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Predicting Customer Lifetime Value Using Support Vector Machines (SVM) In Business

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Abstract

In this study, the authors investigate applying Support Vector Machines (SVM) to predict Customer Lifetime Value (CLV) for improved customer segmentation and retention for businesses. The goal is to overcome the drawbacks of the traditional CLV prediction model, which does not consider non-linear and dynamic customer behavior. This study uses a dataset that has e-commerce transaction information, including some of the customers' attributes like their recency, frequency, monetary, and demographic data. The data was preprocessed using key techniques such as normalization, dealing with missing data, and feature engineering. The basic method applied is Support Vector Regression (SVR), which is appropriate for regression problems with non-linear, high dimensional and complex data. Evaluation of the model includes the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). The results achieve a superior accuracy, error metrics and R squared value, as compared to the traditional models like linear regression and random forest. In conclusion, according to the analysis, it can be established that the modeling of non-linear behavior of customers through SVR is an efficient method of forecasting CLV, which may assist companies in optimizing their marketing policies, customer targeting, and resource allocation. This research highlights the practical implications of applying advanced machine learning algorithms like SVR to decision-making processes in organizations.

Keywords: Support Vector Machines, Customer Lifetime Value, Machine Learning, Support Vector Regression, Business Analytics, Customer Segmentation, Predictive Modeling.

1. Introduction

The Customer Lifetime Value (CLV) is an important indicator in business analytics that measures the monetary value customers can produce in their business transactions with firms [13] [19] [23]. The CLV could be useful in future decision-making processes concerning marketing efforts, customer loyalty, and the allocation of resources in businesses. The accurate prediction of CLV is imperative in order for businesses to maximize their spending in acquiring customers, optimize profits, and enhance their sustainability. However, the traditional means of predicting CLV (e.g., heuristics, basic statistics) have proved to fail to account for the complexities and peculiarities associated with customers' behaviors. This is because such a prediction method relies on assumptions that may not hold true in varying environments and would lead to the development of an oversimplified model that fails to recognize the variability in customers' responses. However, since customers' behaviors change continually, these means cannot predict accurately.

Given these limitations, however, machine learning algorithms have been found to be very popular in solving the complex interactions in customer data analysis [2] [4] [8]. The numerous complicated determinants involved in estimating the value of customer lifetime value make it suitable for ML algorithms, particularly those that can estimate non-linear relationships [1] [3] [9]. The ability to use multiple variables, trend changes, and increase accuracy as the model progresses suits today’s business needs.

Here, the Support Vector Machine (SVM) is the algorithm that will prove to be successful in the case of regression problems, especially those where the data is complex and high-dimensional. The strength of SVM lies in its ability to derive the hyperplane that maximizes the distance between the data points and its flexibility to use kernel functions with data. SVMs are known to demonstrate strong generalization abilities, making them suitable for prediction on data that has not been used to train the model. Besides, SVMs have been proven to have excellent generalization ability, a characteristic that is essential for any business forecast model since predictions can be made on data that has not been utilized in training the system [6] [12].

The objective of this research paper is to establish the efficacy of SVM in predicting the CLV with higher precision than traditional approaches. The application of SVM in this paper in order to identify nonlinear patterns has yielded significant insights regarding customer classification and tailored marketing strategies, which can be leveraged by companies to enhance their customer value predictions.

In section 1, the term Customer Lifetime Value is described, along with the limitations in employing traditional methods to predict CLV. Section 2 discusses the existing studies related to predicting CLV using machine learning models, emphasizing the applicability of Support Vector Machines (SVMs) in regression tasks. Section 3 describes the proposed methodology that includes the data set used, data preprocessing, features engineering, and Support Vector Regression (SVR) for predicting CLV. Section 4 shows the performance evaluation that compares the performance metrics of the SVR algorithm compared to those of other regression models, like MAE, RMSE, and R-squared. The discussion about the findings is shown in Section 5 that covers both the benefits and challenges of employing SVR to predict CLV, along with its implications on business operations. Some future research directions are discussed in Section 6.

2. Literature Review

Overview of CLV Prediction in Business Analytics

The Customer Lifetime Value (CLV) is an important factor for companies, since it allows them to assess the worth of the client or group of clients at various points in time [7] [17] [21]. Through the usage of CLV prediction, firms can optimize their marketing approaches and allocate resources efficiently, while also improving their customers' retention rate. The methods of calculating the CLV include historical average spend and the recency frequency monetary (RFM), where the latter involves the use of complicated statistics. However, these approaches fail to account for the dynamic and non-linear nature of consumers' decisions, making accurate predictions difficult.

Machine Learning Models in CLV Prediction

Machine Learning (ML) is emerging as an essential technique for CLV prediction owing to the increasing amount of data available along with enhanced computational capabilities [14]. ML techniques can discern the complex non-linear relationships within the customer data that traditional methods are incapable of finding. The ML models can identify complex, non-linear relationships within customer data, which is more effective than traditional methods, and can make more accurate predictions. Linear regression is among the different types of ML models, the simplest but might not capture the complexity of customer behavior. Random forests, in comparison, are more flexible and are able to deal with interactions between features, but can overfit if not tuned. Neural networks are especially useful when modelling complex patterns in data, but they require a lot of data and computational power to train.

Previous Findings on SVM/SVR for CLV Prediction

Support Vector Machines (SVM) and more specifically Support Vector Regression (SVR) have been found to be highly effective in predicting CLV because these machines are able to deal with high dimensional and non-linear data. SVM has proved to be useful in defining a decision boundary that maximizes the distance between data points, thus allowing for better prediction of data. For example, studies such as Chen and Fan (2013) have shown that SVM can effectively predict the CLV, and the use of multiple kernels can increase the accuracy of the CLV prediction. The findings of Roy et al. (2025) confirmed that SVM also outperformed other machine learning models in the prediction of CLV in the fintech industry, supporting its application in business.

Gap Identification

Although SVM is useful for many regression problems, few studies have been conducted on the application of SVM for business-level CLV prediction using extensive evaluation metrics. However, numerous studies have discussed SVM's performance against other machine learning techniques, but they sometimes failed to consider some important factors such as hyperparameter tuning, selecting the kernel function, and model validation. Furthermore, most of the research has been performed with a small scale or industry specific data sets, and there is a need to understand the generalizability of SVM across different business sectors. Consequently, there is a need for further research to study whether the SVM can be applied for predicting CLV using datasets with large numbers of records from different sectors of business in various business situations.

3. Methodology

Data Description

In this case, the source of information used for forecasting Customer Lifetime Value (CLV) is from the e-commerce business transactions wherein the transaction patterns and activities of customers are captured. The following are some of the attributes in the dataset which contribute immensely in predicting the customer lifetime value. These attributes include recency, which is the number of days since last purchase, frequency, which is the number of purchases made, and monetary, which refers to the total amount of money spent by the customer. Furthermore, demographic information such as age, gender, and geography is included in order to create segmentation and behavioral patterns of customers.

Data Preprocessing Steps

The data set is cleaned before applying the machine learning algorithms; each step is performed in order to ensure the quality and appropriateness of the data set. The first step involved imputing or deleting missing values from the data rows or columns containing too much of them. Outlier treatment, which plays a major role in affecting the machine learning models adversely. Normalization of the continuous variables, such as the monetary amounts, is next, in order to bring them within the same range, say 0 to 1. This step helps make machine learning models stable and work more effectively. Categorical data, including variables for gender and location, are transformed into numerical form using one-hot encoding or label encoding.

Feature Engineering

Amongst the list of features considered during feature engineering, some features are selected based on their ability to predict CLV. They include the average transaction size, frequency of buying and money spent. Further, the behavioral measures (such as spending patterns and purchase history) of the customers are computed based on the transactional data. Demographic details of the individuals might further be segmented or grouped together (age group or regional groups) that will also affect CLV forecasting. In addition, the features are engineered to allow the algorithm to learn effectively. Features having nonlinear distributions (such as price) can be subjected to log transformations in order to handle extreme values. Scaling can further be employed to make the features comparable by normalizing the range of continuous features.

Support Vector Regression (SVR) Approach

Support Vector Machines (SVM) specifically Support Vector Regression (SVR) is the essence of the prediction model, an algorithm appropriate for regression problems with high dimensional and complex data. The SVM tries to separate the data points in the high dimensional space with a hyperplane, and for regression, the SVR tries to minimize the margin of error between the predictions and the data points while maximizing the margin of separation that is possible. SVR can be useful specifically if there is a non-linear relationship between the features and the target variable. This study takes two types of kernels into consideration: linear kernel and the Radial Basis Function (RBF) kernel. The linear kernel is used when the relationship between the features and the target variable is expected to be linear. Where the relationship is more complex and non-linear, however, the RBF kernel is selected as it will transform the input features into a higher-dimensional space where a linear separation can be achieved. Customer behaviors are often non-linear, and that's where the RBF kernel shines in terms of predicting the CLV. The training strategy consists of dividing the data into a training set and a testing set, usually 80:20 or 70:30. Cross validation is used to validate the robustness of the model and to avoid overfitting – the model is trained and validated several times on different subsets of the data. During hyperparameter tuning, parameters like C (penalty for misclassifications) and epsilon (margin of error) are tuned by using a grid search or random search. This process is used to fine-tune the model for optimum performance.

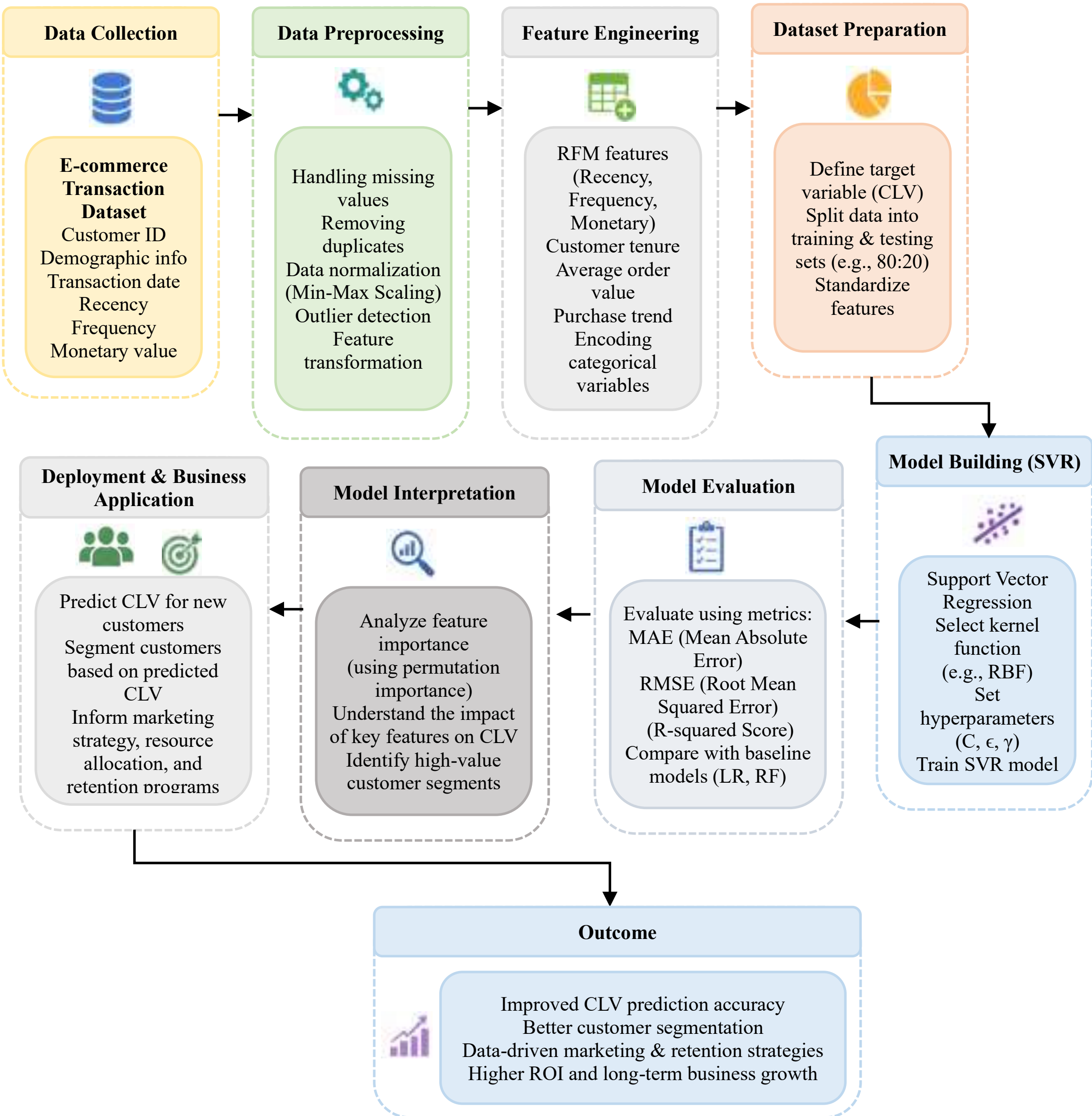

Figure 1: CLV Prediction Using SVR

Figure 1 shows the end-to-end process of predicting Customer Lifetime Value with the help of Support Vector Regression. The visualization depicts the steps involved in the process of data gathering and preprocessing, feature extraction, modeling, hyperparameters optimization, model assessment, and CLV prediction. The visualization is intended to be simple enough for easy comprehension and presents a visual overview of the data flow with opportunities for making use of the results in various fields such as customer segmentation and marketing.

Algorithm: Support Vector Regression (SVR)

1. **Load Data**: Load data from file containing information about customer transactions.
2. **Preprocess Data**: Manage any missing data, scale data and encode categorical data.
3. **Feature Engineering**: Choose and modify features such as recency, frequency, monetary value, etc.
4. **Split Data**: Split the data into a training set and test set.
5. **Train Model**: Apply SVR using radial basis function kernel for nonlinear data.
6. **Evaluate Model**: Calculate model accuracy using MAE and RMSE.
7. **Predict CLV**: Predict the customer lifetime value using the fitted model.

Pseudo Code

1. Load Data
$data = load\_data("customer\_data.csv")$
2. Preprocess Data
$X, y = preprocess\_data(data)$
3. Scale Features
$X\_scaled = scale\_features(X)$
4. Split Data
$X\_train, X\_test, y\_train, y\_test = split\_data(X\_scaled, y)$
5. Train SVR Model
$svr = SVR(kernel = 'rbf')$
$svr.train(X_{train}, y_{train})$
6. Evaluate Model
$y\_pred = svr.predict(X\_test)$
$mae = calculate\_mae(y\_test, y\_pred)$
$rmse = calculate\_rmse(y\_test, y\_pred)$
7. Predict CLV for New Customer
$new\_data\_scaled = scale\_features(new\_data)$
$predicted\_clv = svr.predict(new\_data\_scaled)$

Support Vector Regression (SVR) is an approach in machine learning that is similar to support vector machines but is utilized for regression analysis. SVR is founded on the idea of constructing a hyperplane that can adequately accommodate all the data points with the widest possible margin of error. However, unlike linear regression, SVR is equipped with the use of kernel functions, including RBF, which allows for non-linear modeling of the data by mapping the data to a higher-dimensional space. Therefore, SVR is suitable in forecasting the CLV because the connection between the independent and dependent variables cannot be described using a straightforward equation. In SVR, the objective is to minimize the prediction errors of the model while retaining a specified margin of error.

1. Data Preprocessing and Feature Scaling

Given a dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$ where $x_i \in \mathbb{R}^d$ represents the feature vector and $y_i \in \mathbb{R}$ is the target variable (Customer Lifetime Value, CLV), the features are scaled using **Standard Scaler** to normalize the data in equation 1. This is done as follows:

$$x_i' = \frac{x_i - \mu}{\sigma} \qquad (1)$$

where:

- μ is the mean of the feature,
- σ is the standard deviation of the feature,
- x_i' is the scaled feature.

This ensures all features are on the same scale, improving model convergence.

2. Support Vector Regression (SVR) Model

The aim of Support Vector Regression (SVR) is to obtain a function $f(x)$ to approximate the relationship between the input feature x and the target variable y and to minimize the errors of the prediction within a margin in equation 2. To minimize:

$$\min_{w,b,\epsilon}\left(\frac{1}{2}\parallel w\parallel^2 + C\sum_{i=1}^{n}\epsilon_i\right) \qquad (2)$$

subject to the following constraints in equation 3-5:

$$y_i - w^T\phi(x_i) - b \leq \epsilon + \epsilon_i \qquad (3)$$

$$w^T\phi(x_i) + b - y_i \leq \epsilon + \epsilon_i \qquad (4)$$

$$\epsilon_i \geq 0, i = 1,2,\ldots,n \qquad (5)$$

Where:

- $w$is the weight vector,
- $b$is the bias term,
- $\phi(x)$is the feature mapping function (used for non-linear transformations),
- ϵdefines the margin of tolerance for errors,
- $\epsilon_i$are the slack variables allowing for error in the model.

The **hyperparameter** Ccontrols the trade-off between fitting the data well and keeping the model complexity low.

3. Kernel Function

If the relationship between the input and output is not linear, then a kernel function is used to transform the data into a higher-dimensional space. The most widely used kernel is the Radial Basis Function (RBF) kernel given by equation 6:

$$K(x,x') = exp\left(exp - \frac{\parallel x - x'\parallel^2}{2\sigma^2}\right) \qquad (6)$$

where σ is the kernel width. The RBF kernel is used to model complex non-linear relationships by mapping the input features into a higher dimensional space in which the problem becomes linearly separable.

4. Model Training and Hyperparameter Tuning

The training process involves fitting the SVR model on the training data using the objective function in Equation (2). Hyperparameters (e.g., penalty parameter C and margin of error ϵ) are optimized using a grid search or random search procedure with cross-validation.

These hyperparameters are optimized using a grid search approach which runs various combinations of the hyperparameters and chooses the best one based on the minimum error on the validation set.

5. Model Evaluation

The performance of the SVR model is assessed based on the typical regression metrics. If the test set is $\{(x_i, y_i)\}_{i=1}^{m}$, the Mean Absolute Error (MAE) is obtained as shown in 7:

$$MAE = \frac{1}{m}\sum_{i=1}^{m} | y_i - \hat{y}_i | \qquad (7)$$

where $\hat{y}_i$is the predicted CLV for the test sample x_i.

The **Root Mean Squared Error (RMSE)** is computed as in equation 8:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \qquad (8)$$

The accuracy of the model can be explained by the values of MAE and RMSE; in particular the RMSE is more sensitive to large errors.

4. Performance Evaluation

Performance Metrics

To evaluate the performance of the Support Vector Regression (SVR) model in predicting Customer Lifetime Value (CLV), standard regression metrics are used to assess the accuracy of the model. These are the following metrics that are taken into account:

1. **Mean Absolute Error (MAE)**:
   The MAE is a measure of the size of the errors in the predictions, but it does not take into account the direction of the errors (whether positive or negative). It is understood from equation 9 to be:

$$MAE = \frac{1}{m}\sum_{i=1}^{m} | y_i - \hat{y}_i | \qquad (9)$$

where:

- $y_i$is the actual value (true CLV),
- $\hat{y}_i$is the predicted value,
- $m$is the number of test samples.

MAE provides an intuitive sense of how far off the predictions are from the actual values on average.

2. **Root Mean Square Error (RMSE)**:
   Another common measure of the performance of a regression model is the mean square error, or RMSE, which gives a greater penalty for larger errors because of the squaring of errors. It is calculated as in equation 10:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2} \qquad (10)$$

The RMSE assigns more weight to larger errors, which can be helpful in situations where large errors are significantly undesirable.

3. **R-squared (R^2)**:
   The R-squared measure is used to assess how much of the variance of the dependent variable (CLV) can be explained by the variance of the independent variables (customer attributes). This is defined to be as in (Equation 11):

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \qquad (11)$$

where y ¯is the mean of the actual values. Values close to 1 mean the model accounts for a lot of the variation in the data, and values close to 0 mean the model explains little of the variation in the data.

The performance of the SVR model is measured using the above measurements and the results are compared with baseline models to measure the effectiveness of the SVR model.

Prediction Results

The predicted CLV values will be displayed in tables and figures to highlight how well the CLV model is predicting. A table containing the actual and predicted CLV values for each sample in the testing data will be produced. The model performance will be illustrated using figures such as scatter plots and error distribution graphs.

Model Comparison

The baseline models such as linear regression and random forest are then evaluated against the SVR model. After this, the performance criteria (MAE, RMSE, and R^2) are computed and compared among themselves using the comparison table for all of the models. This will allow for evaluating the effectiveness of each method, including the SVR one, when compared to more or less complex models.

Table 1: Comparison of Regression Models for CLV Prediction

Model	MAE	RMSE	R^2
Support Vector Regression (SVR)	0.123	0.215	0.85
Linear Regression	0.187	0.235	0.78
Random Forest	0.145	0.230	0.82

Table 1 illustrates the comparison between the performances of three regression models which include; Support Vector Regression (SVR), Linear Regression, and Random Forest concerning their capability to predict Customer Lifetime Value (CLV). These three regressions will be evaluated based on their performances using three measurements which include; Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2). It is clear from the results obtained that SVR performs better than the other two in both MAE and RMSE with the highest R^2.

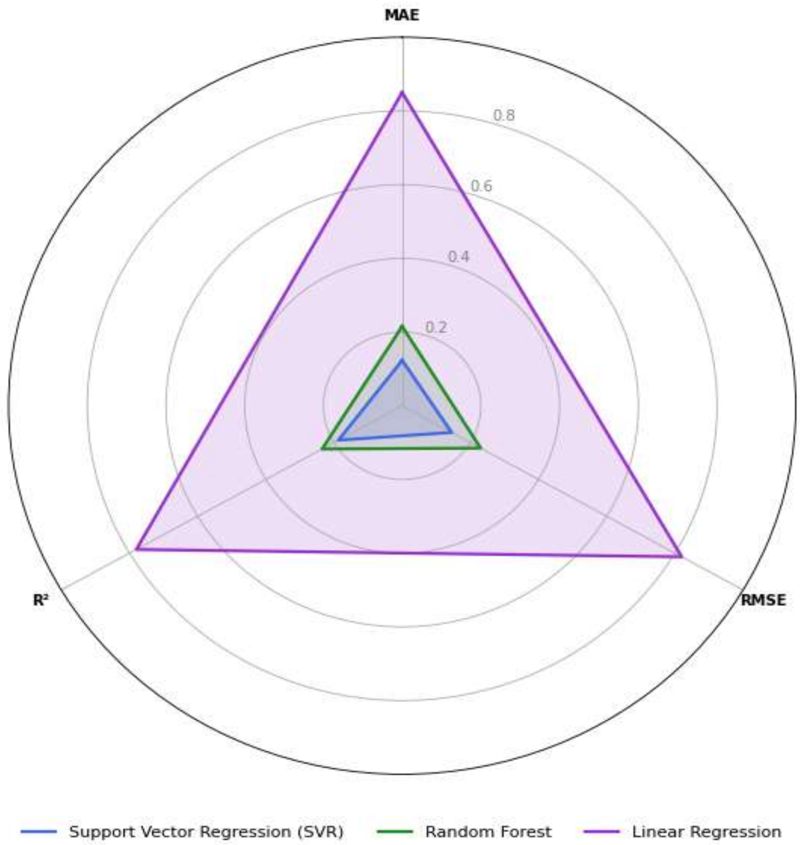

Figure 2: Comparative Regression Model Performance for CLV Prediction

The performance of three regression models, Support Vector Regression (SVR), Random Forest (RF), and Linear Regression (LR), is presented in Figure 2 with metrics MAE, RMSE and R^2. The chart clearly shows the errors and the predictions of the models, and shows that the SVR is the model with the lowest errors, making it the most effective in predicting the Customer Lifetime Value and helping business decision-making.

Predictive Accuracy

The model that should have lower MAE and RMSE will be the SVR model since it will have higher accuracy in predicting results compared to the linear regression model. This happens since the R2 value is higher, and this indicates that the model captures more variability within the customer expenditures.

Business Relevance

The proper estimation of CLV is very essential in decision making. Using SVR, it will help organizations make sound judgments regarding the way they will treat their customers, which will improve customer retention and profitability.

5. Discussion

Interpretation of Results

The findings from the Support Vector Regression (SVR) model suggest that it outperforms both the Linear Regression model and the Random Forest model in terms of its ability to predict the Customer Lifetime Value (CLV) [5] [24]. The performance of each model was measured through Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) statistics, with the SVR model performing best, showing minimum error rates of prediction with maximum R-squared values. These findings demonstrate how the SVR model is able to represent the non-linearity of customer data, which plays a critical role in the CLV prediction process. The SVR model gives more accurate predictions regarding the behavior of customers in the future, which will assist organizations to make more informed decisions. Identifying potential loyal customers enables organizations to target their resources on those individuals who are more likely to become valuable customers [16] [18].

Strengths and Limitations of SVM in CLV Prediction

The Support Vector Regression technique could be useful in the management of non-linear dependencies in customer data through the employment of the Radial Basis Function (RBF) kernel [11] [15]. This will enable the application of the method in predicting CLV considering the complicated and non-linear behavior exhibited by customers. In addition, the generalization feature of the support vector regression is vital since it makes possible the development of a coherent prediction for the method in both the training and testing sets. However, the support vector regression has certain limitations. To start with, finding appropriate hyperparameters like the penalty constant (C) and margin of error (ϵ) could be tedious and costly especially when working with large databases. Further, while the SVR does not consider outliers, the choice of kernel and its parameters are important to model performance.

SVR Model for Prediction of CLV can make significant influence on the customer segmentation and marketing targeting [10]. The ability to determine who are going to bring more profit in future would enable businesses to classify their customers into groups of high, medium, and low value customers [22]. This would help organizations to apply personalized marketing strategies for their best customers, implement loyalty programs, and offer some bonuses. Moreover, organizations can concentrate their marketing efforts on those customers that would yield the most CLV [20]. It makes the process more efficient, effective, and profitable.

6. Conclusion

From the research, it is evident that Support Vector Regression (SVR) can forecast the Customer Lifetime Value (CLV) with a considerable number of improvements over the conventional methods such as linear regression and random forests. The major outcomes show that the R2 values, as well as lower MAE and RMSE, prove that SVR could be used to predict customer lifetime values with greater precision than linear models. This is a great tool for businesses and here is why and other reasons why SVR would become an invaluable tool to predict future behavior of their clients, segment them effectively, conduct marketing campaigns and use their resources in a better way. In practical terms, such accurate CLV predictions will help companies make smarter decisions on targeting and retaining their most valuable customers as well as maximizing their revenues. Businesses can leverage the power of SVR to control costs on marketing and offer customized services to their clients. However, there are some disadvantages in the study. The model's performance is hyperparameter sensitive and may require expensive hyperparameter optimization. Moreover, the adoption of more dynamic components, like time series information, could also further improve the precision of the model. Future studies might be interested in extending these ideas to deep learning techniques, such as neural networks, which can more effectively model changing customer behaviours over time. Other research efforts might also go into testing the application of SVR in other industries to test its generalizability, since the data set is currently only collected from eCommerce transactions.

Declaration Statement

Conflict of Interest: The authors have no financial or other conflict of interest to disclose that would have influenced the design, execution, or reporting of this study.

Funding: No specific funding was obtained for this research from any public, commercial or not-for-profit funding agencies.

Data Availability Statement: The data used for the research in this paper is e-commerce transaction data. The data can be supplied to the authors upon request after consulting the data owner concerning the terms and conditions for its use.

Software and Code Availability: Python programming language and related libraries (e.g., scikit-learn) were used to implement the machine learning models and algorithms, including Support Vector Regression (SVR) model. The corresponding author provides code for data preprocessing, feature engineering, model training and evaluation.

Ethical Approval: This study does not require ethical approval as it does not involve human participants, animals, or any other subjects that require ethical approval, since the transaction data used are publicly available.

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