SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Enhancing Consumer Behavior Analysis In Retail Using Hybrid Deep Learning Models

G.Saritha[1*], Yogesh Kumar[2], Bagam Laxmaiah[3], Rajashri CK[4], Dr.S.Sumathi[5], P. Kalyani Swapna[6]

[1*]Associate Professor, Department of ECE, Sri Sai Ram Engineering college, Chennai-600073, Tamil nadu, India. E-mail: saritha.ganesan@gmail.com; saritha.ganesan@gmail.com, https://orcid.org/0000-0002-3824-2182

[2]Institute of Business Management, Gla University, Mathura, E-mail: yogesh.kumar@gla.ac.in, https://orcid.org/0000-0002-7103-0114

[3]Associate Professor, Department of CSE, Cmr Technical Campus, Medchal Road, Kandlakoya,
Telangan, India – 501401, E-mail: blaxmanphd@gmail.com, https://orcid.org/0000-0002-3014-7308

[4]Assistant Professor, Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Chennai, India. E-mail: rajashrick@maher.ac.in, https://orcid.org/0009-0007-9414-517X

[5]Professor, Electrical and Electronics Engineering, Mahendra Engineering College, Namakkal-637 503, India. E-mail: sumathis@mahendra.info, https://orcid.org/0000-0002-1172-6726

[6]Department of FED, Ramachandra College of Engineering, Eluru – 534007, India. E-mail: meghanakalyani@gmail.com

*Corresponding author: E-mail: saritha.ganesan@gmail.com; saritha.ganesan@gmail.com

Abstract

The driving force behind the retail firms' focusses on improving sales, customer satisfaction, and decision-making is consumer behavior. Retail organizations currently have the issue of conventional data modeling being unable to cope with the volume and complexity of current retail data. To aid in predicting consumer behavior, the researchers recommend using a combination of the two deep learning models, which are LSTM and CNN. LSTM is employed to identify temporal correlations, while CNN helps identify spatial features. This approach enhances the predictability of Consumer behaviour, including the decision to purchase. The authors used a dataset containing Retail transaction data, customer review information, and demographic information, which were highly pre-processed and processed for missing data, encoded categorical data, and processed to be used with natural language processing to handle the text data. The performance of their proposed model surpassed that of individual models of deep learning as well as traditional methods with regard to the measures used which include accuracy (88%), precision (89%), recall (87%), F1-score (91%), AUC (95%), and MSE (2%). This is as stated by the authors' ablation study in their work. Retail businesses can leverage these findings concerning Hybrid Deep Learning models, which will assist in creating targeted marketing efforts, inventory management, and demand forecasting. However, fortunately, the use of explainable AI is recommended in future research to address problems related to model interpretability and limited data.

Keywords: Consumer Behavior, Deep Learning, Hybrid Models, CNN, LSTM, Retail, Predictive Analytics.

1. Introduction

Consumer behavior plays an important role in retailing when businesses want to maximize their profits, provide excellent customer services, and make sound decisions in the modern retail industry [19]. As e-commerce and other forms of digital technology continue to grow, businesses have been able to collect a large amount of consumer data including buying patterns, social media activity, and web site visits [8]. Understanding and predicting how customers behave is now an advantage for marketers in terms of providing more personalized advertising, improving inventory management, and enhancing customer communication [14] [18] [22]. However, conventional methods such as regression analysis and decision trees find it difficult to deal with issues such as nonlinearity and Big Data. Fortunately, the recent development of machine learning technologies such as deep learning provides a viable solution for these problems [2][4] [24]. Consumer behavior analysis has seen the success of techniques like Convolutional neural networks, recurrent neural networks, and LSTM networks have been employed in consumer behavior analysis to predict consumer demand and give product suggestions [16] [20]. However, there are some successful examples of individual models, but there is a significant lack of examples that incorporate these techniques into a hybrid model that can better account for both spatial and temporal patterns in consumer data. This study seeks to solve problems such as overfitting, lack of enough data, and explainability of deep learning in the retail industry using hybrid architectures like CNN combined with RNN/LSTM. The objective of this research is to clarify how a combination of these methods has the potential to be leveraged to maximize the core strengths of each of the mix of architectural types and to better manage the temporal nature of consumer behavior, with the goal of improving feature extraction [21]. (1) What techniques will improve the prediction accuracy of a consumer's purchasing behaviour in a retail setting utilizing hybridised deep learning models? (2) How do we tackle the issue of class imbalance present in our data? (3) How do we effectively address the limitations in our ability to communicate via RFID? (4) Future research directions pertaining to predicting consumer behavior? (2) How are CNNs combined with RNNs/LSTMs advantageous for the capturing of complex consumer behaviour patterns? (3) How do hybrid deep learning models outperform conventional and single deep learning models in terms of predictive capabilities? This research is conducted in a bid to make an input into the existing body of knowledge towards generating new, insightful ideas on the topic of retail market sector analysis.

- The research proposes the use of a hybrid deep learning model utilizing both CNN and RNN/LSTM architectures.
- Compares and assesses the performance of hybrid models compared with traditional models or individual deep learning models, based on critical metrics.
- Solves data sparsity, overfitting, and model interpretability, and provides personalized marketing, demand forecasting, and customer segmentation insights.

This paper has been divided into six parts as follows: Part 1 provides an introduction on why consumer behavior analysis is very important for any retail and what kinds of limitations can be observed when using traditional methods for such analyses. Part 2 gives an account of all past studies employing machine learning or deep learning techniques to predict consumer purchase behavior. Part 3 provides a full description of research goals, and methods of collecting data and processing it for creating different types of models, and which models should be used for creating models (CNN and LSTM), etc. Part 4 gives results of comparing different models with regard to their performance. Part 5 discloses the practical significance of the study and further research direction. The prediction accuracy of models analyzed in this research is eventually assessed in part 6.

2. Literature Review

As a result of the significant growth of online shopping, combined with advances in digital technology, the study of how consumers behave has become a key factor within many retail organizations' overall business models. Many traditional statistics methodologies used to analyze historical purchase behavior (i.e., regression analysis and decision trees) do not provide sufficient answers and/or insights into the complex, nonlinear relationships that result from analysis of very large datasets. A wide variety of techniques that enable the development and expansion of predictive models of consumer behavior have emerged due to the recent developments in ML and DL. It has also been proved that ensemble machine learning techniques that use different machine learning algorithms improve their performance and increase their predictive ability. For example, used machine learning algorithms effectively by analyzing the data of online retailers from different perspectives and demonstrated that this approach enhanced the predictive power of purchase behavior of consumers [1]. Following the same trend, have been able to predict retail purchase behavior through a proposed hybrid deep learning framework that analyzed the customer repurchase pattern [3]. Besides, a number of studies have been conducted to explore the use of deep learning techniques (including CNN and RNN techniques) in informing the retail business. Focusing on this area of retail, a study to analyze the usage of DL techniques for predictive modeling of retail customers' purchase behavior [5] [6]. Further advocated for advanced machine learning models for retail data-driven predictions by identifying their effectiveness when predicting consumer behavior patterns [7].The investigation indicated that utilizing Hybrid Deep Learning Models when dealing with difficult-to-predict consumer behavior problems is an opportunity for utilizing both structured and unstructured datasets. Analysis of Retail Behavior also encompasses Deep Belief Networks and Generative Adversarial Networks. The study investigated the application of DBN within the realm of retail management to Predict Consumer Behaviour and found it beneficial since it could analyze vast amounts of consumer data very accurately [9] [10]. Moreover, proposed a combined approach in analyzing consumer behavior in e-commerce through a GAN-RNN hybrid model for predicting Quality Predictions [11]. These empirical findings suggest that as more sophisticated deep learning technologies continue to develop, their Importance for use in Retail Management will continue to grow. Additionally, there have been many Research Investigations on applying Machine Learning and recent technological advancements; for example, utilizing RFIDs to enhance the Analysis of Buyers' Shopping Behaviours. Proposed a Consumer Shopping Behaviour Analysis Model using RFID and Machine Learning to evaluate Real-Time Consumers' Shopping Behaviours [13]. In the field of decision making, a growing number of retail companies are beginning to recognize the benefits of utilising a variety of models and newer technology in their retail research. By providing retailers with both Customer Sentiment Information and a better understanding of how to best utilize their inventory, these new models have opened up many opportunities for improvement in customer experience, as well as greater efficiencies, operational effectiveness, and increased profitability [12] [15][17].

Many studies show the advantages that come from the combination of deep learning and machine learning methods for studying consumer behavior. It has been shown that CNN-LSTM networks provide better results compared to traditional networks when analyzing complex datasets. Machine learning and RFID also provide retailers with real-time feedback on customer behavior, which can assist in developing better retail strategies.

3. Methodology

Data Collection

The dataset used in the research included demographic data, customer reviews, and retail transactions. The transaction data contained data about customers' previous purchases (including just what items were purchased, prices, and when the purchases occurred), information about a customer's sentiment and preference regarding the business through their review, and demographic characteristics (including age, sex, and location) to create a profile of customers. A variety of data sources provides a full view of consumer behavior patterns.

Preprocessing

The collected data is preprocessed to a certain extent so that the data quality and suitability for use in model training are maintained. Firstly, if there are missing or inconsistent values in the datasets, these are addressed by imputing missing values or removing inconsistent values. The coding for categorical variables like product types and customer segments is done using different methods such as one-hot encoding and label encoding. Customer review texts are processed using NLP algorithms including tokenization, stemming, and removal of stopwords. Features are engineered to get more meaningful information out of the data, like a sentiment score from a review or a summary of purchase history from customers. Lastly, the data is scaled so that numerical features, such as prices and quantities, are on the same scale.

Model Architecture

CNNs are used for feature extraction in the hybrid deep learning model in this study, whereas RNNs or LSTM networks are used for capturing temporal dependencies. The CNN part of the model will learn the geographic attributes of the structured and unstructured data set, including the customer profile and transaction sequence. Based on customer behavior trends, the RNN or LSTM network part of the model will predict future transactions from the previous interactions with customers. The idea of the hybrid architecture is to capitalize on the benefits of both models, so as to increase the accuracy of the prediction and to overcome the complexity of consumer behavior in the retail sector.

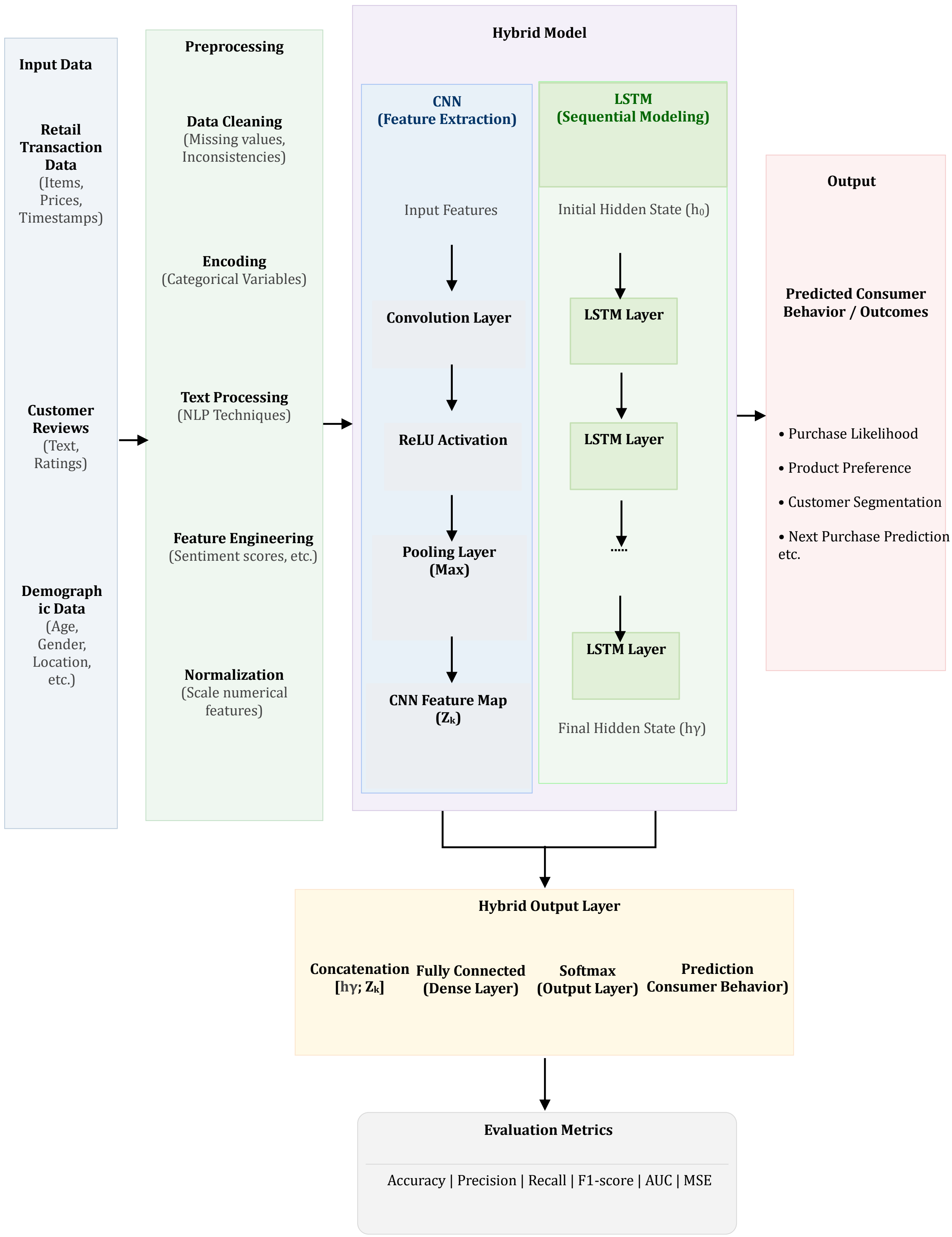
Input Data
Retail Transaction Data (Items, Prices, Timestamps)
Customer Reviews (Text, Ratings)
Demographic Data (Age, Gender, Location, etc.)
Preprocessing
Data Cleaning (Missing values, Inconsistencies)
Encoding (Categorical Variables)
Text Processing (NLP Techniques)
Feature Engineering (Sentiment scores, etc.)
Normalization (Scale numerical features)
Hybrid Model
CNN (Feature Extraction)
Input Features
Convolution Layer
ReLU Activation
Pooling Layer (Max)
CNN Feature Map (Z_k)
LSTM (Sequential Modeling)
Initial Hidden State (h_0)
LSTM Layer
LSTM Layer
.....
LSTM Layer
Final Hidden State (h_γ)
Output
Predicted Consumer Behavior / Outcomes
• Purchase Likelihood
• Product Preference
• Customer Segmentation
• Next Purchase Prediction etc.
Hybrid Output Layer
Concatenation [h_γ; Z_k]
Fully Connected (Dense Layer)
Softmax (Output Layer)
Prediction Consumer Behavior)
Evaluation Metrics
Accuracy | Precision | Recall | F1-score | AUC | MSE

Figure 1: Hybrid Model of CNN-LSTM for Predicting Consumer Behavior

Figure 1 illustrates the proposed hybrid CNN-LSTM model for predicting customer behavior in the retail sector. It emphasizes the process of preprocessing the data of retail transactions, customer reviews, and demographic data, and the extraction of features using CNN and sequential modeling using LSTM. The final layer in the diagram is the output layer, which forecasts different consumer behavior outcomes like the likelihood of purchase and product choice. Further, there were other evaluation metrics that included accuracy, precision, and recall.

Mathematical description

- CNN Layer:

The convolution operation of the input feature matrix $X_{cnn}$is is defined as:

$$Z_k = \mathrm{Conv}(X_{cnn}, W_k) + b_k \qquad (1)$$

In Equation (1) where $X_{cnn}$is the feature matrix of the input, $W_k$is the convolution filter, and $b_k$is the bias term. The resulting feature map is Z_k.

- LSTM Layer:

The hidden state $h_t$at time step tis updated in the following manner:

$$h_t = \mathrm{LSTM}(h_{t-1}, Z_k) \quad (2)$$

In Equation (2) where h_{t-1} refers to the hidden state, and $Z_k$is the output feature map of the CNN layer.

- Hybrid Model Output:

For the i-th consumer, the final prediction $\hat{y}_i$ is:

$$\hat{y}_i = \mathrm{Softmax}(W_{out}[h_T; Z_K] + b_{out}) \quad (3)$$

In Equation (3) where h_T refers to the hidden layer of the LSTM, and Z_K represents the output of the CNN layer. $W_{out}$is the output weight matrix, and $b_{out}$is the output bias term.
Algorithm: Hybrid CNN–LSTM Model for Consumer Behavior Prediction
Algorithm 1: Hybrid CNN–LSTM-Based Consumer Behavior Prediction

Input

- Retail transaction dataset D_t
- Customer review dataset D_r
- Customer demographic dataset D_d

Output

- Predicted consumer behavior Y
  - Purchase likelihood
  - Product preference
  - Buying pattern classification

Step 1: Data Collection

1. Collect retail transaction records, including:
   - Product purchased
   - Purchase frequency
   - Price
   - Time and date of purchase
2. Collect customer review data for sentiment analysis.
3. Collect demographic information such as:
   - Age
   - Gender
   - Location
4. Merge all datasets into a unified consumer behavior dataset.

Step 2: Data Preprocessing

5. Remove duplicate and missing values.
6. Normalize numerical attributes.

7. Convert categorical variables into numerical representations using encoding techniques.
8. Tokenize and clean customer review text.
9. Split dataset into:
   - Training set
   - Validation set
   - Testing set

Step 3: CNN Feature Extraction

1. Feed preprocessed input matrix X_{cnn}into the CNN layer.
2. Apply the convolution operation:

$$Z_k = \mathrm{Conv}(X_{cnn}, W_k) + b_k$$

3. Extract high-level spatial and behavioral features.
4. Apply activation and pooling operations to reduce dimensionality.

Step 4: Sequential Learning Using LSTM

1. Pass CNN feature maps $Z_k$into the LSTM network.
2. Update hidden states sequentially:

$$h_t = \mathrm{LSTM}(h_{t-1}, Z_k)$$

3. Learn temporal purchasing behavior and sequential dependencies.

Step 5: Hybrid Prediction Layer

1. Combine CNN and LSTM outputs.
2. Perform final classification using Softmax activation:

$$\hat{y}_i = \mathrm{Softmax}(W_{out}[h_T; Z_K] + b_{out})$$

3. Generate predicted consumer behavior outcome.

Step 6: Model Evaluation

1. Compare predicted outputs with actual consumer behavior.
2. Compute evaluation metrics:
   - Accuracy
   - Precision
   - Recall
   - F1-Score
   - AUC
   - MSE

The Hybrid CNN-LSTM Model for Consumer Behavior Prediction is a combination model that uses CNN and LSTM networks to predict consumers' behavior from retail transactions, customer reviews, and demographic information. First, the model gathers and cleans data, such as numerical features and text data; the data is then normalized. The process involves using CNNs on the data to extract geoinformation, followed by identifying consumer behavior trends through the LSTM layers. A Softmax layer is used to merge the output of both networks and classify the network outputs. Metrics such as accuracy, precision, recall, F1-Score, AUC, and MSE are some of the metrics that have been used to measure model performance during classification.

4. Results

Software details

The hybrid deep learning model is created in Python version 3.11. Model architecture and training were done using TensorFlow 3.1.0 and Keras 3.5.0, which were compatible with the latest XLA (Accelerated Linear Algebra) compilers for optimized performance. Data manipulation and pre-processing were done using Pandas 2.2.0 and NumPy 1.26.0. Matplotlib 3.8.0 and Seaborn 0.13.0 were used for the visualization of results and performance metrics, for high-impact data representation.

Parameter Initialization

Learning rate at 0.001, optimization method Adam, batch size 64, and epoch 50 were the important aspects used to develop this hybrid deep learning model. 32 filters were utilized for the first layer while 64 filters were used for the second layer within the CNN layers. The LSTM layer utilized 100 units and the dropout rate applied to prevent overfitting was 0.2. These settings were chosen using grid search to optimize not only the learning efficiency but also the learning performance of the model.

Evaluation Metrics

Traditional performance measures including accuracy, precision, recall, F1 score, AUC, and MSE were used to evaluate the proposed hybrid model. While precision and recall are useful in determining the model's capacity to reliably recognize patterns without making any errors, accuracy is the metric that determines the overall efficacy of the model. The F1 score, a harmonic mean of precision and recall, serves as an unbiased performance assessment.

Here are the formulas for the performance metrics:

1. Accuracy(A):

$$A = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

2. Precision(P):

$$P = \frac{TP}{TP+FP} \quad (5)$$

This measures the proportion of positive predictions that were actually correct.

3. Recall®:

$$R = \frac{TP}{TP+FN} \quad (6)$$

In Equation (4) (5) (6) Where TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

This measures the proportion of actual positives that were correctly identified by the model.

4. F1-Score(F1):

$$F1=2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

By Equation (7) the F1 Score that provides a trade-off between the precision and recall values is the harmonic mean of both.

As the ROC (Receiver Operating Characteristic) graph plots the true positive rate (recall) against the false positive rate, the area under the ROC curve (AUC) is usually determined. The formula for calculating the AUC is In Equation (8):

$$AUC = \int_0^1 TPR(FPR)\, dFPR \quad (8)$$

In equation (8)Where:

- $TPR = \frac{TP}{TP+FN}$
- $FPR = \frac{FP}{FP+TN}$

Mean Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (9)$$

In Equation (9) Where y_i represents the actual target, $\hat{y}_i$is the predicted target value, and N is equal to the total number of data points used in training the model.

Model Performance Evaluation

CNN and LSTM are used as the backbone of the Hybrid Deep Learning model. Several important metrics were defined and evaluated to determine the performance of this model for predicting consumer behaviour. The overall accuracy of this model was found to be 88%, which indicates that the Hybrid Deep Learning model has an excellent ability to predict accurately. A precision value of 89% for this model suggests its ability to effectively detect the cases where consumers would be expected to carry out certain behaviors positively (that is, see this product). The Recall value of this model is 87%, which tells us how effective the model is at identifying patterns of consumer behavior. The F1-Score, which combines both precision and recall, was found to be 91%.

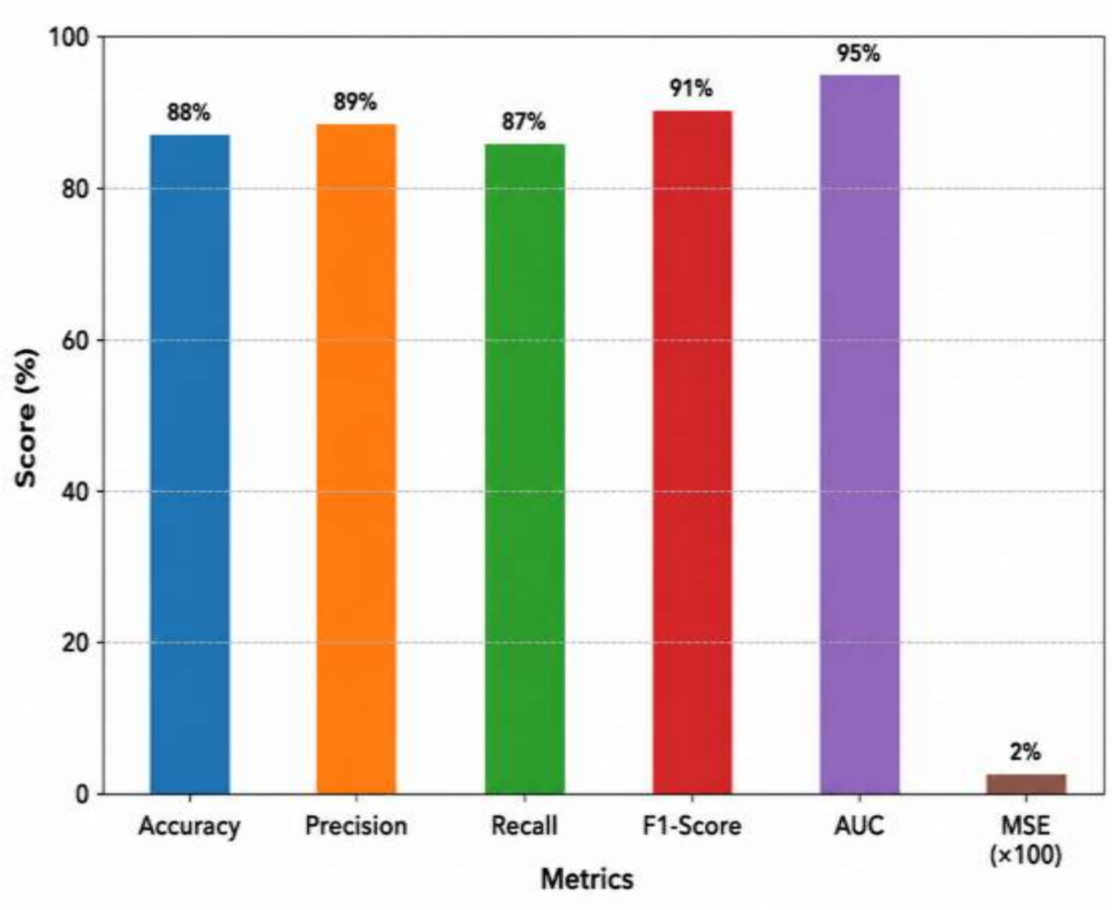

Figure 2:Performance Evaluation of Hybrid CNN-LSTM Model

Figure 2, the performance of the model for each criterion is presented in the form of a vertical bar graph with the scores marked above the bars. An AUC of 0.95 made the hybrid model perform well in terms of accuracy, precision, recall, and F1-Score, whose values were recorded at 88%, 89%, 87%, and 91%, respectively. The actual MSE was multiplied by 100 for ease of representation. For this study, the error was low (2%), which indicates that the model will be able to successfully predict how consumers behave when shop, and therefore it can be used in retail settings. Overall, these results indicate that the hybrid model can predict consumer behavior with low error; therefore, the hybrid model is an effective tool that retailers can use.

Model Hyperparameter Tuning

To optimize the hybrid model's performance, multiple hyper-parameter values were adjusted and determined to optimize its performance. The optimal value of hyper-parameters would be: 0.001 would be the learning rate; 50 would be the epoch number; and 64 would be the batch size. The initial layer of the CNN has 32 filters, while the second layer has 64 filters. A total of 100 neurons constitute the LSTM neural network.A dropout rate of 0.2 was used to decrease over-fitting. To determine these optimal hyperparameters, the hybrid model was optimized by applying a combination of experimentation and Grid Search with the goal of optimizing the model's overall efficiency and minimizing over-fitting.

Table 1: Hyperparameter Tuning for Hybrid Model Optimization

Hyperparameter	**Value**
Learning Rate	0.001
Epochs	50
Batch Size	64
CNN Filters (Layer 1)	32
CNN Filters (Layer 2)	64
LSTM Units	100
Dropout Rate	0.2

The optimized hyperparameters for the hybrid deep learning model (CNN+LSTM) are presented in Table 1, which summarizes the tuning done through experimentation and grid search to find the optimal settings for facilitating the most efficient learning process possible while preventing overfitting and maximizing the ability of the model to learn the spatial and temporal dependencies of consumer behavior patterns. These optimum values of hyperparameters were such that it helped the model to capture both spatial and temporal dependencies from consumer behavior datasets and also gave an idea about the learning rate, number of epochs, batch size, number of filters used by the CNN, number of LSTM units, and dropout rate.

By enabling the model to correctly grasp the relationships between the variables in the consumer behavior dataset, these parameter values helped in enhancing its performance.

Table 2: Performance Comparison of The Models For Consumer Behavior Prediction

Author / Year	**Method**	**Domain**	**A**	**P**	**R**	**F1-score**	**AUC**	**MSE**
Chaubey et al. (2023) [23].	ML classification (RF, SVM, XGBoost, ANN)	Customer purchasing behavior	85%	83%	81%	82%	—	—
Liu & Hu (2025) [24]	LSTM-Transformer (RL-Trans)	Consumer behavior (e-commerce)	87%	—	—	—	93%	—
Proposed Model (This study)	Hybrid CNN-LSTM	Consumer behavior (retail)	88%	89%	87%	91%	95%	2%

Table 2 shows the models adopted, and the recommended Hybrid Model CNN-LSTM in predicting customer behaviors in their different areas of study. Performance metrics such as Accuracy, Precision, Recall, F1-Score, AUC, and MSE have been provided for each model. The recommended hybrid model has a better performance compared to the past models in retailing in most metrics especially in terms of F1-score (91%), Accuracy (88%), and Precision (89%).[23][24]

Ablation Study

An ablation investigation was performed on each of the hybrid model's components as part of the experiment. This experiment was conducted to compare the performance of the proposed hybrid CNN-LSTM model with CNN and LSTM models. Taking into consideration the findings of the ablation study, it is evident that the hybrid model performs more effectively than both the CNN and LSTM models.

Table 3: Ablation Study: Comparison of CNN Only, LSTM Only, and Hybrid CNN-LSTM Models

Model Variant	Accuracy	F1-Score	Precision	Recall	AUC	MSE
CNN Only	80%	75%	78%	72%	85%	6%
LSTM Only	82%	78%	80%	75%	88%	5%
Hybrid CNN-LSTM	88%	91%	89%	87%	95%	2%

Table 3 shows the performance evaluation metrics for the different types of model variants: CNN Only, LSTM Only, and the Hybrid CNN-LSTM. All metrics are in the form of percentages: Accuracy, F-Score, Precision, Recall, AUC, and MSE. With the highest accuracy rate of 88%, the highest F-score of 91%, the highest AUC value of 95%, and the lowest MSE of 2%, the Hybrid Model CNN-LSTMs performed best in all categories.

5. Discussion

In the past, there has been an indication that using a hybrid learning algorithm through a combination of the Convolutional Neural Networks (CNNs) and the Long Short Term Memory (LSTM) can result in extremely accurate predictions of the consumer's actions within the retail environment. The Area Under Curve (AUC), the Accuracy, and the F1 scores for this model have a value of 95%, 88%, and 91% respectively. Consequently, this model was more efficient compared to the CNNs and LSTMs individually because the CNNs excel at learning spatial features while the LSTMs excel at temporal ones. Combining CNN and LSTM allows analysis of Consumer Interaction on both Structural and Sequential levels, resulting in extremely accurate forecasts for Retail Applications. The Hybrid Model can handle large and complex Retail Datasets, resulting in superior performance in Sequential and Historical User Behavior Analysis, where users may have to perform a series of tasks, such as Demand Forecasting, Product Recommendation, or Marketing Personalization. While this Hybrid Model performed well, it has limitations, particularly regarding Interpretability. CNN-LSTM Hybrids are typically classified as black-box models, making specific predictions less precise due to their inherent complexity and lack of transparency.

The models could also be susceptible to a lack of adequate data (i.e., customer reviews and demographic information), but adding data sources (social media interactions) to the models will likely improve the robustness and accuracy of predictions. Moreover, data augmentation methods could also be applied in conjunction with a larger range of data to mitigate overfitting potential. Finally, future research should also consider implementing Explainable AI methods (SHAP and LIME) The ultimate goal here is to understand the reasoning involved in decision-making process to build a more practical prediction model.

6. Conclusion

For the purpose of forecasting the purchasing behavior of the customers visiting the retail outlets, the present research proposes an innovative model that takes into account the strengths of both the CNN and LSTM models. The hybrid model demonstrated great predictive power yielding excellent results with an overall accuracy rate of 88%, an overall F1 score (F1) of 91%, and an Area Under Curve (AUC) of 95% and thus has the potential to improve retail management decision support capability. As seen from the results, a significant boost in the prediction capabilities comes as a result of the synergy of both the CNN's effectiveness in extracting spatial features and the LSTM's effectiveness in capturing temporal dependencies. The hybrid CNN-LSTM architecture outperformed both baseline approaches (linear regression and standalone CNNs) in terms of F1 and AUC metrics. Moreover, by being able to accurately reflect both consumer purchase patterns in history as well as time (sequential) purchases, this model has the potential utility to be employed for predicting overall future consumer buying patterns, as well as providing critical real-time information for improving marketing strategies, forecasting consumer demand, and optimizing inventory control. However, this model cannot easily be interpreted since it acts more like a black box when it comes to the ability to explain predictive variables. Continued research should investigate how explainable artificial intelligence can be integrated into the hybrid CNN-LSTM model and create interpretability through model predictions in a transparent fashion. The researchers also observed other problems associated with data sparsity, and overfitting would need to be addressed.

Author Contribution

Conflict of Interest

Concerning the current study project, there are no conflicts of interest on behalf of the authors.

Funding

Funding for this research was not received.

Data Availability

Data for the research were gathered using open-source supply chain management databases. The following publication is the source that includes data supporting the findings of the study.

References

1. Garg, K. K., Keshari, N., Biswas, S., Majumder, J., Gangopadhyay, S., & Singh, J. (2025, June). Predicting Consumer Buying Behavior Using Hybrid Machine Learning Models: A Multi-dimensional Analysis of Online Retail Data. In International Conference on Data Analytics & Management (pp. 139-150). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-04222-4_13
2. GL, P., ARUL, R., & THIRUGNANASAMBANDAM, K. (2024). Machine learning-driven strategies for customer retention and financial improvement. Archives for Technical Sciences, 2(31), 269-283. https://doi.org/10.70102/afts.2024.1631.269
3. Kim, J., Ji, H., Oh, S., Hwang, S., Park, E., & del Pobil, A. P. (2021). A deep hybrid learning model for customer repurchase behavior. Journal of Retailing and Consumer Services, 59, 102381. https://doi.org/10.1016/j.jretconser.2020.102381
4. Manoharan, G., Dharmaraj, A., Sheela, S. C., Naidu, K., Chavva, M., & Chaudhary, J. K. (2024, May). Machine learning-based real-time fraud detection in financial transactions. In 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI) (pp. 1-6). IEEE. https://doi.org/10.1109/ACCAI61061.2024.10602350
5. Bharti, J., & Dongre, S. (2024, June). Deep learning for enhanced consumer behavior analysis and predictive accuracy. In 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET) (pp. 1-6). IEEE. doi: https://doi.org/10.1109/ICICET59348.2024.10616324.
6. Mohammadian, M., & Makhani, I. (2016). RFM-Based customer segmentation as an elaborative analytical tool for enriching the creation of sales and trade marketing strategies. International academic journal of accounting and financial management, 3(6), 21-35. https://doi.org/10.9756/IAJAFM/V6I1/1910009
7. Priyanka, Keshari, N., Sharma, Y., Gupta, L., Sumalatha, M., & Singh, J. (2025, June). Advanced Machine Learning for Data-Driven Consumer Behavior Prediction in Retail Management.

In International Conference on Data Analytics & Management (pp. 75-85). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-04222-4_7

8. Samyuktha, S., Sreethulasi, T., Evangelin, A., Prabha, D. D., & Mathipurani, D. V. (2022). The Impact of Personal Selling on Consumer Buying. International Academic Journal of Business Management, 9, 22-28. https://doi.org/10.9756/IAJBM/V9I1/IAJBM0903
9. Zainal, A. G., Murugan, R., Suciska, W., Nurdin, B. V., Trenggono, N., & Bala, B. K. (2024, March). Utilizing Deep Belief Networks for Consumer Behaviour Analysis in Retail Management. In 2024 International Conference on Emerging Smart Computing and Informatics (ESCI) (pp. 1-6). IEEE. https://doi.org/10.1109/ESCI59607.2024.10497400
10. Najafi, A. (2016). Developing efficient model of customer relationship management for banks. International Academic Journal of Economics, 3(1), 12–18.
11. Victor, S., Kumar, K. R., Praveen, R. V. S., Aida, R., Kaur, H., & Bhadauria, G. S. (2025, August). GAN and RNN Based Hybrid Model for Consumer Behavior Analysis in E-Commerce. In 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-6). IEEE. https://doi.org/10.1109/IACIS65746.2025.11210909
12. Vazifehdust, H., & Farahmand, A. A. (2017). Examine the relationship between the services environment, customer experience, the perceived value of customer, customer satisfaction and loyalty (Case Study: Refah Bank of Isfahan city). International Academic Journal of Humanities, 4(2), 101–113.
13. Alfian, G., Octava, M. Q. H., Hilmy, F. M., Nurhaliza, R. A., Saputra, Y. M., Putri, D. G. P., ... & Syafrudin, M. (2023). Customer shopping behavior analysis using RFID and machine learning models. Information, 14(10), 551. https://doi.org/10.3390/info14100551
14. Klein, D., & Dech, S. (2024). The Role of Big Data Analytics in Enhancing Customer Relationship Management. International Academic Journal of Innovative Research, 11(3), 27–33. https://doi.org/10.71086/IAJIR/V11I3/IAJIR1121
15. Kanavos, A., Vonitsanos, G., & Mylonas, P. (2025, November). Integrating Machine Learning Approaches for Consumer Behavior Analysis in Retail Transactions. In 2025 20th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP) (pp. 7-12). IEEE. https://doi.org/10.1109/SMAP66932.2025.00010
16. Maidanov, K., & Fratlin, H. (2025). Demandflex-Lstm: A Long Short-Term Memory Model for Forecasting Adaptive Material Requirements in Lean Manufacturing. International Academic Journal of Science and Engineering, 12(3), 51-58. https://doi.org/10.71086/IAJSE/V12I3/IAJSE1226
17. Kaur, G., & Sharma, A. (2023). A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. Journal of big data, 10(1), 5. https://doi.org/10.1186/s40537-022-00680-6
18. Praveenraj, D. D. W., Prabha, T., Ram, M. K., Muthusundari, S., & Madeswaran, A. (2024). Management and sales forecasting of an e-commerce information system using data mining and convolutional neural networks. Indian Journal of Information Sources and Services, 14(2), 139-145. https://doi.org/10.51983/ijiss-2024.14.2.20
19. Shafa, H. (2022). Integration Of Machine Learning and Advanced Computing For Optimizing Retail Customer Analytics. International Journal of Business and Economics Insights, 2(3), 01-46. https://doi.org/10.63125/p87sv224
20. Arifa, P. A., & Devasenapathy, K. (2025). Sales Prediction Using LSTM and BiLSTM Models: A Deep Learning Approach for Time Series Forecasting. J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl., 16(3). https://doi.org/10.58346/JOWUA.2025.I3.023
21. Mishra, R., & Saini, R. K. (2023). A Systematic Analysis and Adaptive Hybrid Machine Learning Framework for Online Shopping Behavior Prediction. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 6(6), 9567-9572. https://doi.org/10.15662/IJARCST.2023.0606026
22. Bose, S., & Kulkarni, T. (2024). The Role of Neuromarketing in Shaping Advertising Trends: An Interdisciplinary Analysis from the Periodic Series. Digital Marketing Innovations, 18-23.

23. Chaubey, G., Gavhane, P. R., Bisen, D., & Arjaria, S. K. (2023). Customer purchasing behavior prediction using machine learning classification techniques. Journal of Ambient Intelligence and Humanized Computing, 14(12), 16133-16157. https://doi.org/10.1007/s12652-022-03837-6
24. Liu, N., & Hu, D. (2025). The design of consumer behavior prediction and optimization model by integrating DQN and LSTM. PloS one, 20(7), e0327548. https://doi.org/10.1371/journal.pone.0327548