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Product Demand Forecasting System for SMEs Using Extreme Gradient Boosting

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Abstract - **The success of Small and Medium-sized Enterprises (SMEs) is mainly dependent on inventory management; yet, many businesses struggle with the use of traditional methods of demand forecasting, which leads to overstocking or understocking that negatively influences business operations. This study aims to integrate machine learning techniques into the prediction of product demand and efficient inventory management. The dataset used was sourced from Kaggle, and feature engineering and categorical encoding were applied to prepare the data for analysis. A classification-based predictive model was implemented using Random Forest and Gradient Boosting machine learning algorithms to categorize demand into high, medium, and low levels. Metrics including accuracy, precision, recall, and F1-score were used to evaluate the system, and the results showed that Gradient Boosting performed better, with an accuracy rate of 87%, while Random Forest achieved an accuracy rate of 85%. The study concludes that machine learning techniques, particularly the Gradient Boosting classifier, can effectively forecast product demand for SMEs. The system has the potential to help minimize inventory risk while increasing operational efficiency. It is recommended that more advanced machine learning models be used to further improve demand forecasting.**
Keywords: **Demand Forecasting, Extreme Gradient Boosting, Inventory Management, Machine Learning, Product Prediction**

I. INTRODUCTION

One of the most essential roles for Small and Medium-sized Enterprises (SMEs) is proper inventory management, especially where customers' demand is unstable in a retail setting. The ability to balance the right stock levels can affect customer satisfaction, organizational profits, and the overall operational efficiency of the business. While inventory management deals with tracking the goods and items that companies sell, it is all about making the right product available at the right time. This involves being aware of which product to order, the quantity to order, when to place the order, and where to store the product [1]. [2] argued that numerous business owners are yet to understand the application of machine learning in managing the supply chain. Such business owners tend to seek ways to use machine learning insights without facing challenges in creating meaningful analyses [2].

Using a computer system to mimic human thinking abilities, such as learning and reasoning, is what Artificial Intelligence (AI) entails. It basically refers to situations where a machine exhibits intelligent behaviours [3]. Furthermore, [4] opined that machine learning (ML), as an aspect of Artificial Intelligence, allows algorithms to identify patterns from large datasets and make accurate predictions; it can recognize patterns, make decisions, and solve problems by analysing data without human interference. According to [5], supervised learning is a type of machine learning where algorithms learn from a labelled dataset; that is, input is paired with an accurate output. It is also subdivided into two types: regression, such as linear regression, and classification methods, which were integrated in this study.

Integrating AI and ML into inventory management offers useful information for businesses and enables effective decision-making, as it analyses huge amounts of data to easily identify patterns in the supply chain [6]. It can also be used to predict requirements by processing and analysing orders from various regions [7]. The application of a model's learning ability in the inventory management system, specifically in predicting product demand based on seasons, real-time information, and external factors, can be used to detect trends, forecast demand, and optimize inventory levels, thereby aiding decision-making. The model improves accuracy in demand forecasting and operational efficiency, allowing decisions to meet customers' demand and providing recommendations based on analysed data in order to avoid situations such as stock-outs and overstocking, both of which lead to financial loss [8].

Businesses such as SMEs often face challenges in forecasting product demand due to limited resources, unpredictable consumer behaviour, and fluctuating seasonal trends. AutoRegressive Integrated Moving Average (ARIMA) is a traditional method that assumes linearity, but it is often at a disadvantage when handling large-scale categorical data or nonlinear relationships in a modern retail environment. The combination of multiple machine learning algorithms usually performs better than traditional methods in handling complex and high-dimensional retail data [9]. This is particularly essential for SMEs that require high accuracy in making timely stocking decisions. Inaccurate demand forecasting leads to overstocking, resulting in wasted capital and storage costs, or understocking, which causes dissatisfied customers and lost sales. Therefore, Extreme Gradient Boosting (XGBoost) and Random Forest (RF), in particular, are more effective in capturing complex relationships in sales data to enable more accurate predictions.

II. LITERATURE REVIEW

An advanced machine learning technique, namely the gradient boosting model, is used to predict demand levels after analysing seasonality, past sales, and external events. It enables dynamic inventory allocation, timely restocking, and reduces both stock-outs and overstocking to improve operational efficiency [10]. [11] developed a Voting Ensemble Learning Model (VELM) for classifying harmful gases. The model demonstrated superior performance, achieving a classification accuracy of 99.46%, and the findings highlighted the transformative potential of ensemble learning in environmental monitoring and provided a foundation for future research.

Amazon's DeepAR model uses an autoregressive recurrent network to produce a complete predictive distribution for future sales. This approach outperforms traditional time-series methods on large retail datasets. It effectively captures seasonality and product-level variations, allowing probabilistic stocking decisions [12]. Additionally, a study by [13] showed a high level of accuracy of advanced machine learning models in the diagnosis of brain tumours.

In a study by [14], machine learning was applied to forecast the demand of SMEs where data are scarce. Algorithms such as XGBoost and RF reduced the rate of stock-outs and improved customer satisfaction. Long Short-Term Memory (LSTM) and XGBoost models were compared in forecasting monthly sales for products in a retail environment. XGBoost delivered more accurate results on retail datasets, demonstrating that simpler ensemble methods can sometimes outperform complex deep learning algorithms in certain scenarios [15]. The integration of Singular Spectrum Analysis also improves supply chain demand forecasting accuracy by capturing patterns and generating predictions that are useful in real-world applications [16].

Maximizing sales of fresh produce may be challenging, but [17] illustrated possible strategies for pricing to increase demand levels. Using XGBoost in forecasting sales of perishable items, accuracy increased, with time identified as a key determinant. Other challenges faced in predicting demand and optimizing inventory levels for small businesses were addressed using regression ensemble methods to reduce wastage and holding costs in the supply chain [9]. Consequently, [2] considered a different approach that incorporates machine learning-driven dashboards into supply chains. The dashboard enhances decision-making capabilities, as it was constructed using various algorithms and business intelligence tools, but it was mostly developed for Business-to-Business (B2B) industries, thereby limiting its usability for retailers.

In another study by [18], the authors developed a model that demonstrated how machine learning can be used to maximize profit in Forex trading, particularly using binary options trading within the Forex market, achieving an accuracy of 86.28%. In addition, [19] developed a model capable of interpreting human facial expressions and behaviours in varied circumstances using Convolutional Neural Networks (CNNs). The results showed high performance and accuracy.

III. METHODOLOGY

The implementation of this study involves designing and developing a predictive model by combining machine learning techniques, and the system flow is visually represented to show the steps involved in the study, from data collection to the final prediction. Two ensemble classification models, XGBoost and RF, were chosen based on their ability to detect complex, nonlinear relationships in data and make accurate categorical predictions. The model was integrated into an interactive web-based user interface built with Streamlit, enabling small businesses to input product details and receive real-time demand predictions with visualizations after evaluation. Figure 1 illustrates the system's architecture.

A. Data Collection

The development of the product demand forecasting system for SMEs starts with the collection of raw data sourced from Kaggle, containing approximately 1,000 instances across various product categories such as electronics, clothing, books, toys, skincare, and games. The dataset also contains attributes such as Product ID, category, price, discount, city, stock quantity, sales volume, and date, spanning from January 2023 to June 2024, making it sufficient to train a predictive model focusing on features related to stock levels, sales trends, and seasonal demand.

B. Data Preprocessing

Before training the model, the training dataset must first be preprocessed to ensure consistency. The preprocessing phase started with addressing missing and duplicate values, which were either removed or replaced with the overall average. The Date feature was then converted into a proper datetime format, enabling the extraction of additional features such as Year, Month, and Season to detect variations in seasonal demand. A new categorical variable, Demand Level, was derived from the Sales values by segmenting them into Low, Medium, and High categories using the 33rd and 66th percentiles, thereby transforming the problem from continuous regression to a classification problem. In addition, the Revenue feature was engineered using the formula:

$$Revenue = Sales \times Price \times (1 - Discount / 100)$$

Categorical variables such as Product Category, City, and Season were encoded into numerical values using one-hot encoding methods, and all numerical features were scaled to ensure that no feature dominated during training.

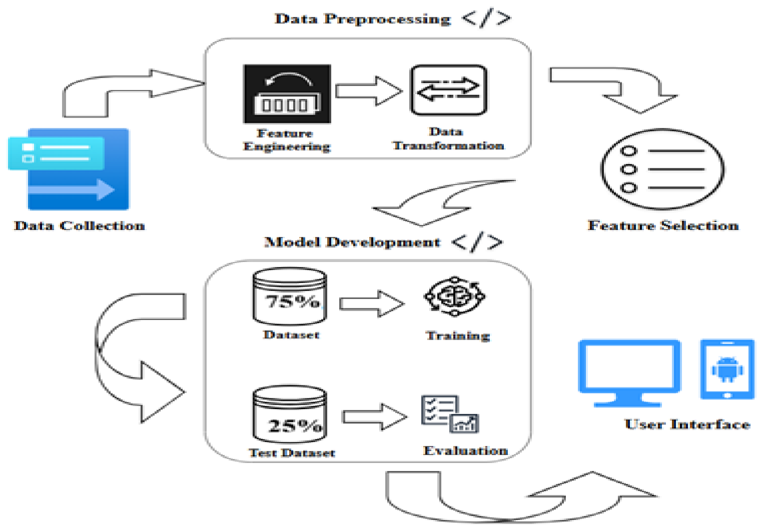

Fig.1 System Architecture

C. Model Selection

Rather than relying on traditional predictive algorithms such as K-Nearest Neighbors (KNN) and the Autoregressive Integrated Moving Average (ARIMA), this study employs ensemble classification models such as XGBoost and RF. RF was selected for its ability to combine multiple decision trees, which reduces variance and improves stability. In contrast, XGBoost uses an iterative approach to reducing errors and handling complex decision-making, making it suitable for capturing non-linear and complex relationships in the dataset while providing clear categorical outputs that inventory managers can use for decision-making. After a comparative analysis of their performance on the validation set, XGBoost achieved higher accuracy and more balanced precision–recall metrics.

D. Model Evaluation

After choosing the appropriate model, the dataset was divided into labelled training and testing sets. The split was performed such that 75% of the dataset was used for training and 25% for testing. During the training phase, the pre-processed training dataset was used to train the selected algorithms implemented within the Scikit-learn pipeline. The model was trained using K-fold cross-validation with k = 5 to reduce overfitting. In each fold, the model was trained and validated on portions of the training data, with results averaged across all folds. Hyperparameters were fine-tuned based on cross-validation scores. This iterative tuning process balanced model complexity and avoided the tendency to memorize patterns in the training data. The testing phase determines whether the model's predictions can be applied in a real-world project. The testing set was used to evaluate how well the model can classify demand categories for unseen inventory data.

Classification metrics such as F1-score, precision, accuracy, and recall help in understanding the balance between false positives and false negatives. Accuracy measures the correctness of the predictions, while precision measures the proportion of correctly predicted positive instances. Recall shows the proportion of actual positives that the model predicts accurately, while the F1-score is the harmonic mean of precision and recall. The confusion matrix was used to provide a visual summary of prediction results by showing how many instances were correctly classified or misclassified across all categories. These evaluation metrics determine the model's strengths and weaknesses and guide further improvements in model tuning and data preprocessing. For the Random Forest model, the confusion matrix showed perfect precision and recall for the High category but slightly misclassified the medium category. XGBoost displayed better overall results, with improved bias toward a particular demand level.

IV. RESULTS AND DISCUSSION

A. Random Forest (RF)

TABLE I SHOWING CLASSIFICATION METRICS OF RF ALGORITHM

Accuracy	precision	Recall	F1-score
Low	0.88	0.89	0.88
Medium	0.78	0.75	0.76
High	0.94	0.92	0.93
Accuracy			0.85

The RF classifier achieved an overall accuracy of 85% on the test dataset, showing improved results for the High and Low demand categories. However, performance for the medium demand category was weaker, with precision and recall values of 0.78 and 0.75, respectively, indicating some misclassification within the category. Table I presents the classification metrics for the RF algorithm, and Figure 2 shows the confusion matrix of the RF algorithm.

The RF confusion matrix shows that while High-demand products have higher accuracy, Medium-demand products are more prone to being classified as High. This may be due to overlapping features such as pricing and seasonal demand fluctuations. The model is still capable of accurately identifying most highly demanded products, making it valuable, as it helps prevent stock-outs.

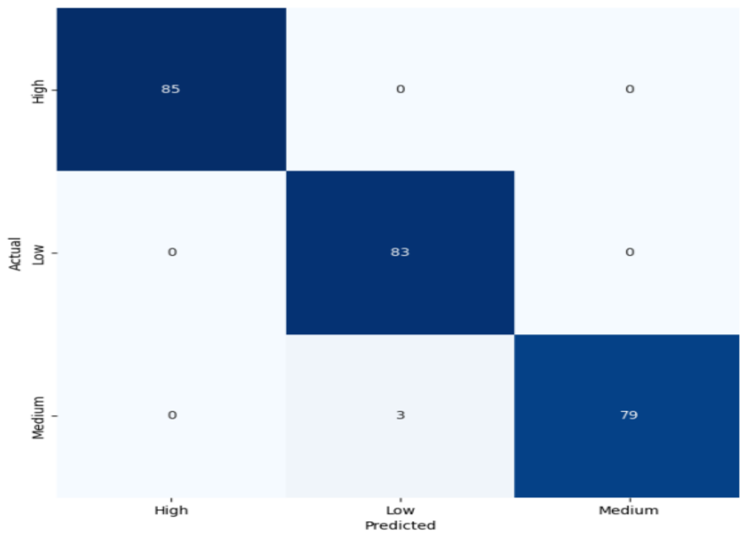

Fig.2 Random Forest Confusion Matrix

B. Extreme Gradient Boosting

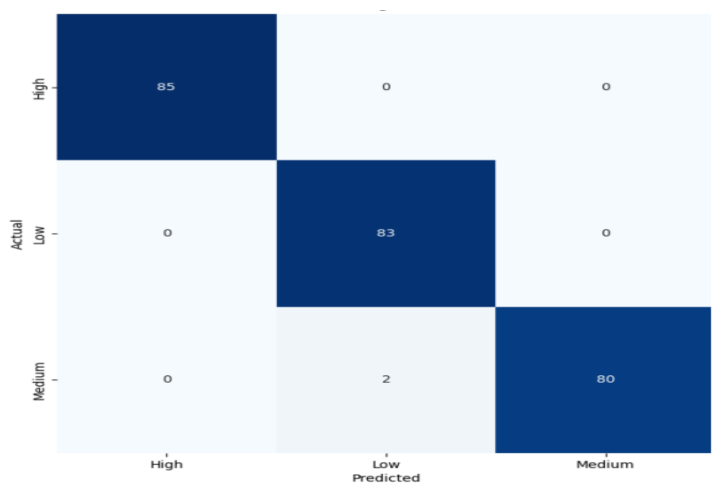

Fig.3 Gradient Boosting Confusion Matrix

TABLE II SHOWING CLASSIFICATION METRICS OF XGBOOST ALGORITHM

Accuracy	precision	Recall	F1-score
Low	0.91	0.90	0.90
Medium	0.88	0.84	0.86
High	0.93	0.92	0.92
Accuracy			0.87

The XGBoost classifier demonstrated better performance, achieving an overall accuracy of 87% with balanced results across all demand categories. Table II presents the classification metrics for the XGBoost algorithm, and Figure 3 shows the confusion matrix of the XGBoost algorithm. The confusion matrix highlights that XGBoost reduced misclassification in the medium demand category compared to Random Forest. This improvement is vital for SMEs, as moderately demanded products often have borderline sales, making prediction more challenging. The model's ability to continuously learn from previous errors and correct them demonstrates the overall balance and stability of the predictions.

V. CONCLUSION

The study shows that machine learning techniques, particularly the Gradient Boosting classifier, can effectively forecast product demand for SMEs. By using historical sales data and essential selected features, the model also provides useful insights into demand patterns, allowing businesses to optimize stock levels, reduce wastage, and increase profits for more efficient operations. The performance metrics indicate that the model is reliable for demand classification, although future improvements could further enhance its accuracy. Importantly, to improve the accuracy and effectiveness of this approach for SMEs, future studies should focus on improving model generalization using larger datasets and cutting-edge machine learning techniques. Additionally, exploring other factors that may affect predictions, such as seasonal trends and competitor pricing strategies, could support better decision-making and more useful recommendations.

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