

Research Article

Artificial Intelligence Enabled Demand Forecasting for Sustainable Fashion Retail

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Abstract

The intensive growth of fashion e-commerce sites, the necessity of proper demand forecasting has grown in order to facilitate sound inventory control and make right time decisions in the retail business. The fashion industry is especially difficult to predict because of changing customer tastes, the circumstantial product life cycle and marketing trends. This paper suggests a hybrid demand forecasting model sustainable fashion retail based on a retail sales data collected at Kaggle, that contains both transactional and customer demographic characteristics. The data is formatted and processed to get valuable information about the customer behavior and the sales trends. The proposed method incorporates both the use of Random Forest and XGBoost in order to best reflect both linear and nonlinear data relationships. Regression metrics used to assess the model performance include the R^2 , RMSE, MAE, and MAPE. The experiments show that the hybrid model provides a better performance of R^2 of 0.90, RMSE of 2.81, MAE of 2.27 and MAPE of 13.72. By contrast the predictive accuracy and error values of baseline models such as Linear Regression, LSTM, and Support Vector Machine (SVM) indicate low predictive accuracy and high error values and therefore indicate the success of the proposed hybrid approach.

Keywords: Demand Forecasting, Fashion Retail, Regression Metrics, Hybrid Model, E-Commerce, Fashion Industry

Introduction

Considering that a significant increase in the number of digital platforms of fashion stores and enterprises, the customers are able to visualize and select a huge amount of online fashion products displayed virtually[1]. A radical change in the purchasing behaviour of customers has occurred and it is influenced by a plethora of factors, including social media, fashion activity, etc. People are now more and more willing to choose their products among the vast array of choices and have them delivered in the most minimal amount of time possible [2]. Fashion retailers are faced with the challenge of satisfying the consumers within a small-time frame. As a result, merchants of trendy apparel must make quick and efficient decisions on stock replenishment in advance based on demand trend projections.

An essential component of effective supply chain management in the retail fashion sector is demand forecasting. Obsolescence, sloppy stock inventory management, and unorganized resource use are all consequences of upstream supply chain problems caused by inaccurate forecasting models[3].

Typically, forecasting models are much more of a concern to profit-oriented companies because most decisions that make in their business are contingent on the forecasted future uncertainties on the demand and sales of their products [4]. It is easy to make poor or inaccurate predictions about future demand or sales in the fashion apparel sector due to the industry's defining characteristics, such as Product Styles, patterns, designs, short life cycles, Fluctuating Needs, and Long Replenishment cycles[5]. The apparel fashion sector is now working on robust forecast models, which would improve the efficacy of sourcing and sales-related decision-making.

The rate of appearance of new fashions products in the market is itself very high. The main concern is often how the fashion supply chain's decision-makers handle the new items' market share in terms of sales and demand[6]. It is become more difficult for fashion merchants to forecast demand and sales of new fashion products due to a number of variables, including fluctuating consumer tastes, unpredictable markets, supply chains, and poor predictability on a weekly or item level[7]. The fashion apparel retail business generates significant levels of sales and item related data in the epoch of big data, and in case of the effective management and utilization of the newest data analysis tools, the performance of the business within

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the fashion industry could be enhanced substantially[8][9][10].

Traditional fashion retail management approaches include leveraging historical product data, such as SalesRecords and Image Data features, to train prediction models aimed at forecasting product demand and sales. However, the required historical data is not always available for the new fashion product. Without access to pertinent historical data, it is hard to forecast future sales and demand for a new fashion item. Historical product data mainly consists of two things: sales data and product image data[11][12]. Product characteristics including color, style, pattern, and other pertinent information are the basis for data from photographs. To effectively estimate the demand for fashion garments, the forecasting models must be augmented with new data, such as product Image Data, Social Media data, and Consumer Data, since the historical sales data used to develop them is not completely reflective of all product qualities[13]. The new fashion product items might have numerous differences from the current products, but numerous similarities, like colour, size, and style, among others, might be shared and exist within the HistoricalProductData that can be brought out, and whose influence can be investigated in forecast modelling.

The swift development of fashion online stores has greatly changed the customer buying behaviour, with the growth in demand of a variety of products and higher expectations on quick delivery. This volatile environment poses a problem to retailers in estimating demand and having an efficient way of dealing with inventory. Forecasting in the fashion retail sector is further complicated by the factors of transformation in the consumer preferences, short life-cycles of the products and lack of past records on the newly introduced items. Inability to predict demand accurately may lead to overstocking, stockouts and wasteful use of resources. Thus, there is a high demand of sophisticated and dependable forecasting methods that are able to manage complex retail and make better decisions. The development of sustainable hybrid models is therefore encouraged as a means to improve the accuracy of demand forecasts in the sustainable fashion retail industry. The article contribution is as follows:

Introduces a hybrid demand prediction model (Random Forest and XGBoost (RF XGB)) to achieve better demand forecasting in sustainable fashion retail. Systematically pre-processes data and transforms features in preparation of retail sales data to be efficiently learned by a model.

Compares the performance of the proposed model with regression indicators, including R², RMSE, MAE, and MAPE, and is sure of an accurate evaluation of the prediction validity.

Shows that the RF-XGBoost hybrid model is effective to capture nonlinear relationships appearing

in retail data, and it is a scalable solution to demand forecasting and inventory optimization.

The paper follows the following structure: Section II contains the literature review, Section III explains the methodology, Section IV displays the results and analysis, and Section V contains the conclusion and recommendations for further research.

Literature Review

In this section, the literature concerning the use of AI in the retail industry will be discussed, such as the demand forecasting and customer behavior analysis. Table I gives the key findings and approaches of these studies.

Dharani (2025) examines how AI may be used to predict sustainable fashion trends, emphasizing the technology's capacity to handle enormous volumes of consumer data, sentiment on social media, and new design developments. They address AI's role in the adoption of Sustainable Materials, Circular Economies, and responsible fashion design, focusing on its potential to improve accuracy, reduce waste, and promote sustainability in the fashion sector. The study's conclusion looks at issues such data bias, the necessity for industry-wide acceptance, and the absence of uniformity in sustainability indicators[14]. Riachy et al. (2025) presents a plan to improve the accuracy of demand forecasts after a pandemic. Along with lockdowns and store closures, this comprehensive approach accounts for indirect factors that impact retail sales, such as telecommuting and school closures. The suggested method was thoroughly tested using a real-world dataset acquired from the footwear retailer Charles Clinkard in the UK. The findings shown that in this real-world situation, forecasting accuracy increased steadily over three layers of product aggregation and four deep probabilistic models[15].

Ankam (2025) delves into the development of demand forecasting methods, obstacles to application, and measurable performance indicators in different retail industries. Data quality management, organizational change procedures, model maintenance needs, ethical issues, and legacy system integration are some of the significant implementation problems that the paper goes on to discuss. This study gives a comprehensive approach for examining the current capabilities and possibilities of AI-driven demand forecasting in retail enterprises, integrating real data from varied retail scenarios[16].

Anitha and Neelakandan (2024) proposes a ML-based methodology to analyze consumer preferences and predict future product demand. Fitting room data is evaluated and customer profiles are made in order to comprehend customer preferences. K-means clustering is an unsupervised ML technique that groups similar characteristics to create clusters. Weights based on the proportion of product in each cluster were given to the clusters. The new product is classified into one of the predetermined groups using a DT classification model

after the clustering procedure in order to forecast demand for the new product. Retailers may minimize excess inventory by stocking items that fit with consumer preferences using this demand forecasting technique[17].

Patil, Kamble and Mam (2023) focuses on how ML algorithms are altering the creative process as it examines the dynamic interaction between AI and fashion design. This research illuminates the significant influence of technology on the fashion industry by examining the function of AI in Pattern Recognition, Color Analysis, Style Prediction, and even AI-generated designs. Additionally, it suggests direction for future research and delves into the ethical considerations of AI in the fashion industry. The results highlight AI's

potential to change fashion design, improve creativity, and impact the industry's future[18].

Although AI continues to be applied in retail to forecast demand, analyze customers, and predict trends, there remain a number of research gaps. The majority of works are dedicated to particular applications and not on uniting customer insights, predictive analytics and personalization into a single system. Additionally, there is a lack of adequate discussion around data bias, data quality, and interoperability with existing retail systems. It is also not well researched as to how to integrate various sources of data like social media, consumer behavior and retail transaction data to give a more detailed analysis.

Table 1 Comparison of Recent Studies on Ai-Based Applications in Retail

Author(s) & Year	Study Objective	AI / ML Techniques Used	Diseases / Scope	Challenges	Future Directions
Dharani (2025)	To explore the role of AI in forecasting sustainable fashion trends and promoting responsible fashion practices.	AI-based data analysis, sentiment analysis, trend forecasting	Sustainable fashion and trend prediction	Data bias, lack of standard sustainability metrics, limited industry adoption	Improve sustainability metrics and promote wider AI adoption in the fashion industry
Riachy et al. (2025)	To improve demand forecasting accuracy in the post-pandemic retail environment.	Deep probabilistic models, AI-based forecasting models	Retail demand forecasting using real-world retail dataset	Impact of external factors such as lockdowns, remote work, and store closures	Develop more robust forecasting models incorporating external socio-economic factors
Ankam (2025)	To analyze the evolution and effectiveness of AI-driven demand forecasting techniques in retail sectors.	AI-driven predictive analytics and demand forecasting models	Retail demand forecasting across multiple sectors	Data quality issues, legacy system integration, organizational change, ethical concerns	Develop better data management frameworks and scalable AI forecasting systems
Anitha & Neelakandan (2024)	To forecast new product demand by examining customer preferences.	K-means clustering, DT classification	Customer preference analysis and product demand prediction	Data processing complexity and accurate customer profiling	Improve clustering models and integrate additional behavioural data for better predictions
Patil, Kamble & Mam (2023)	To examine the impact of AI on fashion design and creativity.	Machine learning algorithms, pattern recognition, color analysis, style prediction	AI in fashion design and creative processes	Ethical concerns and technological adaptation challenges	Explore AI-assisted creative tools and ethical frameworks for AI in fashion

Methodology

The proposed approach is systematic to demand forecasting in sustainable fashion retail, which initiates with data exploration to comprehend the fashion sales patterns and customer behaviour. Pre-processing of data and preparation of relevant features are done to optimize the performance of the models. A hybrid modelling approach is implemented to help the main complex relationships in the data in order to train and validate it with the help of the proper data split. Regression measures of R^2 , RMSE, MAE and MAPE are used to determine the model performance as they would be accurate and reliable. Figure 1 shows the suggested model's flow chart.

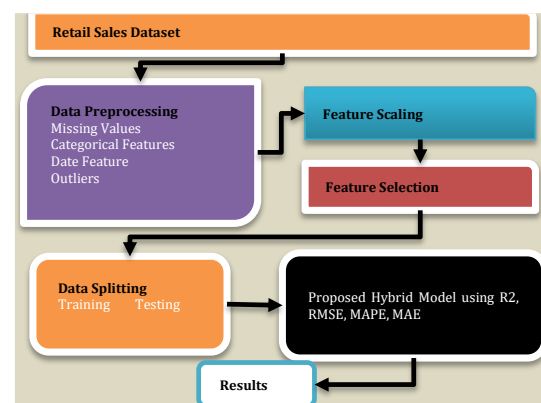


Fig.1 Flowchart of the Proposed Model Based on Demand Forecasting for Fashion Retail

Data Exploration and Analysis

The Retail Sales Dataset utilized in this research is derived on Kaggle and is a fake setting of a retail store, meant to study customer behaviour and demand curves in a sustainable retail setting in fashion, and the details of the features are given in Table II. It also has transactional and demographic data with transactionID, date, customer, gender, age, product category, quantity purchased, the price per unit of product and the amount purchased. These characteristics allow the analysis of purchasing behavior in detail, customer segmentation and fluctuations in sales in relation to various categories and time. The retail sales data has offered a systematic basis on which demand forecasting models can be developed and meaningful insights can be mined to aid in decision making within the retail operations.

Table 2 Dataset feature description

Feature Name	Description
TransactionID	A unique number for every transaction
Date	Date of the transaction
CustomerID	Unique identifier for each customer
Gender	Gender of the customer (Male/Female)
Age	Age of the customer
ProductCategory	Category of purchased product
Quantity	Number of units purchased
Price per Unit	Price of a single unit
TotalAmount	Total value of the transaction

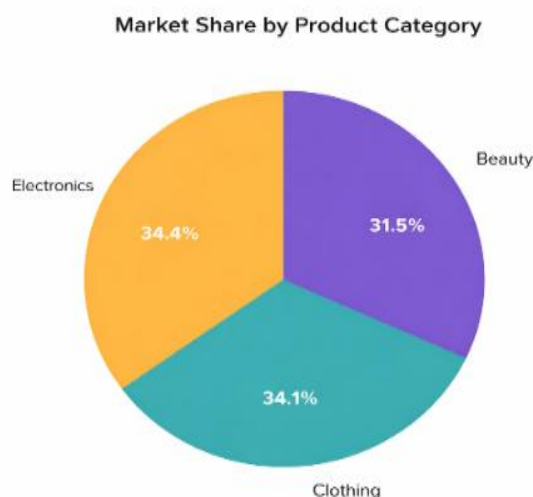


Fig. 2 Market Share by Product Category Performance Analysis

The PieChart of Figure 2 indicating the distribution of the three segments: Electronics (34.4%), Clothing (34.1%), and Beauty (31.5%). The separate segments are marked with different colors (orange representing the Electronics, teal representing the Clothing, and

purple representing the Beauty), the percentages are entered within the slices, and the labels of the categories are placed around the chart, which represents a fairly equal share of the market between the three categories.

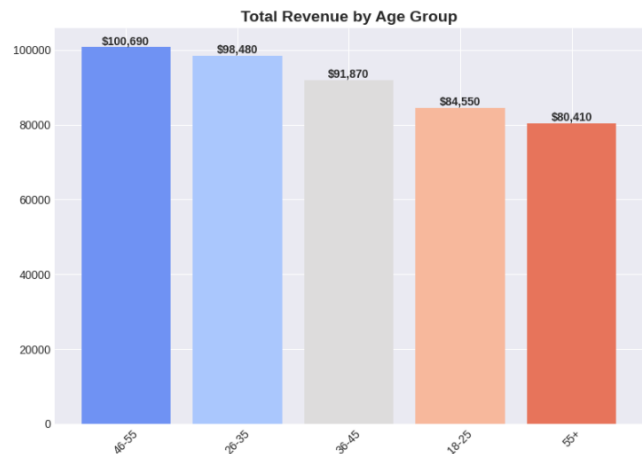


Fig.3 Total Revenue by Age group

The revenue generated by various age groups as shown in Figure 3. The groups that have the highest revenue are 4655 and 2635 with a 100690 and a 98480 respectively and the youngest (1825) and the oldest (56+) have relatively lower revenue of 84550 and 80410 respectively. All the bars are clearly identified with specific colors and the corresponding value, which perfectly demonstrates a downward trend in revenue beyond the middle age categories.

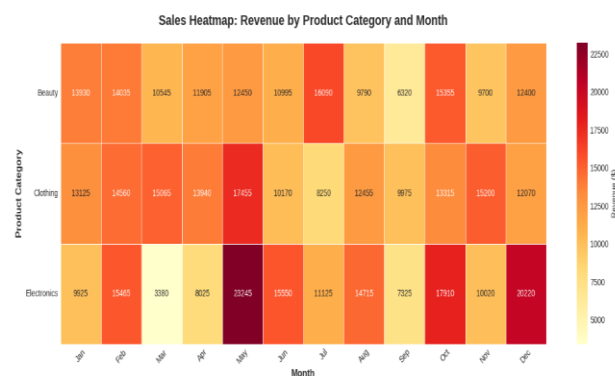


Fig.4 Sales Heatmap: Revenue by Product Category and Month

In Figure 4, the heatmap of monthly revenue of Beauty, Clothing and Electronics is presented, and the values are indicated in every cell. The highest number of Electronics is in May (22,345) and December (20,220), Clothing in May (17,455) and Beauty in July (16,090). Smaller values are observed in other months such as March in case of Electronics (3,880) and September in the case of Beauty (8,320) indicating that the performance is stronger in the middle and the end of the month.

Data Preprocessing

To guarantee the quality and reliability of the retail sales dataset, there were a number of pre-processing methods that were used before developing the model. The steps assist in data cleaning, feature transformation, and data preparation to make the data useful in demand forecasting sustainable fashion retail[19]. Pre-processing process enhances consistency of the data and minimizes noise as well as increases overall model performance. The most important pre-processing actions performed on the retail data include the following:

Missing Values: Screened the retail data on the missing or null values and processed them accordingly. It guarantees the consistency of data and enhances the overall quality of data to train the models.

Categorical Features: Transformed categorical variables including gender and product type into numbers[20]. The retail data were encoded to fit in the machine learning models.

Date Feature: The date column has been converted into the meaningful elements of day, month, and year[21]. This is useful in the capture of time pattern and trends in retail sales information.

Outliers: Detected outliers in numerical characteristics such as quantity and total amount with the help of statistical techniques. To reduce the effects of these outliers, they were mitigated.

Feature Scaling

Numerical feature scaling or normalization where required. This makes sure every feature plays an equal role as the training of the model.

Feature Selection

Eliminated extraneous or redundant characteristics in data. This assists in the simplification of models and enhancing efficiency.

Data Splitting

The data was split into a training and a test set in the 80:20 ratio. This enables the adequate testing of the model on the invisible data.

Proposed Hybrid Model in forecasting for Fashion Retail

Proposed hybrid models the hybrid model is based on random forest and XGBoost to enhance accuracy of prediction in fashion retail demand forecast. Random Forest is employed to create a starting prediction with a combination of decision trees and to give consistent and generalized predictions whilst XGBoost continues to optimize the prediction based on the remaining errors and complex nontrivial relationships[22]. This attribute aids in curbing excessive overfitting as well as improving the performance of the model through the use of both bagging and boosting.

The hybrid model is mathematically formulated using the residual learning theory, such that the final prediction is the summate of the base model prediction and the learnt residual correction as illustrated in Equation (1): $\hat{y} = f_{RF}(x) + f_{XGB}(x)$ (1) and the residual value is defined as, as shown in Equation (2): $r = y - f_{RF}(x)$ (2) and XGBoost is also trained to estimate this residual, and it can be written as in Equation (3): $f_{XGB}(x) \approx$ (3). Therefore, the overall model is the prediction of the Random Forests, plus the predicted residual, which is shown in Equation (4): $\hat{y} = f_{RF}(x) + \hat{r}$ (4)

This expression is aligned to the concept of gradient boosting where the following models are modelled using residual errors to enhance predictive accuracy. The hybrid structure thus improves the capacity of the model to reflect general trends and intricate variations in retail sales data, rendering it extremely useful in demand forecasting of sustainable fashion retailing.

Model Evaluation

An effectiveness of a proposed model is measured by regression measures including R2 score, RMSE, MAE[23], and MAPE which are effective measures of prediction accuracy and error in demand forecasting of sustainable fashion retail as shown in Equations (5) through (8).

R2 score

R-Squared is used to determine the closeness of the values to actual values and it measures whether the model is able to explain the variance in demand forecasting (5):

$$R^2 = 1 - \frac{\sum_{i=1}^n (\text{actual} - \text{predicted})^2}{\sum_{i=1}^n (\text{actual} - \text{mean of actual})^2} \quad (5)$$

MAE

A popular statistic for assessing a prediction model's accuracy is the MeanAbsoluteError (MAE). Equation (6) shows how it is determined by adding together the expected and actual values:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\text{actual} - \text{predicted}| \quad (6)$$

RMSE

The square root of MeanSquaredError, the RMSE, gives an error measure in the original scale of the retail sales, thus it can be easily interpreted in the demand forecasting of sustainable fashion retail. It represents the mean size of prediction errors but emphasizes more heavily on large deviations (7):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

MAPE

MAPE provides the percentage of the error of prediction, providing a transparent and

understandable picture of the accuracy of the forecasts. It is especially beneficial in the demand forecasting in retail since it enables one to compare the error margin between various products and sales volumes (8): $MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$ (8). These performance metrics are also used to evaluate the models' performance in sustainable fashion retail demand forecasts and to compare the outcomes.

Results and Discussions

The proposed method for fashion retail demand forecasting is tested using the retail sales dataset's experimental outcomes. An experiments have been conducted on a system that has an Intel i5 (9th generation) processor, 8 GB RAM, and NVIDIA GTX 1650 as its video card, and the implementation was performed in Google Colab, where the libraries utilized included Pandas, NumPy, Scikit-learn, Matplotlib, and Seaborn to process the data, create models, and visualize the outcomes. The hybrid model of Random Forest and XGBoost as the results in Table III show has good predictive performance, with the R^2 value of 0.90, which is a high level of variance accounted. Besides, MAPE, RMSE, and MAE errors are low with the model showing a MAPE of 13.72, RMSE of 2.81 and MAE of 2.27. The findings suggest that the hybrid method is efficient in capturing complex patterns in retail sales data and gives correct and realistic demand forecasts in fashion retail applications.

Table 3 Experiment Results of Proposed Models for Demand Forecasting Fashion Retail

Measures	Hybrid Model (RF + XGB)
R2	0.90
MAPE	13.72
RMSE	2.81
MAE	2.27

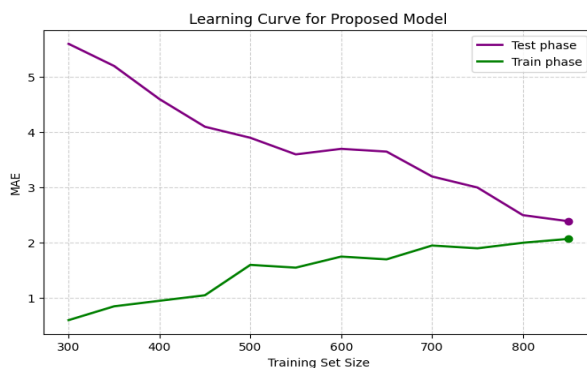


Fig.5 Learning curve of Proposed Model

Figure 5 displayed the learning curve of the proposed model by plotting Mean Absolute Error (MAE) versus the training set size during both training and test phases. The larger the training size between 300 and 850, the smaller the test MAE (purple line) is between

5.5 and about 2.4, and thus, the larger the training size, the better the generalization performance. On the other hand, the training MAE (green line) smoothly rises and reaches about 0.6 up to a little higher than 2.0 as the model progressively receives increased data volumes.

The Figure 6 represents a scatter diagram, which compares the actual target values and the predicted outputs of the proposed hybrid model. The points are almost on the diagonal reference line ($Y = T$) which means that the predicted and the actual values have a great deal of accordance. The value of high R^2 of 0.9031 presented in the plot indicates that the model can forecast a considerable amount of variability hence this is effective in the prediction of retail sales.

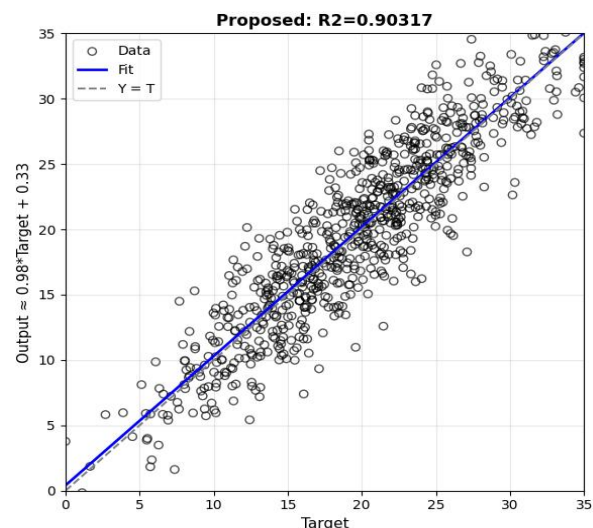


Fig.6 Regression chart to predicting customer order volume

Comparative Analysis

The comparison outcomes reveal that the Proposed Hybrid Model of the combination of RF and XGBoost is the best model as it can predict more and minimize errors better than the other models. It has the greatest R^2 of 0.90 and low RMSE (2.81) and MAE (2.27) which means that it is highly reliable and generalizes. Comparatively, Linear Regression can give moderate results with an R^2 of 0.85 but it is restricted in identifying nonlinear trends. The error values in the LSTM model are more significant such as the MAPE of 16.21 and extremely high RMSE and MAE, which indicates that the model does not fit the data well or that the data were not scaled properly. Similarly, Support Vector Machine (SVM) has the smallest R^2 of 0.73, and extremely high error values; hence, it is not applicable in this case. Table IV displays a comparison of the baseline and suggested model's performance based on retail sales data, summarizing these findings and demonstrating how the hybrid method is better.

Table 4 Performance Comparison models between baseline and proposed Models based on Retail Sales Dataset

Models	R2	MAPE	RMSE	MAE
Hybrid Model (RF + XGB)	0.90	13.72	2.81	2.27
Linear Regression[24]	0.85	-	0.37	0.25
LSTM[25]	-	16.21	65,350.01	43,299.81
SVM[26]	0.73	4663848.50	2159.59	1315.55

The hybrid model that is proposed to be used in combination with the random forest and XGBoost has better performance in terms of retail sales forecasting because it is capable of representing complicated nonlinear trends and interactions among the data. Combining the advantages of the two ensemble methods, the model is more accurate and has less prediction errors. It has the greatest R^2 value that is of 0.90 that portrays a great predicting capability and reliability. The findings validate the fact that the hybrid model is a powerful and efficient method of precise demand prediction in the fashion retailing field.

Novelty and Justification of the Study

In response to the ever-increasing demand complexity in the fashion retail sector, this research proposes a new hybrid forecasting methodology, which predicts with higher accuracy, due to the complementary nature of the methods it employs. The proposed approach has the advantage of harnessing the strength of ensemble models to enhance the accuracy of forecasting in contrast to traditional single model approaches that tend to fail at capturing dynamic and nonlinear retail behaviors. The innovation of the work is that it utilizes a hybrid residual-based structure for the retail sales data, making it easier to deal with the variability of customer demand and product trends. Moreover, the research focuses on an approach based on data, in which the demographics of customers and types of products were connected with the process of demand forecasting, thus providing a more extensive and feasible approach to sustainable fashion retail demand forecasting.

Conclusion and Future Work

The fashion retailing business relies on accurate demand forecasts to maximize efficiency and make informed decisions, especially considering the ever-changing preferences of customers and the market. In this work, the authors suggested a hybrid model of forecasting by advancing Random Forest and XGBoost to improve the accuracy of prediction with regards to sustainable fashion retail. The experimental findings reveal that the proposed hybrid model has better performance with a large value of R^2 of 0.90, low values of RMSE, MAE and MAPE values, which determine a high predictive performance and reliability. The hybrid

model is effective in removing complicated nonlinear relationships in retail sales data and predicting it more accurately than the baseline models, including Linear Regression, LSTM and Support Vector Machine. Nevertheless, there are also some limitations of the study, such as the use of a synthetic retail dataset and the lack of external modulating variables such as social media trends, seasonal modifiers, and economic situations. Future research can concentrate on the usage of a real-life dataset and adding more features to enhance the models even further. Moreover, developing more sophisticated deep learning methods and real-time predictors can be used to increase scalability and flexibility in the real-world retail environment.

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