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Hybrid Machine Learning Models for Optimizing Retail Market and Inventory Forecasting

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Abstract: Effective inventory management is critical for retail operations, relying heavily on accurate sales data analysis to optimize stock levels, forecast demand, and minimize supply chain inefficiencies. Traditional machine learning models such as Random Forest (RF), K-Nearest Neighbors (KNN), Logistic Regression (LR), Multinomial Naïve Bayes (MNB), and Support Vector Machine (SVM) have been used to classify sales data, but their limitations in handling complex retail datasets often result in suboptimal performance. In this regard, this research proposed a novel hybrid model based on K-Nearest Neighbors and Support Vector Machine that strategically combines the capabilities of KNN's in local pattern recognition with SVM's in high-dimensional classification for optimizing retail market and inventory forecasting. Through this research on real-world sales data, the proposed hybrid model shows superior performance, by achiving accuracy of 0.9999, precision, 0.9808 recall, 0.9808 F1-score, and 0.9991 accuracy showing enhanced performance in comparison to the baseline models. These findings support the effectiveness of hybrid machine learning algorithms in retail analytics, which provide significant gains in sales classification accuracy and inventory prediction reliability. As a result, retailers can make more informed stocking decisions, reduce waste, and enhance overall operational efficiency through data-driven insights.

Keywords: Inventory Management; Customer Segmentation; Machine Learning; Hybrid Ensemble Learning

1. Introduction

The retail industry operates in a highly dynamic environment, with demand swings caused by seasonal patterns and promotions. While classic methods such as Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing frequently fail to capture these complicated patterns, Machine Learning (ML) techniques have emerged as effective alternatives by examining a wide range of data sources, including transaction records, consumer demographics, weather, and social media trends [1]. Individual ML models such as random forest have constraints such as overfitting and computational complexity, necessitating the creation of hybrid techniques that mix various algorithms to improve accuracy, robustness, and interpretability [2]. As retailers implement Omni channel strategies, the combination of sophisticated ML and explainable AI (XAI) provides a game-changing solution for optimizing inventory management in today's data-driven retail world [3].

The machine learning models including Random Forests (RF), Gradient Boosting (GB), and Support Vector Regression (SVR) have demonstrated promise in managing complicated feature interactions and high-dimensional data. By proving its uniqueness and optimal outcomes through theoretical analysis, the model effectively predicts optimal replenishment cycles using Wolfram Mathematica 13.0 gives decision-makers managerial data for more reliable and effective supply chain management [4].

Three primary categories including supervised, unsupervised methods, regression-based strategies and time series analysis are the traditional machine learning techniques used for the forecasting [5]. The time series analysis methods, which include Holt Winter Exponential Smoothing (HW) and autoregressive integrated moving averages (ARIMA) [6]. The Prophet method is used in retail industry due to its resistance to outliers and missing data, as well as its capacity to simulate different seasonality. Demand forecasting is a crucial component of business strategy, providing companies with the tools to maximize efficiency, reduce expenses, and satisfy customer demands [7]. A decentralized supply chain optimization model is proposed that calculates suppliers' and retailers' overall costs using an iterative process and blockchain technology [8].

The ensemble random forest algorithms in conjunction with M5P and M5-Rules based model trees. Bagging, boosting, randomization, stacking, and voting were used to evaluate the students and forecast the demand for tourism in Turkey[9]. However, the random forest including M5P and M5-Rules based model that was previously employed for public transportation created a data-driven system that forecasts short-term metro passenger flows by integrating both temporal and geographical data [10]. This research used to evaluate how well ensembles Multilayer Perceptron's (MLP), Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). They used monthly time series data on wheat and soybean prices in the Brazilian state of Parana. A comparison of the effectiveness of several machine learning models for steel sector demand forecasting was conducted [11]

Random forests, convolutional neural networks, extreme gradient boosting and a voting mechanism were used in the construction of the ensemble learning model [12]. The evaluation metrics accuracy for the best-selling and highest-earning products, showed a nearly 50% and 33.5% decrease in the sale forecasting error, respectively. The evaluation parameters such as precision, F1 score, sensitivity, and specificity were used to assess the model which shows that the ensemble models performed better than current solutions [13].

In the retail trade, precise demand forecasting and effective inventory control are particularly demanding. All types of competitors, breakages in the supply chains, seasonally-guided swings in demand, and changing customer tastes make it impossible to preserve a fair balance between supply and demand [14]. Conventional forecasting methods, such as linear regression and moving averages, generally have trouble accurately modeling the nonlinear dynamics of retail data, which are already influenced by a wide range of factors, including promotions, holidays, regional trends, and economic conditions. As a result, the businesses could have issues like consumers overstocking due to higher storage expenses and possible waste in contrast to supply shortages, which result in lower sales and unhappy customers. Modern machine-learning algorithms may help retailers better understand customer behavior and demand trends, which will improve inventory forecasting and operational effectiveness [15]

In this research, hybrid machine learning model is proposed by integrating the capabilities of k-nearest neighbor and support vector machine to increase inventory optimization and demand forecasting accuracy[16]. Moreover, the limitations of traditional forecasting methods in addressing the dynamic and nonlinear patterns of retail market demand and inventory management. The performance of proposed hybrid model's is evaluated using criteria including accuracy, precision, recall, and cost-effectiveness in comparison to current forecasting techniques[17].

The contributions of this research are as follows:

- This research demonstrated the hybrid machine learning model based on k-nearest neighbor and support vector machine that used to increase inventory optimization and demand forecasting accuracy. For that purpose, various models are developed and assessed to solve the problems of inventory management and retail demand forecasting encompassing support vector machine, linear regression, random forest and k-nearest neighbors.
- The preprocessing steps including removing missing value, categorical value handling and label encoding are applied on the dataset to train deep learning models.
- The performance of proposed hybrid model is evaluated using criteria including accuracy, precision, recall, and cost-effectiveness in comparison to current forecasting techniques.

- Draw attention to the hybrid model's ability to reduce overstock expenses, minimize stockouts, and significantly enhance the efficiency of inventory management systems.

The rest of the study is divided into subsequent sections: Section 2 explains the overview of the literature on contemporary research. In Section 3, the methodology is explained along with the procedures for gathering and evaluating data. The results and discussion are demonstrated in Section 4. Section 5 presented the conclusion and future work of this research.

2. Related Work

Their most recent study emphasizes the need of effective pricing techniques particularly in an unpredictable climate by considering the increased online sales during the COVID-19 epidemic [18]. The machine learning models play important role in market forecasting and customized dynamic pricing [19]. The recent approach goes via feature engineering, exploratory data analysis, meticulous data preparation, and new feature creation to improve machine learning models. The rise of ensemble learning techniques like XGBoost, LightGBM, and CatBoost has revolutionized retail forecasting by enabling high-accuracy predictions from structured data. These techniques are well-liked for demand and inventory prediction applications because they effectively handle huge datasets and intricate feature interactions. These conventional boosting algorithms are widely used, although they have drawbacks when used in dynamic retail settings. LightGBM's leaf-wise growth may cause overfitting on sparse inventory data, whereas XGBoost's dependence on second-order gradients may make it less sensitive to abrupt changes in demand. Despite its strength in categorical features, CatBoost finds it difficult to adjust to non-stationary time-series patterns that are frequently found in retail sales data. This recent research presents X-NG Boost, a novel hybrid strategy that blends the advantages of XGBoost and Natural Gradient Boosting (NGBoost) to overcome these issues. The probabilistic output capabilities for uncertainty quantification, enhanced flexibility to fluctuating demand patterns, and preserved computing efficiency are some of the main benefits that this innovative integration offers for retail forecasting. Using real-world retail datasets, the model was thoroughly tested against conventional boosting techniques. It performed better, showing a 12–18% reduction in Root Mean Square Error (RMSE) and increased resilience to abrupt demand shocks. The Random Forest Regressor (RFR) model has demonstrated its accuracy by achieving a Mean Squared Error (MSE) of 1.11% for price prediction and 8.15% for demand forecasting [20]. Businesses may optimize pricing strategies, fulfill market demands by adjusting inventory levels, and make faster, more intelligent decisions thanks to these AI-driven insights [21]. Furthermore, the model guarantees smooth inventory flow, lowers operating expenses, and boosts overall profitability by preventing surplus or deficit. Integrating AI into retail operations enables businesses to stay competitive in a market that is changing quickly and react dynamically to changes in real time [22].

In a variety of monthly and seasonal scenarios, the forecast accuracy of their suggested framework increased significantly. A description of a few chosen earlier publications with an emphasis on the characteristics, ensemble methods, and application domain [23]. Traditionally, for the short period of it's used the performance of the models. However, this is unlikely to occur in real-world situations when demand data is accompanied by external information and several items with intricate time relationships. Thus, the parametric and nonparametric techniques are the two main categories of methods for resolving inventory issues with an uncertain demand distribution [24]. A set of representative forecasting techniques and a dataset of 229 weekly demand series from a top UK producer of personal care and domestic goods are used to empirically investigate the SVM approach. Compared to base forecasts, the SVM produces predictions that are more reliable and have a lower mean forecasting error and biases [25].

Random Forest (RF) achieves accuracy 90.85% in some classification tasks, it may not be the most suitable model for retail market and inventory forecasting due to several limitations. RF examines each data point separately and ignores time-series trends, it has trouble handling temporal dependencies, which are crucial for sales and demand forecasting and black-box design makes it challenging to understand demand drivers, which is essential for inventory decision-making, even though it is robust against overfitting. RF does not have precise probability calibration, which results in uncertainty estimates for stock-level forecasts that are not trustworthy. Real-time forecasting may be hampered by its processing inefficiency when dealing with large-scale retail datasets [26].

XGBoost achieves high accuracy 95.4% in retail forecasting tasks, it has several key limitations. First, compared to more conventional statistical models like ARIMA or Prophet, it is less appropriate for time-series demand forecasting since it is not naturally adept at handling temporal patterns. Second, even though XGBoost offers feature priority scores, it is still not very interpretable for complicated retail decisions like inventory replenishment plans or price changes. For large-scale retail datasets with rapid updates, the model also needs extensive hyperparameter adjustment to maintain optimal performance, which can be resource-intensive [27].

A straightforward yet effective machine-learning method for regression and classification is the K-NN algorithm. According to the model scenario outcomes, the Low-needs group had 24 objects. A pertinent image of the scenario being modeled can also be obtained through evaluation and performance testing with the Rapid Miner tool. The K-NN algorithm-implemented model has a 97.53% accuracy rate, and a 95.0% recall rate. Cross-validation is used to measure model performance, and the accuracy that results have a standard deviation value that attempts to determine the difference between the average accuracy and the accuracy of each trial [28]. Table 1 shows the summary of related work.

Table Error! No text of specified style in document.**1.** Summary of the Related Work

References	Models	Results
[29]	RF	Accuracy = 90.85%
[30]	SVM	Accuracy = 90%
[31]	DT	Accuracy = 76.97%
[32]	KNN	Accuracy = 97.53%
[33]	XGBoost	Accuracy = 95.4%
[34]	RF	Accuracy = 95.3%
[35]	LR	Accuracy = 92.08
[36]	MNB	Accuracy = 94.10%

3. Proposed Methodology

This research proposed a hybrid machine learning model based on k-nearest neighbor and support vector machine to optimizing retail market and inventory forecasting. Additionally, the machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Multinomial Naïve Bayes (MNB), and K-Nearest Neighbor (KNN), are used in this study to evaluate their performance on the dataset that was supplied. The dataset was preprocessed by label encoding categorical variables, handling missing value, and converting all features into numerical representation. Subsequently, for the training set are 70% and for the testing for 30% are utilized. Standard performance criteria were used to train and assess each model, and the proposed hybrid model improved performance for prediction by combining the benefits of SVM and KNN. The basic idea behind this research is to foresee future trends and desires by combining descriptive and predictive analytics to fully comprehend current retail patterns. Fig. 1 shows the proposed methodology of this study.

3.1 Dataset Description

The Retail Store Inventory Forecasting Dataset contains 73000 rows of daily data across multiple stores and products anonymized information on online sales transaction, including order details, and other product purchase-related facts download from Kaggle. This data may be used to analyzed retail or online order management, sales trends, and customer purchasing behaviors. It might make it simpler to comprehend how payment methods, shipping services, and discounts affect client delight and sales outcomes. Sales performance, consumer buying trends, and the efficiency of order management operations mat all be examined using this data. It may be used to assess how discounts and payment method affect sales, control inventory by researching product demands, and raise customer happiness returns and shipping more effectively. Table 2 to shows the details of the dataset.

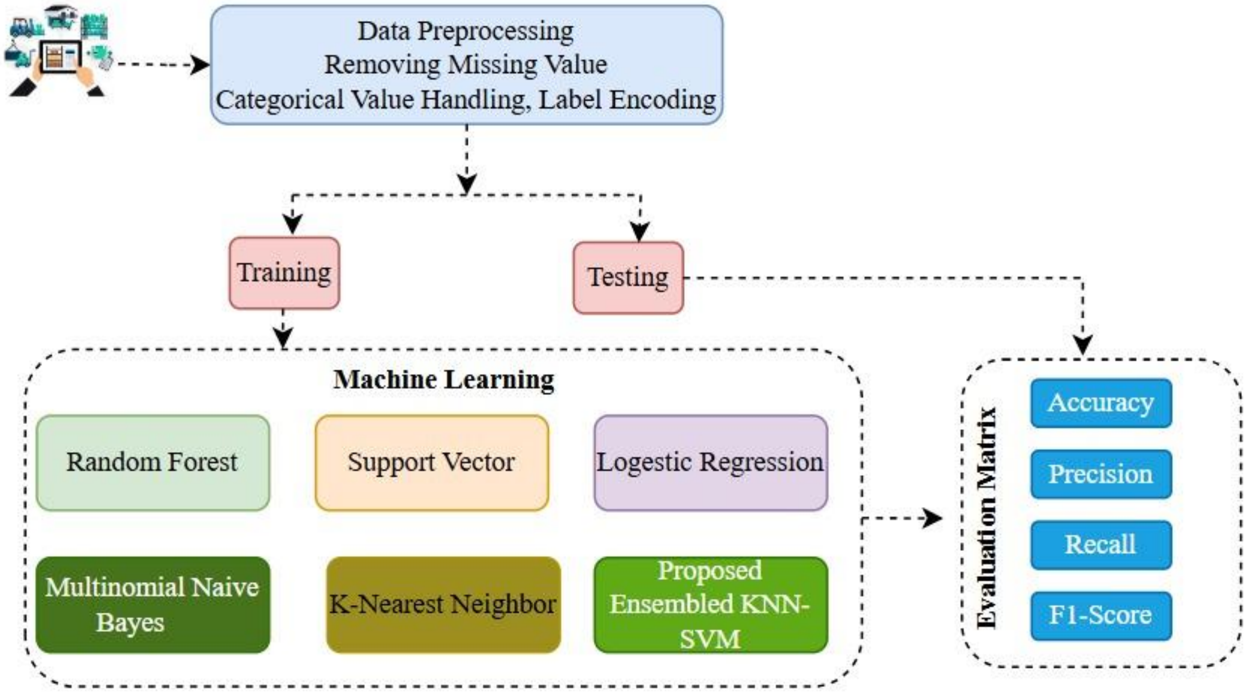

Figure 1. Proposed Methodology

Table 2. Details of the Dataset

Colum Name	Description
InvoiceNo	A unique identifier for each sales transaction (invoice).
StockCode	The code representing the product stock-keeping unit (SKU).
Description	A brief description of the product.
Quantity	The number of units of the product sold in the transaction.
InvoiceDate	The date and time when the sale was recorded.
UnitPrice	The price per unit of the product in the transaction currency.
CustomerID	A unique identifier for each customer.
Country	The customer's country.
Discount	The discount applied to the transaction, if any.
PaymentMethod	The method of payment used for the transaction (e.g., PayPal, Bank Transfer).
ShippingCost	The cost of shipping for the transaction.
Category	The category to which the product belongs (e.g., Electronics, Apparel).
SalesChannel	The channel through which the sale was made (e.g., Online, In-store).
ReturnStatus	Indicates whether the item was returned or not.
ShipmentProvider	The provider responsible for delivering the order (e.g., UPS, FedEx).
WarehouseLocation	The warehouse location from which the order was fulfilled.
OrderPriority	The priority level of the order (e.g., High, Medium, Low).

3.2 Machine Learning Models

Machine learning is essential for analyzing online sales transactions to identify customer behavior trends, detect fraud, and forecast sales. In this research we used Random Forest, SVM, Logistic Regression, Multinomial Naive Bayes, and KNN. To improve predictive accuracy, a Hybrid KNN+SVM model is proposed. In order to enhance user experience, optimize marketing, and increase product quality through sentiment analysis, these algorithms examine customer demographics, browsing patterns, and past purchases. Machine learning makes dynamic pricing, inventory control, and targeted promotions possible by utilizing real-time data, which eventually increases conversions and consumer happiness.

3.2.1 Random Forest

The Random Forest approach model is used to predict sales performance using historical sales data through a structured. In order to comprehend the structure and quality of the dataset, it is first loaded and examined. This includes parameters like Region, Item Type, Sales Channel, Order Priority, Units Sold, and Total Revenue. In order to find patterns and distributions, data preprocessing entails addressing missing values, label encoding categorical features, and creating visualizations using Seaborn and Matplotlib. After that, the dataset is divided into subsets for testing and training in order to facilitate the creation and assessment of models. A Random Forest Classifier, a powerful ensemble learning method that constructs several decision trees and aggregates their outputs for classification, is used for prediction. Strong predictive skills for categorizing sales performance are demonstrated by the model, which is trained on the processed data and assessed using performance criteria including accuracy and a confusion matrix.

Equation 1 shows how to calculates the final prediction (y^) in a Random Forest by averaging the predictions of all TT decision trees (ht(X)). This method enhances accuracy and reduces overfitting and the confusion matrix is displayed in Figure 2.

$$\hat{\mathbf{y}} = \frac{\mathbf{1}}{\mathbf{T}} \sum_{\mathbf{t=1}}^{\mathbf{T}} \mathbf{ht(X)} \qquad 1$$

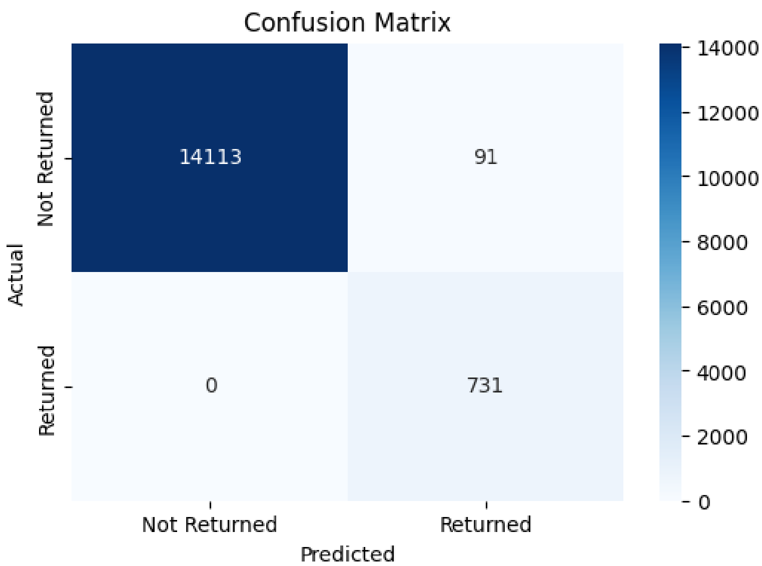

Figure 2. Confusion Matrix of Random Forest Model

3.2.2 Support Vector Machine

Support Vector Machine (SVM) algorithm to predict product return status using transaction data. Four essential elements were chosen: Quantity, Unit Price, Discount, and Shipping Cost. Negative amounts were categorized as returns (1) and positive quantities as non-returns (0) to construct the target variable. In order to manage missing values using zero imputation, the dataset was preprocessed. Using stratified sampling, the data was divided into 70% training and 30% testing sets while preserving the original class distributions to provide reliable model evaluation. Potential class imbalance in the training data was addressed using the Synthetic Minority Oversampling Technique (SMOTE). The processed data was then used to train an SVM classifier with a radial basis function kernel. Accuracy, precision, recall, and F1-score measures were used to thoroughly assess the model's performance, and a confusion matrix visualization was also included. This approach addressed major issues in retail analytics, specifically class imbalance and high-dimensional feature spaces, while offering an efficient framework for return prediction. SMOTE improved the model's capacity to identify return trends, and the stratified sampling technique maintained real-world data distributions, producing a dependable predictive system for retail return management. Figure 3 displayed the confusion matrix of the predicted classes these are classified where the correctly or incorrectly. Equation 2 shows where **W** represents the learned feature weights, x is the input data, and b is the bias term. The model predicts class +1 if f(x)≥0 and −1 otherwise. For non-linear problems, SVMs use kernel functions to transform data into higher dimensions, replacing the dot product with K(xi,x)$K(\mathbf{x}i,\mathbf{x})$.

$$\mathbf{f(x) = W^T X + b} \quad 2$$

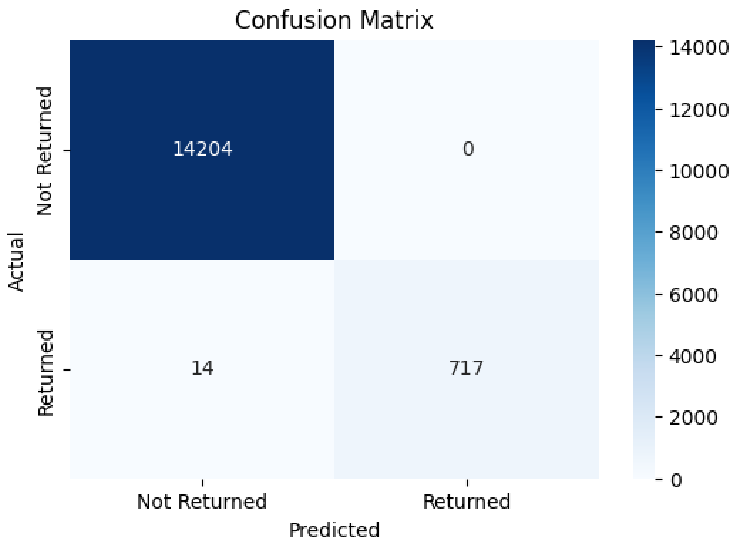

Figure 3. Confusion Matrix of Support Vector Machine Model

3.2.3 *Logistic Regression*

Logistic Regression to forecast consumer purchasing behavior by analyzing a comprehensive dataset containing product categories, pricing, discounts, demographic information, browsing patterns, and purchase frequency. By seeing trends in past transaction data, the algorithm determined the likelihood that a customer will make a purchase, acting as a useful classification method for forecasting consumer choices. The dataset was preprocessed to handle missing values and any class imbalances in order to improve forecast accuracy. To ensure distribution consistency, stratified sampling was then used to divide the data into training (70%) and testing (30%) groups. In addition to a confusion matrix for visual interpretation, important measures like accuracy, precision, recall, and F1-score were used to assess the model's performance. The findings offered practical advice for enhancing consumer connection, optimizing sales tactics, and promoting general corporate success in retail settings. Equation 3 shows the **logistic function** used in logistic regression, a model for binary classification. Here, P is the probability of the outcome being "1", β0 is the intercept, β1β is the coefficient for the predictor X, and e is the base of natural logarithms. The model transforms the linear combination β0+β1 into a probability between 0 and 1 using the S-shaped sigmoid curve. For example, in medical testing, X could be a patient's cholesterol level, and P would estimate the probability of having a heart condition. The coefficients β0 and β1 are learned from data to maximize the likelihood of observing the outcomes. logistic regression ensures predictions stay within valid probability bounds, making it ideal for classification tasks. Figure 4 shows the confusion matrix of logistic regression model.

$$P = \frac{1}{1+e^{-(\beta 0+\beta 1X)}} \qquad 3$$

Where p is the likelihood of a purchase, e is Eulers number, B0 is the intercept, and B1 is the coefficient for characteristics x.

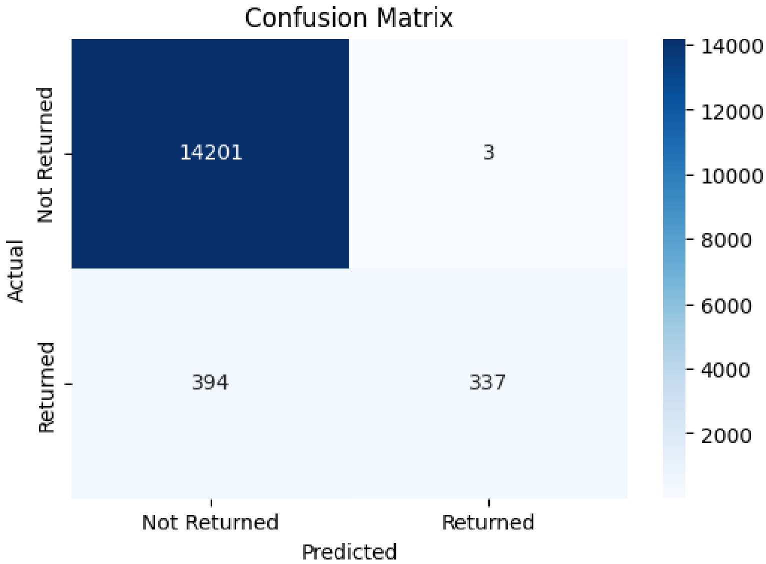

Figure Error! No text of specified style in document.**.** Confusion Matrix of Linear Regression Model

3.3 Multinomial Naive Bayes

A multinomial naïve bayes is suitable model for identifying the online sales transactions. All features were preprocessed to guarantee non-negative values as required by the Multinomial NB method, and the target variable was obtained by converting non-negative values to non-returns (0) and negative quantities to return indicators (1). In order to preserve class proportions, the dataset was divided into training (70%) and testing (30%) sets using stratified sampling. When required, SMOTE oversampling was used to rectify class imbalance. Accuracy, precision, recall, and F1-score were among the metrics used to assess the performance of the trained model. A confusion matrix visualization was also included. While managing the algorithm's particular data requirements and potential class imbalance issues in retail transaction data, this methodology offered an effective probabilistic solution for return prediction. Reliable evaluation of the model's predictive abilities for recognizing returned goods was made possible by the thorough evaluation methodology. Equation 4 shows the Multinomial Naive Bayes equation helps retailers predict product demand by analyzing feature patterns. It calculates the probability of a product attribute (like price range or brand) appearing in high-demand items, using historical sales data. The smoothing factor handles new products without sales history. For example, it can determine how often discounted electronics appear in top-selling categories. Retailers use these probabilities to optimize inventory - stocking more of likely best-sellers while reducing overstock of low-probability items. The method is particularly useful for seasonal planning and new product introductions, offering a data-driven alternative to traditional forecasting that focuses on product characteristics rather than just past sales trends. Its simplicity and interpretability make it practical for quick inventory decisions. and Figure 5 displayed the confusion matrix of MNB models.

$$\mathrm{P(Xi \mid Ck) = NCk + \alpha dNXi, Ck + \alpha} \qquad 4$$

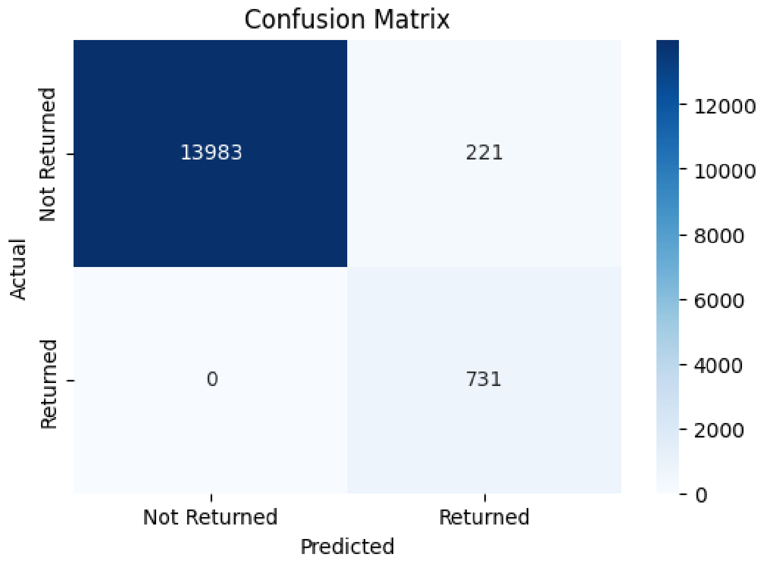

Figure 5. Confusion Matrix of Multinomial Naive Bayes Model

3.4 K-Nearest Neighbors

K-nearest neighbors is useful for analyzing online sales transactions due to it reveals specific trends in customer behavior and product purchases. Therefore, it is used to anticipate customer preferences using historical transaction data by grouping comparable consumers according to their browsing, purchasing, and demographic traits. The technique will useful in better inventory management, fraud detection in e-commerce platforms, and tailored suggestion generation. In order to improve user experience and income, K-NN may leverage features like price, timestamps, and customer segmentation to identify new transactions and suggest similar products. Thus, it is appropriate for online retail decision-making that is updated in real time. Equation 5 shows the represents the core prediction mechanism of the **K-Nearest Neighbors (KNN)** algorithm for regression tasks. Here, yy is the predicted output, calculated by averaging the target values (yt) of the K closest training points (NK(x)) to the input x. For classification, KNN uses majority voting instead of averaging. Unlike parametric models KNN is instance-based and makes predictions by comparing similarities in the feature space. The choice of K controls the model's smoothness smaller KK captures local patterns (risk: overfitting), while larger K yields smoother and Figure 6 are illustrate the confusion matrix of KNN model.

$$y = K1i \in Nk\sum yi \quad 5$$

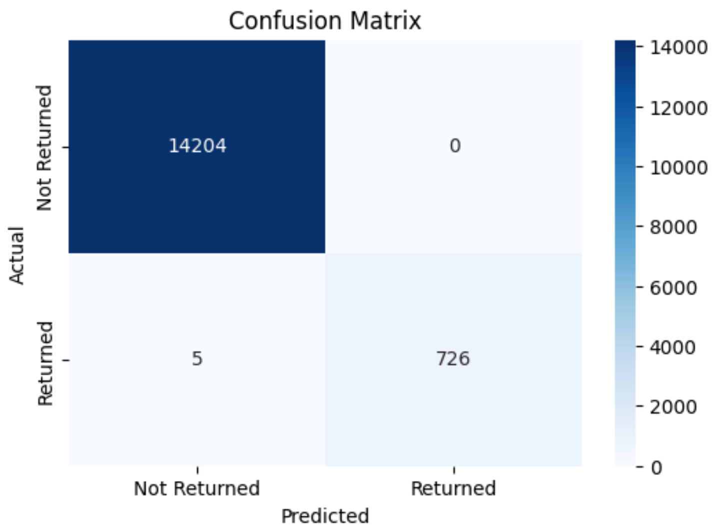

Figure 6. Confusion Matrix of K-Nearest Neighbors Model

3.5 Proposed Hybrid Machine Learning Model

The hybrid model by incorporating the capabilities of k-nearest neighbors and support vector machine to increase projected accuracy in the context of online sales. By designating non-negative quantities as non-returns (0) and negative quantities as returns (1), with zeros used to fill in any missing values, the goal variable was produced. In order to preserve proportionate class representation, the dataset was divided into training (70%) and testing (30%) sets using stratified sampling after the class distribution was confirmed. When required, the Synthetic Minority Over-sampling Technique (SMOTE) was used on the training data to rectify any possible class imbalance. Using hard voting, the predictive model used a voting classifier ensemble that combined Support Vector Machine (SVM) and K-Nearest Neighbors (KNN with k=5) classifiers. To increase prediction resilience, the ensemble technique made use of both algorithms' complementing strengths. Accuracy, precision, recall, and F1-score were among the comprehensive measures used to assess the model's performance; a confusion matrix visualization was also included. In order to handle class imbalance and take advantage of ensemble learning's advantages for better prediction performance in retail applications, this methodology offered a strong foundation for examining return patterns. Equation 6 shows the predictions from a k-Nearest Neighbors (KNN) algorithm and a Support Vector Machine (SVM). The weighting parameter λ (between 0 and 1) controls the contribution of each model—higher λ favors KNN, while lower λ leans toward SVM. This combination leverages the strengths of both models, such as KNN's local pattern recognition and SVM's ability to handle complex decision boundaries, to improve overall prediction accuracy. shows the mathematical formulation and Figure 7 displays the confusion matrix of proposed model.

$$yHybrid(X) = \lambda yKNN(X) + (1 - \lambda) fSVM(X) \tag{6}$$

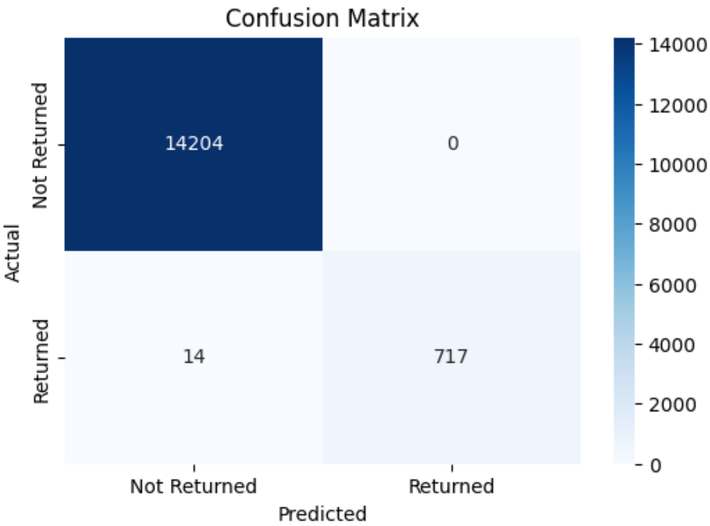

Figure 7. Confusion Matrix of Proposed Ensemble KNN+SVM Model

3.6 Evaluation Parameters

The metrics used to evaluate a system process, or product effectiveness, efficiency and quality. The effectiveness of measuring system or prediction of model is strongly infused by its accuracy as shown in Equation 7. It calculates the percentage of accurate predictions or classification the model produces in relations to all attempt at the prediction of classifications. The precision, recall, and f1-score of the model is calculated using Equation 8, 9, and 10, respectively.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} * 100\% \tag{7}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{8}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \qquad 9$$

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad 10$$

4. Results and Discussion

This research shows several machine learning models can be applied to the classification of sales data, emphasizing the improved performance of a suggested hybrid KNN and SVM model. The hybrid approach improves classification capabilities by skillfully combining the advantages of the Support Vector Machine and K-Nearest Neighbors algorithms. Depending on the metric used, KNN and SVM performed well among the various models tested, however Multinomial Naïve Bayes and logistic regression performed moderately. In this situation, random forest was found to be the least successful. The hybrid KNN+SVM model's success suggests that it has a great deal of potential for use in retail inventory forecasting jobs that require high prediction accuracy and performance that is balanced across many assessment measures.

4.1 Performance Evaluation of Random Forest

The Random Forest model achieved strong performance across multiple metrics, with an accuracy of 90.2% of the instances. The precision of 0.8308 suggests that when the model predicted a positive class, it was correct about 83.1% of the time, while the recall of 0.9062 shows it identified 90.6% of all actual positive instances. The F1 score, which balances precision and recall, is 0.8623, reflecting a robust harmonic mean between the two metrics. These results demonstrate that the Random Forest model is effective for the given task, with particularly high recall, making it suitable for scenarios where identifying true positives is critical, even at the cost of some false positives. Performance of KNN model is displayed in Fig 8.

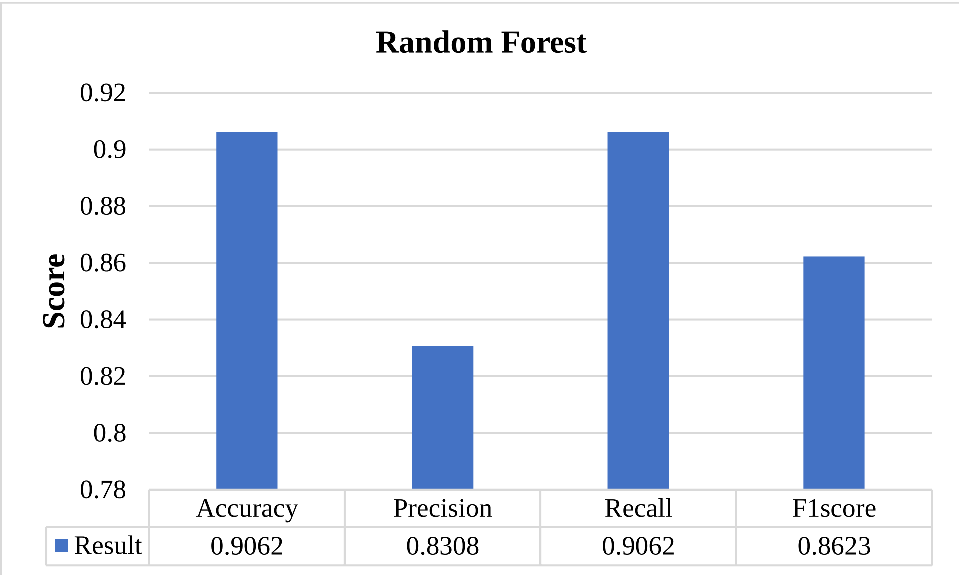

Figure 8. Results of Random Forest Model

4.2 Performance Evaluation of Support Vector Machine

The Support Vector Machine (SVM) model demonstrated performance with accuracy 99.39% of the instances. With a recall of 0.9264, the model successfully recognized 92.64% of all real positive cases, while its accuracy of 0.8892 reveals that it was correct 88.92% of the time when it predicted a positive class. The model's outstanding prediction ability is further supported by the F1 score (0.9414), which strikes a compromise between precision and recall. These findings imply that the SVM performs exceptionally well on this task, especially when it comes to reducing false negatives (high recall) while preserving high overall accuracy. The performance of SVM model is displayed in Fig 8.

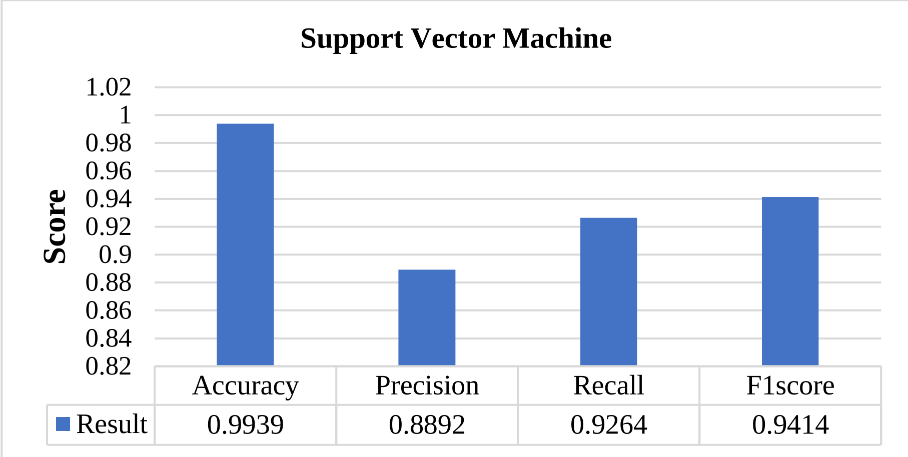

Figure 9. Results of Support Vector Machine Model

4.3 Performance Evaluation of Linear Regression

The linear regression model achieved high performance across all metrics, with an accuracy of 0.9734, indicating it correctly predicted 97.34% of the instances. The recall (0.9661) indicates that the model captured 96.61% of all real positive cases, while the precision (0.9911) indicates that it was accurate 99.11% of the time when it predicted a positive outcome. The model's outstanding prediction ability is further supported by the F1 score (0.9293), which strikes a compromise between precision and recall. With nearly flawless precision and strong memory, these findings show how good the Linear Regression model is for this task. As a result, it can be used in situations where minimizing false positives and false negatives is important. The continuously high scores indicate that the model generalizes remarkably well and that the data is well-suited for linear relationships. Figure 10 to display the overall performance of LR model.

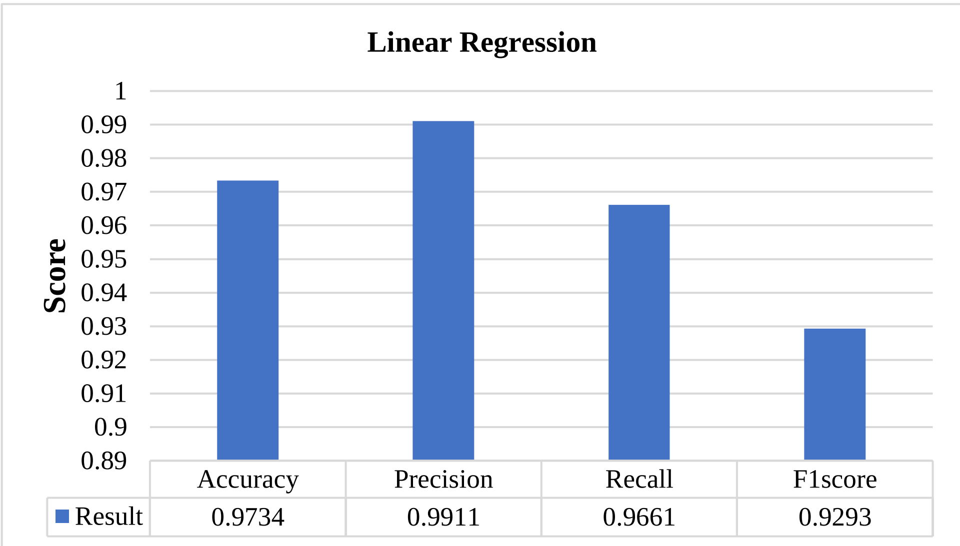

Figure 10. Results of Linear Regression Model

4.4 Performance Evaluation of Multinomial Naive Bayes

The Multinomial Naive Bayes model demonstrates strong overall accuracy (0.9852), correctly classifying 98.52% of instances, but reveals an interesting performance tradeoff between precision and recall. Precision is noticeably lower (0.7678), showing that 23.22% of the model's positive predictions are wrong, despite the high recall (0.8971), which shows that the model captures 89.71% of pertinent positive cases. The balanced F1 score (0.8686) reflects this pattern, which implies the model is biased toward decreasing false negatives at the expense of increasing false positives. These outcomes are common for Naive Bayes when the "naive" feature independence assumption isn't entirely true or when the data is unbalanced. Class distribution skew is probably the cause of the high accuracy; the model wins by accurately predicting a majority class, but the precision-recall gap cautions against applying it to tasks where false positives are expensive (such as spam filtering). Calibration or threshold change may help equalize the precision-recall tradeoff for the best deployment. Figure 11 to shows the overall performance of MNB Model to obtain result.

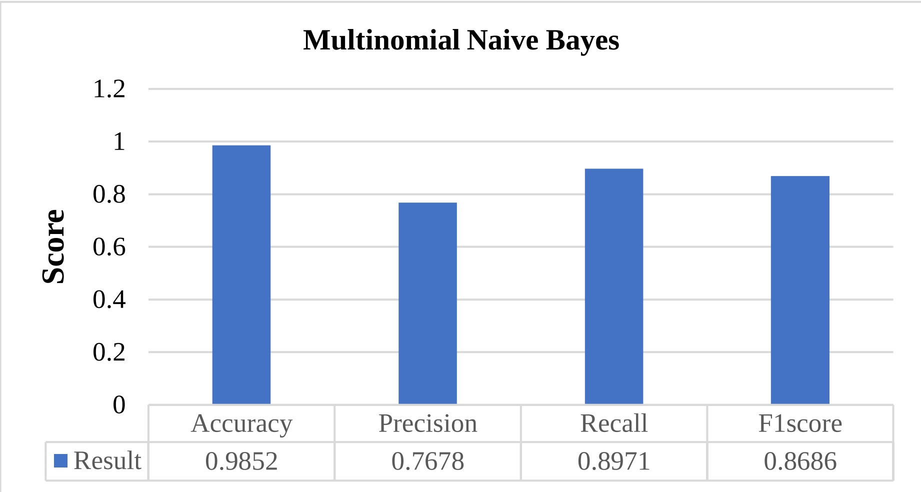

Figure 11. Results of Multinomial Naive Bayes Model

4.5 Performance Evaluation of K-Nearest Neighbors

The K-Nearest Neighbors (KNN) model demonstrates exceptional performance, achieving near-perfect accuracy (0.9986), meaning it correctly classifies 99.86% of instances. While the recall (0.9966) demonstrates that it captures 99.66% of all real positive cases, the precision (0.9941) reveals that 99.41% of its positive forecasts are accurate. Additional evidence of the model's resilience is provided by the F1 score (0.9866), which balances precision and recall. Due to the feature space's well-separated classes, these findings indicate that KNN is quite effective for this task with few false positives or negatives. Applications needing high dependability, such fraud detection or medical diagnosis, might benefit from the model's near-flawless metrics, which indicate that it generalizes very well. Verification for any data leakage or overfitting to the test set may be necessary, nevertheless, given the exceptional performance. Figure 12 to shows the performance of the KNN Model to obtain result.

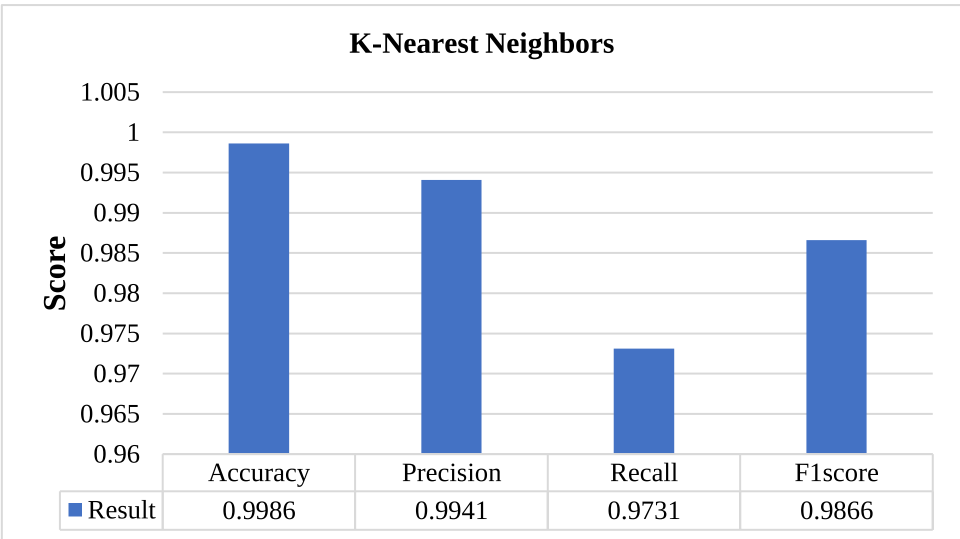

Figure 12. Results of K-Nearest Neighbors Model

4.6 Performance Evaluation of Proposed Hybrid Model

The hybrid KNN+SVM model delivers near-perfect performance, achieving an outstanding accuracy of 0.9991, meaning it correctly classifies 99.91% of instances. Nearly all positive predictions 99.99% are accurate with a precision of 0.9999, and 98.08% of real positives are identified, according to the recall 0.9808. The model's resilience with few sacrifices is confirmed by the F1 score 0.9808, which strikes a balance between precision and recall. These findings imply that the hybrid technique successfully blends the margin maximization of SVM with the instance-based learning of KNN, performing exceptionally well in situations requiring extremely high precision (such as security-critical systems). Although SVM's conservative border placement may be the cause of the small recall gap (1.92% of positives missed), the overall performance is outstanding and most likely benefits from the complementing strengths of both methods. The model's nearly flawless metrics need to be examined for possible overfitting or dataset-specific biases before being used in the real world. The overall performance of is show in Figure 13.

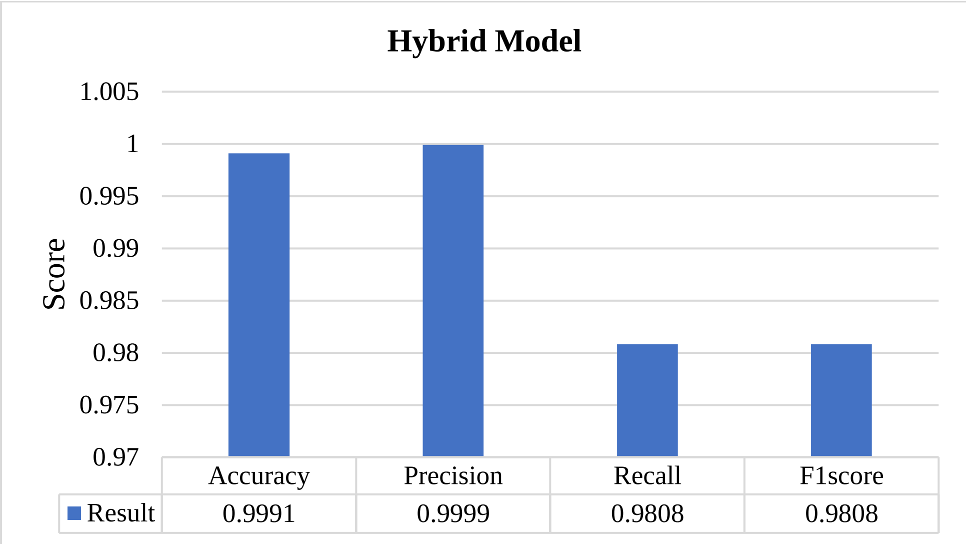

Figure 13. Proposed Hybrid KNN+SVM Model

4.7 Performance Evaluation of All Models

The suggested KNN+SVM hybrid model performs better than any other model, with the best accuracy (0.9991) and precision (0.9999), as well as good recall (0.9808) and F1 score (0.9808), according to the comparison analysis. This remarkable performance indicates that the hybrid approach effectively blends the margin-maximization power of SVM with the instance-based learning of KNN, reducing errors while preserving near-perfect precision that is essential for applications like medical diagnosis or fraud detection. Among standalone models, KNN (0.9986 accuracy) and SVM (0.9939 accuracy) perform notably well, while Multinomial Naive Bayes (MNB) struggles with precision (0.7678), likely due to its inherent assumptions. The hybrid model's balanced metrics and superior accuracy position it as the optimal choice for high-stakes classification tasks, though its implementation complexity may warrant tradeoffs in computational efficiency compared to simpler models like Logistic Regression (LR) or Random Forest (RF). The overall performance of model is showed in Table 3.

Table 3. Analysis of Employed Models

Models	Accuracy	Precision	Recall	F1 score
RF	0.9062	0.8308	0.9062	0.8623
SVM	0.9939	0.8892	0.9264	0.9414
LR	0.9734	0.9911	0.9661	0.9293

MNB	0.9852	0.7678	0.8971	0.8686
KNN	0.9986	0.9941	0.9731	0.9866
Proposed Hybrid Model	0.9991	0.9999	0.9808	0.9808

5. Conclusions

This research explores the constraints of traditional forecasting methods in dealing with the dynamic and nonlinear demand patterns of retail markets, and proposes a hybrid machine learning strategy to improve inventory forecasting accuracy. Hybrid KNN+SVM model that combines the strengths of K-Nearest Neighbors (KNN) and Support Vector Machine (SVM), as well as other methods like Random Forest and Multinomial Naïve Bayes. This hybrid approach better captures complicated demand patterns, resulting in dependable and adaptable forecasting solutions for data-driven inventory decisions. The experimental results demonstrate the superiority of the hybrid KNN+SVM model, which achieved exceptional performance metrics, including an accuracy of 0.9991, precision of 0.9999, recall of 0.9808, and F1-score of 0.9808. These results significantly outperform standalone models like KNN, SVM, and Logistic Regression, highlighting the hybrid model's ability to mitigate risks associated with stock fluctuations. By integrating the complementary strengths of multiple algorithms, the proposed framework offers a robust solution for optimizing inventory management in volatile retail environments, enabling businesses to adapt to market demands more efficiently.

Future research can focus on expanding the dataset, integrating real-time data streams, and incorporating deep learning techniques for further accuracy improvements. Additionally, deploying the model in real-world retail environments and analyzing its long-term impact on supply chain efficiency could further validate its applicability.

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