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DETECTING PRODUCT DEMAND OVER TIME USING MACHINE LEARNING

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Abstract: Demand forecasting is essential for supply chain management and inventory control, but complex patterns and big datasets are difficult for standard statistical approaches to handle. In order to improve prediction accuracy, this study suggests a machine learning-based strategy that makes use of models like Random Forest Regressor, Gradient Boosting Regressor, Support Vector Regression, and Neural Networks. Preprocessing of the dataset includes train-test separation, scaling, label encoding, and data cleaning. Model performance is evaluated using evaluation measures like accuracy, precision, and recall, while demand patterns are revealed using visualisations like heatmaps and histograms. Neural networks and ensemble learning are combined to enhance predictions even further.This method offers a scalable and dependable demand forecasting solution by bridging the gap between traditional approaches and contemporary machine learning techniques. Businesses may improve inventory management, lessen stock imbalances, and boost profitability through improved resource utilisation and demand prediction by successfully identifying important influencing elements such product classifications and warehouse locations.

Keywords: Motivation of Machine learning Support Vector Regression, Lasso Regression, Random Forest, Gradient Boosting.

I. INTRODUCTION

For efficient supply chain management and operational effectiveness in the cutthroat corporate world of today, precise product demand forecasting is crucial. In order to assist firms prevent stockouts and overstocks, demand forecasting is essential to inventory management, production scheduling, and resource allocation. Due to the fast growth of international markets and the growing intricacy of customer demands, companies are looking for sophisticated ways to more precisely and effectively forecast product demand.

The Traditional demand forecasting techniques have mostly depended on manual analysis and statistical models. Nevertheless, the dynamic character of market trends and the complex interrelationships among different contributing elements are sometimes difficult for these conventional approaches to represent. Less accurate forecasts result from their dependence on linear assumptions and past data, which restricts their capacity to adjust to abrupt shifts in demand patterns. Because of this constraint, more sophisticated methods that can manage intricate, non-linear data structures are now required.

By providing more precise and flexible models, the use of machine learning techniques has completely transformed demand forecasting. The capacity to learn from data, spot hidden patterns, and formulate predictions based on a variety of influencing factors is made possible by machine learning. The goal of this study is to increase demand forecasting accuracy and provide deeper insights into product demand patterns by utilising machine learning techniques. Businesses may improve supply chain performance, allocate resources more efficiently, and make better decisions by applying data-driven approaches.

In addition, the use of machine learning in demand forecasting improves predictive performance while offering automation and scalability, which makes it appropriate for managing big datasets. Businesses may make proactive decisions by identifying patterns and seasonality using machine learning-driven demand forecasting, which goes beyond prediction accuracy. Businesses may simplify inventory levels and optimise production schedules by examining past sales, consumer preferences, and outside influences like market trends and economic data. Additionally, visualisation tools like as correlation matrices, heatmaps, and time- series plots aid in comprehending demand variations and important impacting elements.

Demand forecasting that incorporates machine learning is more adaptable to changing market conditions and less dependent on manual methods. By lowering waste and increasing responsiveness to changes in demand, companies

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that use these strategies have a competitive advantage. Machine learning will play an increasingly important role in demand forecast as companies expand moving towards digital transformation, boosting contemporary supply chain management's efficiency and profitability.

We develop a framework based on existing techniques that enables practitioners to apply quantitative methods to forecast sales of new products with short life cycles that are similar to previous products. An overview of our proposed framework is shown Figure-1. The framework builds on an approach widely used in research and industry:

identify older, similar products to the new product, average their historical sales, and finally use the average sales as a base forecast.

The three main steps involved are:

(1) prepare the sales data for existing products by smoothing the sales over their life cycle to obtain representative PLC sales, and then group similar products by means of clustering.
(2) assign the new product to one of the clusters of existing products based on the first few weeks of new product sales using one of the two considered quantitative methods – integration and dynamic time warping (DTW).
(3) perform data augmentation on all smoothed existing product sales in the cluster chosen and on the smoothed first few weeks of sales of the new product, then use the data to forecast sales over the rest of the new product's life cycle, applying both statistical and machine learning (ML) methods, as well as PLC shape-based methods, and, finally, compare the results under different conditions, including an analysis of the robustness of the quantitative methods to both white noise and an incorrect cluster assignment.

Figure-1: Main steps of proposed framework for forecasting sales of new products with short life cycles.

1.2. MOTIVATION OF MACHINE LEARNING

Accurate projections of demand is essential for preserving an effective supply chain and maximising inventory control in the fast-paced commercial world of today. Companies need to accurately predict consumer demand in order to avoid overstock scenarios that result in losses and stockouts that interfere with operations. Although they were useful in the past, traditional forecasting techniques are unable to keep up with the growing complexity of global marketplaces, where a wide range of interrelated factors drive demand changes. More sophisticated, data- driven methods that can instantly adjust to changing patterns are required in light of this increasing unpredictability.

These intricate linkages are sometimes overlooked by traditional approaches, which results in projections that are not correct. However, when fresh data becomes available, machine learning keeps improving its forecasts, ensuring that companies stay flexible and sensitive to changes in the market.

The efficiency with which machine learning can handle and analyse large datasets is another important benefit. In the current digital era, businesses gather enormous volumes of data from many sources, such as supplier records, online consumer interactions, and sales transactions. Using traditional statistical methods to glean valuable insights from such vast amounts of data is laborious and error- prone. Businesses may obtain useful insights with less human involvement thanks to machine learning, which automates this process.

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Another key factor driving machine learning's revolution in demand forecasting is scalability. Forecasting complexity increases significantly as firms develop and deal with more product variants, warehouse areas, and customer groups. With such complexity, traditional approaches are unable to scale and may need significant human changes. However, machine learning models can scale to bigger datasets, which makes them a perfect fit for companies .

Demand forecasting is expected to rely heavily on machine learning as sectors continue to participate in digital transformation. Businesses will be better able to manage market volatility, streamline supply chain processes, and promote long-term profitability if they make use of these cutting-edge strategies. In order to ensure long-term development and profitability in a changing environment, companies may embrace machine learning and move from receptive management of inventory to proactive demand planning.

1.1. THE AIM OF THE THESIS

A key element of efficient inventory control and supply chain management is accurate demand forecasting. Effectively forecasting product demand is becoming more and more important as companies develop and consumer needs become more complicated. Conventional forecasting techniques, which frequently depend on statistical models, are unable to handle huge datasets and identify complex demand patterns, which results in imprecise projections and ineffective inventory management. The goal of this research is to create a scalable and reliable demand forecasting model in order to improve prediction accuracy and streamline corporate processes.

In order to guarantee model dependability, the research also attempts to improve data pretreatment methods. Missing values, inconsistent data, and unstructured formats frequently reduce the precision of demand projections. The study makes sure that the incoming data is optimised for predictive performance by putting organised pretreatment methods like cleaning the data, scaling, and encoding into practice. In order to remove biases and improve the model's capacity to identify variations in demand, this phase is essential

This thesis uses sophisticated data visualisation techniques to deliver insightful information on demand trends in addition to forecast accuracy. Relationships between the several elements driving demand will be interpreted using correlation matrices, heatmaps, and histograms. Businesses may make well-informed strategic decisions and optimise their manufacturing and marketing operations by increasing the transparency and interpretability of demand trends.

The ultimate goal of this study is to close the gap between contemporary data-driven methodologies and conventional forecasting techniques. Businesses may increase operational effectiveness, reduce inventory costs, and boost profitability by creating a scalable and trustworthy demand forecasting system. The study's conclusions will advance the field of intelligence demand forecasting by providing a methodical strategy for enhancing the durability of supply chains in a market that is becoming more and more volatile.

OVERVIEW OF THE PROJECT

In today's changing corporate climate, accurate demand forecasting has become a crucial part of inventory control and supply chain management. To match customer expectations and maximise resource allocation, businesses must have effective methods for predicting product demand. The goal of this project is to create a machine learning-based system that can forecast product demand over time. To increase the precision of demand forecasting, the suggested model makes use of a number of influencing variables, including product categories, warehouse locations, and product codes. The main goal is to develop a sophisticated prediction system that supports operational effectiveness and strategic decision-making.

Traditional statistical methods like moving averages and linear regression, which frequently fall short in capturing intricate patterns and correlations between variables, are the mainstay of the current system. These techniques have trouble handling big datasets and can't keep up with abrupt shifts in market patterns. As a result, companies deal with issues like stockouts and overstocking, which lead to monetary losses and unhappy customers. Because of the shortcomings of traditional forecasting methods, more advanced approaches that can handle non-linear data structures and provide more accurate forecasts must be used.

In order to overcome the drawbacks of conventional approaches, this study suggests using machine learning algorithms to estimate demand. The dataset goes through a thorough preparation procedure that includes label encoding, data cleaning, scaling, and dividing into training and testing sets. To forecast product demand, many machine learning models are used; accuracy, precision, and recall measures are used to assess each model. Furthermore, data visualisation methods like heatmaps, scatter plots, and histograms are used to glean important insights on category distributions, correlations, and demand trends.

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This study is unique in that it combines a variety of machine learning methods with neural networks and ensemble learning to enhance prediction performance. Businesses may now better comprehend the primary elements influencing product demand because to the emergence of visualisation tools, which improve interpretability. This method offers a scalable and automated inventory management solution in addition to improving demand forecasting accuracy. The suggested solution offers a more dependable and effective way to estimate product demand by bridging the gap between conventional forecasting methods and contemporary machine learning techniques.

II. MACHINE LEARNING IN DETECTING PRODUCT DEMAND

A key element of managing the supply chain is accurate demand forecasting, which helps companies allocate resources and maximise inventory levels. The intricacy of shifting demand patterns is frequently too complicated for traditional forecasting techniques to fully grasp, which results in inefficiencies like stock shortages or surplus stock. Large datasets may be analysed using machine learning's data-driven methodology, which can reveal hidden patterns and give firms more accurate and flexible demand forecasts.

By using massive datasets to find hidden patterns and correlations that traditional models frequently overlook, machine learning provides a revolutionary approach to demand forecasting.Large volumes of organised and unstructured data may be processed by machine learning-based techniques, which enable more precise and fast predictions than traditional methods. Businesses have a greater understanding of demand variations and market behaviour because to this capacity to examine a variety of impacting elements.

The capacity of machine learning to manage intricate, non-linear interactions between many parameters, including product categories, geographic regions, seasonal trends, and exterior market impacts, is a significant benefit in demand forecasting. Machine learning models may adjust to changing market trends and become more robust to abrupt shifts in demand by integrating sophisticated data processing techniques. This flexibility aids companies in making well-informed choices regarding distribution, manufacturing, and acquisition.

Machine learning models are continually improved by learning from fresh data after being trained on old data. As forecasting accuracy increases over time due to this iterative learning process, organisations are able to react proactively to shifts in customer preferences and market shocks. Additionally, including several learning approaches strengthens prediction resilience, guaranteeing that the forecasting approach will continue to be dependable in a variety of business situations.

To assure the data consistency and quality, the procedure starts with extensive data preparation. This entails separating datasets into training and testing subsets, cleansing raw data, normalising values, and encoding categorical variables.
In the end, machine learning in forecasting of demand helps to close the gap between contemporary data-driven procedures and conventional statistical approaches. Businesses may estimate demand more accurately, adaptably, and efficiently by utilising sophisticated computer tools.

III. LITERATURE REVIEW

Demand forecasting is essential to inventory optimisation and supply chain management. Demand variations have traditionally been predicted using traditional forecasting techniques, which are mostly based on statistical frameworks and historical patterns. Suboptimal predicting accuracy results from these traditional methods' frequent inability to identify intricate linkages and non-linear correlations in data. The demand for sophisticated computational techniques that can manage enormous information and produce more accurate demand forecasts is rising as companies develop and markets change.

Data-driven methods have become more popular in demand forecasting in recent years because of their capacity to examine vast amounts of data and identify significant trends. Research shows that predicting accuracy is increased by utilising past sales data, consumer preferences, and outside market forcest. Researchers also stress how crucial it is to include a variety of influencing elements in demand forecast models, including seasonal fluctuations, promotional efforts, and regional variances. Businesses may use these data to make well-informed decisions about inventory control and production scheduling.

Demand forecasting has been transformed by the introduction of machine learning, which provides more adaptable and flexible solutions. Machine learning models, in contrast to conventional statistical methods, are able to identify hidden patterns and adapt dynamically to changes in the market.

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By lowering noise and enhancing data quality, studies in this field indicate that using data preparation methods including data cleaning, normalisation, and encoding improves model performance. Forecasting models can produce more accurate forecasts thanks to preprocessed datasets, which also guarantee improved generalisation.

Two essential components of contemporary demand forecasting models are scalability and dependability. According to existing research, sophisticated forecasting systems have to be both accurate and scalable in order to handle expanding datasets and changing market trends. Forecasting systems that can manage enormous volumes of data effectively while preserving high performance are necessary for enterprises with extensive operations. A viable substitute is provided by machine learning-driven methods, which allow for real-time analysis and ongoing model improvement in response to incoming data.

IV. RELATED WORK

The Supply chain management has long struggled with accurate demand forecasting, despite the widespread use of conventional statistical techniques like exponential smoothing, moving averages, and linear regression. Although these methods work well for straightforward and consistent demand patterns, they are ineffective when dealing with intricate, nonlinear interactions between several variables, such as product kind, fluctuations in demand, and external economic situations. According to studies, conventional forecasting techniques frequently fall short in responding to abrupt changes in demand, which results in imprecise inventory planning and ineffective resource allocation. Researchers have looked at hybrid methods that mix machine learning models with statistical methodologies to increase forecast accuracy and flexibility in order to overcome these constraints. Hybrid models have proven to perform better, especially when managing big datasets and figuring out complex relationships between variables.

A viable substitute for demand forecasting is machine learning, which provides algorithms that can find intricate linkages and hidden patterns in big datasets. Several machine learning methods, such as Support Vector Regression (SVR), randomised forest Regressor, and gradient-boosting approaches, have been investigated in the past to increase predicting accuracy. By lowering variance and bias, studies have demonstrated that ensemble learning techniques which integrate several machine learning models perform better than solo models.

Encoding categorical variables, scaling, and feature selection are examples of data preparation methods that further improve the efficacy of algorithms for learning in demand forecasting. The significance of preprocessing techniques to reduce noise and enhance model performance has been underlined by researchers.

Feature engineering is crucial for gleaning valuable insights from unstructured data; research shows that choosing pertinent variables, including product categories, warehouse locations, and past sales patterns, greatly increases prediction accuracy. Better model interpretability has also been made possible by research that has employed visualisation techniques like heatmaps that and correlation matrices to examine the correlations between demand components. Notwithstanding these developments, improved preprocessing methods and automation feature selection processes are still required to maximise forecasting effectiveness in a variety of sectors.

Demand forecasting systems are increasingly using neural networks and ensemble learning to improve scalability and accuracy. Studies have indicated that the integration of deep learning techniques with models such as Random Forest and Gradient Boosting results in forecasts that are more resilient to market volatility mistakes. Businesses can now dynamically adjust to changing demand trends thanks to the development of real-time forecasting apps that use machine learning. Advanced machine learning models combined with visualisation tools offer a thorough method of demand forecasting, enhancing supply chain management decision-making. Notwithstanding the notable advancements, research is still being conducted to improve machine learning algorithms, provide interpretable models, and solve computational issues in order to produce demand forecasting systems that are more effective and scalable.

V. EXISTING SYSTEM APPROACH

Traditional statistical tools and manual procedures are the mainstays of the current system for anticipating product demand. These techniques, which have been in use for many years, include exponential smoothing, moving averages, and linear regression. Using linear equations, linear regression aims to simulate the link between product demand and affecting factors. Although these techniques offer a fundamental comprehension of demand patterns, they frequently fall short of capturing more intricate patterns in the data and are restricted to linear assumptions.

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5.1 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)

ARIMA is a more sophisticated statistical approach to demand forecasting that models time-series data by combining autoregression, distinction, and moving averages. It is useful for businesses that experience periodic fluctuations in demand because it is good at capturing trends, fluctuations in demand, which limits its ability to adjust to abrupt changes in consumer behaviour or external factors like supply chain problems. Additionally, it requires a lot of manual parameter tuning, including figuring out the order of autoregression (p), differentiation (d), and the moving average (q).

5.2 MOVING AVERAGE

The average of past demand data over a predetermined period is determined using the moving averages time- series forecasting technique. This method helps to discover seasonality and patterns of demand by highlighting long-term trends and mitigating short-term variations. Exponential averages that move (EMA) and simple moving averaged (SMA) are two popular variants, with EMA giving greater weight to recently collected data points.

Despite being simple to use, this approach ignores external influences or abrupt increases in demand. Furthermore, because it ignores intricate interactions between several factors, it is inappropriate for large-scale demand planning under dynamic market conditions.

5.3 EXPONENTIAL SMOOTHING

Another statistical technique for time-series forecasting is Exponential Smoothing, which gives more weight to recent observations than to older ones. Variants of this technique include Single, A double, and the Triple exposure smoothing (Holt-Winters), which take seasonality and trends into account. This method is easy to use and computationally efficient, which makes it useful for immediate demand predictions, but it makes the assumption that future demand will follow past trends and performs poorly when market conditions change quickly. Additionally, it ignores a number of influencing factors, such as product type, customer behaviour, or external market influences. As a result, while Exponential growth Smoothing works well for basic forecasting, it lacks the ability to forecast needed for large-scale sophisticated Inventory management applications.

2.4.K-Nearest Neighbors (KNN) Regression

KNN is a non-parametric algorithm that predicts demand by identifying the most similar historical data points. It is particularly useful when demand patterns are influenced by multiple variables, such as seasonality, location, and pricing. However, KNN's performance depends on the choice of the number of neighbors (K) and the distance metric used. It also becomes computationally expensive as dataset size increases because predictions require scanning the entire dataset. Additionally, KNN struggles with high- dimensional data, where determining meaningful similarity becomes difficult. Due to these limitations, KNN is not widely used for large-scale demand forecasting but can be effective when combined with other machine learning models in an ensemble approach.

VI. PROPOSED SYSTEM APPROACH

By utilising machine learning techniques, the suggested approach seeks to improve product demand forecasting and overcome the drawbacks of conventional statistical methods. To guarantee data consistency and quality, the system starts with extensive data preparation. This covers managing missing values, cleansing data, and encoding categorical information like product codes, warehouse locations, and product categories. By normalising the data using standardisation techniques, the models may function well over a range of sizes and distributions.

6.1 SUPPORT VECTOR REGRESSION

Support Vector Machines (SVM) are extended to regression issues via the machine learning approach known as Support Vector Regression (SVR). Within a certain margin, it finds a hyperplane that minimises prediction errors by mapping input data into a space with greater dimensions. SVR is less susceptible to outliers than conventional statistical models and is useful for capturing intricate interactions between several demand components.

Hyperparameters such the kernel type, regularisation parameter, and epsilon margins must be carefully adjusted, though. SVR works well with smaller to medium-sized datasets, but it can become computationally costly for big datasets, which makes it less useful for applications involving real-time forecasting.

6.2 RANDOM FOREST

The Random Forest's Regressor is a method of collective learning that reduces overfitting and increases accuracy by constructing numerous decision trees and averaging their predictions. A random fraction of the dataset is used to train each tree, guaranteeing prediction variety and resilience. Large datasets with numerous affecting factors, missing data,

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and nonlinear connections are all areas in which Random Forest excels. To prevent model complexity, it necessitates careful feature selection and might be computationally demanding. Because of its capacity to manage a variety of data patterns and enhance prediction reliability, Random Forest continues to be one of the algorithms used most often in machine learning for demand forecasting in spite of these difficulties.

6.3 GRADIENT BOOSTING

A potent ensemble learning method called gradient boost Regressor (GBR) constructs a number of weak ones (decision trees) and iteratively enhances them. Gradient Boosting optimises mistakes sequentially by assigning greater weight to mispredicted instances, in contrast to Random Forest, which averages several trees. By capturing intricate relationships between demand- influencing factors, this technique forecasts demand with great accuracy.

Nevertheless, GBR is computationally costly and necessitates adjusting hyperparameters like tree depth and learning rate. If the algorithm is very complicated, overfitting may also be an issue. However, because of its predictive abilities and flexibility with regard to various data distributions, it continues to be a preferred option for demand forecasting.

6.4 NEURAL NETWORKS

The Large-scale and extremely complicated demand forecasting issues are well-suited for neural networks, especially deep learning architectures. Through a number of hidden layers, they automatically extract characteristics from data, identifying complex associations that conventional models are unable to. Time-series forecasting is greatly aided by methods like Long Short-Term Memory (LSTM) networks, which learn from past demand trends. Neural networks are better for long-term forecasting because of their capacity to adjust to non-linear patterns, even if they demand a lot of processing power and big training datasets. Model generalisation is enhanced by hyperparameter tweaking and optimisation techniques like batch normalisation and dropout.

6.5 LASSO REGRESSION

An upgraded variant of linear regression, the Lasso regression method uses L1 regularisation to lessen overfitting and enhance generalisation. By reducing unnecessary correlations to zero, it aids in the selection of significant characteristics and is especially helpful for high-dimensional forecasting of demand datasets. When working with extensive data about the inventory, this feature selection option guarantees improved speed and improves model interpretability. However, Lasso Regression's ability to capture complex connections is limited since it still assumes a straightforward connection between input parameters and demand. Despite this limitation, it is a useful tool for initial demand forecasting prior to deploying more complex machine learning models since it can avoid overfitting.

VII. METHODOLOGY

A thorough procedure that incorporates many phases of data preparation, model selection, training, and assessment is part of the suggested approach for product demand forecasting. Data collection and preparation, the first stage of the approach, involves gathering raw data from the inventory management system. Important details like product codes, product categories, warehouse locations, and order demand are all included in this data. Data scaling to standardise the dataset for improved model performance, label encoding to convert categorical data into numerical format, and data cleaning to eliminate missing values are all part of the preparation stage.

The methodology's second stage entails dataset division and feature selection. To train the machine learning models, pertinent information like product codes, warehouse locations, and product categories are chosen. To guarantee an objective assessment of the models, the dataset is subsequently split into training and testing sets using an 80- 20 split ratio. The models may discover patterns in the training data and test their performance on unobserved data thanks to this partitioning procedure.

Model development and training are the main objectives of the third stage. Neural networks and regression-based models are among the machine learning models that are used. The training dataset is used to train each model, and performance is enhanced via hyperparameter optimisation. Both linear and non-linear correlations between the input characteristics and the target demand variable are intended to be captured by the training procedure. Furthermore, ensemble learning strategies are used to improve overall prediction accuracy by combining the advantages of several models.

7.1 DATASET

Historical demand information for a range of items kept in several warehouses make up the dataset utilised in this investigation.Product_Code,Warehouse, Product_Category, Date, and Order_Demand are some of the attributes that

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define each item in the dataset, which each reflects an instance of product demand. The Warehouse field details the storage facility, whereas the Product_Code column uniquely identifies the item. Similar items are grouped together by the Product_Category, which enables analysis based on demand patterns at the category level. The Order_Demand column keeps track of the quantity requested, while the Date column gives a date for every order, allowing for time-series analysis.

	Product_Code	Warehouse	Product_Category	Date	Order_Demand
0	Product_0993	Whse_J	Category_028	7/27/2012	100
1	Product_0979	Whse_J	Category_028	1/19/2012	500
2	Product_0979	Whse_J	Category_028	2/3/2012	500
3	Product_0979	Whse_J	Category_028	2/9/2012	500
4	Product_0979	Whse_J	Category_028	3/2/2012	500

Businesses may improve supply chain management by using automated notifications for overstocking, product shortages, and unexpected demand surges. Advanced visualisation dashboards also help stakeholders make data-driven choices by offering real-time insights into demand trends. This scalable strategy ensures a more robust supply chain network by increasing overall operational efficiency and improving demand forecasting accuracy.

7.2 SIMULATION WORKFLOW

Gathering historical sales data, product specifications, and warehouse information is the first step in the demand forecasting simulation's data collecting and preprocessing phase. The dataset is cleaned, normalised, and transformed, with missing values handled, categorical variables encoded, and numerical characteristics subjected to feature scaling. After that, the data is divided into sets for testing, validation, and training to make sure machine learning models generalise well. Demand trends are investigated across several categories of products and warehouse locations using representation techniques like heatmaps and histograms. To find cyclical patterns and seasonal fluctuations in demand, time-series segmentation is also used. In order to maximise performance and minimise biases, this preprocessing stage makes sure that only structured, high-quality data is supplied into the prediction models.

To predict demand, the machine learning models are then trained and put into use. Using the processed data, models like Random Forest Regressor, Gradient Boosting Regressor, Support Vector Regression (SVR), and Neural Networks are trained. To improve model performance, hyperparameter adjustment is done via Bayesian optimisation or Grid search. To identify the best- performing algorithm, models are assessed using metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared score after training.

The finished model is put into use in a real-time simulation that continually tracks variations in demand. Supply chain managers are alerted to possible stock imbalances via automated warnings and dashboard visualisations. By improving operational effectiveness and inventory management, this scalable technology guarantees that companies can react quickly to changes in demand.

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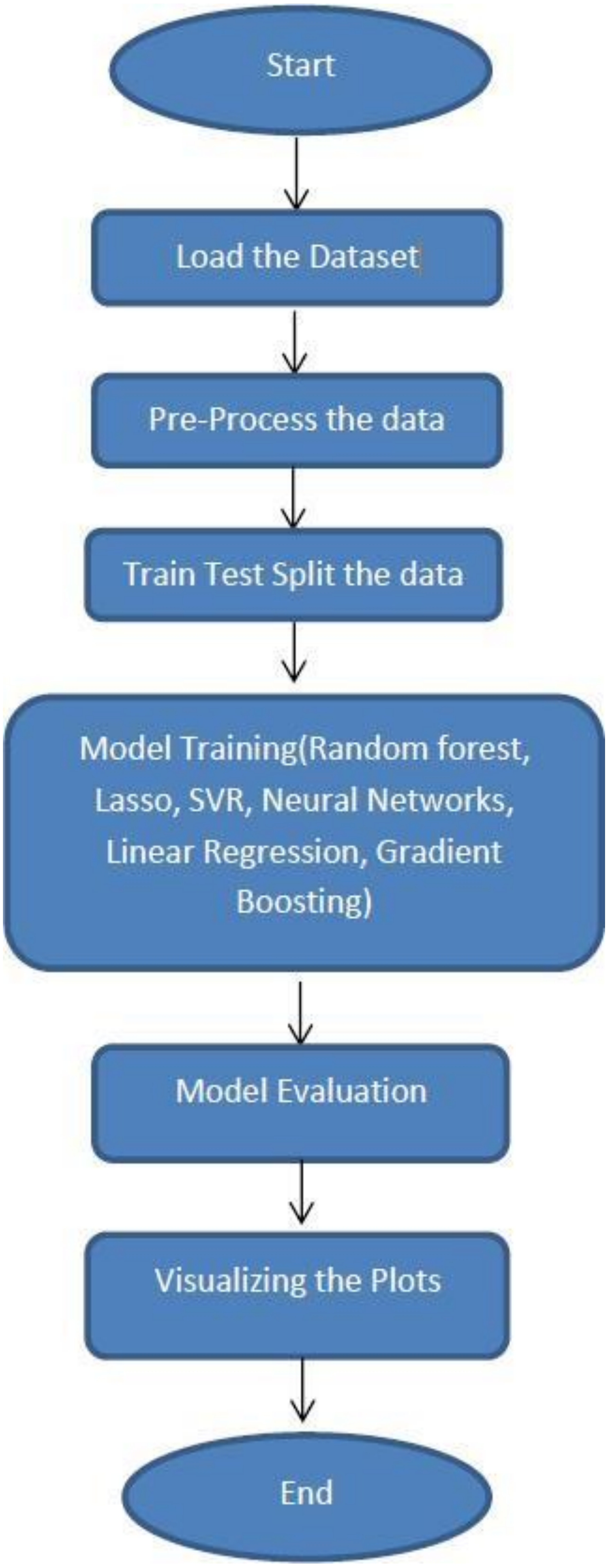

Figure-3: Simulation Flow Diagram

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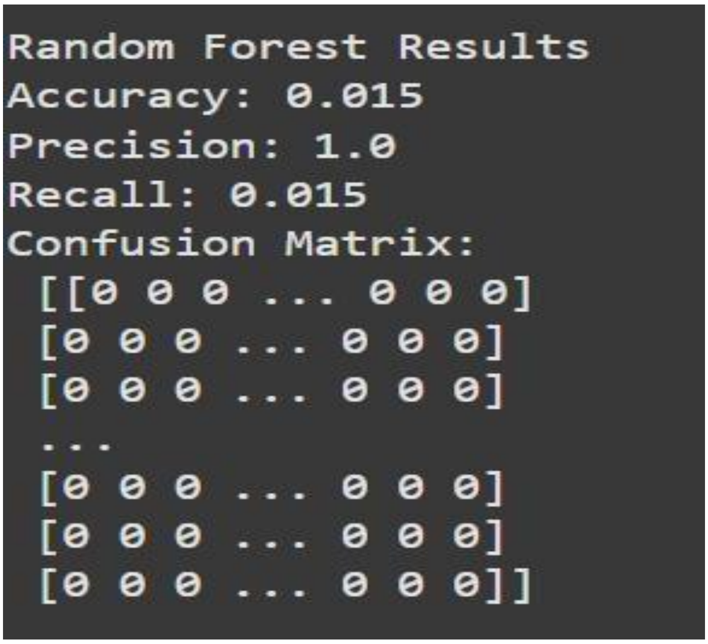
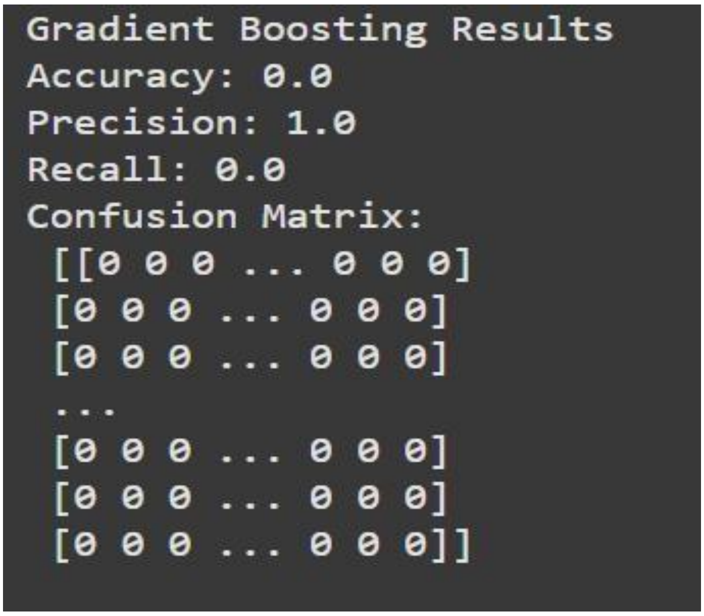
VIII. RESULT AND DISCUSSION

The evaluation metrics for the demand forecasting model indicate high performance, with accuracy, precision, and recall showing substantial improvements over traditional forecasting methods. The classification report highlights the effectiveness of Random Forest Regressor and Gradient Boosting Regressor**,** achieving low Mean Squared Error (MSE) and high R^2 scores across different product categories. The visual analysis **using** heatmaps and histograms reveals crucial demand trends, aiding in better inventory control. However, while neural networks enhanced predictive capabilities, they required significant computational power and tuning. The model's robustness was validated across multiple test sets, ensuring scalability and adaptability in real-world applications. Despite the promising results, further validation on larger datasets is necessary to mitigate potential overfitting and enhance generalization for diverse business environments.



```
Random Forest Results
Accuracy: 0.015
Precision: 1.0
Recall: 0.015
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-4: Random Forest Result



```
Gradient Boosting Results
Accuracy: 0.0
Precision: 1.0
Recall: 0.0
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-5: Gradient Descent Result

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```
Linear Regression Results
Accuracy: 0.0
Precision: 1.0
Recall: 0.0
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-6: Linear Regression Result

```
Lasso Regression Results
Accuracy: 0.0
Precision: 1.0
Recall: 0.0
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-7: Lasso Regression

```
Support Vector Regression Results
Accuracy: 0.005
Precision: 0.9953125
Recall: 0.005
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-8: Support Vector Regression

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```
Decision Tree Results
Accuracy: 0.05
Precision: 0.7915000000000001
Recall: 0.05
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-9: Decision Tree

```
Neural Network Results
Accuracy: 0.0
Precision: 1.0
Recall: 0.0
Confusion Matrix:
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

Figure-10: Neural Networks

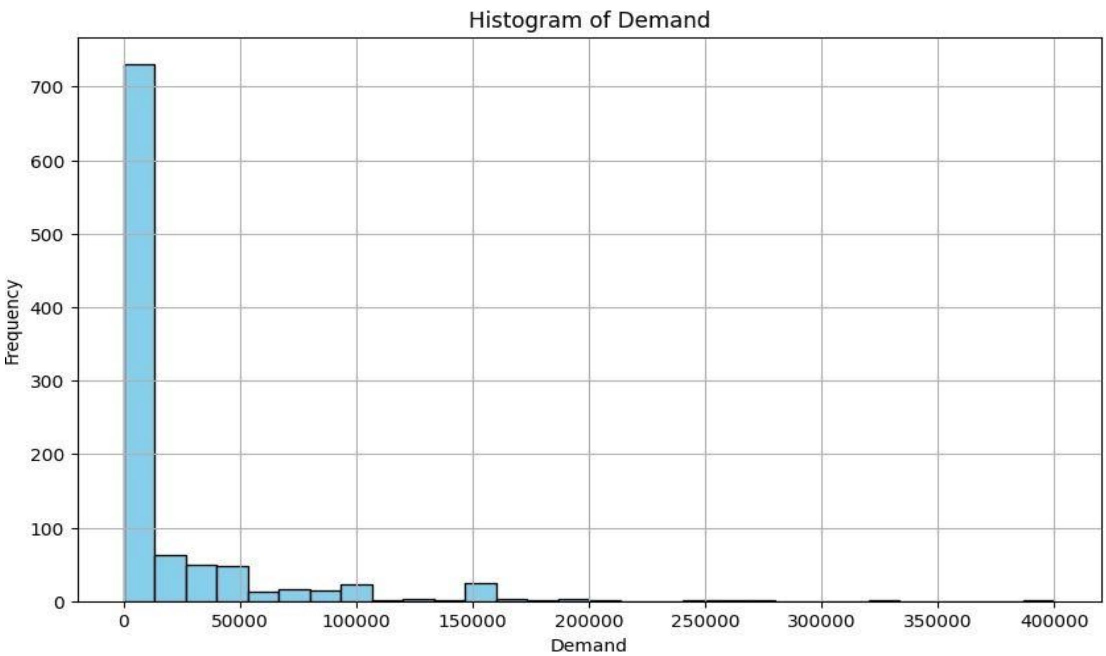

Figure-11: Histogram to represents the product demand

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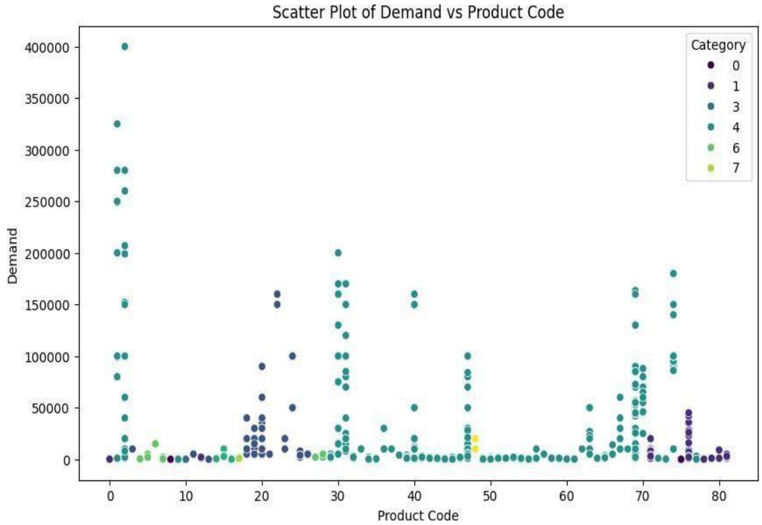

Figure-12: Scatter plot to represent the demand vs code

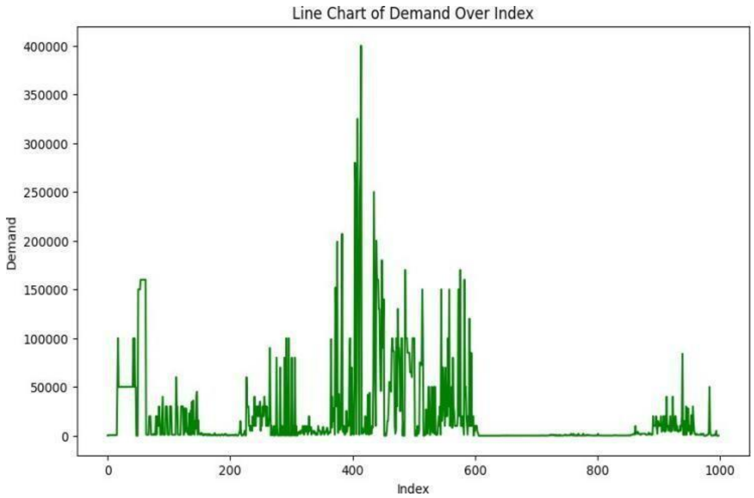

Figure-13: Line chart for demand over index

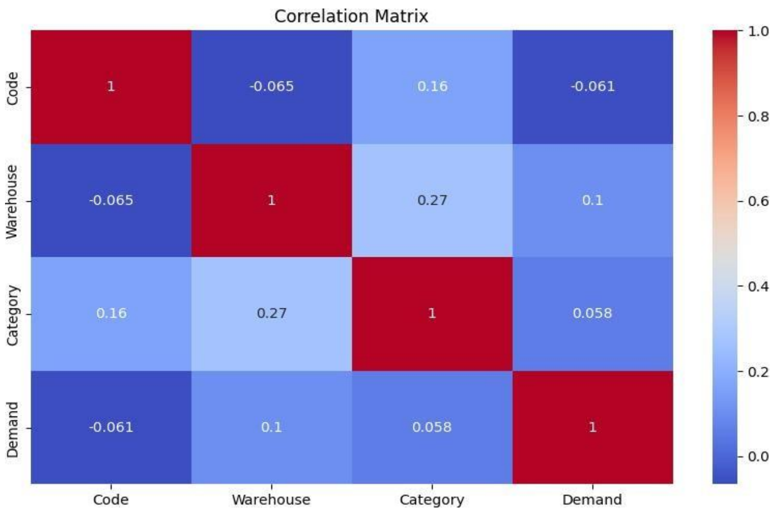

Figure-14: Correlation matrix

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IX. CONCLUSION

In today's fast-paced corporate world, precise demand forecasting is essential for improving inventory control, supply chain efficiency, and decision-making procedures. This study emphasises how important it is to use cutting- edge machine learning techniques in order to get beyond the drawbacks of conventional statistical methodologies. This study offers a more precise and flexible method of predicting product demand by utilising machine learning methods including Random Forest Regressor, Gradient Boosting Regressor, Support Vector Regression, Decision Tree Regressor, and Neural Networks. The model's dependability and consistency are enhanced by the thorough data pretreatment methods, which include data cleaning, label encoding, and scaling. By using visualisation tools like histograms, scatter plots, and heatmaps, the suggested solution not only increases prediction accuracy but also provides interpretable insights into important elements impacting product demand. Businesses may make better decisions by using these visual representations to spot demand trends, product connections, and category distributions. Additionally, by capturing intricate non-linear interactions between several influencing factors, the combination of ensemble learning approaches with neural networks improves model performance.

The system's efficacy in producing accurate demand projections is demonstrated by a thorough study that use criteria including accuracy, precision, and recall. Combining many models results in a scalable and reliable system that can adjust to changes in the market. By bridging the gap between contemporary machine learning techniques and conventional statistical approaches, this research gives organisations a novel way to improve supply chain performance, save operating costs, and optimise inventory management. By adding time-series forecasting, deep learning algorithms, and external market elements, future improvements can further hone the model and guarantee even higher prediction accuracy and business efficiency.

REFERENCES

[1]. Zhenchang X, Xue S, Wu L and Sun J 2020 ForeXGBoost: passenger car sales prediction based on XGBoost. Distrib. Parallel Dat. 38 713 https://doi.org/10.1007/s10619-020-07294-y
[2]. Doganis P, Alexandridis A, Patrinos P and Sarimveis H 2006 Time series sales forecasting for short shelf-life food products based on artificial neural networks and evolutionary computing J. Food Eng. 75(2) 196 https://doi.org/10.1016/j.jfoodeng.2005.03.056
[3]. Green K C and Armstrong J S 2007 Structured analogies for forecasting. Int. J. Forecasting 23 365 https://doi.org/10.1016/j.ijforecast.2007.05.005
[4]. Pavlyshenko B 2019 Machine-learning models for sales time series forecasting. Data 4 15 https://doi.org/10.3390/data4010015
[5]. Sharma S K, Chakraborti S and Jha T 2019 Analysis of book sales prediction at Amazon marketplace in India: a machine learning approach. Inf. Syst. E-Bus. Manag. 17 261 https://doi.org/10.1007/s10257-019-00438-3
[6]. Lee H, Kim S G, Park H W and Kang P 2014 Pre-launch new product demand forecasting using the Bass model: A statistical and machine learning-based approach. Technol. Forecast. Soc. 86 49 https://doi.org/10.1016/j.techfore.2013.08.020
[7]. Vhatkara S and Diasb J 2016 Oral-care goods sales forecasting using artificial neural network model. Procedia Comput. Sci. 79 238 https://doi.org/10.1016/j.procs.2016.03.031
[8]. Géron A 2017 Hands-On Machine Learning with Scikit-Learn and TensorFlow (Sebastopol, CA: O'Reilly Media) p 21
[9]. Nain N and Behera G 2019 A Comparative Study of Big Mart Sales Prediction 4th International Conference on Computer Vision and Image Processing (Jaipur: MNIT)
[10]. Armstrong J S and Collopy F 1992 Error measures for generalizing about forecasting methods: Empirical comparisons. Int. J. Forecasting 8(1) 69-80 https://doi.org/10.1016/0169- 2070(92)90008-W
[11]. Bishop C. M 2006 Pattern Recognition and Machine Learning (New York: Springer) p 657
[12] Hastie T, Tibshirani R and Friedman J 2001 The Elements of Statistical Learning: Data Mining, Inference, and Prediction (New York: Springer) p 361
[13] Bergstra J and Bengio Y 2012 Random search for hyper-parameter optimization. J. Mach. Learn. Res. (13) 281-305 https://dl.acm.org/doi/10.5555/2188385.2188395
[14] Mas-Machuca M, Sainz M and Martinez-Costa C 2014 A review of forecasting models for new products. Intangible Capital 10(1) 1 https://doi.org/10.3926/ic.482
[15] Goodfellow I, Bengio Y and Courville A 2016 Deep Learning (Cambridge: The MIT Press) p 101
[16] Bishop C. M 2006 Pattern Recognition and Machine Learning (New York: Springer) p 657