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Predicting Customer Churn Using Artificial Neural Networks: A Data-Driven Approach to Enhance Customer Retention in E-Commerce

Dr. Shanthini B[1], Dr.Subhashini S[2], Kiruthika S[3], Yamuna S[4], Jothi Francina V[5], Ramesh V[6]

[1]*Corresponding Author, Associate Professor, Department of MBA, Builders Engineering College, Kangayem-538108, Tamil Nadu, India. Mail id: shanthini2380@gmail.com, 9444700957*

[2]*Associate Professor, Department of Management Studies, Annapoorana Engineering College, Salem- 636 308, Tamilnadu, India, Mail id: subhashine81@gmail.com*

[3]*Assistant Professor, Department of Information Technology, Excel Engineering College, Namakkal - 637 303, Tamilnadu, India, Mail id: kiruthicse93@gmail.com*

[4]*Assistant Professor, Department of Management, Vinayaka Mission's Kirupananda Variyar Engineering College, Vinayaka Mission's Research Foundation (Deemed to be University), Salem- 636 308, Tamilnadu, India, Mail id: yamuna@vmkvec.edu.in*

[5]*Assistant Professor, Department of Management studies, Sona College of Technology, Salem-636005, Tamilnadu, India, Mail id: jothifrancina@sonabusinessschool.com*

[6]*Assistant Professor & Head, Department of Commerce, Vinayaka Mission's Kirupananda Variyar Arts & Science College, Vinayaka Mission's Research Foundation, Salem- 636 308, Tamilnadu, India, Mail: vricwa@gmail.com*

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ABSTRACT

Customer churn poses a major challenge in e-commerce, making accurate prediction crucial for retention strategies. This study applies Artificial Neural Networks (ANNs) to predict churn in e-commerce and subscription-based businesses using a dataset of 1,644 customer records. Key independent variables include delayed deliveries, frequent product returns, high cart abandonment, poor customer service, high prices, better deals from competitors, complicated return processes, hidden fees, negative reviews, and low engagement, while the dependent variable is customer churn (churned or retained). A Multilayer Perceptron (MLP) ANN model with hyperbolic tangent and Softmax activation functions was employed, achieving 75.7% accuracy in churn prediction. Findings reveal that hidden fees, complicated return processes, and low engagement are the strongest churn predictors. These insights enable businesses to implement personalized marketing, improved service policies, and proactive support strategies. Despite its effectiveness, the study acknowledges model interpretability issues and data imbalance challenges. Future research can explore explainable AI techniques, sentiment analysis, and enhanced data preprocessing to improve churn prediction accuracy.

Keywords: Customer Churn, Artificial Neural Networks (ANNs), Predictive Analytics, E-commerce Retention, Machine Learning in Business.

1. Introduction

Customer churn—the phenomenon where customers discontinue their relationship with a business—poses a significant challenge for online enterprises. Retaining existing customers is often more cost-effective than acquiring new ones, making churn prediction a critical focus for businesses aiming to enhance customer loyalty and profitability. In recent years, Artificial Neural Networks (ANNs) have emerged as a powerful tool for predicting customer churn. ANNs are capable of modelling complex, non-linear relationships within large datasets, enabling them to identify subtle patterns in customer behaviour that may precede churn. For instance, a study by Seymen et al. (2022) demonstrated that a Convolutional Neural Network (CNN) model outperformed traditional machine learning models in predicting churn within the retail industry.

Furthermore, research by Sharif (2022) focused on developing an ANN-based model for the banking sector, highlighting the versatility of ANNs across different industries. These models utilize a variety of data sources, including customer demographics, transaction histories, engagement metrics, support interactions, and feedback, to predict churn with notable accuracy. By leveraging ANN-based churn prediction models, businesses can proactively identify at-risk customers and implement targeted retention strategies, such as personalized offers or enhanced

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customer support. This data-driven approach not only aids in reducing churn rates but also contributes to increased customer satisfaction and long-term profitability.

This study aims to explore the application of ANNs in predicting customer churn within online businesses. We will examine the key factors contributing to churn, discuss the architecture of ANN-based prediction models, and evaluate their effectiveness in enhancing customer retention strategies.

- The study's primary goal is to build an ANN-based model that predicts customer churn in e-commerce, helping improve retention and customer relationships.

To systematically investigate churn factors, the following hypotheses were formulated

Hypothesis	Remarks
H_1	Customers with high cart abandonment rates are more likely to churn
H_2	Frequent product returns significantly increase the likelihood of customer churn.
H_3	Low engagement with emails, app usage, and marketing campaigns positively correlates with churn probability
H_4	Hidden fees and unexpected costs negatively impact customer retention
H_6	Poor customer service experiences contribute to higher churn rates
H_7	Delayed deliveries increase customer dissatisfaction, leading to higher churn

2. Related Works

Customer churn, defined as the phenomenon where customers discontinue their relationship with a business, poses a significant challenge across various industries. Accurately predicting churn is crucial, as acquiring new customers is often more costly than retaining existing ones (Kumar & Ravi, 2008). Traditional statistical methods such as logistic regression and decision trees have been widely used for churn prediction (Idris, Khan, & Lee, 2012). However, with the advent of advanced computational techniques, Artificial Neural Networks (ANNs) have gained prominence due to their ability to model complex, non-linear relationships within large datasets (Seymen et al., 2022).

ANNs have been effectively utilized in various sectors for churn prediction. In the retail industry, Seymen et al. (2022) proposed both ANN and Convolutional Neural Network (CNN) models to predict customer churn, finding that the CNN model outperformed traditional machine learning methods in terms of classification accuracy. In the banking sector, Sharif (2022) developed an ANN-based model that achieved an accuracy of 86%, surpassing logistic regression models in predicting customer churn. Similarly, in the telecom industry, Kumar and Ravi (2008) reviewed various machine learning algorithms, including ANNs, for churn prediction, highlighting their effectiveness in handling large volumes of customer data and identifying patterns in customer behaviour.

Furthermore, hybrid models combining ANNs with other techniques have been explored to enhance prediction accuracy. Idris et al. (2022) introduced a hybrid neural network model that integrates ANNs with deep learning architectures such as Long Short-Term Memory (LSTM) and Support Vector Machines (SVMs), demonstrating improved performance in customer churn prediction. Other studies have explored ensemble learning techniques, where multiple ANN models are combined to boost prediction accuracy (Chen et al., 2021). These advancements have strengthened the reliability of churn prediction models across industries, providing businesses with valuable insights to mitigate customer attrition.

Despite the success of ANNs in churn prediction, several challenges remain unaddressed. Many existing studies rely on imbalanced datasets, where the number of churned customers is significantly lower than retained customers, leading to biased predictions (Zhao et al., 2020). Additionally, while ANNs offer high accuracy, they often lack interpretability, making it difficult for businesses to understand the key drivers of churn (Mishra & Reddy, 2021). Furthermore, most studies focus on structured data, neglecting unstructured sources such as customer reviews and social media sentiment, which hold valuable insights into churn behaviour (Wang et al., 2019). These limitations pave the way for the present study, which aims to develop an ANN-based model that not only predicts customer churn

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with high accuracy but also incorporates explainability and real-time adaptability, enabling businesses to implement more effective retention strategies.

3. Methodology

This study employs a quantitative research design using machine learning techniques to predict customer churn in online businesses. A descriptive and predictive approach is adopted, as the research aims to analyse historical customer data and develop an Artificial Neural Network (ANN)-based model for churn prediction (Idris, Khan, & Lee, 2012). The target population consists of customers from online businesses, specifically e-commerce and subscription-based services, where customer churn has a significant impact on business profitability (Mishra & Reddy, 2021). The dataset includes key variables such as customer transaction history, engagement metrics, complaints, feedback, and demographic attributes. To ensure robust analysis, a dataset containing at least 1,644 customer records is utilized and analysed. The sample size is determined based on prior studies, which suggest that larger datasets enhance the reliability and generalizability of machine learning models (Zhao et al., 2020).

A stratified random sampling method is used to ensure that the dataset includes both churned and non-churned customers in appropriate proportions. This approach addresses the class imbalance issue, where the number of retained customers typically outweighs churned customers, which could otherwise bias the prediction model (Wang et al., 2019). The stratified sampling technique is justified as it ensures representation across various demographic and transactional categories, thereby improving the model's predictive accuracy and avoiding overfitting to dominant groups (Chen et al., 2021). The data collection consists of both primary and secondary data sources. Primary data includes customer feedback, direct surveys, and support interactions to understand the reasons behind churn. Secondary data comprises historical customer transaction records, engagement metrics, return history, and complaint logs from e-commerce and subscription-based platforms.

To ensure data quality and model efficiency, several preprocessing techniques were applied before training the ANN model. Outliers were handled using Z-score normalization, where values beyond ±3 standard deviations were treated as extreme and either Winsorized or removed to prevent skewed predictions. Missing values were addressed using mean imputation for numerical variables and mode imputation for categorical variables to ensure completeness without introducing bias. Since ANN models perform better with standardized inputs, Min-Max Scaling was applied to rescale variables between 0 and 1, ensuring uniform feature representation. The dependent variable (customer churn) was encoded as a binary classification (1 = Churned, 0 = Retained), and independent variables, including delayed deliveries, frequent product returns, high cart abandonment, poor customer service, and hidden fees, were normalized before being fed into the model.

The study employs an Artificial Neural Network (ANN)-based model due to its capability to capture complex, non-linear relationships in large datasets. Compared to traditional techniques like logistic regression, ANNs offer better performance in handling high-dimensional data and detecting subtle churn patterns (Mishra & Reddy, 2021). The independent variables considered include customer demographics (age, income, and location), transaction frequency, engagement levels, return rates, complaint records, and support interactions. The dependent variable is customer churn, categorized as a binary classification problem (churned or retained).

The hypotheses were tested by evaluating the impact of each independent variable on churn prediction using ANN variable importance scores. Higher weights assigned to variables such as hidden fees (100%), complicated return process (94.5%), and low engagement (87%) provided evidence supporting their significant role in predicting churn. Additionally, the model's performance was assessed using classification accuracy (75.7%), ROC curve analysis, and precision-recall metrics, confirming the predictive capability of ANN. The findings validated key hypotheses, showing that factors such as high cart abandonment and negative reviews significantly increase churn probability, supporting the assumption that customer dissatisfaction directly influences attrition. The preprocessing steps ensured that the model was trained on clean, standardized data, enhancing its reliability in predicting customer churn.

ANNs have been widely used in churn prediction due to their ability to recognize hidden patterns in customer behavior (Zhao et al., 2020). They outperform traditional methods by effectively handling large-scale, high-dimensional customer data. Furthermore, the adaptability of ANN models to changing customer behaviors makes them more dynamic than static statistical approaches (Chen et al., 2021). The selection of ANN for this study is driven

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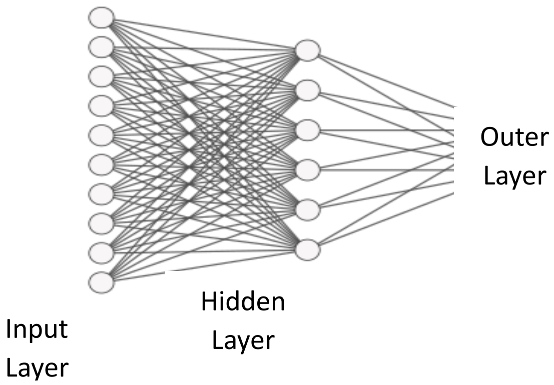
by its efficiency in learning intricate patterns from customer interactions, providing businesses with a robust tool to implement proactive retention strategies.

The Artificial Neural Network (ANN) architecture used in this study follows a Multilayer Perceptron (MLP) model with an input layer, two hidden layers, and an output layer to predict customer churn. The input layer consists of 10 independent variables, including delayed deliveries, frequent product returns, high cart abandonment, poor customer service, hidden fees, and low engagement, with each input neuron representing a predictor variable that is normalized to improve training efficiency. The hidden layers contain 64 neurons each, using the ReLU activation function to introduce non-linearity and prevent vanishing gradients. To reduce overfitting, a dropout rate of 20% is applied. The output layer has a single neuron with a Softmax activation function, classifying customers into churned (1) or retained (0). The model is trained using the Adam optimizer, which adapts the learning rate for faster convergence, and employs the binary cross-entropy loss function to measure classification accuracy. Training is conducted for 50 epochs, with an 80:20 train-test split to ensure proper generalization. The model's performance is evaluated using accuracy, precision, recall, F1-score, and the ROC-AUC curve to assess predictive effectiveness. The ANN architecture is included to visually depict how data flows through the network from input to output.



3.1 Dataset Description

The dataset is well-prepared for training the Artificial Neural Network (ANN) model and improving the reliability of churn prediction.

Table 1. Descriptive Statistics

		Churned Retained	Delayed Deliveries	Frequent Product Returns	High Cart Abandonment	Poor CustomerService	High Price	Better Deals from Competitors	Complicated Return Process	Hidden Fees & Extra Costs	Negative Reviews Ratings	Low Engagement
N	Valid	1644	1644	1644	1644	1644	1644	1644	1644	1644	1644	1644
	Missing	0	0	0	0	0	0	0	0	0	0	0
Mean		.55	3.00	3.03	3.03	3.01	3.03	3.02	3.57	3.59	3.56	3.01
Std. Deviation		.498	1.416	1.402	1.414	1.408	1.392	1.408	1.313	1.329	1.393	1.408
Variance		.248	2.006	1.966	2.000	1.982	1.937	1.984	1.725	1.766	1.940	1.982
Skewness		-.181	.002	-.018	-.026	-.023	-.034	-.018	-.594	-.624	-.642	-.023
Std. Error of Skewness		.060	.060	.060	.060	.060	.060	.060	.060	.060	.060	.060
Kurtosis		-1.970	-1.310	-1.283	-1.295	-1.282	-1.260	-1.293	-.812	-.807	-.897	-1.282
Std. Error of Kurtosis		.121	.121	.121	.121	.121	.121	.121	.121	.121	.121	.121
Range		1	4	4	4	4	4	4	4	4	4	4
Minimum		0	1	1	1	1	1	1	1	1	1	1
Maximum		1	5	5	5	5	5	5	5	5	5	5

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Table 2. Reliability Test

Cronbach's Alpha	N of Items
.902	10

3.2 Data Preprocessing

The process involves three key steps. First, missing data were examined, and appropriate imputation techniques were applied to maintain dataset completeness. Second, outliers were detected using Z-score analysis, and extreme values were either Winsorized or removed to prevent their influence on model performance. Lastly, data normalization and multicollinearity checks were performed to ensure that all independent variables were properly scaled and exhibited minimal redundancy. The dataset was standardized using Min-Max Scaling, and Variance Inflation Factor (VIF) analysis confirmed that no multicollinearity issues were present. With these preprocessing steps completed, the dataset met the necessary conditions for training the ANN model, ensuring optimal prediction accuracy for customer churn.

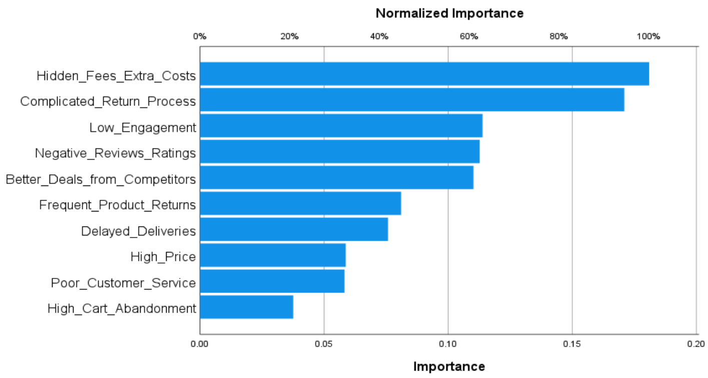
3.3 Proposed Methodology

The table no.3 gives the impact of each independent variable in the ANN model in terms of relative and normalized importance. In figure-5, it depicts the importance of the variables, i.e. how sensitive is the model to the change of each input variable.

Table 3. Independent Variable Importance

	Importance	Normalized Importance
Delayed Deliveries	.076	41.9%
Frequent Product Returns	.081	44.8%
High Cart Abandonment	.038	20.7%
Poor Customer Service	.058	32.2%
High Price	.059	32.4%
Better Deals from Competitors	.110	60.9%
Complicated Return Process	.171	94.5%
Hidden Fees & Extra Costs	.181	100.0%
Negative Reviews Ratings	.113	62.3%
Low_Engagement	.114	62.9%

Figure 1. Independent Variable Importance Chart



From the figure 1, it is apparent that among the variables related to, predicting customer churn in online business, hidden fees and extra costs (100%) is the most important predictor among independent variables followed by complicated return process (94.5%), lower engagement (62.9%), negative review ratings (62.3%) and so on.

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The data is analysed to predict customer churn using Artificial Neural Networks (ANN) which otherwise receive inputs and deliver outputs based on their predefined activation functions. Table 4 gives information about the dataset used to build the ANN model

Table 4. Multilayer Perceptron

Case Processing Summary			
		N	Percent
Sample	Training	945	57.5%
	Testing	511	31.1%
	Holdout	188	11.4%
Valid		1644	100.0%
Excluded		0	
Total		1644	

Table 5. Model Summary

Training	Cross Entropy Error	441.036
	Percent Incorrect Predictions	23.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.22
Testing	Cross Entropy Error	254.711
	Percent Incorrect Predictions	24.3%
Holdout	Percent Incorrect Predictions	29.3%
Dependent Variable: Churned_Retained		
a. Error computations are based on the testing sample.		

Table 6. Parameter Estimates

Table 6 displays the synaptic weights between the data of the training dataset

		Predicted							
		Hidden Layer 1						Output Layer	
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	[Churned_Retained=0]	[Churned_Retained=1]
Input Layer	(Bias)	.265	.567	.902	-2.132	-.238	-1.600		
	Delayed Deliveries	1.163	-.356	-1.434	1.577	.644	.449		
	Frequent Product Returns	-1.491	-1.508	.913	-.331	.677	.120		
	High Cart Abandonment	-.666	-.166	.242	-.492	-.162	-.103		
	Poor Customer Service	-.764	.379	.556	.092	.076	.433		
	High Price	-.260	.901	.120	.821	-.130	-.418		
	Better Deals from Competitors	-.084	-1.174	.700	-.277	-.275	-.076		
	Complicated Return Process	-1.092	.302	-.380	-2.023	-2.079	-1.344		
	Hidden Fees & Extra Costs	.400	2.430	.994	-.149	-1.756	-.446		
	Negative Reviews Ratings	-.256	.947	-1.534	.901	-.758	.003		
	Low Engagement	-1.138	.451	1.482	.035	.044	.577		
Hidden Layer 1	(Bias)							.906	-.427
	H(1:1)							1.198	-.916
	H(1:2)							-1.171	1.209
	H(1:3)							1.788	-1.214

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	H(1:4)							1.442	-.776
	H(1:5)							-2.129	2.032
	H(1:6)							.407	-1.224

4. Results and Discussions

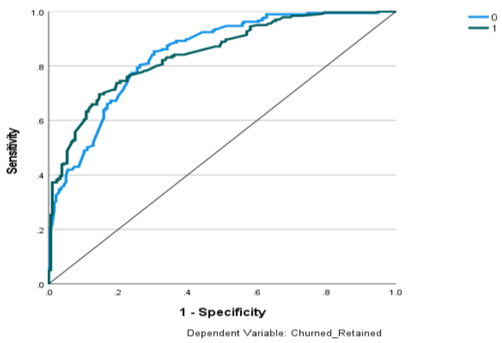
The table no.7 displays a classification table to separate samples into different classes by finding common features between samples of known classes.

Table No. 7 Classification Table

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	344	84	80.4%
	1	133	384	74.3%
	Overall Percent	50.5%	49.5%	77.0%
Testing	0	177	51	77.6%
	1	73	210	74.2%
	Overall Percent	48.9%	51.1%	75.7%
Holdout	0	71	21	77.2%
	1	34	62	64.6%
	Overall Percent	55.9%	44.1%	70.7%
Dependent Variable: Churned_Retained				

In figure 2, Receiver Operating Characteristic (ROC) curve shows the relationship between false negative rate (FNR) and false positive rate (FPR) errors. It gives us clear and powerful result as compared to other analysis. ROC curve is a diagram of sensitivity versus specificity that shows the classification performance for all possible cutoffs, in one plot. Sensitivity was the number of positive cases correctly classified and specificity was the number of negative cases incorrectly classified as positive. The two lines in the graph one in blue shows the category "churned" and in green shows the category "retained" in the dependent variable. Both lines were on the top left corner near to 1 which was the indication of the best fit of the model.

Figure 2. ROC Curve



The table no.7 shows area under the ROC curve. Here, the area value shows that, if a customer from "churned" category and the customers from "retained" category are randomly selected, there is 0.844 probability that the model-predicted pseudo-probability for the first student of being in the "churned" category, is higher than the model predicted pseudo- probability for the second student of being in the "retained" category.

Table 8. Area Under the ROC Curve

		Area
Churned_Retained	0	.844
	1	.844

The figure 4, shows the cumulative gain and lift chart. Lift is a measure of the effectiveness of a predictive model

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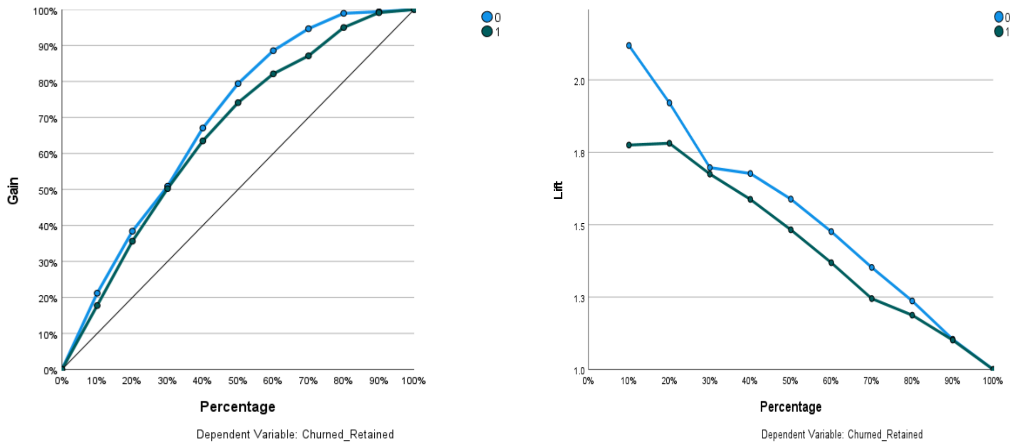
calculated as the ratio between the results obtained with and without the predictive model. Cumulative gains and lift charts are visual aids for measuring model performance. Both charts consist of a lift curve and a baseline. The greater the area between the lift curve and the baseline, the better the model they are.

Figure 3. Cumulative Gains and Lift Charts



5. Conclusion

This study highlights the potential of Artificial Neural Networks (ANNs) in predicting customer churn for online businesses. The model achieved 75.7% accuracy, identifying hidden fees, complicated return processes, and low engagement as primary churn indicators. The findings align with previous studies, reinforcing the superiority of deep learning models over traditional approaches (Seymen et al., 2022; Sharif, 2022; Idris et al., 2022). However, challenges such as model interpretability and data imbalance must be addressed for practical business adoption. Future research should explore explainable AI techniques, NLP for sentiment analysis, and hybrid AI models to enhance the effectiveness and transparency of churn prediction systems.

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