-stationary data like economics, weather, stock price, and retail sales.

Two main goals of time series analysis are as follows-

1. identifying the nature of the phenomenon represented by the sequence of observations
2. forecasting (predicting future values of the time series variable)

3.3. Demand Forecasting

Estimation and prediction of demands for a particular product according to the future is called Demand Forecasting which is generally based on analysis and insights of past demands or present market conditions.

3.3.1 Objectives of Demand Forecasting

Demand forecasting is a pivotal concept required for making important business decisions.

a) **Formulating Production Policy**
b) **Formulating Price Policy**
c) **Controlling Sales**
d) **Arranging Finance**
e) **Deciding the Production Capacity**

3.3.2 Factors affecting Demand Forecasting

Demand forecasting helps in determining the place, time, and quantities of particular products. Several factors affect demand forecasting.

a) **Types of Goods**
b) **Competition Level**
c) **Price of Goods**
d) **Level of Technology**
e) **Economic Viewpoint**

3.3.3 Process of Demand Forecasting

A systematic and scientific approach can lead us to an effective, fruitful, and required Demand Forecasting process for an organization.

a) **Setting the Objective**
b) **Determining Time Period**
c) **Selecting a Method for Demand Forecasting**
d) **Collecting Data**.

Estimating Results: The estimation of the demand forecasting for a specific span of time should be made abstract and simple to be interpretable and presentable easily.

IV. Data Flow Diagrams

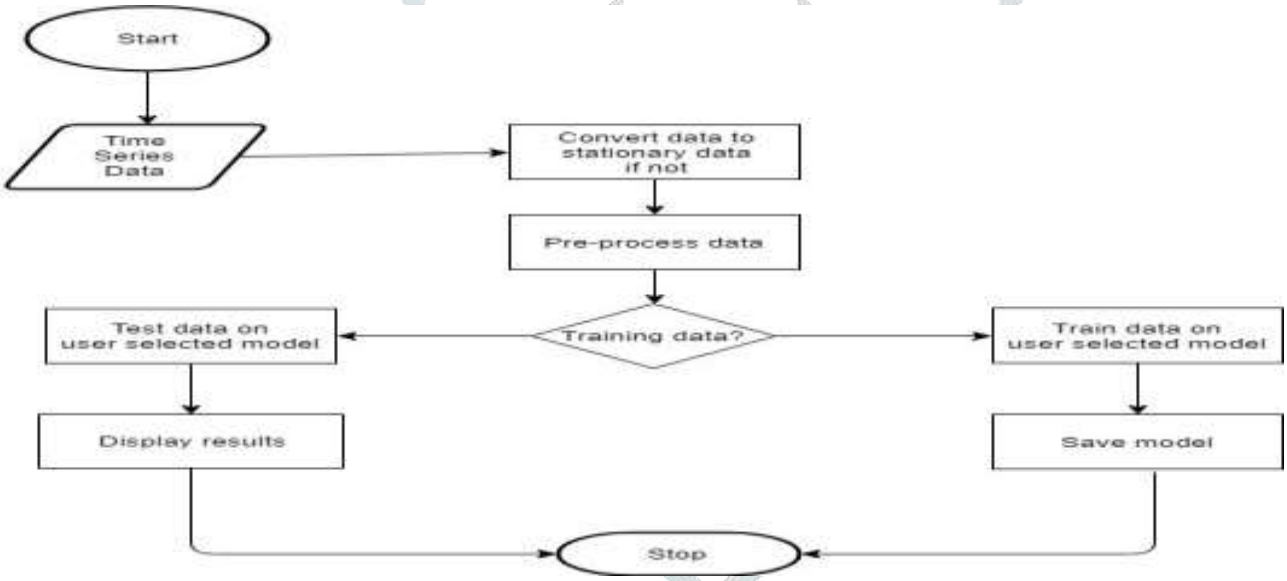

Figure 4.1: Data Flow Diagram

4.5 UML Diagrams

4.5.1 Activity Diagram

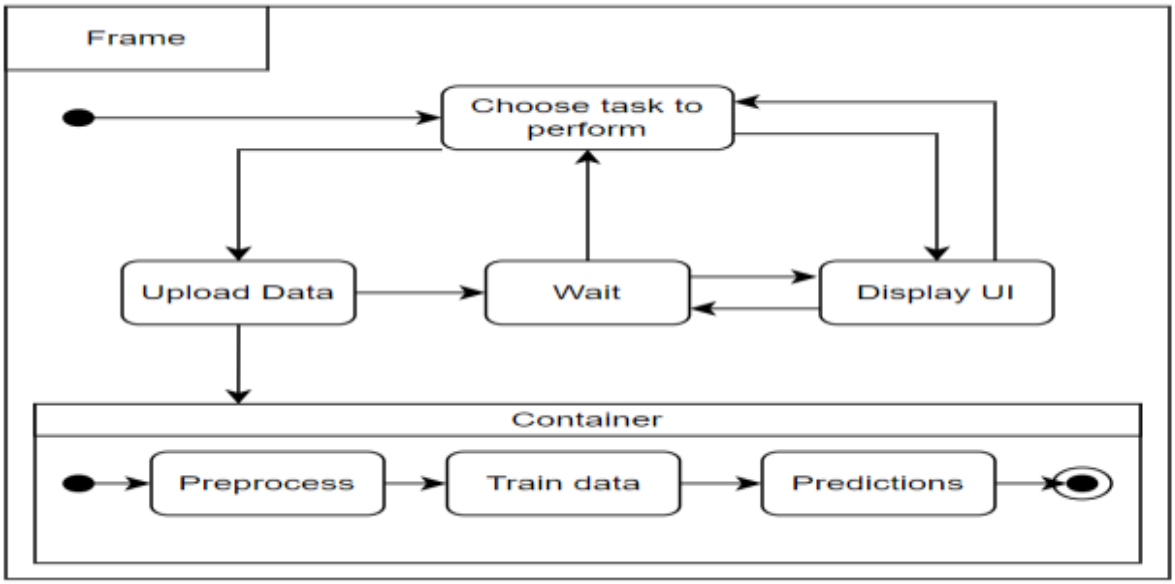

Figure 4.2: Activity Diagram

4.5.2 Use Case Diagram

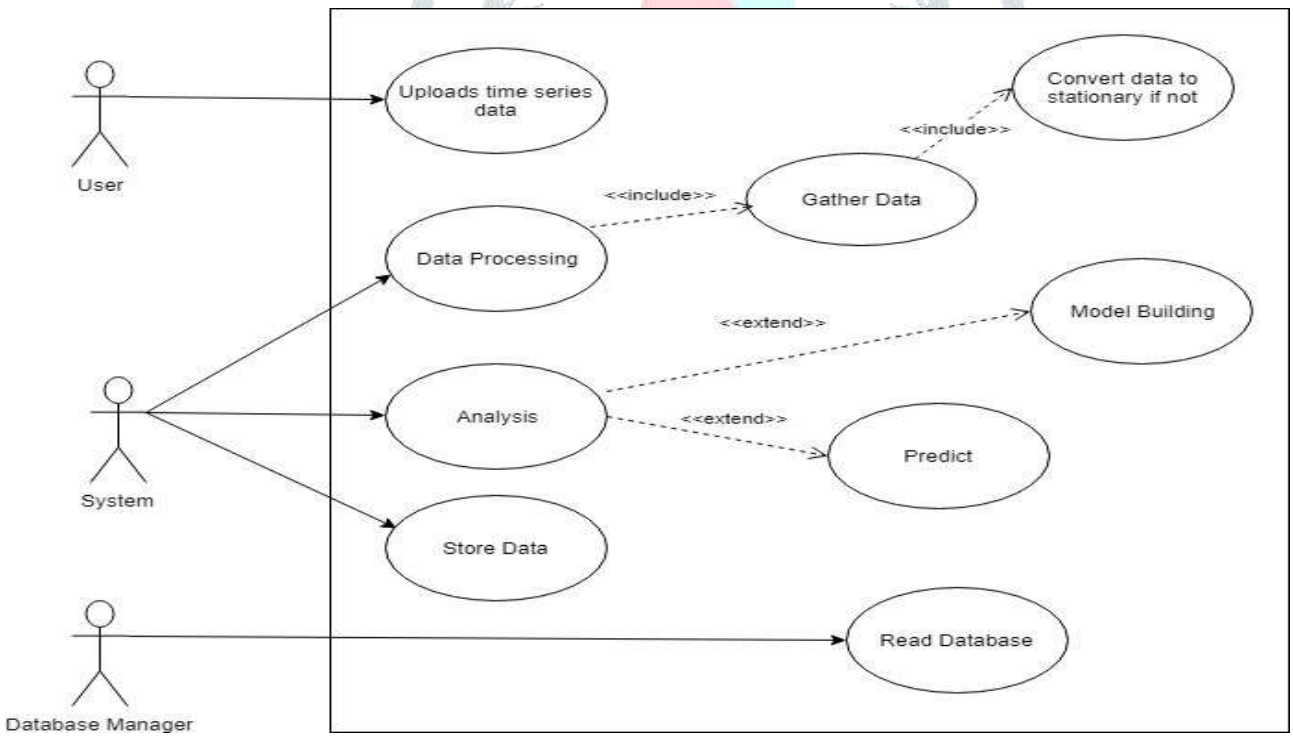

Figure 4.3: Use Case Diagram

V. PROJECT IMPLEMENTATION

5.1 Overview of Project Modules

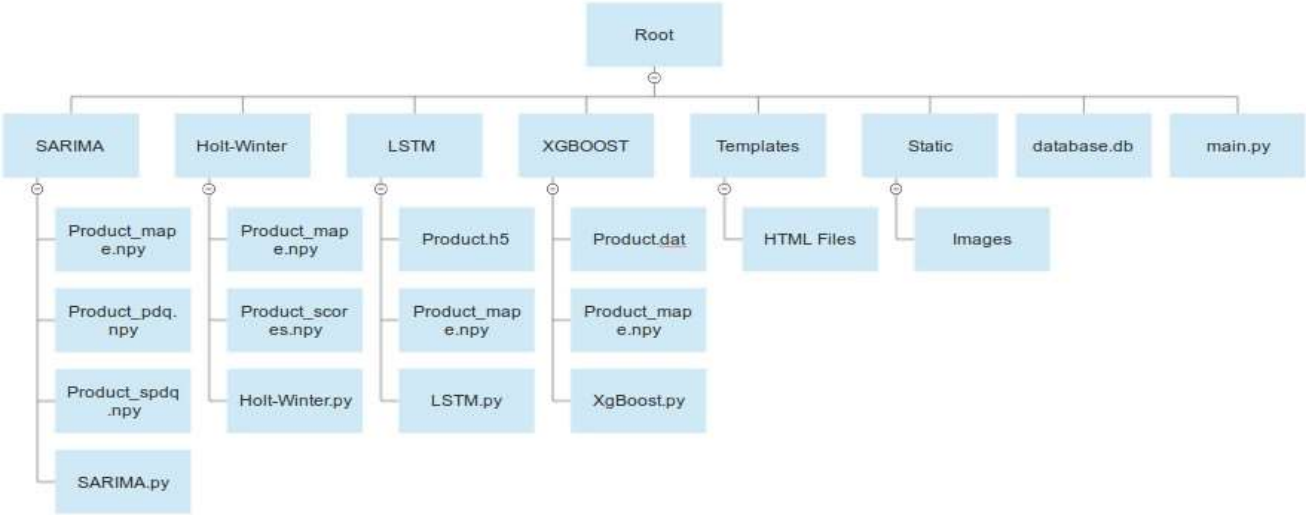

Figure 5.1: Project Module

5.2 Tools and Technologies Used

1. Operating System: Linux Ubuntu 16.04
2. Programming Language: Python (3+)
3. Machine Learning/ Deep Learning libraries: sklearn, NumPy, pandas, etc.
4. IDE: Jupyter Notebook/ Sublime Text
5. SQLite Server (For system administrator only)
6. Application Server: Flask
7. Front End Web Browser: Google Chrome, Mozilla Firefox, etc.
8. Analytic toolkit: bokeh, matplotlib

5.3 Algorithms

5.3.1 S-ARIMA

Autoregressive Integrated Moving Average, or ARIMA [1] [7][14], is one of the most widely used forecasting methods for univariate time series data forecasting. Although the method can handle trends, it does not support time series with a seasonal component. An extension to ARIMA that supports the direct modeling of the seasonal component of the series is called SARIMA.

5.3.2 Holt-Winters' Forecasting Method

This algorithm extracts data and analyses it to characterize it accurately, this classification helps us predict future estimates. It allows users to smoothen the samples from time series and thus will forecast specific valuable areas of interest

Three types of exponential smoothing methods used in the Holt-Winters Forecasting Method:

a) Single Exponential Smoothing, b) **Double Exponential Smoothing**, c) **Triple Exponential Smoothing**

5.3.3 XG-Boost

It is based on the Ensemble Learning Method which is the aggregation of various weak learning models to develop a 'strong' model. There are two types of ensemble learning.
Bagging: Parallel execution of all the weak learners. The result is the average of all the obtained results.
Boosting: Sequential execution of all models.

5.3.4 LSTM

The Long Short-Term Memory network (LSTM) [13], is a type of Recurrent Neural Network (RNN). LSTMs have chain-like structures, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way. An LSTM has three gates, to protect and control the cell state.

1. Input Gate
2. Output Gate3. Forget Gate

The LSTM layer is provided with a matrix as an input with the following dimensions:
Samples: Independent observations, several data points.
Time steps: It is the number of times you want to run LSTM.
Features: Refers to several variables we have for the corresponding true values of y.

VI. RESULTS

The results were deemed satisfactory with an average accuracy **greater than 80 percent** for all different models used during research work.

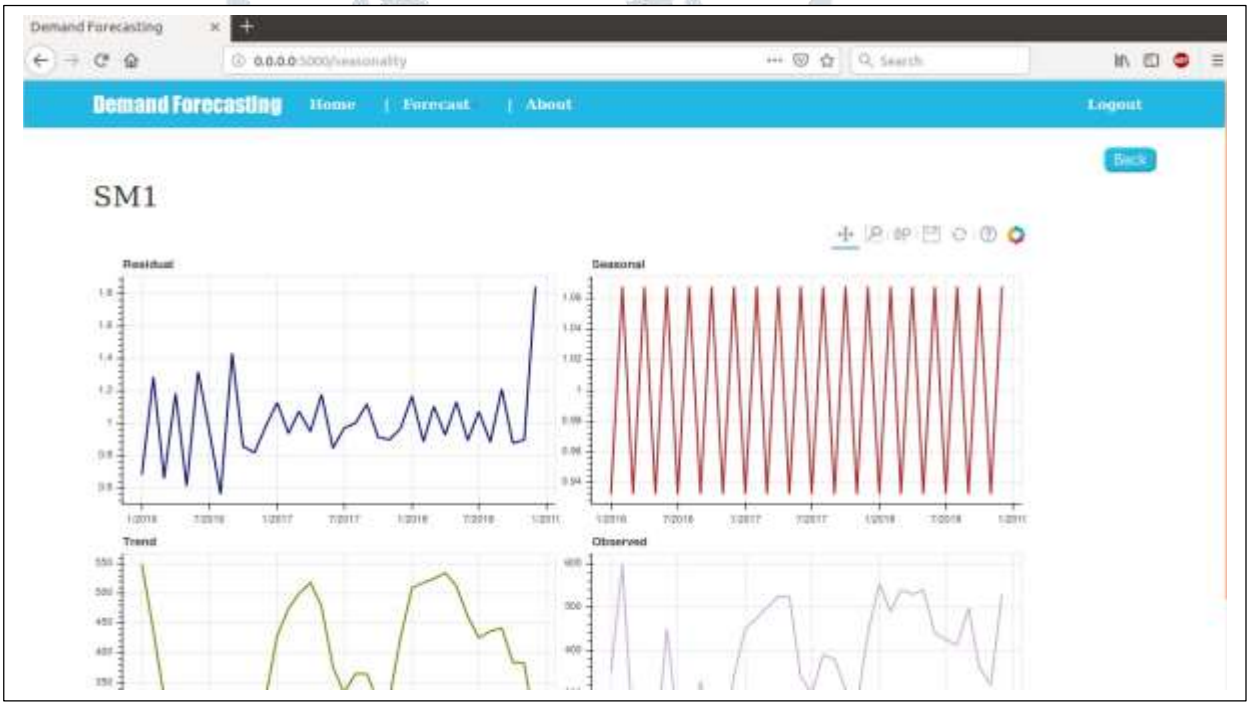

Figure 6.1: Seasonality Analysis – Univariate

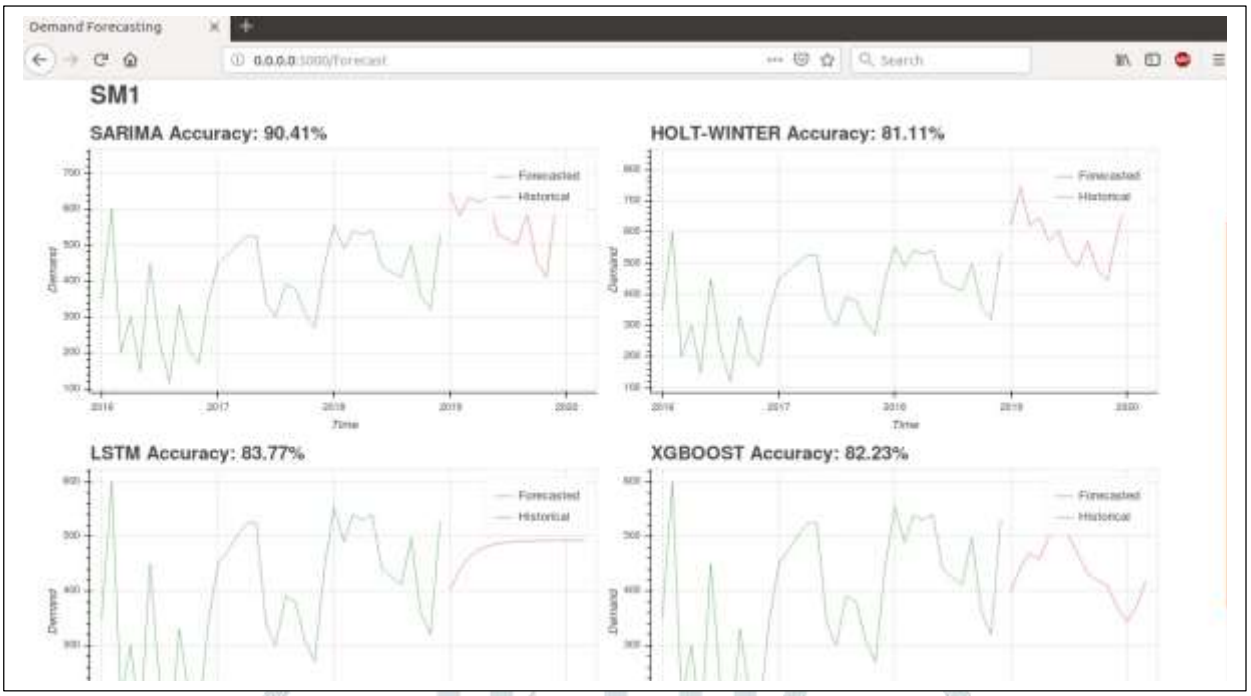

Figure 6.2: Forecasting Demand - Univariate

Figure 6.3: Seasonality Analysis - Multivariate

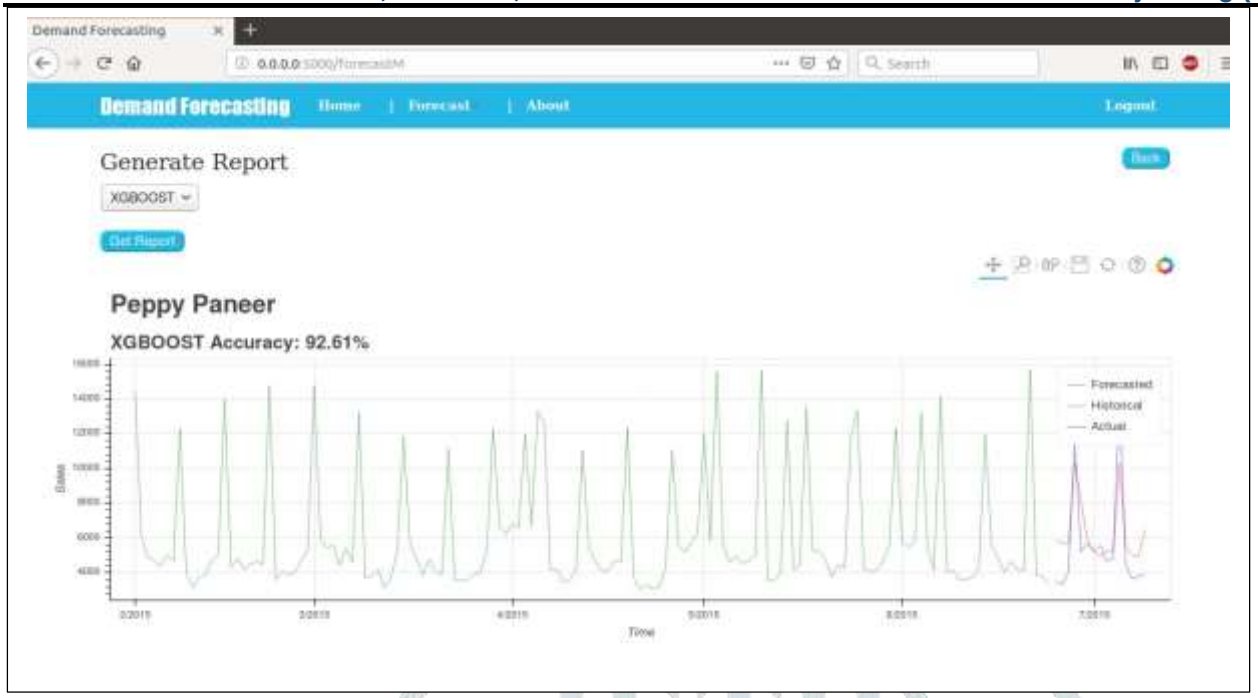

Figure 6.4: Forecasting Demand - Multivariate

Figure 6.1 shows the seasonality analysis on a specific product with code SM1 based on univariate data.

Figure 6.2 shows the forecasted value for SM1 with univariate data based on different models i.e., SARIMA, HOLT WINTER, LSTM, and XGBoost, etc.

Figure 6.3 shows the seasonality analysis on a specific product with code SM1 based on Mutivariate data.

Figure 6.4 shows the forecasted value for SM1 with multivariate data based on different models i.e., SARIMA, HOLT WINTER, LSTM, and XGBoost, etc.

VII. RESEARCH WORK ADVANTAGES, LIMITATIONS AND APPLICATIONS

Advantages

1. The system can be used successfully by any corporate firm for predicting the demand for the goods it manufactures and inventory optimization.
2. The product can be of great help in budget optimization while influencing decision-making policies aiming at achieving maximum profit at the cost of minimum resources.
3. The product can avoid situations for the firm such as understock or overstock, which, at times, may prove fatal.
4. Using a machine learning engine, the system can provide valuable insights of the business which may be rewarding to the organization.
5. The system can assist the corporate elites in tedious processes such as budget optimization, etc.

Limitations

1. The system will not be able to incorporate the effects of natural calamities in real-time.
2. The system will not be able to make predictions based on altered government policies in real-time unless modified for the same.

3. The system will be able to make predictions with decent accuracy only if the input data provided is accurate. The machine-learning engine-generated business functions are largely dependent on the data and any flaw would result in the generation of incorrect functions.

4. The system will not be in a state to predict sales in an entirely new region of operation for the firm.

Applications

1. The developed system as a website would be able to assist the decision-makers of the firm regarding inventory and budget optimization.

2. The system can be utilized as a machine-learning-based predictor for the demands of different products manufactured or sold by the firm.

VIII. FUTURE WORK

The system can be scaled according to the requirements of multi-national corporations and personalized as desired by the key decision-makers of the firm. The system can also be helpful in the analysis of the sentiments of users towards different products at different points of time-based on figures of sales. The system can also be expanded to produce an apt geographical location, such as a warehouse, for storing additional products to minimize transportation costs of the firm in real-time.

IX CONCLUSIONS

The system can be used successfully in different corporate sectors for demand forecasting, inventory optimization, and budget optimization for desired products and regions of operation. Any machine learning algorithm cannot be deemed perfect for making predictions. Hence, the predictions are generated based on the time-series analysis of the dataset of sales and inventory details of the product using different machine-learning and statistical algorithms as SARIMA, Holt-Winter, XGBoost, and LSTM. The user will thus, be independent to choose a particular model as suited in the situation. The system achieved an average accuracy greater than 80 percent for all different models used during research work.

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