RESEARCH ARTICLE

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AI-Powered Data Analytics for Strengthening Customer Loyalty and Personalization in Retail

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Abstract

An essential prerequisite for the growth of client loyalty is the assessment of customer loyalty. Over the past few decades, marketing academics have created a variety of client loyalty assessment tools. Because service marketplaces are getting more competitive, businesses are having trouble bringing in and keeping clients. Consequently, there is an increasing need to encourage client loyalty. This study presents a machine learning (ML) approach to customer loyalty prediction using the Online Retail II UCI dataset, a sizable collection of actual transactions. The data set was preprocessed by addressing missing data, data outliers, and data normalization using Z-score to enhance data quality. The Multilayer Perceptron (MLP) model has been created and assessed based on the indices like R 2, RMSE, and MSE indicating the good predictive ability of the model with an R 2 value of 93.98. Additionally, the comparison research showed that the MLP outperformed other models. The results point to the efficiency of advanced methods of learning in cognizing customer behavior and data-driven decision-making in the retail field.

Keywords: Customer Loyalty, Retail Industry, Machine Learning, Online Retail, Decision-Making.

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Introduction

As a result of growing market globalization, businesses now operate in an environment of fierce rivalry. Customers' requirements have grown more sophisticated as market borders have expanded and consumer categories have expanded [1]. In this setting, businesses have found it challenging to outperform rivals using conventional marketing techniques. In order to provide a differentiating edge, brand equity has grown in importance.

In light of the continuously evolving distribution landscape, retailer equity is increasingly playing a significant role in defining discriminatory competitive advantage. In this difficult climate, merchants are having difficulty meeting a wide range of consumer needs, slow-growing markets, and fierce competition. The goal of most retailers' product, pricing, and marketing strategies is to draw in consumers and get a competitive edge. However, reciprocal learning and imitation lessen the impact of pricing, advertising, and product tactics, making it challenging to keep customers loyal [2]. To put it another way, a retailer's marketing efforts are insufficient to sustain both a competitive edge and consumer loyalty.

In recent decades, one of the most contentious issues in marketing literature has been customer loyalty. The significance of customer loyalty in attaining long-

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term financial results and competitive advantages explains the high level of interest in it. [3]. Positive consumer sentiments about a business or brand that lead to frequent repurchases and less sensitivity to rivals' prices and services are referred to as customer loyalty. Because they spend more with the company and have fewer maintenance expenses, loyal clients are more lucrative than new ones. Therefore, it is strategically necessary for businesses to manage and enhance client loyalty. Through efficient management of brand awareness and image, brands gain significant relevance in enhancing client loyalty [4]. Customers who are emotionally attached to a brand develop affective commitment, which motivates them to consistently rely on that company's products, make repeat purchases, promote positive word of mouth, and avoid going to competitors' stores.

Artificial Intelligence (AI) is fast becoming a pilot application that is used in marketing practices. It now has been implemented to serve the customer, personalize, price, and make decisions, changing the marketing cycle altogether. The technological change brings new possibilities to businesses to become more efficient and provide customers with their personalized experiences, but one can also find some urgent questions concerning trust, transparency, and ethical responsibility. Nonetheless, even though the previous studies have enhanced the perception of the technical and operational advantages of AI [5], much less has been done in exploring the human aspect of the adoption- specifically examining how the consumers assess AI-based personalization in perspectives of trust, ethics, and identity [6]. The successful use of data mining and machine learning (ML) models during the last two decades has improved time series forecasting. A variety of learning algorithms may be used in ML forecasting techniques to predict future demand and trends by utilizing a substantial quantity of demand-related data and attributes. Recently, deep learning (DL) approaches have been quite popular among ML techniques and have been applied in several domains, including image and audio recognition, machine translation, and natural language processing (NLP) [7]. In a number of research, DL approaches have produced better predictions and outcomes than conventional ML algorithms.

Motivation and Contribution of Paper

The increasing complexity of customer needs, intense global competition, and the limited effectiveness of traditional marketing make it difficult for retailers to maintain customer loyalty, despite its importance for long-term profitability and brand strength. This research is driven by the fact that the sophisticated and data-driven approaches are required to measure complex customer behavior more efficiently than the conventional techniques. Due to the emergence of AIs and ML, particularly, DL models that surpass traditional methods, a definite possibility to improve the prediction of loyalty can be identified. This work addresses the gap by applying modern ML models to support retailers in achieving sustainable competitive advantage. The key contributions of the study are listed below:

- Have used the Online Retail II UCI data to examine customer related retail pattern with the help of real-life transactional data.
- Applied extensive data pre-processing, i.e. treatment of missing values, treatment of outliers, and implemented normalization to enhance the quality of the data.
- Trained and created a Multilayer Perceptron (MLP) model to predict customer loyalty at a retail scale.
- Performed model analysis based on predictive performance measured by R-squared, RMSE and MSE.

Justification and Novelty of the Study

The present research is justified by the fact that there is an increasing demand to use data-driven approaches to forecast customer loyalty in the changing climate of consumer behavior and rising retail competition. It provides the more efficient and correct method of determining the patterns of loyalty and guiding strategic choices by employing a ML tool to a large real-world dataset. It has the advantage of novelty, combining a Multilayer Perceptron model with thorough preparation, including handling missing values, outliers, and normalization, thereby increasing its reliability and performance. Traditionally, a comparison study demonstrates the model's efficacy and applicability to modern retail analytics.

Structure of paper

This paper is organized as follows: Section II reviews the existing literature on Customer Loyalty in Retail, Section III presents the proposed methodology comprising of description of the data and modelling, the findings of the experiment and the most important findings are presented in Section IV, Lastly, Section V is the conclusion of the study, its shortcomings and suggestions for further study.

Literature Review

This literature review gives a holistic review of the current researches and findings of Customer Loyalty in Retail in Table 1 is used methodology, dataset and key finding are discussed below:

Naz and Popowich (2019) analyzed how supervised learning methods may be used in retail telecom businesses. In particular, they examined how nearest neighbour methods, artificial neural networks that feed forward and support vector machines, and Bayesian classifiers were applied to retail phone data. Their first results, which include a 95.5% accuracy rate, a 94.7% recall rate, and a 95.1% f-measure, demonstrate their capacity to categorize retail telephony data based on profitability [8].

Kalra and Prasad (2019) To predict the movements of the Indian stock market, a daily prediction model based on news articles and historical data is offered. The Naïve Bayes classifier is used to categorize news texts with positive or negative emotions. For forecast purposes, historical data, the number of positive and negative sentiment news stories for each day, and the variance of the close prices of the previous days are utilized. Using a variety of ML approaches, the accuracy is between 65.30 and 91.2% [9].

Liu et al. (2018) In order to assess the viability of applying the unstaffed retail shopping style, a creative unstaffed retail store design based on artificial intelligence (AI) and the internet of things (IoT) was developed. An end-to-end classification model trained with the MASK-RCNN technique is developed for SKU counting and recognition using a data set of 11,000 images taken in various environments, including 10 different types of stock keeping units (SKUs). The suggested approach in this study can achieve 97.7% counting accuracy and 98.7% identification accuracy on the test dataset, demonstrating that the system can compensate for the shortcomings of traditional unmanned container [10].

Sun et al. (2017) also suggested a prediction model that forecasts market direction based on mood in chat rooms and creates a trading plan that makes use of the forecasts as indications. Promising portfolio results are achieved by back testing with their approach. When slippage and commissions are taken into consideration, At the end of the seven-month period, the total return was 19.54%, whereas a passive buy-and-hold baseline strategy would have produced a loss of -25.26% [11].

Kaneko and Yada (2016) The study developed a sales prediction model that uses three years' worth of point-of-sale (POS) data from a retail company to forecast changes in sales the next day depending on sales on a certain day. As a result, a DL model that takes the L1 regularization into account produced an 86% accuracy rate in sales estimation. The goods at the retail store have been thoughtfully categorized. Even when the features of the product categories were enlarged from tens to thousands, the projected accuracy did not drop by more than about 7%. But the accuracy dropped by around 13% when the logistic regression model was applied [12].

Rosado et al. (2016) When combining images with a high degree of similarity, perspective distortion correction is employed to handle the various camera translation motions. After the recommended OOS detection, the generated panoramas are classified using Support Vector Machines. The experimental testing was carried out across the retail area using actual data from supermarket shelves with labels adjacent to the visible ruptures. In OOS and label detection, the detection accuracy is 84.5% and 86.6%, respectively [13]

Methodology

The suggested methodology starts with the Online Retail II UCI data obtained on Kaggle and then proceeds to the pre-processing tools that comprise the correction of missing values, outliers, and Z-score normalization. The data is subsequently divided into training (70%) and testing (30%) sets to create a Multilayer Perceptron model. Lastly, To assess the model's performance, R-squared, RMSE, and MSE are used. Figure 1 shows the general flow of the investigation.

Each step and process of a flowchart are explained below:

Dataset Analysis

The dataset in this study was the Kaggle-hosted Online Retail II UCI, which is a real-world log of transactions of an online retail company based in the UK during the time frame from December 2009 to December 2011. There are 1,067,371 rows and 8 columns in the dataset, with the description of invoice data, product characteristics, quantity, price, customer IDs, and countries. It is suitable in ML because of its sophisticated design, which is applicable in classification, regression, clustering, and studying customer behavior. The data visualizations are shown Figure 1.

A heatmap of correlation thatdisplays the relationship between the numeric and encoded categorical variables in the dataset, is shown in Figure 2. There is very little

Table 1: Summary of Recent Studies on Customer Loyalty in Retail

Author & Year	*Objective / Focus*	*Method / Model Used*	*Dataset / Application Area*	*Key Findings / Accuracy*
Naz & Popowich (2019)	Use supervised learning to categorize retail telecom data based on profitability	Nearest Neighbour, ANN, Bayesian Classifiers, SVM	Retail Telecommunication Data	Achieved 95.5% precision, 94.7% recall, 95.1% F-measure
Kalra & Prasad (2019)	Predict Indian stock market trends using historical data + news sentiment	Naïve Bayes + ML Classifiers	Stock market data + news articles	Achieved accuracy 65.3% to 91.2% across models
Liu et al. (2018)	Develop AI-based solution for unstaffed retail shops	MASK-RCNN for SKU counting & recognition	11,000 images of 10 SKU types	98.7% identification accuracy and 97.7% counting accuracy were attained.
Sun et al. (2017)	Predict market direction using chat-room sentiment & build trading strategy	Sentiment Analysis + ML Trading Strategy	Chat room sentiment data	Portfolio achieved 19.54% return vs. –25.26% loss in buy-and-hold baseline
Kaneko & Yada (2016)	Predict next-day sales using POS data	Deep Learning with L1 Regularization	3 years of POS data from a retail store	Achieved 86% accuracy; DL outperformed logistic regression by maintaining stability with increasing product attributes
Rosado et al. (2016)	Detect out-of-stock (OOS) situations in retail shelves	Perspective correction + SVM Classification	Real supermarket shelf images	Achieved 84.5% OOS detection accuracy, 86.6% label detection sensitivity

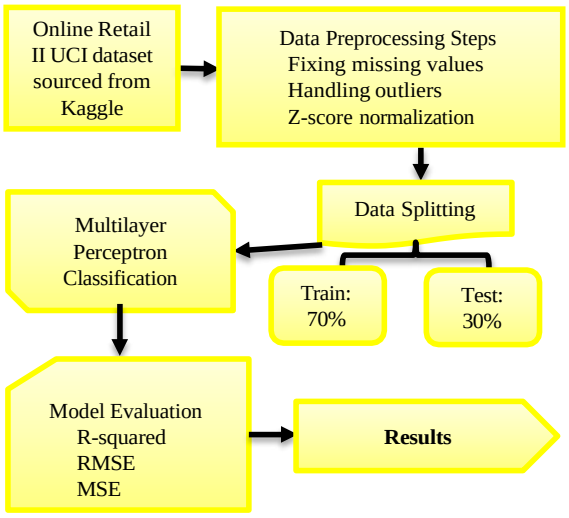

Figure 1: Flowchart Diagram of Customer Loyalty in Retail

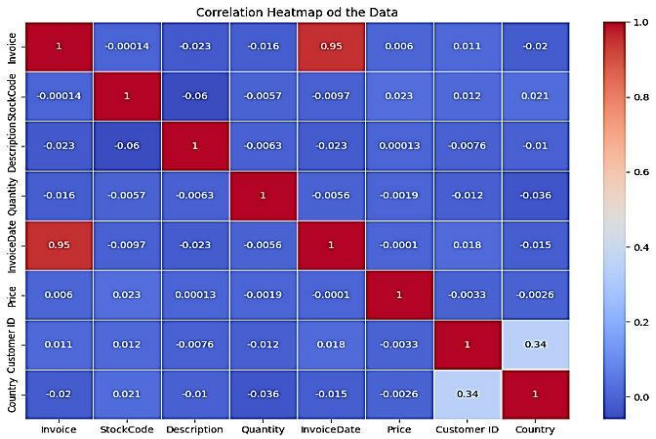

Figure 2: Correlation Heatmap of the Database

or no linear correlation between most of the variables, with very few being strongly positively correlated, such as the Invoice and InvoiceDate variables.

The Figure 3 indicates the distribution of transactions per country with the United Kingdom leading with a huge share and the rest of the countries have a small portion of the total. This indicates that the dataset is highly concentrated in UK-based retail activity.

Data Preparation

The data pre-processing process is an important element of both the data analysis and ML pipeline that consumes raw data and processes it into a clean, structured and useable format. The preprocessing pipeline involved in this study includes fixing missing values, handling outliers and z-score normalization as defined below:

- **Fixing the Missing Values:** Data quality and reliability of analysis is paramount as missing data contents need correction and incomplete information in transactional fields such as invoice, description, customer ID, and country need to be fixed.
- **Handling Outliers:** Handling outliers can be considered as determining the data points that are out of the range that analysis or model should be and handling them to avoid distortion during

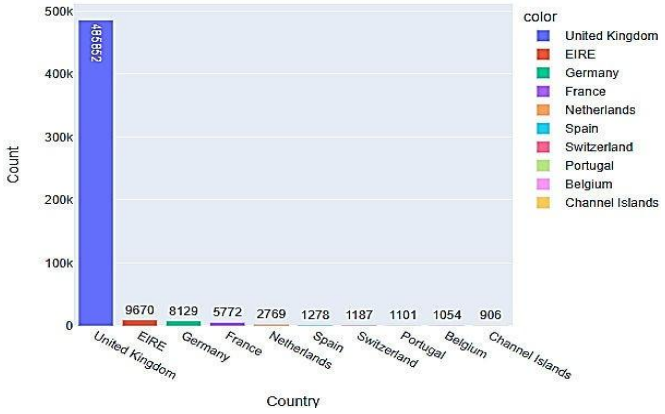

Figure 3: Customer Base by Countries

analysis or model performance. This guarantees clean, more stable and representative data on reliable results.

- **Z-score normalization:** The z-score is calculated by dividing the difference between the number and the mean by the standard deviation. The z-score indicates the location of the data point within the total dataset as well as the degree to which the score deviates from the mean. It refer to this procedure as standardization. Equation (1) provides the following transformation formula:

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

The distribution that results from this transformation has a mean of 0 and a standard deviation of 1 for each feature.

Data Splitting

The dataset was divided into 70:30 training and testing subgroups, with the remaining 30% being used for testing data and the remaining 70% being used to train the model so it may learn from the training data, where the model evaluates the parameters to calculate the accuracy and other parameters.

Model classifcation of MLP Model

An artificial neural network's feed-in class is an MLP, or multilayer perceptron. It makes use of back-propagation training, a supervised learning method. MLP is composed of three layers: input, hidden, and output. Each node uses a non-linear ReLu activation function and is called a neuron, except for the input nodes. It contains several layers and non-linear activation, which sets it apart from a linear perceptron. Compared to alternative activation functions, training a network using the ReLu activation function has been shown to converge fast and reliably, demonstrating its simplicity and efficiency. Further, it helps identify data that is not linearly separable. An ANN with one input layer, one or more hidden layers, and one output layer makes up the MLP model. The MLP is trained using the backpropagation approach.

An activation function receives the result of multiplying a perceptron's inputs by the weights. The mathematical operation of each perceptron can be represented by the following Equation (2).

$$y_{xw} = f\left(\sum_{i=1}^{m} w x_i + b\right) \quad (2)$$

The perceptron's output is expressed as y_{xw}, where y stands for the output, x for the input data vector of size m, w_i for the weights, and b for the bias component. By adding the activation function f to the total of the input characteristics and their accompanying weights, the output becomes non-linear.

Model Performance Assessment

The validation dataset assesses the trained model's performance. The validation data is used to make predictions, which are then contrasted with the actual results. As discussed below, a number of evaluation metrics are used, such R-squared (R2), mean squared error (MSE), and mean square error (RMSE):

Coefficient of Determination (R2)

The coefficient of determination R2, is a measure of the degree to which predictions of a model are accurate and representative of the actual values. A higher R2 shows that the algorithm describes a greater percentage of variance in the target variable. Mathematically, it is represented in Equation. (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \hat{y})^2} \quad (3)$$

Root Mean Square Error (RMSE)

RMSE represents the mean error between the actual and predicted values with more weight going towards the large ones and providing an idea of the scale of the error. Equation. (4) depicts the formula:

$$RMSE = \sqrt{\frac{1}{n} \Sigma \left(y_i - \hat{y}_i \right)^2} \quad (4)$$

Mean Squared Value (MSE)

The mean square of the discrepancy between the predicted and actual values is known as MSE. It is

computed as the square of the individual errors with much weight on large errors compared with small ones. The formula for MSE is described as Equation (5):

$$MSE = \frac{1}{n}\sum_{I=1}^{N}\left(y_i - \hat{y}_i\right)^2 \quad (5)$$

Results Analysis and Discussions

An Intel Core i5 8th generation CPU running at 2.30GHz with 8GB of RAM is used for the experiment. Spyder and JupyterNoteBook are the IDEs utilized, and they are set up within the Anaconda Python 3.7 environment. Table II reports the performance of the MLP model for predicting customer loyalty in the retail domain. The model possesses good predictive power since its R2 value is 93.98 which implies that a significant portion of The model describes the variability of the target variable. The error measures indicate that the model is fairly accurate, with average and absolute prediction errors of 132.75 and 17,622.20, respectively, as indicated by the error measures.

Figure 4 is a scatter acts of predicted against actual total amounts, and each point has been colored by the size of its error. The points mostly coincide with the dashed diagonal line to perfect prediction; hence, this is a good model prediction in the entire range of values. Bigger errors represented by warmer color occur at higher total amounts and smaller ones are represented by tightly clustered and less error predictions.

Table 2: Results of MLP for Customer Loyalty in retail

Models	*MLP*
R2	93.98
RMSE	132.75
MSE	17,622.20

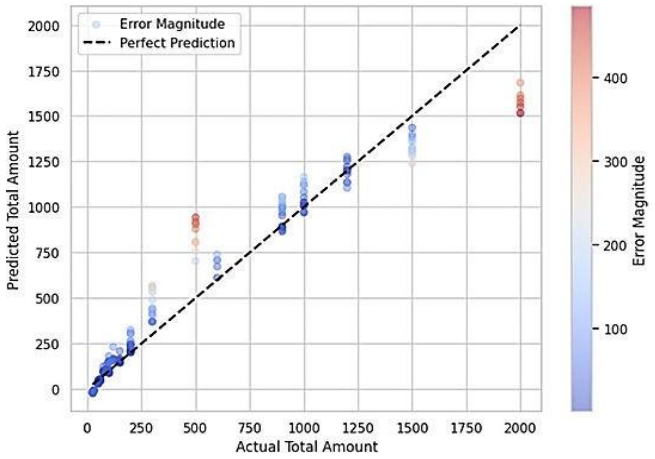

Figure 4: Predicted vs. Actual Regressor Performance of MLP

Table 3: Comparison for Customer Loyalty in retail

Models	*R2*
CNN [14]	92.8
MLP	93.98

Comparative Analysis

A performance comparison of models used to forecast client loyalty in retail is shown in Table III. The Multilayer Perceptron (MLP) has the best accuracy and its R2 score is 93.98 slightly higher than the CNN model which has a score of 92.8.

The MLP model indicates the obvious performance as compared to the alternative approach, with greater predictive reliability and more consistent accuracy throughout the dataset. It outperforms all other models because of its capability to capture underlying patterns inferiorly, leading to the superior model behaviour, making it the more valid and fitter model to use in the prediction of customer loyalty in the retail environment.

Conclusion and Future Work

Competitive pricing, stock availability, a full and suitable product range for traditional retail stalls, and high-quality items are the primary merchandising considerations from suppliers. The ordering apps that conventional retail stalls may use to purchase wholesale goods for suppliers are mostly connected to the website quality element. This paper has shown that ML, in this case Multilayer Perceptron model, has a significant possibility of forecasting customer loyalty in the retail industry. The model used meaningful patterns in customer behavior and was very predictive, as demonstrated by the R2 value which was 93.98, which was because it utilized a big real-world transactional dataset. The results raise doubts about how crucial data-driven approaches are for enhancing decision-making as they give shops additional insight about their clientele, engage strategies better, and achieve better business results. The enhanced performance of the MLP model only goes to support the appropriateness of the model in the practical application to the analytics of retail.

Future studies can consider more ML models, feature engineering to achieve better predictive performance, and consider the effects of temporal or behavioral patterns. The increase in the dataset and additional external factors, the introduction of DL architecture can contribute to the enhancement of customer loyalty prediction and the creation of more dependable and scalable retail analytics solutions.

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