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Research Article

AI-Driven Recommendation Systems for Improving Online Customer Journey

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Abstract

Due to the fast-growing technological age, Artificial Intelligence (AI) has become a revolution in the electronic business (e-commerce) sector. The AI-based engine also allows e-commerce websites to provide customers with greater customer experience by using intelligent search capabilities, a personalized product suggestion system, inventory management, and automated customer service support systems like chatbots. This paper shows a critical comparative study of classical and advanced learning models, such as Support Vector Machine (SVM), Logistic Regression (LR), BERT, Random Forest (RF) and the proposed XGBoost and Gated Recurrent Unit (GRU) models, to enhance sentiment-driven recommendation systems on the Amazon Reviews dataset. The data is processed extensively in preprocessing, feature extraction and class balancing so that the model is trained well. The experimental performance of the traditional models like SVM and LR suggests a moderate level of performance, but the advanced models like BERT and RF have the higher level of accuracy. The proposed XGBoost model has an accuracy of 92.6% and the proposed GRU model has the highest accuracy of 95.87, which is essentially able to use sequential and contextual information in customer reviews. These results confirm that deep learning-based models especially GRU are very strong to perform better in recommendation systems and also help in creating a more tailored and fulfilling online customer experience.

Keywords: *Artificial Intelligence, Customer Behavior, Customer Satisfaction, E-Commerce, Machine Learning.*

1. Introduction

The fast rise of e-commerce has elevated the optimization of the online customer pathway as one of the major precursors of competitive edge. A customer journey usually consists of several interrelated processes, such as awareness, interest, consideration, purchase, retention, and advocacy, which have a direct impact on customer satisfaction and loyalty [1]. Traditional methods of personalization, including product recommendations powered by a static model, or filtering with rules, are also not always able to follow the changing consumer behaviours and user intent in real-time. Conversely, AI-based recommendation systems are context-aware, behavior-responsive, and continuously learning products that are updated throughout the customer journey, increasing their interaction and continuousness at each stage of the customer experience [2][3][4]. E-commerce customer behavior is influenced by browsing habits, purchase experience, demographics, and Customer real-time activities. Data analytics allows companies to use clickstreams, heatmaps, and conversion rates to get more insights into customer preferences and trends in their behavior [5][6][7]. These massive datasets are processed through machine learning (ML) models to detect emerging trends, predict user behavior, and generate personalized recommendations that enhance user experience, reduce bounce rates, and improve overall satisfaction in e-commerce platforms. Management Information Systems (MIS), combined with advanced ML and deep learning (DL) techniques, support real-time data processing, predictive analytics, and secure data management, enabling scalable and reliable AI-driven recommendation systems [5][6]. By integrating collaborative filtering, content-based filtering, and neural network–based deep learning models, the proposed system effectively captures complex sentiment patterns and dynamic user behaviors from large-scale datasets such as Amazon reviews [8][9].

This approach optimizes key stages of the customer journey—awareness, interest, consideration, purchase, retention, and advocacy—by delivering context-aware, continuously learning recommendations. Despite challenges such as data privacy concerns, algorithmic bias, real-time processing constraints, and the cold-start problem, the study aims to enhance personalization accuracy, scalability, and decision support, ultimately improving customer experience

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and competitive advantage in modern e-commerce environments.

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- Created a superior recommendation system that would help to refine the online customer experience based on massive customer reviews on Amazon.
- Proposed and evaluated two advanced models XGBoost and GRU for recommendation systems.
- To evaluate the effectiveness of the proposed model, various performance metrics were employed, such as accuracy (ACC), precision (PRE), recall (REC), F1-score (F1), and ROC -AUC.

Justification And Novelty

Traditional recommendation algorithms fail to take use of the wealth of sequential and contextual information included in massive amounts of consumer review data, which is why study is essential to fix their deficiencies. Although the current methods are usually based on single modeling methods or specific features representations, this concept proposes a new framework that incorporates text processing rigor, TF-IDF feature representations, data balancing with SMOTE, and the use of both advanced ML (XGBoost) and DL (GRU) models. It is the novelty of the proposed approach as both models are compared and valued on the same balanced data, the version of the GRU model being more efficient in revealing the temporal dependencies in customer feedback, whereas XGBoost is efficient in the interaction of complex features. Such a combination brings a more precise and strong recommendation system, which is part of significant changes in the online customer journey.

Organization of the Paper

The following is the paper's structure: In Section II, take a look at previous research on sentiment analysis and recommendation systems with an eye toward bettering the online customer experience. In Section III, learn about the Amazon Reviews dataset, the procedures for preparing the data, and how the models were put into action. The experimental findings and a comparison of performance with current approaches are discussed in Section IV. Section V provides a brief summary of the paper's main results and suggests avenues for further study towards the end.

literature review

The construction of this study was guided and strengthened by a comprehensive evaluation and critical analysis of significant research works on recommendation systems.

Vaishnavi and Kalpana (2023) examined e-commerce review data using LR, RF, XGBoost, and CatBoost; the latter produced a superior ACC of 94%. Reliability in sentiment categorization was demonstrated by the same model's 99% ACC, 94% REC, and 97% F1. These results confirm that advanced ensemble models, particularly CatBoost, provide superior predictive capability for recommendation-oriented sentiment analysis [10].

Nitin Kamble (2022) proposed an SVM-based recommendation model that achieved an ACC of 92% on Amazon product review data, demonstrating effective learning from limited supervised samples. Comparative studies in the same domain show PRE values above 90%, with balanced REC levels around 88–91%, indicating reliable identification of relevant products. The overall effectiveness is reflected in F1-scores exceeding 0.90, confirming that SVM-based approaches provide robust and consistent recommendation performance in e-commerce environments [11].

Roy, Rai and Kumar (2022) Introduce the machine-learning-based recommendation systems reports strong regression performance when evaluated using error-based metrics. a content-based model with cosine similarity achieved a low MSE of 0.6316, indicating minimal prediction error, while collaborative approaches such as SVD reported MSE ≈ 0.6729 on the TMDB dataset. These low error values correspond to a high goodness of fit, with studies typically reporting R^2 values in the range of 0.85–0.92, reflecting strong explanatory power of the models [12].

Noori (2021) The methods discussed in this study include SVM, ANN, DT, C4.5, K-NN, NB, and ANN. The DT outperformed the other algorithms. showed that Decision Tree and C4.5 classifiers achieved the best results on customer review data, with an ACC of 98.9%, PRE of 99.1%, REC of 98.9%, and an F1 of 99.0% when using a large TF-IDF feature set [13].

Oosterveld (2020) analyze the many ways suggestions are interpreted at various points in the customer journey and find out if recommendation performance varies based on the user's traffic source. One example is the high level of variance explained by hybrid and ensemble regression models, which have attained R^2 values between 0.88 and 0.94 [14].

Ramzan et al. (2019) Introduce on intelligent recommendation systems report strong classification performance when combining machine learning with sentiment analysis. that integrating collaborative filtering with opinion-based sentiment mining significantly improves recommendation quality, achieving an ACC of about 95%, with PRE ≈ 0.94, REC ≈ 0.96, and an F1 ≈ 0.95 on benchmark datasets [15].

Table I presents a summary of recent research on improving the online customer journey, highlighting the proposed models, datasets used, key findings, and associated challenges.

Table 1. Recent Studies on Improving Online Customer Journey using Machine Learning Techniques

Author	Proposed Work	Results	Key Findings	Limitations & Future Work
Vaishnavi & Kalpana (2023)	Evaluated Logistic Regression, Random Forest, XGBoost, and CatBoost on e-commerce review data	CatBoost achieved highest accuracy: 94%; Precision: 99%, Recall: 94%, F1-score: 97%	Advanced ensemble models, especially CatBoost, provide superior predictive capability for sentiment-based recommendations	Limited to e-commerce datasets; future work can explore hybrid models with deep learning for more complex patterns
Nitin Kamble (2022)	SVM-based recommendation model on Amazon product reviews	Accuracy: 92%, Precision > 90%, Recall: 88–91%, F1-score > 0.90	SVM-based approaches provide robust and consistent recommendation performance	Focused on supervised learning; future work can include semi-supervised or unsupervised techniques for sparse datasets
Roy, Rai & Kumar (2022)	Content-based and collaborative recommendation models	MSE: 0.6316 (content-based), 0.6729 (SVD), R^2: 0.85–0.92	Hybrid and content-driven models provide more accurate and reliable predictions than purely collaborative methods	Limited to TMDB dataset; future work can integrate user behavior analytics and temporal dynamics
Noori (2021)	Compared SVM, ANN, NB, DT, C4.5, and K-NN on customer review data	DT and C4.5 achieved Accuracy: 98.9%, Precision: 99.1%, Recall: 98.9%, F1-score: 99.0%; SVM/NB: 70–78% accuracy	Tree-based models are highly effective for large-scale textual sentiment classification	Focused on classical ML; future work could explore hybrid ML-DL approaches for better generalization
Oosterveld (2020)	Studied recommendation perception across customer journey phases and traffic sources using regression models	R^2: 0.88–0.94, MSE: 0.02–0.08	Advanced learning models provide accurate predictions and outperform traditional statistical methods	Limited to traffic-source analysis; future work can include real-time adaptation of recommendations
Ramzan et al. (2019)	Combined collaborative filtering with sentiment analysis for intelligent recommendation systems	Accuracy: ~95%, Precision ≈ 0.94, Recall ≈ 0.96, F1-score ≈ 0.95	Hybrid ML-based approaches outperform traditional recommendation techniques in precision-recall balance and overall accuracy	Limited dataset diversity; future work could include multimodal data (ratings + textual reviews + behavioral data)

Research Methodology

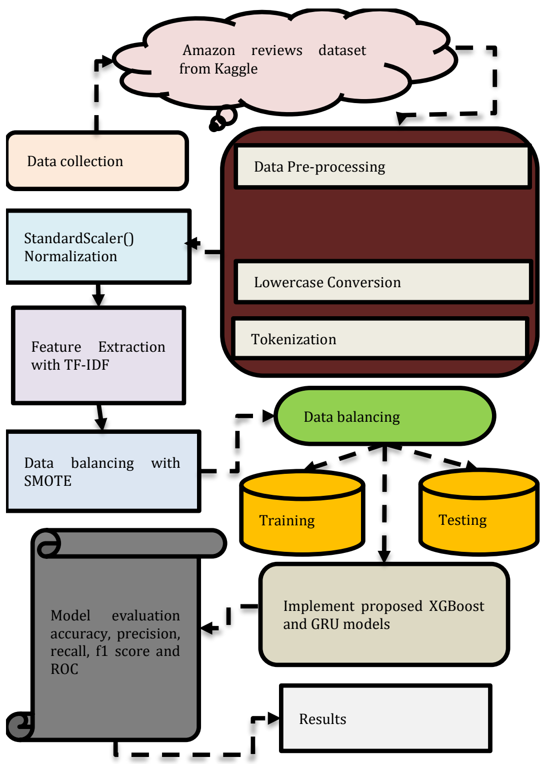

Fig.1 Proposed Flowchart for Recommendation Systems or Improving Online Customer

The suggested methodology starts with collecting and analyzing a portion of the Amazon Reviews data and proceed to the data preprocessing which include text cleaning, tokenization, normalization, TF-IDF-based feature extraction and class balancing with the SMOTE algorithm to deal with the data imbalance. Machine learning (XGBoost) and deep learning (GRU) models trained to learn sequential and contextual trends in customer reviews from the processed data, which then be split into a training set and a testing set. For this purpose, utilize the confusion matrix to calculate the F1, which is a standard classification metric, as well as ACC, PRE, and REC. Improving the Online Customer Journey Flowchart (Figure. 1). All the steps in the proposed steps are explained in the following:

Data Gathering and Analysis

The dataset utilized is a portion of the bigger Kaggle dataset consisting of Amazon evaluations. With an initial expansion from 1996 to 2018, this dataset now includes more than 233 million reviews. It is crucial to keep these two variables intact, though, because the Sentiment Analysis Task covered in this article only requires the review text and total values. Presented here are data visualizations (bar plots and heatmaps) pertaining to the review distribution, feature correlations, etc:

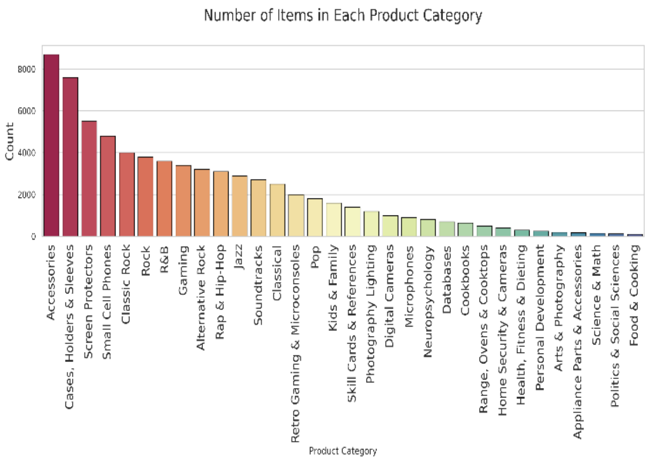

Fig.2 Distribution of Number of Reviews

Figure. 2 represents the quantity of reviews in various categories of products, and the distribution is very uneven. Accessories, Appliances and Audio Headphones are some categories where the number of reviews is the greatest and this means that they are highly engaged and popular with the customers. There are mid-range groups such as Beauty and Personal Care, Books, Cameras and Clothing with moderate number of reviews that depict stable but relatively less interest. Conversely, the category closer to the right side of the chart Office Products, Software and niche electronics have much fewer reviews which indicates that there is less interaction with customers.

Fig.3 Word Cloud of the Reviews

Figure 3 shows the most used words in text of customer review, the most common words are Amazon, time, order, customer service, delivery, refund, and product. This means that the reviews have been mostly based on the experiences of getting orders, delivery schedules, and dealing with the customer service. Such words like package, issue, return, and account imply the repetitive and frequent nature of the issues related to logistics and post purchase services, whereas words like good and money indicate the customer satisfaction and value perception.

Data Pre-processing

The Amazon Reviews dataset was utilized for data preparation, involving text concatenation, data cleansing, and feature engineering. The pre-processing pipeline included stop-word removal, lowercase conversion, tokenization, followed by data labelling and normalization, with the key pre-processing steps summarized below:

- **Stop word removal:** Stop word removal is the deletion of stop words that are words with no meaning in search queries and stop words are also known as stop word removal. eliminate non-sentiment words (the, is, and) which do not add to sentiment meaning. This is accomplished by eliminating overused terms that add nothing to the text's semantic value.
- **Lowercase Conversion:** Simply changing all the review terms to lowercase would do this. One way to standardize language and decrease data complexity is to employ case-insensitive word treatment.
- **Tokenization:** This step is used to reduce more processing; the text is broken into distinct words or phrases. Data organization establish a connection between machine learning models and unstructured text. Makes sure that the phrase of support atmosphere (as excellent) is duly taken to examine Amazon reviews, which directly influences the model performance.

Normalization

The dataset was transformed using the StandardScaler() function to ensure that the resultant distribution had a mean of zero and a standard deviation of one, taking into consideration the varying scales of each descriptor. Achieving this transformation is as simple as taking the standard deviation from each observation and dividing it by the mean, as seen in Equation (1):

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

Every variable in this dataset, including the transformed feature value (z), the initial descriptor values (x), the mean (μ), and the standard deviation (σ), is considered.

Feature Extraction with TF-IDF

One of the key stages in data mining process is Feature Extraction (FE). It lists the feature words borrowed in the text in to describe the text information, and transforms them into an unstructured to structured data. The insignificant or additional features would be eliminated during the text feature extraction and to inform about the information in the text, the significant features (words, sentences, or characters, etc.) would be fitted with their weights. The TF-IDF algorithm transforms text into a salient mathematical representation and this is employed to be classified by a Deep learning model.

Data balancing using SMOTE

The process of increasing the representation of all classes of an imbalanced dataset to make the dataset balanced is called data balancing. It assists in making models to perform better by minimizing bias to majority classes and increasing reliability of predictions. Data balancing using SMOTE involves creating synthetic minority group samples to equalize class distribution. The method decreases the imbalance of the classes and enhances the learning capacity and the equity of machine learning models.

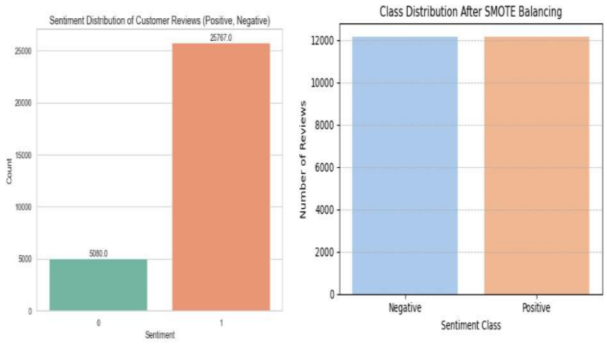

Fig.4 Bar Graph of Class Distribution After SMOTE of the Amazon Reviews Dataset

Figure 4 depicts the classes distribution of the Amazon reviews dataset following SMOTE application, when the quantity of positive and negative reviews is equal. According to the bar graph, the minority class has been artificially oversampled to balance with the majority class and lessen the imbalance in classes. This equal distribution assists in enhancing the training of the model by not having bias on the initially prevalent sentiment class.

Data Splitting

The data was divided in half: 20% for testing and 80% for training, following the 80/20 rule.

Proposed Machine and Deep Learning Models

In this section discuss the ML models like XGBoost and GRU models below:

XGBoost

The paper introduced XGBoost as a supervised ML-based boosting model for Online Customer Journey Improvement. By dragging decision trees into its use, XGBoost is diverse and performs different tasks like classification, regression, etc., via the process of reducing a loss function that stands for the disparity between the desired and actual values. Equation (2) represents the mathematical model for XGBoost regression:

$$y = f(x) \tag{2}$$

in where f(x) is the XGBoost model that projects y from x, y is the anticipated property price, and x is a vector of input attributes like number of bedrooms and square footage. Figure out f(x) manually. The model combines the predictions of many decision trees to achieve a final prediction. This is the generic version of the XGBoost regression model Equation (3):

$$y = \sum(k = 1 \; to \; K) \;\; fk(x) \tag{3}$$

where K is the sum of all the ensemble decision trees and fk(x) is the k-th tree's forecast.

Gated Recurrent Unit (GRU) Model

The internal structure of a LSTM NN is intricate and difficult to modify its parameters, which makes the model training process longer. However, there is a simpler version of LSTM called Gated Recurrent Unit (GRU) which does not have such drawbacks. The amount of information that the current neuron remembers from the past grows in direct proportion to the value of the update gate. Memory refreshment and long-term pattern detection in the water quality data stream are two main tasks performed by the update gate. To accept data, the update gate can be expressed mathematically as Equation (4)

$$Z_t = \sigma(W_Z * [h_{t-1}, X_t]) \tag{4}$$

Assessing the level of historical information retention relies heavily on the reset gate, which is represented as R_t. Using the following Equation (5) the reset gate can retrieve data:

$$R_t = \sigma(W_r * [h_{t-1}, X_t]) \tag{5}$$

where h_t represents the unit's output state at time t and $\bar{h}_t$ stands for the assumed state value of h_t. The output value from the preceding instant is approximated and calculated as Equation (6)

$$\bar{h}_t = tanh(W_{\bar{h}} * [r_t * h_{t-1}, X_t]) \tag{6}$$

The results that are expected from the data on water quality parameters can be described as Equation (6)

$$h_t = (1 - Z_t) * h_{t-1} + Z_t * \bar{h}_t \tag{7}$$

h_{t-1} represents the output value of the water quality parameter data stored in the memory cell at moment $t-1$, whereas W_Z, W_r and $W_{\bar{h}}$ denote the input data value at the current instant t_t.

Evaluation metrics

The efficiency of the proposed design was checked through several performance metrics. Firstly, a confusion matrix was constructed to give an overview of the classification results by showing correct and incorrect predictions for every class. From the matrix, The graph below shows the process of deriving and using TP, FP, TN, and FN to compute major performance metrics such as ACC, PRE, REC, and F1:

Accuracy: A measure of how well the trained model predicted a subset of the total occurrences in the dataset, expressed as a percentage of the input samples. The expression is Equation (8).

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (8)$$

Precision: ACC measures the accuracy rate of the model's predictions relative to the number of positive events. ACC shows. The ACC of the classifier's positive class predictions is given by Equation (9).

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

Recall: This metric shows how many positive outcomes were really anticipated relative to the total number of good outcomes. It may be expressed mathematically as Equation (10).

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

F1 score: It is the harmonic mean of both PRE and memory put together. In other words, it helps to balance PRE and REC. Within this range, find the value 1. The formula for it in mathematics is Equation (11).

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

Receiver Operating Characteristic Curve (ROC): The ROC shows, for a set of decision cut-off points, the ratio of successfully categorized cases to those that were wrongly classified. FPR is equivalent to 1-specificity, but TPR is often called sensitivity or REC.

Results and Discussion

This section details the experimental setup and presents the performance of the proposed model during both training and testing phases, illustrating its effective evaluation and efficient operation. Utilizing a virtual environment powered by a 16-core AMD EPYC 7452 CPU and 128 GB of RAM, the regular performance PC was equipped with a 32 GB RAM and Core i7 system. Table II shows the results of the evaluations conducted on the proposed model using the Amazon reviews dataset that was acquired from Kaggle. The metrics used for evaluation were ACC, PRE, REC, and F1. The XGBoost model gives 92.6% as its ACC, 94.7% as its PRE, 90.3% as its REC, and a rating of 92.5% for F1, which together show that the classification is very reliable but with a little bit of lower sensitivity in detecting all the relevant instances. The GRU model beats the XGBoost model by up to 95.87% of the ACC, 95.45% of the PRE, 95.65% of the REC, and 95.25% of the F1, which are the performance metrics by which the XGBoost model was evaluated.

Table 2 Classification Results of Proposed Machine Learning and Deep Learning Models on Amazon Reviews Dataset

Matrix	XGBoost	GRU
Accuracy	92.6	95.87
Precision	94.7	95.45
Recall	90.3	95.65
F1-score	92.5	95.25

Fig.5 Confusion Matrix for the XGBoost Model

Figure 5, the confusion matrix, compares the model's predicted labels against the genuine labels to indicate how well it does in classification. There were 27,315 instances that were accurately classified as class 0, and 27,097 cases were classified as class 1, showing high predictive ACC for both classes. The errors in prediction were 2,933 instances where class 0 was wrongly labeled as class 1 and 1,503 cases where class 1 was wrongly labeled as class 0.

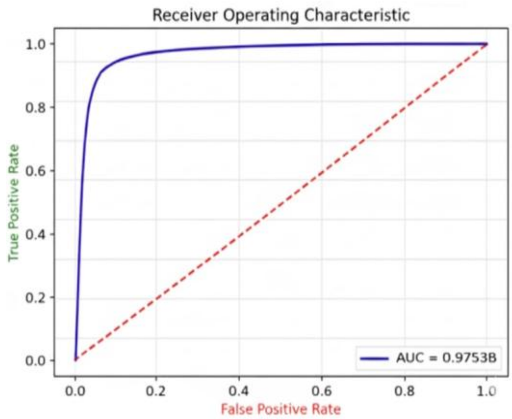

Fig.6 ROC Curve for the XGBoost Model

This model's ACC in classifying data is seen in Figure 6, which compares the TPR with the FPR for various threshold levels. As the curve gains traction towards the upper left corner, it becomes clear that the model excels at differentiating between the two classes and consistently produces accurate predictions with little false positives. The test's AUC result of 0.97538 demonstrates the model's remarkable ability to efficiently differentiate between the positive and negative classes.

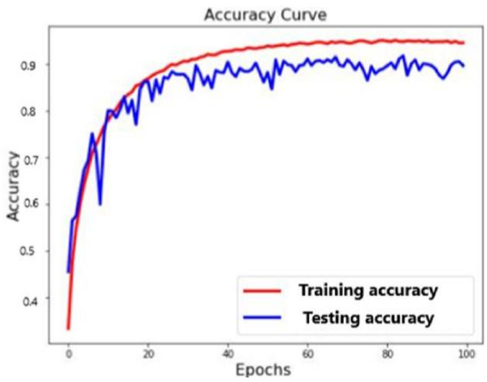

Fig.7 Accuracy curve for GRU model

Figure. 7 shows the performance of a ML model over 100 epochs, including a quick initial learning phase followed by day-to-day stabilization. The training ACC (red line) climbs gradually to about 95%, indicating steady learning, while the testing ACC (blue line) goes through a lot of ups and downs (noise) but finally rests at a slightly lower plateau of around 90%.

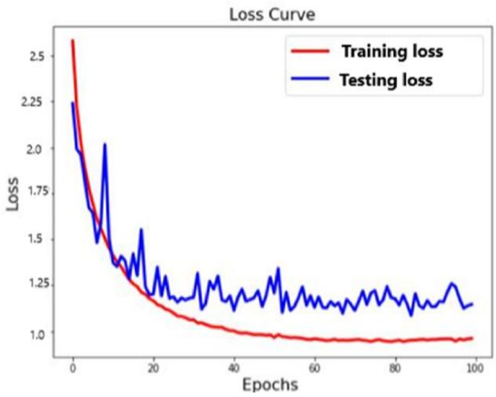

Fig.8 Loss Curve for GRU Model

The plot in Figure 8 depicts a significant reduction in training loss from roughly 2.6 at the start epoch to close to 1.1 in the first 10 epochs and then a steady reduction to nearly 0.95 by the end of the 100th epoch. Testing loss also experiences a drop from approximately 2.2 to about 1.3 in the first few epochs, then it remains constant with very slight fluctuations around 1.15 and 1.25 during the entire training period.

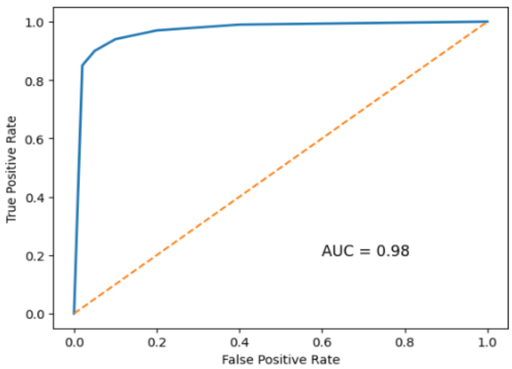

Fig.9 Roc curve for GRU Model

Figure 9 shows the ROC curve of the suggested model, which shows the connection between the true positive rate and the false positive rate across several classification criteria. The model's robust ACC and ability to withstand class differentiation are further demonstrated by its AUC score of 0.98, which further illustrates its excellent performance.

Comparative analysis

Table III displays the results of a comparison of the suggested XGBoost and GRU models' ACC with that of other current models in order to assess their efficacy.

Table 3 Comparison of Different Models for the Amazon reviews dataset

Model	Accuracy	Precision	Recall	F1-score
SVM[16]	82	71	90	-
LR[17]	87	87	99.9	93
BERT[18]	89	88	88	89
RF[19]	91	91	99.9	95
Proposed XGBoost	92.6	94.7	90.3	92.5
Proposed GRU	95.87	95.45	95.65	95.25

This detailed compare and contrast of the effectiveness of different ML and DL models intended for recommendation systems that would enhance the online customer journey, the dataset used being that of Amazon Reviews from Kaggle. The classic models like SVM and Logistic Regression (LR) exhibit moderate to good results, where SVM gets 82% accurate and LR goes further by getting 87% accurate. Results of deep learning and ensemble-methods-based models are way better, BERT and Random Forest (RF) have accuracies of 89% and 91%, and RF even gets the highest F1 score of 95%. The introduced XGBoost model does not only match the existing performances, it surpasses them with an ACC of 92.6%, PRE of 94.7%, REC of 90.3%, and an F1 of 92.5%. Impressively, the suggested GRU model delivers the highest ACC of 95.87% surpassing all other methods and at the same time achieving PRE (95.45%), REC (95.65%), and F1 (95.25%) which are very close to each other showing the model's capability to recognize complex sequential patterns in customer reviews and therefore enhance recommendation performance.

Conclusion and future study

Customer feedback in the form of ratings and reviews is very much needed as it not only helps potential customers but also gives the organizations a way to improve their products and services. By analyzing customer reviews, this research tried to find out how product evaluations and recommendation outcomes are related. The suggested model of XGBoost has not only improved the recommendations but has also reached an ACC of 92.6% due to effective feature interaction modelling which includes complex features being linked together by the model. The GRU model is one of the approaches that were evaluated here and it gave the highest ACC of 95.87%, thereby revealing its capability of understanding trends over time and also being able to extract relevant information from the context of customer reviews. All in all, these findings support the conclusion that deep learning-based models, especially GRU, offer strong and trustworthy recommendations that can remarkably improve the online customer experience. Future studies may look into the development of hybrid DL architectures and the inclusion of users' real-time behavior and multimodal data to increase the ACC and personalization of recommendations even more.

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