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RESEARCH PAPER

Leveraging AI-Powered Business Intelligence for Data-Driven Decision Making in the Retail Industry

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***Abstract*—The constant innovations in artificial intelligence which have acted as a deciding factor in the fast-paced and competitive retail environment, machine learning (ML) and deep learning (DL) applications are gaining relevance in the industry. The demand for and the scarcity of data analytics experts, however, remain. So, there is an urgent need for more efficient and accessible intelligent forecasting systems to meet the demand. To overcome this problem, this work suggests an Ensemble Random Forest (RF) and Gated Recurrent Unit (Ensemble RF+GRU) model for accurate retail sales forecasting and data-driven decision making. The proposed model is a fusion of the advantage of deriving features from a RF with the advantage of sequential learning of a GRU, which improves the accuracy (ACC) of forecasting and the efficiency of prediction. The Retail Sales Forecasting Dataset provided by Kaggle was used for experimentation and data was preprocessed to enhance the quality. The results of experiments showed that the proposed Ensemble RF+GRU model had an R^2 value of 94.5%, MSE of 79564.47, RMSE of 282.07, and MAE of 134.62, which were better than the other models such as LR, SVM, RNN, and ANN. The results proposed that the Ensemble model yields correct, reliable, and efficient forecasting performance and is suitable for intelligent decision-making in the retail industry.**

Keywords—Retail Industry, Business Intelligence (BI), Inventory Management, Predictive Analytics, Machine Learning (ML), Ensemble Model.

I. INTRODUCTION

Rapid digital transformation is taking place in the retail industry as a result of the abundance of consumer and transactional data produced by brick-and-mortar stores, online marketplaces, mobile apps, and Internet of Things (IoT) devices [1][2]. Traditional Business Intelligence (BI) systems have long been used to support organizational decision-making by analyzing historical data and generating reports. However, conventional BI approaches often face limitations when handling large-scale, dynamic, and heterogeneous retail datasets [3]. The ever-increasing demands of customers and increasing competition in the market mean that retailers need state-of-the-art technologies that can turn raw data into actionable, meaningful business insights in real time[4][5]. The application of data science in retail has improved the capability of companies to analyze consumers, streamline operations and react suitably to market shifts [6]. With the development of modern retail environments, which work through various channels, including physical stores, online channels, social commerce, and mobile applications, it generates huge amounts of structured and unstructured data [7][8]. Retailers use analytical tools like predictive analytics, clustering, recommendation engines, and statistical analysis to uncover hidden patterns, preferences, and purchasing trends. Therefore, retailers benefit from intelligent data use in many ways, such as boosting customer satisfaction, cutting operational expenses, and optimizing business operations [9][10][11].

Advanced BI systems like today's have also been advanced by the use of AI, which can learn automatically, reason intelligently, and support decision-making in real time [12]. Complex and high-dimensional retail data that is hard to analyze with traditional methods can be efficiently processed with AI technologies[13]. DL and ML, among the latest technologies of AI, have revolutionized the way retailers analyze data by utilizing systems that can make intelligent predictions, recognize patterns, and automate decisions [14]. These technologies are very efficient in dealing with vast quantities of business transactions data and reveal complex relationships that are hard to achieve with classic analytical techniques [15][16]. Therefore, in order to improve strategic decision-making and guarantee a competitive edge in the modern retail landscape, AI-based BI with the assistance of ML and DL has become an essential strategy.

A. Motivation and Contribution

This study has been motivated by the explosive development of digital retail platforms and multi-channel environments in which a huge amount of customer and transactional data is generated, demanding intelligent analysis to make effective decisions. Many traditional business intelligence systems can be inefficient at processing complex and dynamic retail data, which can make it difficult to get accurate, real-time insights. Retailers can leverage AI, ML and DL in Business Intelligence (BI) to gain a competitive advantage in forecasting, customer analysis, inventory optimization and strategic planning. As a result, the use of AI-driven business intelligence is a must-have to boost efficiency, customer satisfaction, and a competitive edge in today's retail landscape. This study has made several important contributions as follows:

- Utilized the Retail Sales Forecasting Dataset from Kaggle for comprehensive experimentation and model evaluation.
- Enhanced data quality through the use of efficient pre-processing techniques such as z-score normalization, feature engineering, one-hot encoding, and missing value management.
- Retail sales forecasting and data-driven decision-making can be enhanced with the use of an Ensemble RF+GRU model.
- Used R^2, MAE, MSE, and RMSE, among other relevant metrics, to evaluate the proposed model.
- Enhanced retail decision-making by providing reliable sales prediction and efficient business intelligence analysis.

B. Justification and Novelty

Retail inventory management, consumer demand analysis, and smart company decision-making all rely on reliable sales forecasts, which is why the suggested study is necessary. The traditional and standalone ML models for the most part don't have the ability to accurately model complex feature relationships and sales trends over time. The novelty of this work is the development of the Ensemble RF+GRU model, which combines RF for feature extraction and GRU for sequential learning to enhance forecasting performance. The proposed Ensemble method outperformed the traditional methods and proved to be useful for the effective and accurate forecast of the retail sales.

C. Organization of the Paper

This is the paper's structure: The relevant literature is reviewed in Section II, and the dataset, pre-processing, and suggested model are detailed in Section III. Results and comparisons from the experiments are covered in Section IV, and the study is concluded with suggestions for further research in Section V.

II. Literature Review

Key Data-Driven Decision Making in the Retail Industry research studies were comprehensively reviewed and analyzed in order to inform and enhance the development of this study.

Eswaran et al. (2026) provide accurate demand and sales forecasting, a Multilayer Perceptron (MLP) model is used for predictive analytics. The model shows great performance with a low Mean Absolute Error (0.0898) and test loss (0.0293). The optimized parameters of the structured DL model can be generalized to unseen data with ease, a powerful tool for retail decision-making [17].

Nahariya and Bajaj (2025) were trying to train their predicted results to achieve maximum performance and came up with a RF Classifier. Model provided the highest ACC of classification 91.47% compared with other models, which suggests that it can model complex behavioral patterns. Behavior segmentation polishing for modeling ML is an urgent need for both pre-processing and ensemble approaches that are discussed in the paper [18].

Garidzira, Matobobo and Vambe (2025) proposed to evaluate the clusters' quality. The best performance (0.1297) was recorded by Spectral Clustering, but it was followed by GMM (0.1283) and K-Means (0.1281), while Agglomerative Clustering got the lowest Silhouette Score (0.1042) out of all the tested algorithms. It can be seen that although the separation was moderate, there are meaningful segments that could be identified by unsupervised clustering [19].

Lakshmi P (2024) aims to compare several state-of-the-art clustering techniques, including K-Means and K-Means++. Validation of the model was performed using four metrics: Silhouette Index, Dunn's Index, Davies-Bouldin Index and execution time. The proposed K-Means model is compared with the existing clustering methods, where the Silhouette Index is 0.8124, Dunn's Index 0.8045 and Davies-Bouldin Index 0.0254 [20].

Rahman and Zaman (2024) propose a hybrid model of CNNBiLSTM with regularization in BiLSTM layers for its improved forecasting and generalization capabilities; the study uses MAE as error metric along with RMSE and R^2 score. The results show that the proposed approach outperforms the existing ones with an MAE value of 1.25, RMSE of 1.56, and an R^2 value of 0.53 which drastically improved the forecasting ACC. Furthermore, the adoption of regularization highlights model's performance and improves its predictive capabilities [21].

Table I gives a summary of the recent studies done on Retail Sector, their models, main findings and challenges faced in the study.

TABLE I. Summary of Recent Studies Retail Industry Using Machine Learning Techniques

Author	Approaches	Data Used	Results	Limitations & Future Work
Eswaran et al. (2026)	Developed a Multilayer Perceptron (MLP) model for retail demand and sales forecasting using predictive analytics.	Retail sales and demand forecasting dataset	Achieved low Mean Absolute Error (0.0898) and test loss (0.0293).	Limited exploration of hybrid DL models; future work can integrate attention mechanisms and real-time retail analytics.
Nahariya and Bajaj (2025)	Implemented a Random Forest (RF) classifier for behavioral segmentation and prediction.	Customer behavioral and transactional retail data	Achieved highest classification accuracy of 91.47% compared to other models.	Performance may vary with large-scale dynamic datasets; future work can focus on feature optimization and deep ensemble models.
Garidzira, Matobobo and Vambe (2025)	Evaluated customer segmentation using Agglomerative, Spectral, GMM, and K-Means clustering techniques.	E-commerce customer transaction dataset	Spectral Clustering achieved the best Silhouette Score (0.1297), followed by GMM (0.1283) and K-Means (0.1281).	Moderate cluster separation indicates scope for improving feature engineering and hybrid clustering approaches.
P (2024)	Compared K-Means and K-Means++ clustering algorithms using multiple validation metrics.	Customer purchasing and segmentation dataset	The proposed K-Means model achieved Silhouette Index of 0.8124, Dunn’s Index of 0.8045, and Davies-Bouldin Index of 0.0254.	Limited comparison with advanced deep clustering methods; future work may involve scalable clustering on big data platforms.
Rahman and Zaman (2024)	Proposed a hybrid CNN-BiLSTM model with regularization for forecasting improvement.	Retail time-series sales forecasting dataset	Achieved MAE of 1.25, RMSE of 1.56, and R^2 score of 0.53.	Model complexity and computational cost remain high; future studies can optimize lightweight architectures.

Research gaps: Although previous studies summarized in Table I achieved promising results in retail forecasting, classification, and customer segmentation, most approaches focus on single-task prediction using conventional ML or clustering models. There has been limited work on integration of several retail data sources, consumer behavior dynamics, model interpretability, and real-time decision-making with Ensemble intelligent frameworks. Thus, more powerful and flexible models are needed that can improve ACC of the predictions and empower more holistic data-driven retail strategies.

III. Research Methodology

Data collecting, preprocessing, feature selection, normalization, model construction, and assessment make up the suggested technique for retail sales forecasting. Sales patterns were analyzed using data visualization techniques and data preprocessing methods enhanced data quality and consistency. Lastly, the Ensemble RF+GRU model was tested with the metrics of R^2, MAE, RMSE and MSE to achieve accurate prediction of sales and better decision-making in retail. The proposed flowchart for the implementation pipeline shows Fig.1.

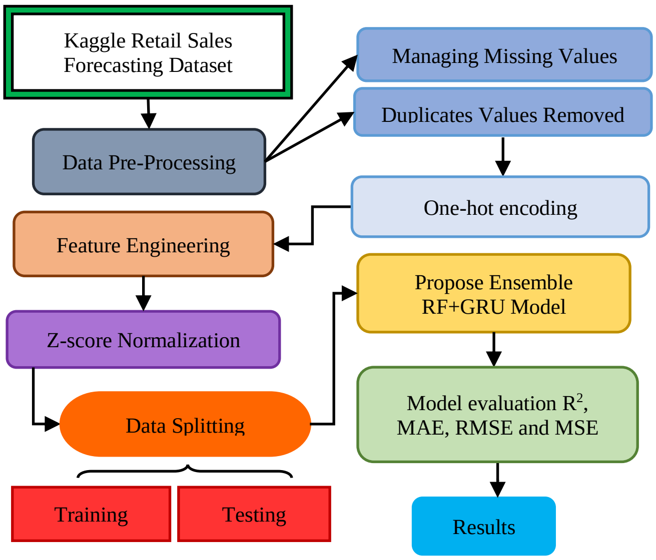

Fig. 1. Proposed flowchart for Retail Sales Forecasting

A comprehensive breakdown of the suggested procedure is provided in the section that follows.

A. Data Gathering and Analysis

This research makes use of Kaggle's Retail Sales Forecasting Dataset. After the dataset was processed, a data frame containing sixteen variables was generated. Each variable has 42,151,570 data points. The study's dependent variable, Weekly Sales, represents each store's sales for the week. Here are some data visualizations like bar plots and heatmaps that were created to look at things like attack distribution and feature correlations:

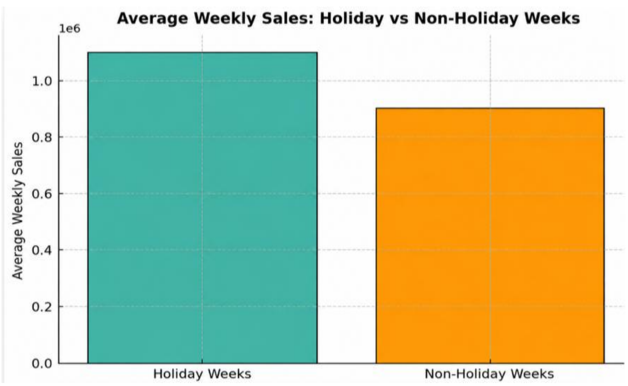

Fig. 2. Bar graph of Average Weekly Sales Distribution

Fig. 2 compares holiday weeks' average sales to non-holiday weeks. It proves that holiday sales are substantially higher than non-holiday sales, which may indicate that shoppers are more inclined to spend money during the holidays. The bar chart clearly shows the positive effect of holidays on retail sales performance.

A correlation matrix heatmap displaying the association between several store variables is shown in Fig. 3. The heat maps show a modest link between Daily_Customer_Count and Store_Sales, but a large positive correlation between Store_Area and Items Available. This visualization helps in identifying important features for effective decision-making and accurate sales forecasting in the retail industry.

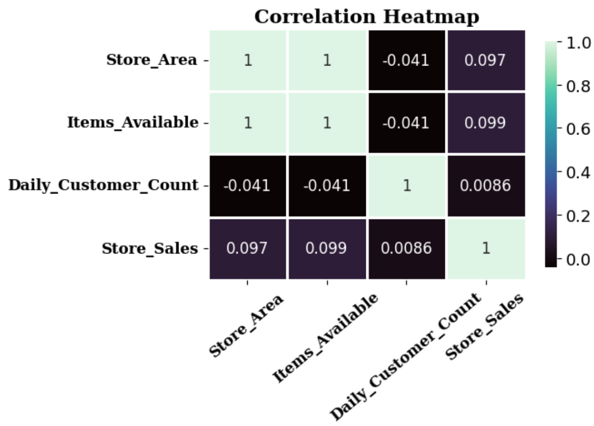

Fig. 3. Plot Correlation Matrix of features

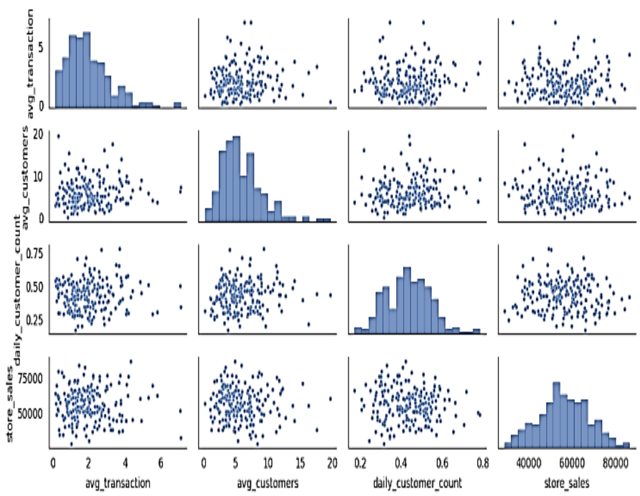

Fig. 4. Pair Plot for average sales data in the Retail Industry

Fig. 4 shows a pair plot of average retail sales data; the relationships among the multiple retail features are shown. Examples of two-variable data sets that might be represented by scatter plots include sales figures, client counts, and the frequency of transactions. Diagonal histograms represent the distribution of the data for each feature and are useful for understanding trends in sales and interactions between features to inform retail decision-making.

B. Data Pre-Processing

The purpose of data preparation is to improve the data's quality and make retail data more suitable for forecasting purposes. Initially, the gaps are filled using suitable imputation methods, which substitute the mean values for numerical characteristics and the mode values for categorical attributes. In order to avoid data duplication and guarantee consistency, duplicate records are removed. A one-hot encoding is used to boost the model learning for categorical information.

C. Feature Engineering

Feature engineering techniques are applied by extracting temporal information such as day, month, and year from date attributes to capture seasonal trends. Additional lag features and interaction terms are generated to model temporal dependencies, promotions, and historical sales behavior, thereby enhancing forecasting performance of the hybrid RF-GRU model.

D. Z-Score Normalization

Data normalization is a process that aims to alter or standardize data in order to make its distribution more uniform. This research made use of z-score normalization, a form of standardization that has a mean of 0 and a standard deviation of 1. Values centered around the average with a standard deviation of one are transformed using this scaling approach. The normalization of the z-score is determined in Equation (1).

$$E' = \frac{E-\bar{M}}{\sigma_M} \quad (1)$$

$\bar{M}$ As the mean, and σ_M is the standard deviation, where E' and E are the new and old values for every data item.

E. Data Splitting

Training data and testing data are the two main parts of the dataset. Training the model required 80% of the data, while testing and evaluation required 20%.

F. Proposed Ensemble Model

The suggested Ensemble RF+GRU model improves learning efficiency and prediction ACC by combining the strengths of the RF algorithm with the GRU network. The RF model is used for good feature learning and complex data patterns; the GRU model is used to capture the sequential dependencies and the temporal relationships between data. Both models consider the strengths of the other to help increase prediction capacity, mitigate overfitting, and boost overall performance in the field of retail sales forecasting. Explanation of the model description individually, in sequence.

1) Random Forest (RF)

RF, an ensemble ML method, uses a large number of decision trees to improve prediction accuracy and reduce overfitting [22]. Building many DTs using a randomly selected portion of the data and then averaging or voting on the predictions is how it is accomplished. RF is very effective for large datasets, learning the important features, and enhancing the performance of classification and forecasting.

$$RF(x) = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \quad (2)$$

The RF prediction process is given in Equation (2), where N denotes the number of DT and Ti(x) denotes the prediction of each individual decision tree.

2) Gated Recurrent Unit (GRU)

The GRU is an advanced RNN that is used to efficiently process sequential and time-series data [23]. It incorporates update and reset gates to preserve vital information and decrease the complexity of computation and vanishing gradients. GRU is highly popular in the field of forecasting because it can effectively model temporal dependencies and long-term relationships within data.

$$z_t = \sigma(W_z[h_{t-1}, x_t]) \quad (3)$$

The update gate (Equation 3) determines how much the model retains from the past when training.

$$h_t = (1 - z_t)\odot h_{t-1} + z_t\odot \bar{h}_t \quad (4)$$

The hidden state computation for combining previous with current information for prediction is shown in Equation (4).

The proposed Ensemble RF+GRU model is implemented using exact hyperparameter values to achieve optimal forecasting performance. Hyperparameters of the RF model are adjusted using grid search or random walk methods; these include n estimator values, max depth, and min samples split. The objective is to identify the set of hyperparameters that reduces the root-mean-square error to its minimum. The GRU network was trained using 64 hidden units, 32 batches, 0.001 learning rate, 0.2 dropout rate, and 50 training repetitions in order to achieve accurate retail sales forecasting.

G. Evaluation Metrics

The ML system's model assessment step is crucial. It provides an opportunity to assess the efficacy of ML models and gain understanding of their strengths and weaknesses. The following are the metrics used to assess the accuracy of the forecasting models: R^2, MSE, RMSE, and MAE.

1) R-Squared

A high R^2 indicates that the independent factors adequately explain the variance in the dependent variable. It gives a number between 0 and 1, indicating how well the model's predictions match the actual data. Its mathematical expression is given by Equation (5).

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (5)$$

2) MAE (Mean Absolute Error)

A lot of people use MAE to measure the ACC of a prediction model. It takes into account just the average size of the mistakes in a group of forecasts and excludes their direction. Reduced MAE indicates improved performance. The Equation (6) for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - y_i^P)| \quad (6)$$

This is where n is the number of observations, Y is the projected value, and Y is the actual value.

3) RMSE (Root Mean Squared Error)

The RMSE measures the degree to which the model's predictions differ from the actual scores. A lower RMSE value is indicative of a more effective model. To find the RMSE, use Equation (7):

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

4) Mean Squared Error (MSE)

The MSE is a statistical measure of the discordance between observed and anticipated values. The MSE is determined using Equation (8) when predicting real estate prices, where y_i is the actual price at time i and y_i^p is the forecasted price at time.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^p)^2 \quad (8)$$

Here, n represents the sum of all observations. At time i, the real estate prices are represented by y_i. The expected Real Estate Prices at time i are represented by y_i^p.

IV. Results and Discussion

The system used for the experiment has 4 GB of RAM, supports GPUs, runs Windows 10, and is equipped with the Python simulation environment. The models' performance results for sales prediction utilizing R-Square, RMSE, MSE, and MAE metrics are shown in this section. Table II shows how well the Ensemble RF+GRU model worked. The R-squared value for the model is 94.5%, indicating good predictive ACC and learning capability. Furthermore, the lower forecasting errors and better prediction consistency are reflected in the lower obtained MAE (134.62) and RMSE (282.07) values. The MSE value of 79564.47 also indicates good stability in the model's performance in the retail sales patterns. In conclusion, the Ensemble integration of RF and GRU improves the forecast ACC, as it can learn the nonlinear relationship and the temporal dependency in the sales data.

TABLE II. Experiment results of models for retail sales forecasting

Performance Matrix	Ensemble RF+GRU Model
R-squared	94.5
MSE	79564.47
RMSE	282.07
MAE	134.62

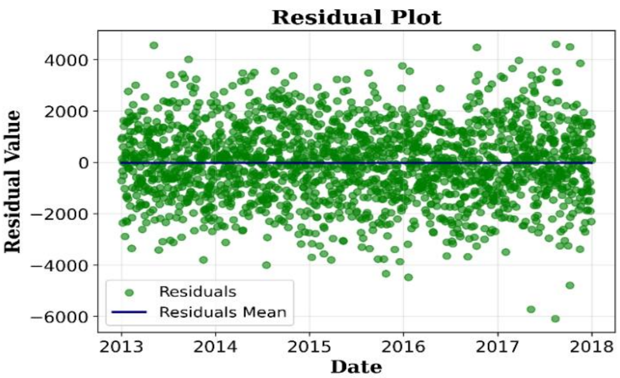

Fig. 5. Residual Plot over Time of the RF+GRU Model

Fig. 5 shows the residuals of a regression model against the time periods 2013 to 2018. The blue line represents the average discrepancy (mean residual), which is nearly zero, and the green dots represent the discrepancy between the anticipated and actual values. Residuals are evenly distributed across the years, reflecting that the model does not have a temporal bias. This visualization validates that errors are randomly distributed, which helps the model to be reliable.

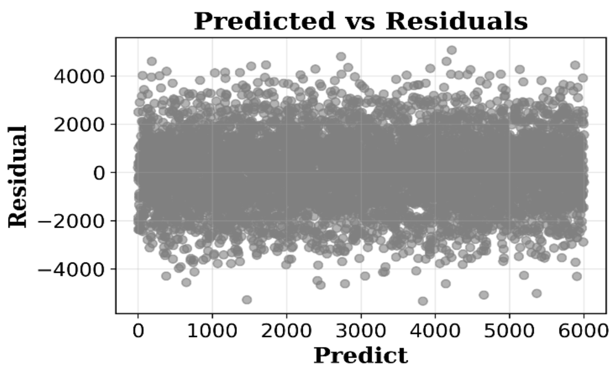

Fig. 6. Scatter Plot for Residuals and Predicted values

The graph of residuals against the predicted values in a regression model is shown in Fig. 6. Every gray point is a prediction-error pair which indicates the variation of residuals from zero. The errors are evenly distributed and there is no pattern, which shows a good fit. The plot supports the assumption of homoscedasticity and unbiased predictions, which are made by the model.

A. *Comparative Analysis*

A comparative performance analysis with existing ML and DL models is presented in Table III. The results showed that the RNN model and the ANN model performed better with R-Squared values of 88% and 90.3%, respectively, in comparison to the LR model and SVM model with R-Squared values of 50.4% and 56.5% respectively. The proposed Ensemble RF+GRU model outperformed other models in terms of ACC in forecasting the sales with the highest R-Squared value of 94.5% and the lowest error values, indicating that the model provides superior sales forecasting ACC and better prediction performance that can be used for data-driven decision making in the retail industry.

TABLE III. Comparison of ML and deep DL Models Sales Forecasting

Model	R-Squared	MAE	MSE	RMSE
LR[24]	50.4	880.99	-	1162.441
SVM[25]	56.5	32.02	-	-
RNN[26]	88	821:29	1945628:38	1394:37
ANN[27]	90.3	2.2773	-	2.8144
Proposed RF+GRU	94.5	134.62	79564.47	282.07

The proposed Ensemble RF+GRU model achieved the highest R-Squared, outperforming the other models in sales prediction performance. By combining RF with GRU, feature learning and sequential pattern analysis are enhanced, thereby boosting forecasting ACC. It also minimizes prediction errors, with lower MAE, MSE and RMSE values. Hence, the proposed model proves to be an efficient tool for data-driven decision-making in the retail industry.

V. Conclusion and Future Study

Demand forecasting is crucial for the retail sector, enabling businesses to keep the right products in stock, reduce stock-outs and enhance supply chain efficiency. In retail settings, sales forecasting helps to make informed business decisions and improve efficiency. In this study, an Ensemble RF+GRU model for retail sales forecasting and data-driven decision making was proposed. Feature learning and pattern extraction were achieved efficiently through the RF model, and temporal dependencies and sequential sales information were captured through the GRU network. The results of experimental analysis showed that the highest R-Squared value was obtained by the model Ensemble RF+GRU with 94.5% compared to the models LR, SVM, RNN, ANN. The results showed that the Ensemble approach not only enhances the ACC of forecasting but also minimizes the prediction error. The proposed model is an efficient and reliable solution for predicting retail sales and making intelligent business decisions. To enhance the forecasting capabilities of the system, future research should incorporate real-time customer behavior, market trends, and external economic indicators. Future research could involve integrating real-time customer behavior, market trends, and external economic factors to further improve the forecasting capabilities of the system.

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