

Machine Learning Enabled Inventory Prediction

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Abstract— Effective inventory management is a critical aspect of business operations, ensuring optimal stock levels, minimizing costs, and meeting customer demand. Accurate inventory prediction plays a pivotal role in achieving these objectives. This project explores the application of the XGBoost algorithm, a powerful machine learning technique, for inventory prediction. XGBoost's ability to handle complex nonlinear relationships and its robust performance make it a promising approach for this task. The project aims to develop an inventory prediction system using the XGBoost algorithm, leveraging historical sales data and other relevant factors to forecast future inventory levels. This project demonstrates the potential of machine learning, specifically the XGBoost algorithm, to revolutionize inventory management practices, enabling businesses to achieve greater efficiency and profitability.

Keyword : Machine Learning, Non-linear Relations, Cost Minimization, Stock levels, Profitability, Inventory Prediction.

I. INTRODUCTION

The problem that we chose to work upon is inventory prediction. Inventory prediction is important because it helps businesses optimize stock levels, reduce carrying costs, prevent stockouts, and improve overall operational efficiency. Inventory prediction has been extensively studied in fields like supply chain management, operations research, and machine learning. Various models, such as time series analysis, deep learning, and demand forecasting algorithms, have been developed to improve accuracy and efficiency in inventory management. Companies have also implemented advanced software and data analytics to enhance their inventory prediction capabilities.

We are working on optimizing inventory levels. Inventory prediction is an interesting field because it directly impacts cost-efficiency, customer satisfaction, and environmental sustainability. The rise of advanced technologies like AI and data analytics offers the promise of ever-improving accuracy and efficiency in inventory management, potentially giving organizations a crucial competitive edge in today's fast-paced,

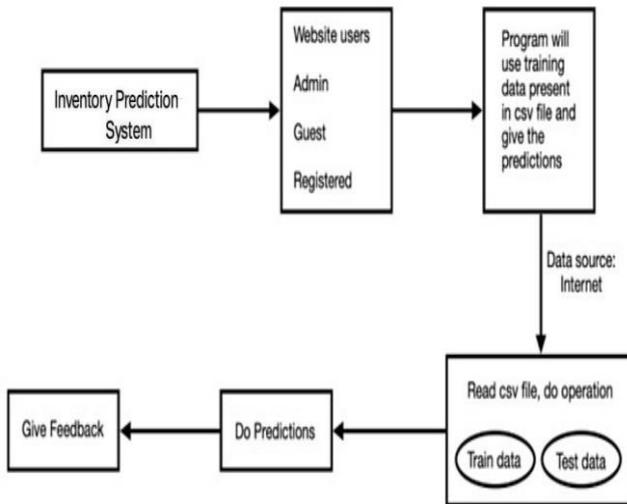
global marketplace. Challenges in inventory prediction include demand volatility, seasonality, lead time variability, data quality issues, and the need for real-time adaptation to changing market conditions.

Our aim is to develop a robust inventory prediction system which will forecast product demand accurately and optimize inventory levels, reducing carrying costs and stockouts while improving customer satisfaction and overall operational efficiency. Our goal is to provide web services to online businesses and to collaborate with them. The rest of the report consists of a literature survey, project statement, system requirements, system design, conclusion and references.

II. LITERATURE REVIEW

This project delves into three inventory management models - Economic Order Quantity (EOQ), Activity-Based Costing (ABC), and Just-in-Time (JIT). The primary focus is on providing decision support through the analysis of these models. However, a limitation is acknowledged, as the study may not cover all possible inventory management models and techniques. Additionally, the effectiveness of the project is contingent on the availability and quality of data, with potential drawbacks arising from data limitations. The project explores the intersection of inventory management, Big Data, and Industry 4.0, specifically emphasizing the demand for big data analytics (BDA) within supply chains[7]. The advantages include applications of BDA for supply chain improvement. However, the project also highlights challenges associated with BDA in the supply chain, particularly in terms of security and privacy concerns related to handling large volumes of data[7]. This reflects the complex landscape of integrating Big Data into supply chain frameworks. This project underscores the significance of accurate forecasting in inventory management through the use of Artificial Neural Networks (ANNs)[9]. It explores ANNs' learning capabilities, various types, and architectures. The advantages include improved forecasting accuracy and the demonstrated feasibility of the knowledge discovery system. However, challenges such as complexity and overfitting are acknowledged. ANNs are noted as potential

"black boxes," introducing difficulty in interpretation,



highlighting the trade-off between accuracy and interpretability in forecasting models[9]. The research employs both Q-learning and Deep Q-Network (DQN) algorithms to optimize ordering strategy and model parameters, aiming to reduce spoilage rates and total inventory costs for fresh product retailers. While the project presents a promising approach for cost savings, it acknowledges potential limitations [8]. The applicability of the model may be restricted to certain ecommerce scenarios, and challenges related to dimensionality solutions are recognized. This underlines the need for careful consideration of the model's scope and potential constraints in practical implementation [8].

III. METHODOLOGY

1.1 Proposed Methodology

XGBoost : This contains the extreme Gradient Boosting machine learning algorithm which is one of the algorithms which helps us achieve high accuracy on predictions. XGBoost is a popular machine learning algorithm that is well-suited for inventory prediction tasks. It is a gradient boosting algorithm that is known for its accuracy and efficiency. XGBoost is highly accurate and can achieve state-of-the-art results on inventory prediction tasks. Linear regression can be used in inventory prediction to model the relationship between independent variables (predictors) and the dependent variable (demand or sales quantity). In this context, the goal is to predict future demand based on historical sales data and other relevant factors.

Benefits of Using XGBoost for Inventory Prediction :

XGBoost is highly accurate and can achieve state-of-the-art results on inventory prediction tasks. → XGBoost is efficient and can be trained on large datasets in a reasonable amount of time. → XGBoost is versatile and can be used to model a variety of inventory-related factors. Overall, XGBoost is a powerful and versatile algorithm that can be used to develop effective inventory prediction systems.

1.2 System Architecture

Figure.1. System Architecture

1. User Interaction: Users access a website where they can browse and purchase products. This interaction occurs directly between the users and the website's interface.

2. Inventory Prediction System: This system sits behind the website and interacts with user activities.

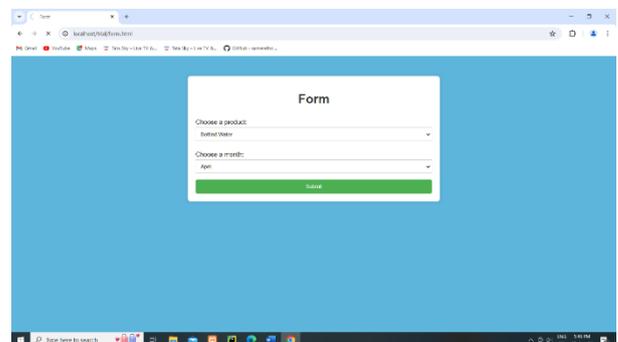
It has several key functions:

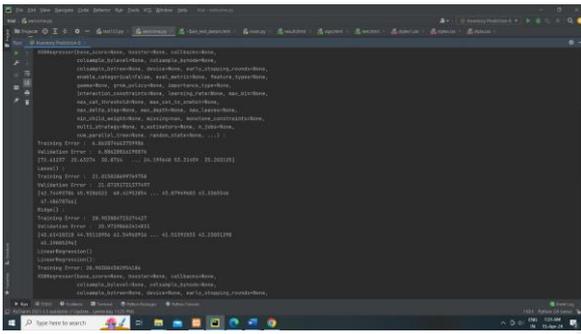
- **Data Source:** It gathers information from the internet. This could involve various sources like supplier databases, market trends, historical sales data, etc. This data is crucial for predicting inventory needs.
- **Prediction Generation:** Using gathered data, the system employs algorithms or models to forecast future inventory levels. These predictions are essential for making informed decisions about inventory management.
- **Admin Interaction:** The system interfaces with an admin panel. This allows administrators or managers to oversee and control inventory-related tasks.

IV. RESULT

We were successfully able to predict the stock amount after training and testing the data. The parameters given to obtain the predicted value are ICode, Month number, Year, Storecode, Dayno, Weekend and Weekdayno.

Inventory Prediction model:





```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

# Load data
data = pd.read_csv('Inventory_Data.csv')

# Data cleaning
data.dropna(inplace=True)

# Feature engineering
data['Year'] = data['Year'].astype(int)
data['Month'] = data['Month'].astype(int)
data['Weekend'] = data['Weekend'].astype(int)

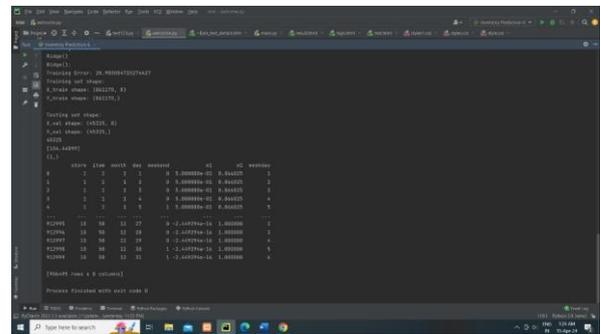
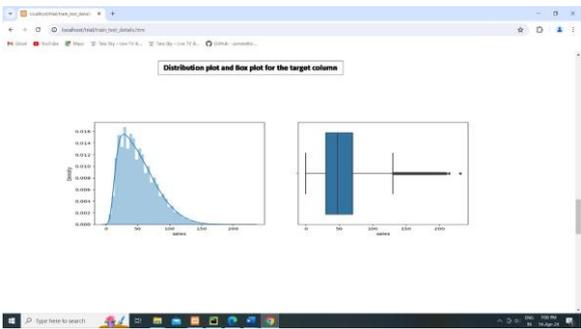
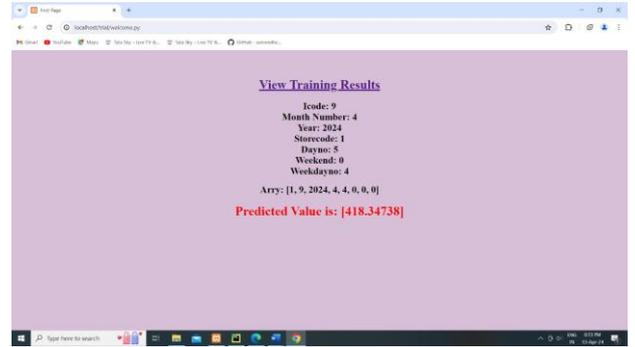
# Train-Test Split
X = data[['Year', 'Month', 'Weekend']]
y = data['Sales']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict on test set
y_pred = model.predict(X_test)

# Evaluate model
mse = np.mean((y_test - y_pred)**2)
print(f'Mean Squared Error: {mse}')
```



```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load data
data = pd.read_csv('Inventory_Data.csv')

# Feature correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')

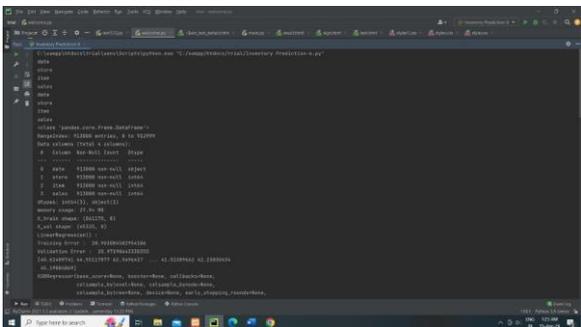
# Feature importance
model = LinearRegression()
model.fit(X_train, y_train)

feature_importance = pd.Series(model.coef_, index=X_train.columns)
feature_importance.sort_values(inplace=True)

print(feature_importance)
```



Test Results:



```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
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# Load data
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# Evaluate model
mse = np.mean((y_test - y_pred)**2)
print(f'Mean Squared Error: {mse}')
```

V. DISCUSSION

Machine learning (ML) is transforming inventory management by offering a powerful tool for predicting future demand. Unlike traditional methods limited to historical sales data, ML algorithms can analyze vast amounts of information. This includes things like customer trends, seasonality, and even social media sentiment to create highly accurate forecasts. These forecasts help businesses maintain optimal stock levels, avoiding the twin pitfalls of overstocking and understocking. With ML, businesses can automate inventory replenishment, ensuring they have the right products in stock at the right time. This leads to improved customer satisfaction, reduced carrying costs, and a more efficient supply chain overall.

VI. CONCLUSION

In conclusion, inventory prediction plays a crucial role in optimizing supply chain management and ensuring businesses can meet customer demand while minimizing holding costs. By leveraging advanced data analytics and forecasting methods, companies can make more informed decisions about stocking levels, reduce the risk of stockouts or overstocking, and ultimately improve their overall operational efficiency.

However, the effectiveness of inventory prediction models depends on the quality and quantity of data, as well as the continuous monitoring and adjustment of these models to adapt to changing market conditions. Therefore, businesses should invest in robust inventory prediction systems and strategies to stay competitive and responsive in today's dynamic marketplace.

VII. REFERENCES

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