



Original Article

Generative AI for Personalized Marketing and Customer Experience in E-Commerce

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Abstract - E-commerce has fast become one of the major components of the worldwide online economy. It has positively affected the relationship between the business and the customer through the application of data and AI. At the same time, changing customer needs have turned understanding their preferences and offering them customized service into a major barrier to competitiveness. The study is focused on building an effective brand loyalty model that is able to not only support but also facilitate personalized marketing and customer service. The procedure is implemented using the E-Commerce Customer Dataset from Kaggle and involves a series of steps that include data cleaning, feature selection, and exploratory visualization through correlation and distribution analyses. Among the evaluated features, Satisfaction Score is found to be a crucial determinant of customer engagement and loyalty. The suggested Generative Adversarial Networks (GANs) model was trained, tested, and compared to several baseline machine learning (ML) methods such as Logistic Regression (LR), Random Forest (RF), and Naïve Bayes (NB). The GAN demonstrated its effectiveness in discovering sequential patterns and long-term relationships in behavioral data with 95.79% accuracy (ACC), 93.8% precision (PRE), 92% recall (REC), and 92% F1-score (F1) attained, surpassing all other models. The results show that GAN and other deep learning techniques outperform the standard models, making them useful tools for e-commerce platforms' predictive analytics, tailored marketing, and customer retention tactics.

Keywords - E-commerce, Customer Behavior Prediction, Personalized Marketing, Generative Adversarial Networks (GANs), Machine Learning, Customer Experience, Data Analytics, Predictive Modeling.

1. Introduction

The e-commerce industry has grown at a very fast pace during the recent past, and this was mainly because of technology breakthroughs, changing consumer tastes, and more customers using online payment options [1][2]. On the other hand, as rivalry grows, firms have to come up with new ideas all the time to keep customers, improve their processes, and extract the most profit from their investments. Generative AI is one of the industry's most revolutionary technologies, allowing firms to turn huge data sets into information with ease, perform even the most intricate tasks, and give customers the most personalized shopping experience ever

[3][4]. E-commerce has these challenges to analyze raging purchasing intent and to create the relevant and customized e-commerce solutions that are delivered through the right channels [5][6]. Buyer intent modelling and mapping are the foundations of the establishment of stronger e-commerce platforms and marketing campaigns [7]. The operators of electronic commerce sites are aware that the customer experience plays a vital role in the time consumed, the percentage of purchases made, loyalty/reward programs, and the overall income of the business.

The most efficient method for maintaining an e-commerce platform that works is to be very acquainted with the customers' behaviour, needs, preferences, and demands as they interact with the platform [8]. The whole customer experience is made up of a business's every aspect. The quality of customer service is one significant factor but it is also crucial to pay attention to the product's promotion, packaging, features, dependability, and user-friendliness [9]. By offering remarkably pleasant experiences throughout the customer journey so that they are better than the competitors', customer loyalty can be built and the likelihood of customers telling their acquaintances about the platform can be increased [10][11]. Personalized marketing and ML, two branches of AI, have been growing in popularity at the same time. ML allows computers to adapt and learn from data. Out with the traditional marketing strategies that relied on wide campaigns and general appeal through the modern, customized approaches.

The term "e-commerce personalization" is the practice of making a customer's online purchasing experience unique by taking into account their demographics, interests, and activities. Actually, this idea has come a long way in the last several years, mostly because of the widespread application of AI and ML [12][13]. The application of AI, indeed, has opened up new avenues of operation in the online store domain such that the very strong technology of generative AI has been the one that has really reversed the whole relationship between firms and consumers. Generative AI has been the most significant technology among others and is altering the customer experience at every point in the process from bespoke recommendations and chatting support to smart reviews' usage [14][15]. Generative AI is a combination of ML techniques that provide the capability of creating completely new content, making accurate predictions

regarding future trends, and automating the decision-making process. Generative AI is causing a sea change in the way online retailers connect with their customers and make money. This technology has several applications, including chatbots driven by AI, automated content production, dynamic pricing, and personalized product recommendations [16][17]. In e-commerce, this paper discusses how generative AI transforms traditional personalized marketing strategies and improves customer experience through the adoption of intelligent automation, predictive modelling, and content generation.

1.1. Motivation and Contribution

The paper's motivation is caused by the increasing requirement for e-commerce firms to provide very personalized and engaging customer interactions in an already crowded, data-driven market. The traditional marketing tactics based on wide segmentation have become out-of-date and thus cannot provide the modern consumers with the relevance and personalization that they expect. Generative AI proposes a very drastic change through content creation, predicting customer behaviour, and personalizing on a larger scale. By adopting smart auto and machine learning, e-commerce companies can raise customer satisfaction levels, fine-tune and increase the efficiency of their marketing strategies, and thus have a higher conversion rate. It is the redefining of personalized marketing and customer experience through generative AI in the fashion of the ever-changing digital commerce landscape that this paper seeks to study. The research contributes the following major points which are outlined below:

- Developed a structured machine learning framework for predicting customer behaviour and applying personalized marketing to e-commerce using real-world data.
- An optimized pre-processing pipeline has been implemented, which includes various tasks such as handling missing values, removing outliers, encoding, normalizing, and selecting features, all aimed at improving the performance of the model.
- A team working on optimizing customer experience has proposed and rigorously tested a Gen AI based Generative Adversarial Networks (GANs) model which, by capturing sequential dependencies, could enhance the customer churn prediction ACC.
- An extensive model evaluation using main performance measures like ACC, PRE, REC, and F1 was conducted to confirm the efficacy and credibility of the suggested strategy.

1.2. Organization of the Paper

The paper is structured in a way to guide the reader through the different sections easily: related work on personalized marketing and customer experience prediction is reviewed in Section II, the dataset, pre-processing steps, and model implementation are described in Section III, Section IV contains the experimental results and a comparative analysis; the study is concluded in Section V by highlighting the key conclusions and making recommendations for further study.

2. Literature Review

To provide a solid theoretical framework and direction for the current investigation, a thorough analysis of previous studies on personalized marketing and customer experience prediction was carried out. Manoharan et al. (2025) The study's main goal is to discover how ML techniques might be applied to forecast annual spending, customer attrition, and the timely delivery of online purchases. The research study has reached a decision that ML techniques are very useful for predicting the attrition and retention of e-commerce customers. The main model, gradient boosting, managed to reach a remarkable 90.67% ACC in forecasting the departure of customers and 73.75% in forecasting the delivery of a product on time [18].

Xu (2025) basically focuses on considering K-means clustering as a PRE marketing strategy applied to online marketplaces. The experiment results showed a huge increase in ACC by 98.2%, F1 grew to 97.7%, and quality of segmentation was also improved. Comparative evaluation shows that K-means is much better than the old models in the aspects of PRE and REC. The model's outstanding performance is credited to its unsupervised learning feature that enables it to automatically reveal hidden patterns that can be scaled and are data-driven, thus easy to use in improving e-commerce marketing performance [19].

Kumar et al. (2025) This study was focused on customer behaviour and the internet buying process. Among the major advantages of using AI in e-commerce, the capability to customize user experiences on e-commerce platforms stands out as the most important one. The AI model surpassed LSTM and CNN in terms of performance, being trained with CNN and Convolutional LSTM according to the key criteria. It dispenses personalized insights and recommendations with a mean ACC of 92.03%. AI-driven personalization has changed the whole e-commerce landscape by giving personalized experiences and product recommendations [20].

Arul Mary Remy et al. (2024) investigate Predictive analytics' potential effects on e-commerce customers' privacy. Specifically, it considers the combination of K-Means clustering and a single BERT-CNN-A-BiGRU model to improve the prediction ACC. The suggested solution exceeds the best-performing methods and reaches the ACC level of 98.30%. The increase in ACC indicates how the suggested method can be very helpful in dealing with privacy issues related to the use of e-commerce predictive analytics [21].

Zulfadli, Ilham and Indrabayu (2023) The primary objective is to develop a sentiment analysis algorithm that evaluates consumer opinions in online product evaluations. The dataset used for evaluation is that of Tokopedia's product reviews. The findings demonstrate that the SV model is better than the SS approach. A 69% ACC rate, 70% PRE rate, 69% REC rate, and 69% f1 are all achieved by the suggested SV model [22].

Masroor et al. (2023) forecast customer churn for a ride-sharing application by training appropriate supervised

ensemble-based machine learning models on customer attributes as well as their loyalty to the application. Gradient Boost and Cat Boost algorithms performed the best in identifying potential churning customers, with AUC-ROC scores of 0.85 and computation times of 58 seconds and 80 seconds, respectively, while XG Boost was not far behind with an AUC-ROC score of 0.84 and the fastest computation time of 45 seconds among all models assessed [23].

Table I gives a summary of the latest studies regarding the application of AI in personalized marketing and customer experience prediction, and it indicates the models that were proposed, the dataset used, the main conclusions drawn by the researchers, and the difficulties met.

Table 1: Recent Studies on Personalized Marketing and Customer Experience Prediction Using Artificial Intelligence

Author(s) & Year	Proposed Work	Techniques	Dataset	Results	Key Findings	Limitations & Future Work
Manoharan et al. (2025)	Investigated the use of ML methods to predict e-commerce product on-time delivery, annual spending, and customer attrition	KNN, Naive Bayes, Gradient Boosting	E-commerce transaction dataset	Gradient Boosting achieved 90.67% accuracy for customer attrition and 73.75% for on-time delivery	ML techniques are effective for forecasting attrition and delivery outcomes in e-commerce	Future work may explore hybrid models and larger datasets for improved prediction accuracy
Xu (2025)	Utilized K-Means clustering to enhance e-commerce client segmentation and optimize precision marketing	K-Means Clustering	Customer behavioral dataset from e-commerce platform	Accuracy: 98.2%, F1-score: 97.7%	K-Means effectively segments customers, enabling targeted marketing campaigns	Integration with dynamic behaviour analysis and other unsupervised learning methods can be explored
Kumar et al. (2025)	Developed CNN and Convolutional LSTM-based AI-driven customization to comprehend online purchasing patterns	CNN, ConvLSTM	Online customer behaviour dataset	Average accuracy: 92.03%	AI personalization enhances user experience and provides deeper behavioural insights	Future research can include multi-modal data and real-time personalization techniques
Arul Mary Remy et al. (2024)	Investigated predictive analytics with K-Means and unified BERT-CNN-A-BiGRU model focusing on consumer privacy	K-Means, BERT-CNN-A-BiGRU Hybrid Model	E-commerce systems' predictive analytics dataset	Accuracy: 98.3%	Achieved high accuracy while addressing privacy concerns in predictive analytics	Future studies may emphasize privacy-preserving techniques and ethical AI frameworks
Zulfadli, Ilham & Indrabayu (2023)	Developed an ensemble learning-based sentiment analysis model for online product reviews.	Soft Voting (SVM, RF, NB)	Tokopedia Product Review Dataset	Accuracy: 69%, Precision: 70%, Recall: 69%, F1-score: 69%	Soft Voting ensemble outperformed the Sentiment Selector model	Model performance could be enhanced using deep NLP models and larger review datasets
Masroor et al. (2023)	Forecasted customer churn in ride-sharing applications using ensemble ML models	Gradient Boost, CatBoost, XGBoost	Ride-sharing customer dataset	Gradient Boost AUC-ROC: 0.85, CatBoost: 0.85, XGBoost: 0.84	Ensemble models effectively identify potential churners in imbalanced datasets	Incorporating temporal features and real-time churn prediction can improve applicability

3. Research Methodology

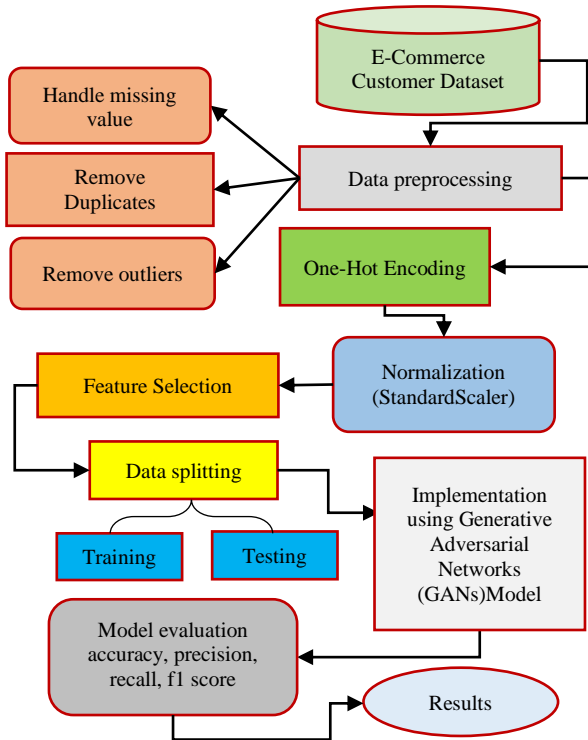


Fig 1: Proposed Flowchart for Personalized Marketing and Customer Experience Prediction

An accurate model for forecasting E-commerce client behaviour shall be established as the purpose of the study. It focuses on enhancing personalized marketing strategies and improving customer experience through data-driven insights. The methodology for implementing the GAN model on the e-commerce customer dataset follows a structured machine learning pipeline, beginning with data pre-processing, as discussed below in Figure 1.

In the section that follows, and lay out the recommended methodology step by step:

3.1. Data Gathering and Analysis

The "E-commerce Customer" dataset has been analyzed as a key factor in this study. The dataset has been obtained from Kaggle. This study uses a dataset of e-commerce behaviour data from a multi-category business from October 2019 to April 2020. The dataset consists of 4 numeric variables which are Event-time, Product-id, Category-id, and Price. Below are given data visualizations such as bar plots and heatmaps that were used for examining attack distribution, feature correlations, etc.:

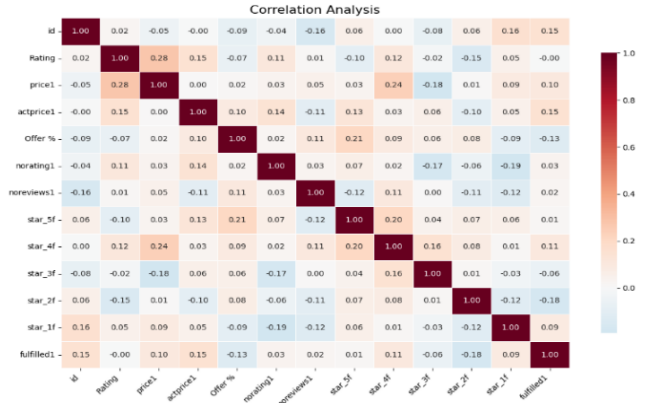


Fig 2: Correlation Analysis

The Figure 2 illustrates a heatmap Correlation Analysis, revealing the pairwise relationships among the major variables in the dataset. The colour scale from dark red to dark blue denotes strong positive to strong negative correlations, respectively. It is important to mention that price_1 and actprice1 present a very high positive correlation, while Rating is positively correlated with high star ratings and negatively with low ones. This heatmap offers an easy-to-understand picture of feature interdependencies, thus helping in pinpointing the main predictors and directing the feature selection process for model development

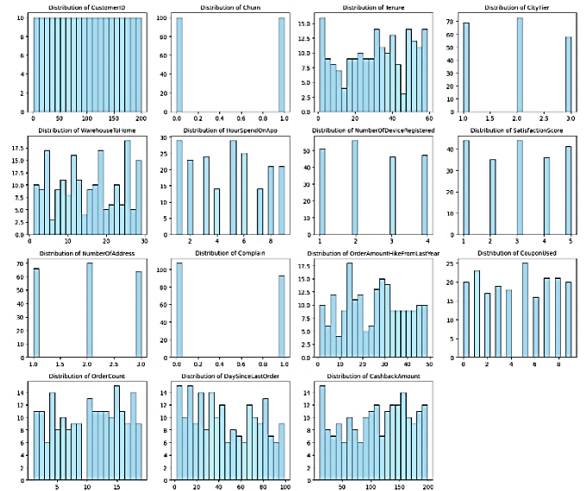


Fig 3: Distribution Plots

In Figure 3, there are 16 bar charts that depict the distribution of important variables concerning customers, such as demographics and behavioural characteristics. The different charts present the number of occurrences for features like tenure, city tier, satisfaction score, app usage, and order activity. Customer Satisfaction Score is one of the most powerful features, illuminating customer engagement and loyalty. The charts prove to be a compact and clear representation of the different customer types and their changes which can be applied for the purpose of exploratory data analysis.

3.2. Data Pre-processing

The dataset of e-commerce customers was used for the data preparation process which included merging of data, cleaning,

and feature extraction. The pre-processing activities included making the missing values, ending duplicate and outlier records, and performing label encoding and normalization on the data. The main methods of pre-processing are enumerated below:

- Handle missing value: The handling of missing values involves the utilization of various methods to tackle the problem of data points that are not present in a dataset, which could be in the form of empty cells, null entries, or indicators like "NA," thereby securing the PRE and trustworthiness of data evaluation and machine learning models [24].
- Remove Duplicate: "Remove duplicates" refers to the process of pinpointing and getting rid of data that are either identical or nearly identical, with the aim of attaining the quality and productivity of the data used.
- Remove outliers: Outlier removal is the act of spotting and then either getting rid of or altering the data points that are highly dissimilar to the largest part of the data in a dataset.

3.3. One-Hot Encoding For Data Encoding

The process of data encoding refers to turning information into a designated format for various purposes, such as transmission, storage, or analysis, making sure that the corresponding data is easily and effectively handled by computers and algorithms. To convert categorical input into a numerical representation that ML models can comprehend, one-hot encoding is a ML technique.

3.4. Normalization (Standard Scaler)

The dataset was normalized employing the StandardAero() method to adjust the data such that the mean of the resulting distribution is 0 and the standard deviation is 1 [25]. The method described in Equation (1) is used to perform this transformation, where each observation's mean value is deducted and the standard deviation is used to divide:

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

The attribute's changed value (z), the attribute's initial value (x) for each descriptor, the average (μ), and the attribute's standard deviation (σ) from the dataset.

3.5. Feature Selection

Feature selection is the technique of identifying and picking the most important input variables (features) from the data set to improve the result, reduce the complexity, and make the ML model more interpretable. In data pre-processing, feature selection is the choice of a subset of relevant features (variables, predictors) from a data set to be applied in the model-building process. This process aims to increase model performance by reducing dimensionality, enhancing interpretability, and also dealing with issues like overfitting.

3.6. Data Splitting

The same data set is used to construct a training set and a testing set, which are then used to train the models and assess

their performance, respectively. The division ratio is such that 70% of data is assigned for training and 30% for testing.

3.7. Proposed Generative Adversarial Networks (GANs) Model

In machine learning modeling, Generative Adversarial Networks (GANs) have advanced. In order to distinguish between artificial and genuine data, this machine learning technique uses discriminating networks. GANs behave in a way that allows them to learn the joint distribution of the entire dataset, in contrast to traditional machine learning techniques. The Generator (G) and Discriminator (D) neural networks are the two neural networks used by GANs. In order to create synthetic data that closely resembles the real data, the G is used to input a random noise vector. Simultaneously, the D's goal is to take actual samples and function as a teacher who can assess the output's performance and determine if the data are authentic or fraudulent. The Min-Max game is used to teach both G and D such that G's losses are kept to a minimum and D's losses are maximized. The function of GAN is given below in Equation (2):

$$\min_G \max_D V(G, D) = E[\log D(x)]_{x \sim P_{data}(x)} + E[\log(1 - D(G(z)))]_{z \sim p(z)} \quad (2)$$

The noise "z" is created at random, and "G(z)" shows how "G" tries to learn a distribution PG from the distribution of noise "Pz," bringing "PG" closer to the distribution of real-world data, represented by "P" data. Furthermore, the Discriminator tries to verify if the sample is authentic or fraudulent.

3.8. Evaluation Metrics

PRE, REC, ACC, and F1 were among the measures used to assess the models' performance and the test set's product suggestion prediction. For a classification task, a confusion matrix summarizes the results of the predictions. The predictions are categorized according to whether they were correct or erroneous. Two possible outcomes are represented by the symbols TP and FP, respectively, for TP and FN, and by the symbols FN and TN, for true negatives. Where, as described below:

Accuracy: The percentage of instances in the dataset (input samples) that the trained model correctly predicted as a function of the total number of instances. It is given as Equation (3)-

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

Precision: A model's predictive ACC is the proportion of true positives in relation to all TP. the ACC of the classifier's positive class predictions is given by Equation (4)-

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: This metric depicts the proportion of positive occurrences that were correctly predicted to all positive occurrences. The formula for it in mathematics is Equation (5)-

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1 score: The combination of REC and PRE strikes a balance between the two, making it a harmonic mean. Between zero and one is its range. According to Equation (6)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

The key evaluation metrics used and applied in the following results are ACC, PRE, REC, and F1 below:

4. Results and Discussion

The experimental setup is shown in this section and the performance analysis of the proposed GAN model utilizing the E-Commerce Customer Dataset. Table II shows that the model was tested with crucial metrics including F1, REC, ACC, and PRE. The implementation made use of Scikit-

learn. A 95.79% ACC rate, 93.8% PRE rate, 92% REC rate, and 92% F1 for the GAN model demonstrate its reliability and the well-balanced Ness of its predictions for consumer behaviour in relation to targeted marketing and improved customer experience.

Table 2: Classification Results of the Proposed Model Using E-Commerce Customer Dataset

Matrix	GAN Model
Accuracy	95.79
Precision	93.8
Recall	92
F1-score	92

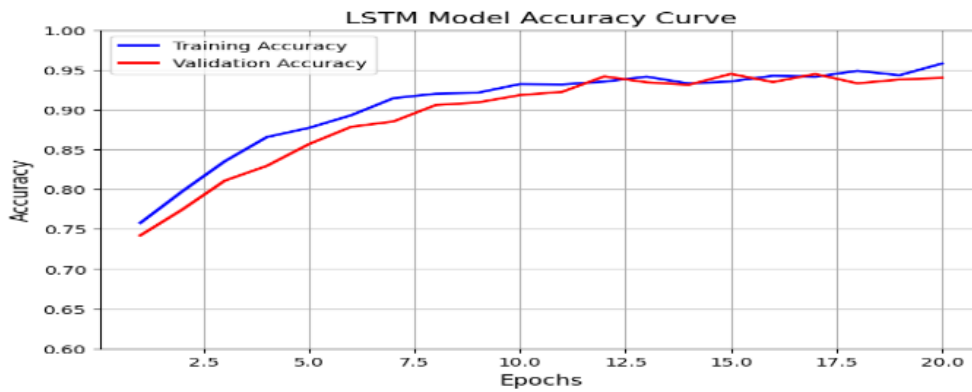


Fig 4: GAN Model Accuracy Graph

The training and validation ACC curves of the GAN model over 20 epochs are shown in Figure 4. ACC curves for both training and validation have been steadily increasing, suggesting that the model is getting better at learning with each cycle. Starting at around 0.75 and gradually increasing to around 0.96 is the training ACC, whereas starting at around

0.72 and ending at around 0.94 is the validation ACC. The closeness of both curves in the last epochs is an indication that the model can apply the patterns it has learnt from the training data to fresh data, thereby exhibiting minimal overfitting and stable learning behaviour.

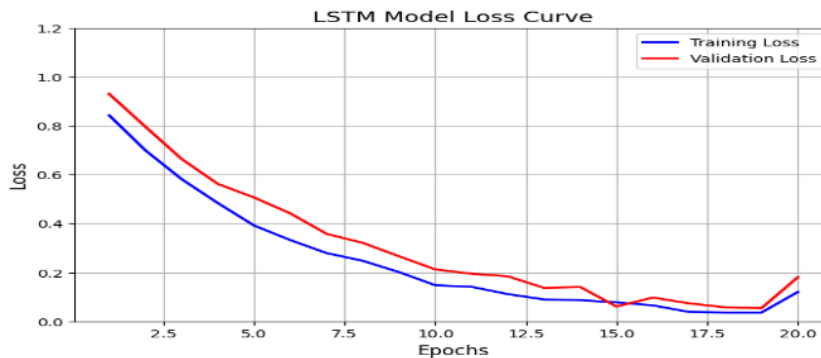


Fig 5: GAN Model Loss Graph

Figure 5 illustrates the loss curves for both training and validation of the GAN model throughout the 20 epochs. The model error is shown to consistently decrease throughout the training process, as both curves have a downward trend. The training loss (blue line) has a rapid drop in the beginning epochs, and then it continues to fall smoothly, reaching a point close to 0.1, where it is somewhat stabilized. On the other side, the validation loss (red line) has a remarkable decrease, ending at around 0.18, with very little change in

between epochs, by the last epoch. The neighbouring position of the two curves is indicative of good model generalization and effective learning without any hint of overfitting.

4.1. Comparative Analysis

Table III shows the results of a performance comparison that was conducted to evaluate the suggested GAN model. The goal was to find out how effective the model was. Performance-wise, the best among the assessed models was

MLP, which got 70.3% ACC, LR, which got 90% and KNN, which got 81.9%. With its highest ACC of 95.79%, the proposed Generative Adversarial Networks (GANs) model beat all and came next with 93.8% PRE, 92% REC, and 92% F1, thus, proving its excellent ability for predicting personalized marketing outcomes and improving customer experience.

Table 3: Comparison of Different Machine and DEEP Learning Based on Customer Experience Prediction

Model	Accuracy	Precision	Recall	F1-score
MLP[26]	70.30	78.10	76	77
LR[27]	90	82	50	62
KNN[28]	81.9	67.2	51.1	47.7
GAN	95.79	93.8	92	92

GAN is a powerful method that practically dominates all the others regarding its capability of learning, handling of sequential data, and generalization, due to its very good performance. The very feature of learning temporal dependencies makes it possible for the customers' behavior patterns to be ascertained more accurately and thus, using the obtained data for predicting marketing outcomes personalized for customers to be more effective. The model, moreover, is not just predictably good across the major metrics but also, in fact, less erroneous and, thus, absolutely dependable and stable in terms of the results produced for the improvement of customer engagement and experience.

5. Conclusion and Future Study

E-commerce, owing to the digital transformation, changes in customer behaviour, and the rising use of smart systems, has become the fastest-growing and most dynamic industry. The companies that decide to win the customer engagement battle by offering personalization will find it inevitable to detect and predict customer preferences. The study is one such project and intends to make a contribution by using ML and DL techniques for predicting customer behaviour via the E-Commerce Customer Dataset. The GAN model has achieved a stunning ACC of 95.79%, thus outdoing simpler models such as LR, KNN, and MLP. Its exceptional performance across PRE, REC, and F1 metrics attests to the fact that it is capable of not only discovering and giving birth to novel marketing strategies based on customer behaviour patterns but also encouraging them. Expanding this study to incorporate real-time consumer data is one potential avenue for future research, the addition of other behavioural and contextual variables, and the exploration of more sophisticated architectures such as transformer-based or hybrid models. Also, the integration of the model into recommendation systems and customer segmentation strategies could result in improved scalability and flexibility, thus enabling companies to provide more accurate and engaging customer experiences in a digital marketplace that gets more and more competitive every day.

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