Forecasting Annual Expenditure in E-Commerce

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Abstract: With the rapid penetration of E-commerce in modern society, there is a need to have a holistic analysis of annual expenditure forecasting in e-commerce, underscoring its importance to modern consumer behaviour and economic growth. To achieve the same, this study explores seven machine learning based methodologies namely linear regression, random forest, decision trees, K-Nearest Neighbors (KNN), AdaBoost, Support Vector Regression (SVR), and XGBoost. Through an extensive examination of the effectiveness of each model, this research aims to provide useful information on the effectiveness of used techniques towards predicting yearly expenditures in a dynamic environment like e-commerce. These findings are important for the stakeholders seeking to improve their management strategies in the e-commerce sector, where it is necessary to understand consumers for sustainable development. Two different datasets namely Open Mart and E-Mart are used, which provides expenditure data of various companies found within different regions operating on e-commerce platforms. Among the used methodologies, the Linear Regression is found to be the most efficient one on both datasets, with 97% and 89% prediction accuracy on the Open Mart dataset and the E-Mart dataset, respectively. In contrast, Support Vector Regression (SVR) performs the worst on both the datasets. In depth analysis of the datasets reveals a strong relationship between the increasing use of apps, membership orders, and consumer expenditure overall. Thus, this study suggests that e-commerce companies may increase revenue and consumer engagement by optimizing app usage and promoting membership programs with the help of this insight.

1 INTRODUCTION

Accurate annual expenditure forecasting is essential for businesses trying to navigate competitive markets and maximize resource allocation in the ever-changing world of e-commerce. This study explores the field of e-commerce spending forecasting using a multivariate regression analysis methodology that is deemed reliable. This paper's primary goal is to provide insights for businesses using in-depth modelling and predictive analysis of e-commerce projects. By understanding trends and drivers, companies can make better decisions about budget allocation, inventory, pricing strategy and marketing campaigns.

In e-commerce, machine learning is beneficial when there is dynamic pricing and it can raise your KPIs. This is because of the ML algorithms' capability to identify new patterns in data. Because of this, those algorithms are always picking up new knowledge and identifying new trends and needs. This is why Machine Learning models are opposed to straightforward price markdowns and are used by online retailers in the e-commerce sector for dynamic pricing. Predictive algorithms help online retailers to find the best deal on a given product, which gives an advantage to online retailers. The best pricing, which also considers condition of the warehouse, can be chosen, along with the offer and real-time discounts displayed. In order to maximize sales and optimize inventory, these are performed predictive modelling of the consumer spending requires a thorough investigation of the delicate relationships between numerous elements and how those ties affect the purchasing behaviour. This study is after investigation revealed significant variables influencing yearly spend, providing essential information for companies trying to maximize their marketing budgets.

Significantly, support vector regression (SVR) performs noticeably worse, particularly for sleep, which displayed a negative R2 score on one data set.

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In contrast, linear regression stands out as a strong model, displaying remarkable accuracies above 90% throughout the data sets. Annual spend is heavily influenced by variables like uptime, and users are more likely to devote their maximum time and resources to mobile applications than to websites. In summary, this study aims to contribute to the field of forecasting analytics for e-commerce by a comprehensive analysis of annual spending forecasts. By providing strategic guidance and actionable insights, it aims to empower E-Commerce businesses to succeed in an increasingly competitive world.

2 LITERATURE REVIEW

Research in expenditure forecasting for e-commerce emphasizes the critical role of predictive analytics methodologies. This research emphasizes on various regression analysis to uncover the best expenditure patterns. In a study [1], which shows how different demographics of age, gender and marital status affect consumer spending, the data was collected from the state of Jammu and Kashmir, India with a total of 234 participants. This research shows young male with marital status as single have a higher chance of e-shopping Which helps the e-commerce website to distribute advertisements accordingly. For owners to understand how the revenue is distributed among different categories, in this study [2], for e-commerce sales forecasting the researcher builds a Directed Acyclic Graph Neural Network (DAGNN). DAGNN is used in deep learning for building neural network in which the layers are presented as a directed acyclic graph. A DAGNN can take inputs from multiple layers and can give output to multiple layers. This will be useful for long-term forecasts of product wise daily sales revenue. The created forecasting will help the owner to accurately predict the sales of the product category for up to three months ahead. E-commerce has helped both retailers and customers in terms of cost, as demonstrated in study [3], which examines how online shopping affects retailers' selling prices and consumers' purchasing costs. The study compared an online store with an offline store and found that online shopping resulted in lower costs for both retailers and consumers. This shows that both retailers and customers have benefited from the impact of e-commerce. In this study [4], research was conducted for forecasting Walmart sales using various machine learning models. The goal of this research was to implement various machine learning classification algorithms on the sales data of Walmart stores present across the United States of America. Algorithms used are Gradient Boosting, Random Forest and Extremely Randomized Tree (Extra Tree) and where compared using MAE evaluation R2 Score. This study shows Random Forest performs the best as compared to other algorithms with the highest R^2 accuracy of (0.94) and minimum MAE value of (1979.4). Research [5] discussed various machine learning algorithms which are commonly used in sales forecasting, aiming to find the best machine learning model with a better business understanding. Algorithms on which the research was conducted are Random Forest, Support vector machine, Decision trees, Naïve bayes and Neural networks. The selected algorithms are compared based on their accuracies. The study shows Random Forest has the highest accuracy score of 85%, making it the most suitable for sales prediction. In this study [6], research was conducted to predict the sales of products based on different factors like past history, seasonal trends, location and festivities, with the help of machine learning algorithms. Researchers selected five algorithms KNN, NV (Naïve bayes), SVR, RF (Random Forest) and MLR (Multiple linear regression). Selected algorithms are compared based on their Root Mean Square Error (RMSE) value. After evaluating different algorithms, the researchers found out MLR gives the most accurate results with an RMSE value of 1.32, which is the lowest as compared to other algorithms, followed by SVR, RF and KNN with RMSE values of 2.35, 2.51 and 2.58 respectively. The algorithm that performed the worst was NV with an RMSE value of 7.02.

3 METHODOLOGY

This paper contains the predictive analysis on the E-commerce dataset with different Machine Learning models to analyze the best model for regression analysis.

3.1 Flowchart of Model

This article analyzes two datasets to get insight into E-commerce clients' spending habits. This study investigates numerous features such as session length, app/website usage, membership term, and annual spending to find hidden underlying patterns. In Figure 1, the Model examines the e-commerce dataset in a systematic manner. Initially, relevant statistics are acquired and checked to ensure their validity and applicability to real-world settings. Second, the data is cleaned and organized to meet the analytical requirements. Finally, numerous machine learning algorithms are used to extract useful insights from preprocessed data. The performance of these algorithms is then rigorously assessed using several assessment metrics. Finally, we compared and analyzed the benefits and drawbacks of each algorithm. Finally, our research presents the findings from this systematic procedure, demonstrating the effectiveness of various algorithms in identifying patterns and practices in e-commerce. This sequential procedure directs our inquiry and facilitates the systematic analysis of e-commerce trends and patterns.

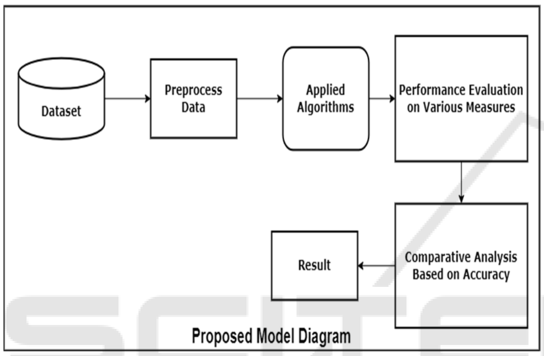
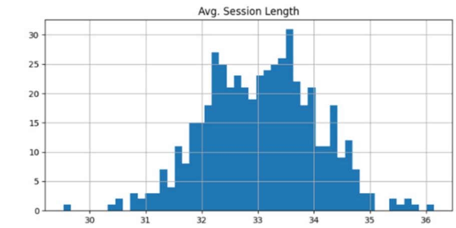


Fig.1. Flow of Machine Learning Model.

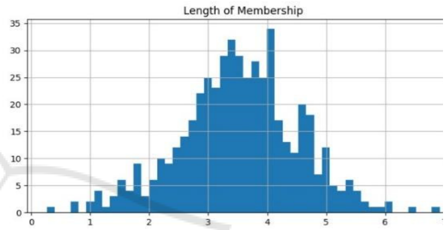
The datasets used are readily available on platforms like Kaggle and Github under the name ‘Ecommerce Customers’, with no missing values for any features.

3.2 Exploratory Dataset Analysis

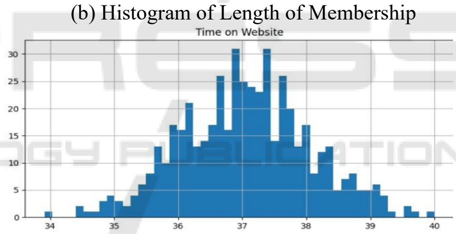
This section of the paper gives an insight to two publicly available datasets which concerns patterns in expenditure of buyers. Open Mart dataset which has eight attributes out of which three are object data type and rest are float data type. Email, Address and Avatar are object data type and ‘Avg, Session Length’, ‘Time on App’, ‘Time on Website’, ‘Length of Membership’ and ‘Yearly Amount Spent’ are float data types and also an important numeric feature for further analysis. The E-mart dataset has only numeric dataset, it has total five numeric features namely Session length, App Screentime, Website Screen Time, Number of purchases and Yearly Amount Spent. Total number of datapoints in Open mart and E-mart are 500 and 1000 respectively.
E-mart dataset has additional feature named ‘Number of Purchases’ which is not available in Open Mart dataset. Fig. 2 and Fig. 3, demonstrates the features of both the datasets using histograms where x-axis shows the time (in minutes) and y-axis shows number of customers engaged in Session, App and Website while purchasing. X-axis in the attribute ‘Length of Membership’ shows time (in months) and for ‘Number of Purchases’ it is the total item purchased



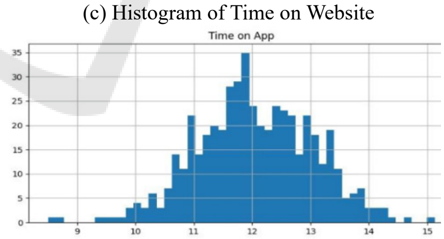
(a) Histogram of Avg. Session Length



(b) Histogram of Length of Membership



(c) Histogram of Time on Website



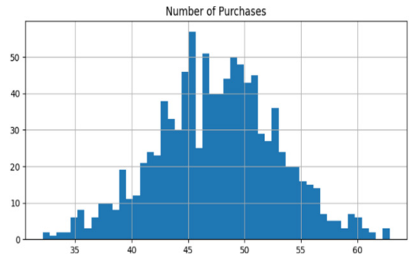
(d) Histogram of Time on App

by a specific user.

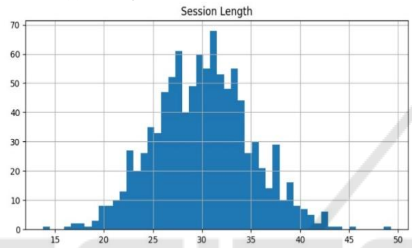
Fig .2. Histograms of different features in Open Mart Dataset

Fig. 2(a) shows that the length of the sessions ranged from about 20 to 40 minutes. Fig. 2(b) depicts that only few people stay members for longer than five months, which indicates that Open Mart is having trouble keeping clients for long time. Fig.2 (c) and (d) shows consumers are spending more time on the website than on the app. This paper also analyses whether people are actually spending more money on websites or apps with respect to Yearly Amount Spent.

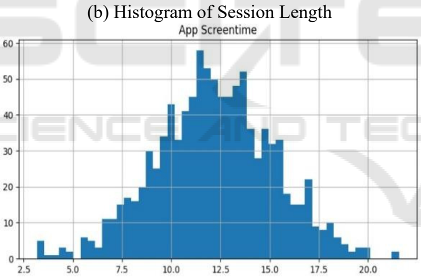
Fig. 3(b) shows that the length of the sessions ranged from about 20 to 50 minutes. Fig. 3(b) shows that E-mart customers are buying more items which indicates higher shopping activity. Fig.3 (c) and (d) shows consumers are spending even more time on the website and app.



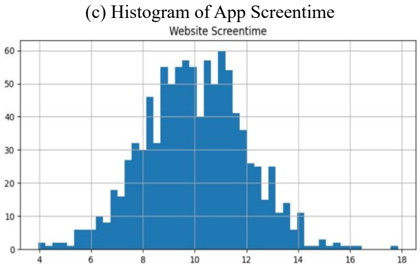
(a) Histogram of Number of Purchases



(b) Histogram of Session Length



(c) Histogram of App Screentime



(d) Histogram of Website Screentime

Fig. 3. Histograms of different features in E-Mart Dataset

3.3 Identifying Correlation among features

The Pearson correlation coefficient (r) is the method to calculate the strength and direction of the linear relationship between two variables in a correlation analysis. The correlation coefficient can be represented as in eq. (1):

$$r = \frac{\sum[(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum(x_i - \bar{x})^2 * \sum(y_i - \bar{y})^2}} \qquad (1)$$

To identify the best correlating attribute, performed correlation among the numeric features and calculated coefficient of correlation(r). The categorization of correlation coefficient for the analysis is given below

r = 0 to 1 (Positively correlated)
r = 0 (No correlation)
r = -1 to 0 (Negatively Correlated)

Table 1. Correlation table of E-commerce Open Mart Dataset

Features	R value
Length of Membership	0.8090
Time on App	0.4993
Avg. Session Length	0.3550
Time on Website	-0.0026

Table 1 shows strong positive correlation of ‘Yearly Amount Spent’ with ‘Length of Membership’ and ‘Time on App’ which shows Open Mart is emphasizing on app optimization. While ‘Avg. Session Length’ shows a moderate positive correlation (0.3550). Least correlated feature is ‘Time on Website’ with r = -0.0026, it demonstrates that website has no impact on annual spend.

Table 2. Correlation table of E-commerce E- Mart Dataset

Features	R value
Number of Purchases	0.7791
App Screentime	0.6253
Session Length	0.6040
Website Screentime	-0.3291

Table 2 shows strong positive correlation of ‘Yearly Amount Spent’ with ‘Number of Purchases’ and ‘App Screentime’ which shows E-Mart is emphasizing on product optimization. While ‘Session Length’ also shows a good positive correlation (0.6040). Least correlated feature is ‘Website Screentime’ with r = -0.3291, it demonstrates that a website has minimal impact on annual spent.

Below Fig. (4) represent correlation heatmaps depicting the associations between features within their respective datasets in the Open Mart dataset. Heat maps are used to visualize and display a geographic distribution of data as it represent different densities of data points on a geographical map to help in better analytic understanding.

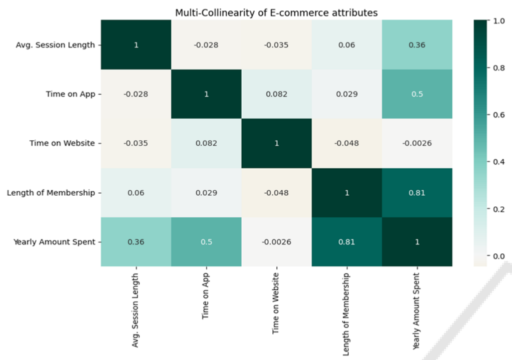


Fig.4. Heat-map of different features in Open Mart dataset

In Open Mart dataset, Length of Membership exhibits a positive correlation with r = 0.890 with the dependent variable, indicating a strong relationship as membership duration increases. Similarly, Time on App shows a moderate positive correlation, suggesting its influence on the dependent variable. Time on Website demonstrates a negligible correlation with the dependent variable.

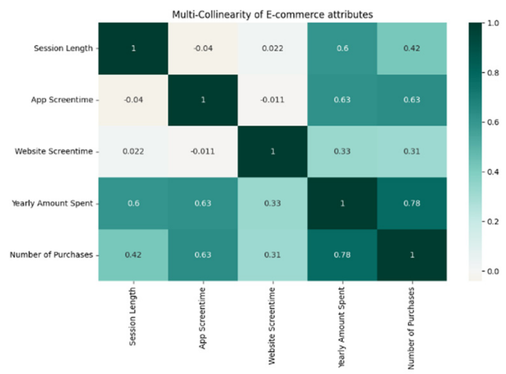


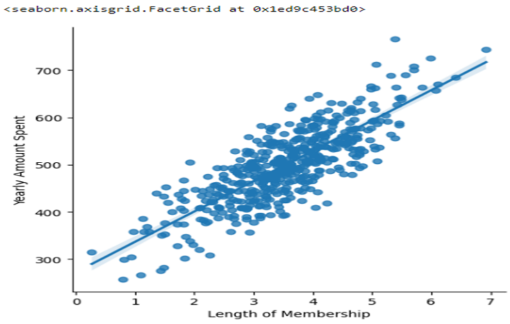
Fig.5. Heat-map of different features in E- Mart dataset

Fig. (5) represents E-mart dataset, Number of Purchases reveals a significant positive correlation with the dependent variable. Moreover, both App Screen Time and Session Length demonstrate moderate positive correlations, indicating their influence on the dependent variable. On the other hand, Website Screen Time exhibits a negative correlation with the dependent variable, suggesting an inverse relationship.

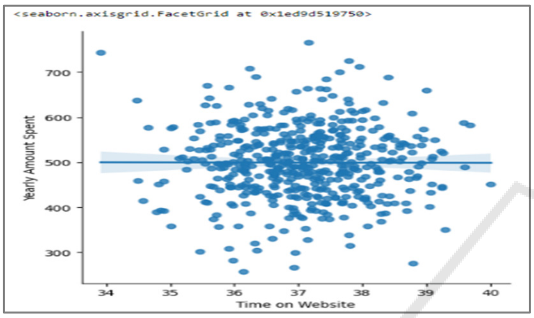
An illustration of the relationship between a number of independent attributes and our dependent feature (annual amount spent) in the Open Mart Dataset in Fig. (6).

Fig. (6), illustrates the strong positive correlation between the parameters Length of Membership and Time on App, while Time on Website exhibits the most negative correlation. The features 'Time on App' and 'Length of Membership' have a positive correlation with 'Yearly Amount Spent' as the line slopes upward from left to right. This implies that the annual expenditure tends to increase together with the increase of membership or app users. On the other hand, if the line is horizontal that suggests no correlation between variables as in Fig. 6 (b). Also, if the data points cluster closely around the line, it shows strong correlation as in Fig. 6 (a). Pictorial representation of relationship between different features with our dependent feature (Yearly Amount Spent) for the E-mart Dataset in Fig. (7).

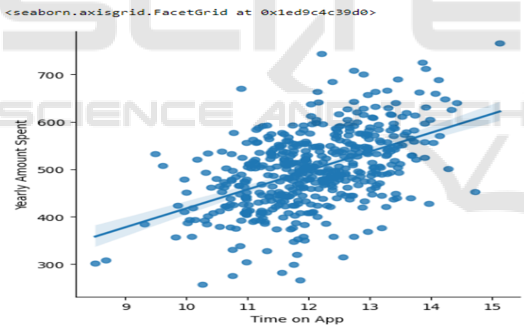
Fig. (7) illustrates the strong positive correlation between the parameters App Screen Time and Number of purchases while Website Screentime exhibits the most negative correlation. The features 'App Screentime' and 'Number of purchases' have a positive correlation with 'Yearly Amount Spent' as the line slopes upward from left to right. This implies that the annual expenditure tends to increase together with the increase of quality product or app users. Also, if the data points cluster closely around the line, it shows strong correlation as in Fig. 7 (b) between 'Number of Purchases' and 'Yearly Amount Spent'.



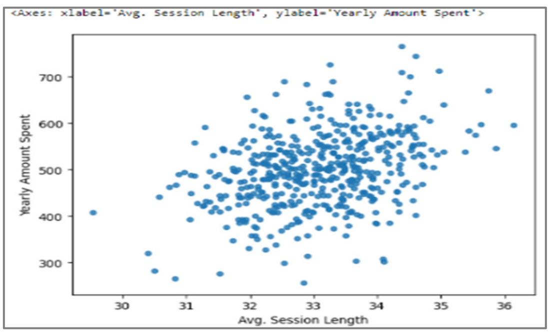
(a) Scatterplot of Length of Membership



(b) Scatterplot of Time on Website

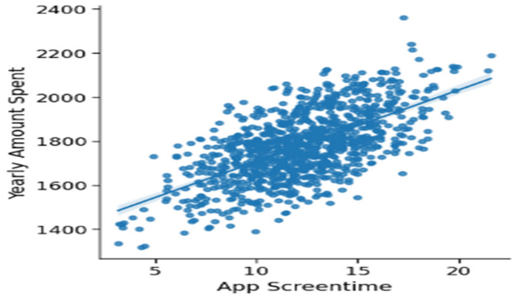


(c) Scatterplot of Time on App



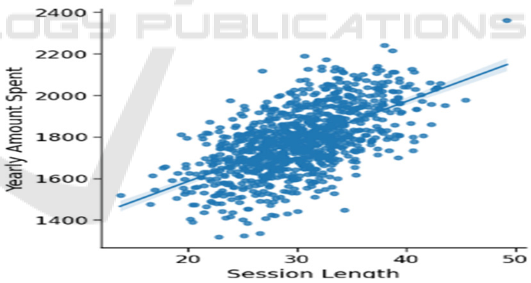
(d) Scatterplot of Avg. Session Length

Fig.6. Scatterplot between different features in Open Mart Dataset

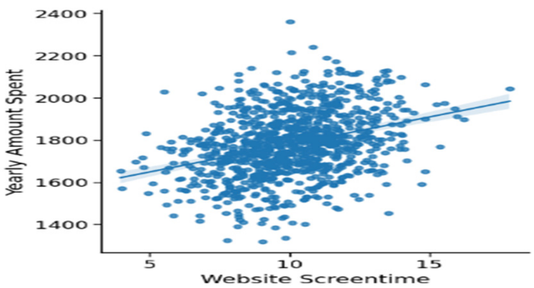


(a) Scatterplot of App Screentime

(b) Scatterplot of Number of Purchases

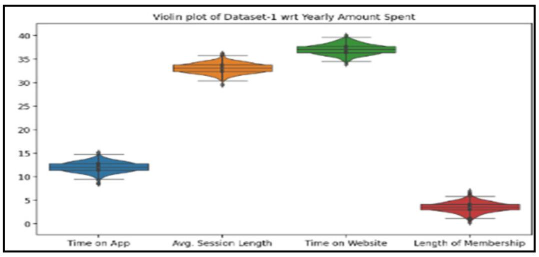


(c) Scatterplot of Session Length

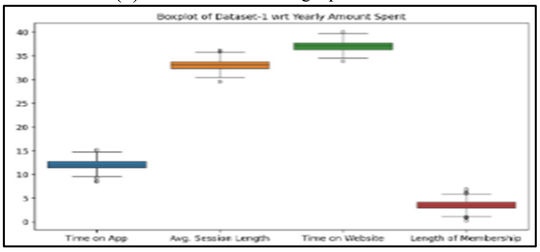


(d) Scatterplot of Website Screentime

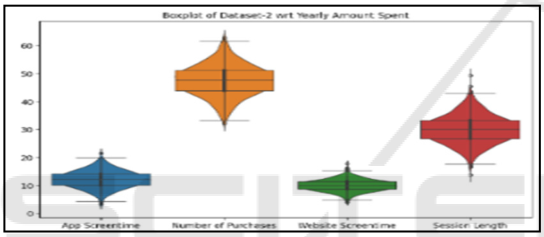
Fig.7. Scatterplot between different features in E- Mart Dataset.



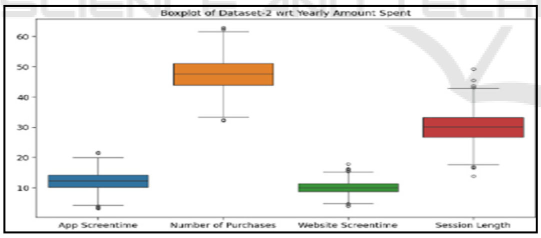
(a) Violin Plot showing Open Mart Dataset



(b) Box Plot showing Open Mart Dataset



(c) Violin Plot showing E-Mart Dataset



(d) Box Plot showing E-Mart Dataset

Fig.8. Violin and Box plot depicting both datasets.

Fig (8). Shows the box and violin plot of respective datasets where it shows important parameters like mean, IQR (Inter-Quartile Range), minimum and maximum value of datasets etc. Fig 8(a) and Fig. 8(b) shows the customers spend 33 minutes a session on average, with a median session length of 33.08 minutes. 25% of sessions last less than 32.34 minutes, according to the distribution, and 75% of sessions last longer than 33.71 minutes. Customers use the platform for an average of 12 minutes on the mobile app and 37 minutes on the website, with respective median times of roughly 12 and 37 minutes. With 25% of customers having a membership term of less than 2.93 years and 75% having a duration of more than 4.13 years, the length of membership demonstrates a median duration of almost 3.53 years. The study of E-mart dataset is shown in Figs. 8(c) and 8(d), and it demonstrates that customers spend about thirty minutes a session on average, with an average of 12.21 minutes spent on apps and 10.01 minutes spent on websites. Furthermore, consumers spend $1778.73 annually on purchases, or about 47.56 transactions annually on average. It also shows that features like “Avg. Session Length”, “Time on App”, “App Screentime” the data cluster closely around their means, with narrow IQR, indicating relatively consistent behavior whereas “Time on Website” displays a wider spread of values, suggesting more variability. “Length of Membership" shows a moderate spread, with a longer right tail indicating some customers with extended memberships. "Yearly Amount Spent" exhibits a right-skewed distribution, with most customers spending lower amounts annually, but with notable outliers spending significantly more.

3.4 Regression Methods

We have used seven important Machine Learning models to perform regression on datasets namely Linear Regression, Random Forest, Ada Boost, Decision Tree, KNN, SVR, XG Boost.

a) Linear regression:

Linear Regression is a supervised ML model which learns through labeled input and output data and used for analysing the relationship between a dependent variable and one or more independent variables as expressed in equation (2). It predicts the best-fit line to the data points., Linear Regression objective is to minimize the difference between the observed and predicted values.

$$y = a + bx \qquad (2)$$

b) Random Forest Regression:

Random Forest is an ensemble learning approach that successively constructs various ML models, such as decision trees, during training and returns the mode of classes for categorization or the average prediction of the individual trees. It is an approach that generates decision trees during training and then combines their predictions. Overall, this prediction improves model accuracy while reducing overfitting.

c) AdaBoost

AdaBoost is an adaptive boosting algorithm that combines multiple weak learners or ML models sequentially to predict or classify. It is also an ensemble learning technique which combines multiple weak models sequentially to create a strong model. It is specifically used for classification tasks.

d) Decision Tree

Decision Tree is a non-parametric supervised learning method which means it does not make any assumptions regarding the sample beforehand and this method is used for classification and regression and can handle both numerical and categorical data. It has tree structure which consist of root node, internal node and leaf nodes. Decision tree is mainly used for classification purpose.

e) K-Nearest Neighbor (KNN)

KNN (K-Nearest Neighbors) is a non-parametric technique that performs classification and regression tasks without making any prior assumptions about the sample. based on the average value or majority class of its k closest neighbors in the feature space, predicts the class or value of a new data point. It employs many distance functions, such as the Euclidean distance (represented in equation (3)), the Manhattan distance (expressed in equation (4)), and the Minkowski distance (expressed in equation (5)), where q denotes the order of norm, to determine the nearest neighbor.

$$E.D = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \quad (3)$$

$$M.D = \sum_{i=1}^{k} x_i - y_i| \; | \quad (4)$$

$$Mink.D. = (\sum_{i=1}^{k}(|x_i - y_i|)^q)^{\,1/q} \quad (5)$$

Where x_i and y_i represents the coordinates of x and y datapoints on i^{th} dimension and q the order of the distance.

f) Support Vector Regression

SVR (Support Vector Regression) is a supervised machine learning model used in regression purpose. It includes the concept of hyperplane which classifies data points in two separate classes. It finds the optimal plane also called hyperplane to separate or classify two datapoints into two different classes. It aims to find a function that has a maximum margin of tolerance to the given data points. SVR is expressed in equation (6).

$$SVR = MIN \sum_{i=1}^{n}(y_i - w_i x_i) \; (6)$$

g) XG Boost

The XG Boost technique optimizes a differentiable loss function for each iteration, such as the mean squared error (MSE) for regression. It constructs several decision trees one after the other, fixing the mistakes of the first tree. It uses an objective function regularization term to penalize and prevent overfitting.

3.5 Result

This section of the paper depicts the experimental results using the selected regression methods. Results are evaluated on Four performance metrics namely Mean Squared Error (MSE), Mean Absolute Error, Root Mean Squared Error, R2(R-Squared). Mean squared error is defined as the average of the absolute squared difference between the output value and the predicted value. MSE is represented as in equation (7). Mean Absolute Error is defined as the average of the absolute difference between the actual output and the predicted output. Mathematically, its represented as in equation (8). Root Mean Squared Error is defined as the square root of the average of the squared difference between the output value and the predicted value. It can be represented as in equation (9). R2 score represents the proportion of the variance in the dependent variable that is explained by the independent variables in the model. Mathematically it is represented as in equation (10).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (7)$$

$$MAE = \frac{1}{N}\sum_{j=1}^{N}|y_j - \widehat{y_j}| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_j)^2} \quad (9)$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_i^n (x_i - \hat{x}_i)^2}{\sum_i^n (y_i - \hat{y}_i)^2} \quad (10)$$

Where $\hat{y}_i$ and $\hat{x}_i$ represents the predicted outcome on i^{th} dimension.

Table.3. Experimental results on Open Mart Dataset

Algorithm	MSE	RMSE	MAE	R2
Linear Regression	109.86	10.48	8.55	0.97
Random Forest	337	18.36	14.04	0.93
AdaBoost	579.09	24.06	19.70	0.88
Decision Tree	802	28.32	22.21	0.83
KNN	465.62	21.57	16.63	0.90
SVR	5024.67	70.88	54.33	-0.014
XG Boost	262.18	16.19	12.36	0.94

As shown in table 3, with the lowest Mean Squared Error (MSE) of 109.86, Root Mean Squared Error (RMSE) of 10.48, and Mean Absolute Error (MAE) of 8.55, as well as the highest R-squared value (97% accuracy), which demonstrates its superior predictive capability, illustrates that Linear Regression is the most accurate model in Open Mart dataset. With an accuracy percentage of almost 94%, an MSE of 262.18, an RMSE of 16.19, an MAE of 12.36, and competitive performance, XG Boost comes in close second. Support Vector Regression (SVR), on the other hand, performs the worst and has the worst error metrics: 5024.67 MSE, 70.88 RMSE, 54.33 MAE, and an extremely low R-squared value, all of which amply demonstrate SVR's inability to make accurate predictions.

Table.4. Experimental results on E- Mart Dataset

Algorithm	MSE	RMSE	MAE	R2
Linear Regression	2693.27	51.89	41.42	0.89
Random Forest	3981.42	63.09	51.09	0.84
AdaBoost	4720.30	68.70	54.34	0.81
Decision Tree	7749.01	88.02	69.65	0.69
KNN	4452.17	66.72	53.37	0.82
SVR	17593	132.64	102.32	0.30
XG Boost	4082.99	63.89	51.13	0.83

Experimental results on E-mart dataset suggests that Linear regression is the best performing model when it is evaluated against various machine learning algorithms. Linear Regression has the lowest Mean Squared Error (MSE) of 2693.27 and highest R-squared value (89% accuracy), the lowest Root Mean Squared Error (RMSE) of 51.89, and the Mean Absolute Error (MAE) of 41.42. This shows that, in comparison to other models, it has better predicted accuracy and precision. As shown in table 4, XG Boost, comes second best with an MSE of 4082.99, RMSE of 63.89, MAE of 51.13, and an accuracy percentage of almost 83%. Support Vector Regression performs the worst out of all the models. It has the highest error metrics, with an MSE of 17593, an RMSE of 132.64, an MAE of 102.32, and a very relatively low R-squared value of 30% accuracy only, which shows that it is not very good at generalizing the patterns in the dataset.

4 CONCLUSION

Linear Regression is the best model with the accuracy of greater than 90% in both the dataset. Furthermore, XG Boost performs second best, with accuracy and precision that are closely behind that of Linear Regression. Support Vector Regression (SVR), on the other hand, performs the worst out of all the models. Its inability to forecast outcomes and capture dataset patterns is highlighted by its high error metrics and low R-squared values (30%) in E-mart and negative R-squared value in Open Mart Dataset. This could me mainly due to potential nonlinear relationships between the set of input features together and the output variable. These findings show model effectiveness for e-commerce prediction tasks.

After analysing the nuances of several attributes and how they relate to each other in the datasets, membership duration and app usage time are the most important and significant factors affecting annual yearly spending. Forecasting annual expenditure of customers shows they prefer app than website for shopping, so to cater large audience, companies should focus to improve working of apps and also offer some discounts and incentives to their loyal customers. E-commerce Companies should focus to improve and work on functioning of their website as it is inversely correlated with annual expenditure. They should improve the user interface and other functionalities of website to make it more user friendly. Number of purchases is highly positively correlated with annual expenditure which tells about their good product quality and trust they built with customers in term of quality assurance.

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