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Discovering the Factors Affecting E-CRM Using Machine Learning Techniques

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Abstract: : The majority of business organizations, especially those in developing nations, have adopted E-CRM as a recent strategy, and as a result, managers have strategically invested in online technologies while putting an emphasis on the creation and maintenance of valuable connections with valuable clients. The purpose of this study is to determine the association between E-CRM and service excellence, client satisfaction, loyalty, and trust in Egyptian commercial banks. This study was conducted with the goal of improving E-CRM. For this, 205 valid surveys from bank customers who used E-CRM services were gathered. Data was collected through a survey and utilized for machine learning-based research model assessment (ML). Artificial neural networks (ANN), linear regression models (LRM), random forests (RF), decision trees (DT), K-nearest neighbours (K-NN), and support vector machines (SVM) are examples of machine learning approaches that applied to develop predictive relationship between E-CRM and the other factors. Model performances were evaluated using various statistical indices including the coefficient of determination (R2), Mean square error (MSE), Root mean square error (RMSE), Mean absolute error (MAE) and Mean absolute percentage error (MAPE). The results revealed that E-CRM had a strong effect on service quality, trust, and customer satisfaction while Very Week effect on customer loyalty where The R2 value equal 0.2%.

Keywords: *electronic customer relationship management, customer satisfaction, service quality, trust, customer loyalty, machine learning*.

1. Introduction

One of the marketing trends, referred to as E-CRM (Electronic Customer Relationship Management), was a direct response to the digital consumer behavior and the E-business, which have been expanding quickly in the modern day [1];[2];[3]. The concept of E-CRM has been the subject of a variety of research and writing efforts; others just view it as a tool or technique This serves as a guide for handling customer encounters [4]. Others, though, saw it as a corporate philosophy or method [5]. E-CRM has been narrowly described as a technology, system, or software application that allows for the tracking of client data and information to give them better services [6];[7]. While some business leaders feel that by making the best use of technology and the knowledge, they have gathered about target consumers, E-CRM is a marketing strategy that attempts to provide the client with higher value and build lasting connections with him [8]. E-CRM promotes the growth of the digital platform, which increases client satisfaction, while also assisting in maintaining long-term connections with consumers [9]. The most important aspect in every business' success is the level of client satisfaction [10]. When clients believe their banks are giving them high-end services, they are more likely to refer them to friends and family, which creates a foundation of loyal clients [11]. Customer loyalty is one of the precursors of satisfaction [12].

Almost all computers are connected to one another via the Internet. The size of computers is likewise decreasing. Industries must leverage technologies for them to remain competitive, businesses need to employ capabilities like the Internet of Things, Cloud Computing, Big Data, Artificial Intelligence, and Machine Learning, as difficulties get more difficult [13];[14]. One of the most significant industries in the current global economy, the banking sector, which aspires to turn the world into a tiny investment town [15]. It has an impact on more than just the level of the bank; it also affects how clients see the banks and how well they perform their services, which is one approach to improve bank productivity [16]. At the local, regional, and international levels, banks have a significant impact on the management and growth of the economy [17]. Additionally, banks' importance has grown recently as a result of the collapse of economic systems like socialism [18].

The current method of diagnosis known as machine learning utilizes a big volume of data and produces more precise outcomes than the conventional methods of diagnosis. Traditional diagnosis has two main flaws: first, it is extremely expensive, and second, the outcomes are inaccurate. The machine learning system examines the incoming data and produces correct results for us [19]. Unsupervised machine learning, supervised machine learning, and reinforcement learning are the three techniques for machine learning (ML) [20]. The computer applies patterns it has learned from the known dataset to the unknown dataset in order to predict the outcome. Machine learning (ML) has become one of the foundations of information technology when it comes to enabling programmes to learn and adapt. Although ML has several applications, data mining is unquestionably the most crucial one [21]. Data cleaning is the process of carefully and regularly preparing data for analysis. The majority of the time, the data gathered will be inconsistent due to errors made during data collection, inaccurate data formats, and missing data values. For the training and testing of the algorithm, the data must be divided into two groups. The model is trained using the training set's well-known classified output before being applied to fresh data [22]. Regression is still extensively studied today, to the extent that it merits mention in major publications [23], The theoretical underpinnings of regression cover a variety of topics that reveal hidden relationships in the data and alternate viewpoints that go as far as being purely hypothetical such as seeing all mathematical instruction as a particular kind of regression [24];[25];[26];[27];[28]. Given the broad factors, it is not surprising that a variety of performance metrics have been developed to be used for evaluation of a regression model, similar to what happened for binary classification [29];[30];[31]. By a comparison of five commonly used measures, the current work contributes to the discovery of important criteria in the selection of an appropriate performance metric in regression analysis.

This study's stated goals are to (a) improve E-CRM by using six ML models (ANN, RF, DT, LRM, SVM, and K-NN); and (b) to assess and evaluate the predictive abilities of ML models using statistical assessment criteria. This study intends to provide more light on the effects of E-CRM on client satisfaction (CS), loyalty (CL), Service Quality (SQ), and trust (CT). According to their chosen characteristics, dataset sources, ML models, output features, and R2 values,

Table 1 presents and summarizes the essential results of some of previous studies attempted to explore the relationships between E-CRM and other factors affected on it.

TABLE 1. COMPARISON OF RELATED STUDIES

Study	Year	Adopted features categories	Dataset sources	models	Output features (R2)
Bataineh [32]	2015	-E-CRM -CS -Electronic word-of-mouth (e-WOM)	507 Customers	Regression Analyses	E-CRM~ e-WOM by CS=.205
Salehi et al., [33]	2015	- E-CRM - CL	90 Customers	Structural Equation Modeling (SEM)	ECRM~CL=.272
Ismail & Yunan [34]	2016	- SQ - CS -CL	400 Customers	SmartPLS	SQ~CS =.551 SQ~CL=.572
Al-Shoura etal., [35]	2017	-E-CRM -CL (Behavioral Loyalty/ attitudinal Loyalty)	481 Customers	Regression Analyses	ECRM~ Behavioral Loyalty =.516 ECRM~ attitudinal Loyalty =.418
ALDAIHANI &ALI [36]	2018	-E-CRM -SQ	541 Customers	Multiple Regression	ECRM~SQ=.41
Mulyono&Situmorang [11]	2018	-E-CRM -Customer Experience (CE) -CS -CL	190 Customers	Partial Least Square-Structural Equation modeling (PLS-SEM)	ECRM~CE=.062 ECRM~CS=.134 ECRM~CL=.543
Al-Dmour et al., [37]	2019	-E-CRM - Customer Retention (CR) -CS -CT - Financial Performance (FP)	343 Customers	SEM	ECRM~CS~ CR=0.30 ECRM~CT~ CR= 0.32 CT~CR~ FP= 0.17 CS~CR~ FP=0.28
Sasono et al. [38]	2021	-e-marketing (EM) -E-CRM -e-loyalty (EL)	170 Customers	Multiple Regression Analysis and PLS-SEM	EM~EL =0.496 ECRM~EL=0.213

2. MATHODOLOGY

Regression analysis, which requires the forecasting of a persistent independent outcome from a collection of other variables that can be predicted, plays a crucial role in supervised machine learning. Binary classification and regression have different objective ranges; in binary classification, the target can only have two values, which are frequently expressed as 0 and 1. but in regression, the target can have numerous values. In this investigation, regression analysis was utilized. The conceptual model in this study predicts dependent variables using ML algorithms using R programming [39]. Since this is one of the few attempts to utilize ML algorithms to anticipate or enhance ECRM in the field of banking, the use of a multi-analytical technique also produces a novel addition to the literature on information systems (IS). The full workflow of our study is illustrated by Figure 1.

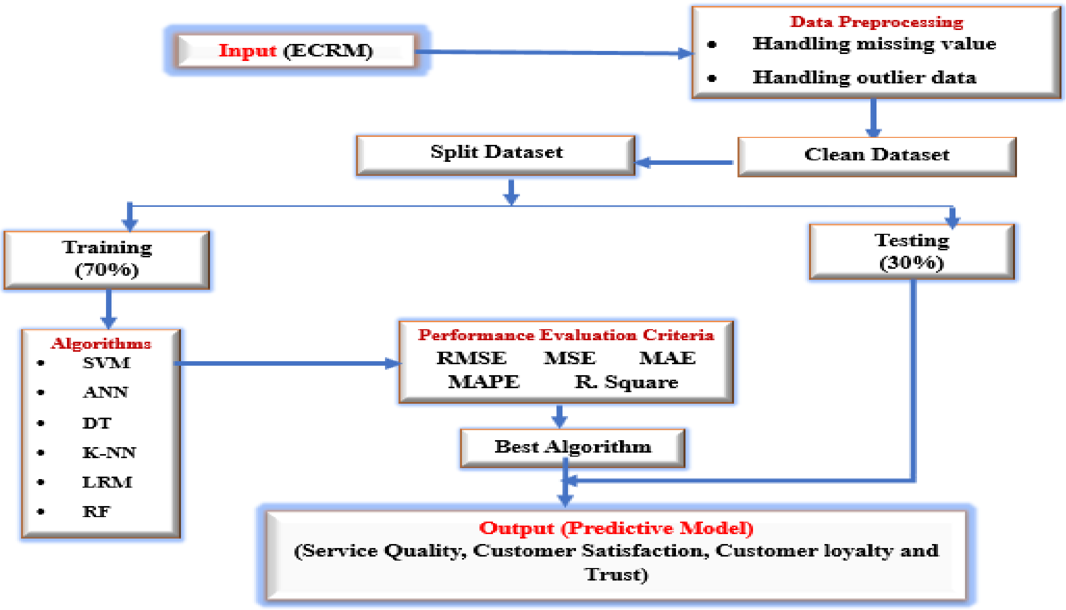

Fig.1: Research Methodology

2.1 Data Set Description

Our dataset for this study came from a self-administrated online survey that was created and then utilized to gather information from banking clients in Egypt. There are 205 rows and one independent ECRM dimension (Technology support, Online communication, Knowledge management). As stated in Table 2, there are four dependent variables: Service Quality, Customer Satisfaction, Customer Loyalty, and Trust. For the investigation, a convenience sample method is employed. A five-point Likert scale is used, with strongly disagree to strongly agree as the extremes.

TABLE 2. DESCRIPTION OF DATA FEATURES

Variables	Questions
E-CRM (Technology Support)	The bank is outfitted with cutting-edge technology
	The servers for online banking services may not work properly and perform wrong banking operations
	The website uses information on how to use electronic banking services
	The bank's website includes a strategy to pinpoint the varied consumer requirements
E-CRM (Online Communication)	The bank maintains constant contact with its customers
	The bank's website contains Many of communication (telephone, fax, e-mail, SMS)
	Use the online complaint form to contact the bank if I have a problem
	The search engine of the bank's website facilitates the browsing process
	The employees of the bank have knowledge to answer various customer questions

E-CRM (Knowledge Management)	The bank takes care of customers' problems and answers their inquiries
	The employees of the bank are always ready to help me
	Employees provide true and detailed information in connection with any Bank transaction
Service Quality	I find it easy to get online banking to do what I want to do
	The way to deal with online banking services is clear and understandable
	The bank offers a wide range of online banking services
	On the internet, the bank has a dedicated page
Customer Satisfaction	The bank strives to satisfy its clients by offering high-quality services
	Employee credibility increases client satisfaction because of how they conduct themselves
	Customer satisfaction is achieved through the speed of service delivery
	The private website helps me save time and makes it possible for me to finish my transactions more quickly
Customer Loyalty	The bank offers a degree of post-purchase support that fosters client loyalty
	Your bank is always able to fulfill its promises to carry out the services I request
	If I face a problem in dealing with this bank, I will not convey my complaint to my close clients
	The bank's website offers programs Loyalty to motivate customers to visit the site again
Trust	I trust to use Internet banking as you have provided me with the necessary online instructions for reference
	When transferring money through online banking services, I am afraid of financial losses due to errors resulting from inattention such as wrong entry of the account number or wrong entry of the value of the transferred
	When errors occur in online banking transactions, I am afraid that I cannot get compensation from the banks
	I do not feel completely safe when I use my personal and confidential information during my Internet Banking implementation

- ## Demographic Profiles of the respondents

Table 3 indicates the respondents' background information. There are 89 (43.4%) male responders and 116 (56.6%) female respondents. According to the data, there were 52 respondents who were under 30 years old (25.4%), 81 respondents who belonged between 30 and 40 years old (39.5%), 51 respondents who were between 41 and 50 years old (24.9%), 15 respondents who came between 51 and 60 years old (7.3%), and 6 respondents who consisted above 60 years old (2.9%). In terms of educational attainment, it can be observed that 1 (0.5%) respondents had no formal education, 9 (4.4%) had high school, 9 (4.4%) had post-graduate education, and 55 (26.8) had no formal education; In terms of Do you have bank accounts in an Egyptian bank?, 158(77.1%) respondents are yes and47(22.9%) respondents are no; in terms of Which E- Banking services you use than more others?126 (61.5%) respondents are using ATM ; 13(6.3 %) respondents are Use internet of electronic banking services ; 66(32.2 %) respondents are Use internet of electronic banking services and ATM. Finally, in terms of What percentage of your banking transactions use e-banking services, 62(30.2%) respondents are at a little rate; 94(54.9 %) respondents are at an average rate; 49(23.9 %) respondents are at a high rate

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Table 3. Summary of Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	89	43.4
	Female	116	56.6
Age	Less than 30	52	25.4
	From 30 to 40	81	39.5
	From 41 to 51	51	24.9
	From 51 to 60	15	7.3
	More than 60	6	2.9
Educational Level	No Education	1	0.5
	High school	9	4.4
	College	55	26.8
	Postgraduate	140	68.3
Having bank accounts	Yes	158	77.1
	No	47	22.9
E- Banking services used	ATM	126	61.5
	E-banking services	13	6.3
	All of that	66	32.2
Times of using of e-banking services	At a little rate.	62	30.2
	At an average rate.	94	45.9
	At a high rate	49	23.9

2.2 Machine learning Models

The phrase "machine learning" is frequently used to describe an analytical technique created to find patterns in data and correlations between data variables. The phrase "machine learning" is frequently used to describe an analytical technique created to find patterns in data and correlations between data variables. Machine learning has an edge over conventional statistical analysis because it prioritizes predicted performance above a priori super-population assumptions and theoretically verifiable features. To achieve this goal, machine learning is utilized. To find models or patterns in data, machine learning techniques are applied, and they are beneficial for decision-making [40]. Several different data mining techniques are employed to uncover hidden knowledge in massive amounts of data. Regression was the ML model used in this study. Also, utilized research Artificial Neural Networks, linear regression models, random forests, support vector machines, decision trees, and K-Nearest Neighbor are a few examples of machine learning models. Artificial Neural Networks: Certainly, one of the most well-liked methods for educational data mining is the artificial neural network (ANN). Synapses on the dendrites of the neural network are where signals are received. linear Regression Model: A supervised machine learning technique with a constant slope and continuous anticipated output is known as linear regression [41]. We think about modelling the dependent variable together with one independent variable. Random Forest: A collection of decision trees constructed with a random element is known as a random forest (RF) [42]. Random forest has been used to study a number of intriguing issues, and it is clear that this method has a lot of potential for producing helpful classification models [43]. Support Vector Machine: The prediction variant of the Support Vector Machine, known as the Support Vector Machine (SVM), assigns support vectors to differentiate between features. SVMs are characterized as a collection of connected supervised learning methods for regression and classification [44]. Decision Tree: have the advantage of defining rules that are easily understood and comprehended by users, requiring minimal data preparation, and working well with numerical and categorical variables [45]. k-Nearest Neighbor algorithms (k-NN): classify objects in the feature space based on the nearby training samples. K-NN is a type of instance-based learning, or lazy learning, in which the complete computation is postponed in expectation of classification and the function is only roughly estimated locally.

2.3 Model Evaluation METRICS

A variety of statistical methods and the built ML model are compared and evaluated using evaluation metrics. The assessment metrics are determined by the ML model's goal [46]. One of the most crucial phases in machine learning studies is model evaluation. The evaluation's objective is to contrast the trained model predictions with the actual (observed) data from the testing data set. As there are several ML models, picking one and proving its superiority needs contrasting its performance. As a result, certain performance comparison metrics are needed. The most often used comparison evaluations are the coefficient of determination (R^2 or R. Square), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). **Coefficient of determination (R^2 or R. Square):** We were able to determine how effectively these outcomes may be approximated thanks to the indicator $\mathbf{R^2}$, $\mathbf{R^2}$ is, thus, the proportion of the response variable's variance that explains how it relates to one or more predictor variables. It may be claimed that the greater the $\mathbf{R^2}$ is the better the model matches the data [21]. **Mean square error (MSE): evaluates** the average difference between the original and predicted values for the data set .It determines the variance of the residuals. **Root mean square error (RMSE):** The square root of the mean squared error. It produces the standard deviation of the residuals. **Mean absolute error (MAE):** the mean of the absolute distinction between the real and projected values in the dataset. It measures the residual average of the dataset. **Mean absolute percentage error (MAPE):** focuses on the percentage error and is hence the preferred measure when relative alterations rather than absolute values have a greater influence on the regression process.

3 RESULTS AND DISCUSSION

3.1 Descriptive statistics and Plots

Using descriptive statistics, the basic traits of the data in an experiment are described. The sample & the results have been

provided in concise summaries. They, in combination with basic graphical analysis, form the basis for essentially all quantitative data examinations. We may rationally simplify huge quantities of information with the use of descriptive statistics.

Table 4. Descriptive Statistics for the dataset

Variables	Min	1st Qu	Median	Mean	3rd Qu.	Max.	NA's
E-CRM	1.25	3.167	3.66	3.53	3.91	5	-
Service Quality	1	3	3.75	3.5	4	5	-
Customer Satisfaction	1	3	3.5	3.40	4	5	-
Trust	1.25	3.25	3.75	3.54	4	5	-
Customer Loyalty	1	3.25	3.75	3.68	4.25	5	-

As shown in table 4, the Mean of E-CRM is 3.53 with SD 0.627, which indicate that the trend of (Trust) is (Agree). The Mean of Service quality was 3.5 with SD 0.750, which indicate that the trend of (Service quality) is (Agree). The Mean of Customer loyalty was 3.68 with SD 0.788, which indicate that the trend of (Customer loyalty) is (Agree). The Mean of Trust is 3.54 with SD 0.706, which indicate that the trend of (Trust) is (Agree). The Mean of Customer loyalty was 3.68 with SD 0.788, which indicate that the trend of (Customer loyalty) is (Agree).

3.2 Analysis of Correlation

A statistical technique known as correlation may determine if and how strongly two variables are connected.

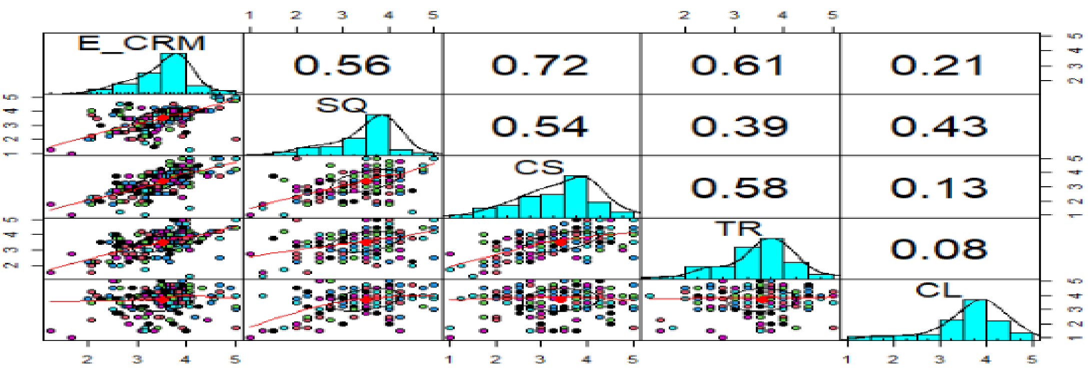

Fig.2: Correlation between variables

The coefficients of correlation refer to strong correlation in to interval [0.700-0.99]. Also, the coefficients of correlation refer to medium correlation in to interval [0.40-0.69]. Finally, the coefficients of correlation refer to weak correlation in to interval [0.-0.39]. The positive signal refers to positive correlation and the negative signal refers to negative correlation. figures.2 that the value of the correlation between the variables is either strong, medium, or weak. The variable names are shown with a histogram along the diagonal boxes. A scatterplot showing the correlation between each pairwise combination of variables is displayed in each of the other boxes below the diagonal. **For example,** the box in the top left corner of the matrix displays a scatterplot of values for **E-CRM** and **SQ**. All other boxes upper the diagonal display the Pearson correlation coefficient between each variable. For example, the correlation between **E-CRM** and **SQ** is 0.56, **E-CRM** and **CS** is 0.72, **SQ** and **CS** is 0.54, **E-CRM** and **TR** is 0.61, **SQ** and **TR** is 0.39, **CS** and **TR** is 0.58, **E-CRM** and **CL** is 0.21, **SQ** and **CL** is 0.43, **CS** and **CL** is 0.13 and finally the **TR** and **CL** is 0.08.

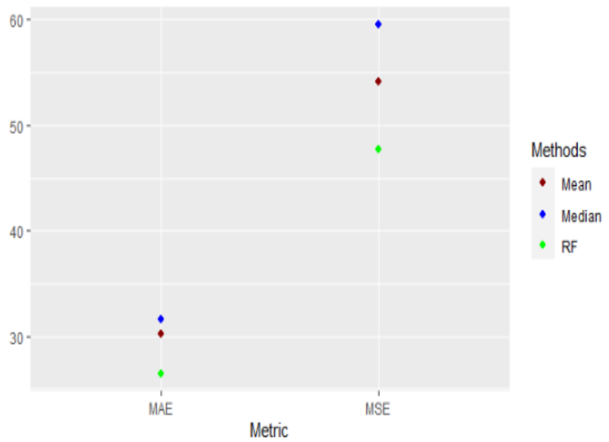

Fig. 4: Boxplot of the raw data before applying TOMI

By deleting these outliers, a recommended methodology called TOMI is used in place of the conventional method. This strategy relies on applying imputation methods to treat outlier data as missing values [21].

The imputation approaches used in this work are based on statistical methodologies like mean and median as well as RF. The Random Forest technique beat the other methods in terms of MAE and MSE, as seen in Fig. 5. This result is further supported by Fig. 5 and Table 5. There are no outlier values in the data, as seen in Fig. 6.

Table 5. Performance Evaluation of Imputation Methods

Metrics	Algorithms		
	Mean	**Median**	**RF**
MAE	28.93	29.60	20.03
MSE	49.95	52.45	31.72

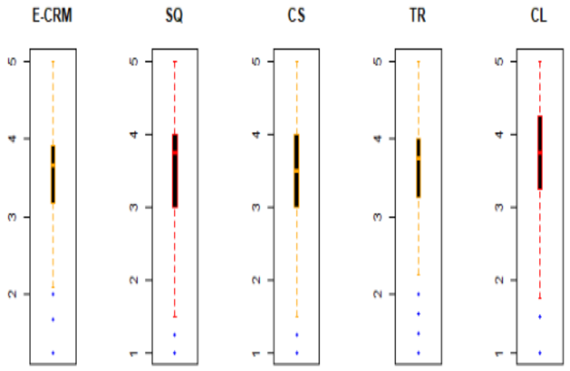

Fig. 5: Imputation Methods

3.3 Missing Value and Outliers data

As can be seen in Fig.3, The dataset we employed for this investigation does not contain any missing values.

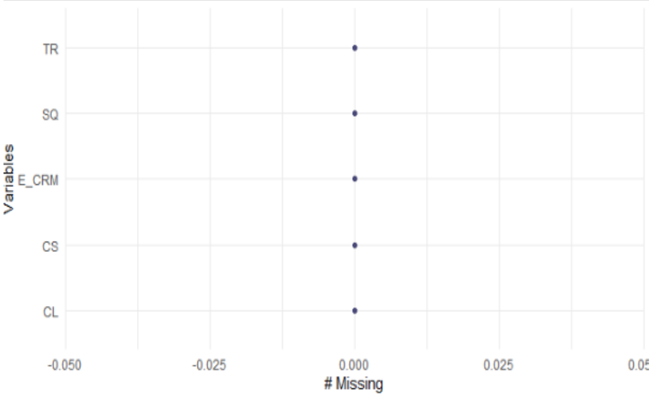

Fig.3: Missing value

Figure 4 shows the outliers in the dataset utilized for this investigation. A few outliers can be seen outside the box plot's whiskers, as shown by the box plot in Fig. 4.

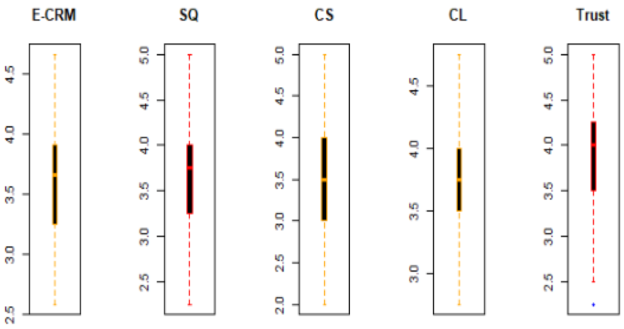

Fig. 6: Boxplot of the raw data after applying TOMI

The axis that runs down the middle of a histogram corresponds to a potential oscillate of data values, as they were the vertical axis correspo nds to the count (frequency). Figure 7 shows the histogram of the raw data After applying TOMI.

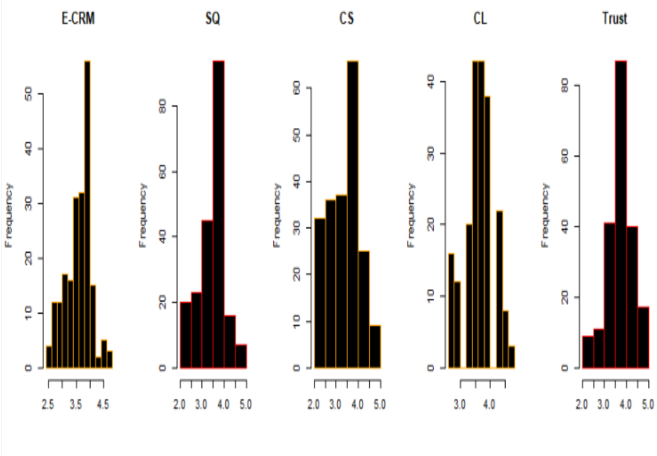

Fig.7: Histogram of the raw data After applying TOMI

3.4 Results

After imputation and data standardization has concluded, the combined dataset is divided into training and testing data with a 70% to 30% split in percentages in order to create a model for categorization. Training (70%) and testing (30%) are the two subgroups of our data that are shown here. To assess how well the categorization models were working, ten-fold cross validation was used. This method involves splitting the entire dataset into 10 subgroups, which are then processed ten times. Nine of the subsets are utilized as testing sets, while the last subset is used for training. The results are then calculated by averaging the last 10 iterations.

3.4.1 Result of E-CRM and Customer Loyalty

The results of MAE, MAPE, MSE, RMSE and R Square for regression, Artificial Neural Networks and linear regression model, Random Forest, Support Vector Machine, Decision Tree, K-Nearest Neighbour algorithms, are provided in Table 6. The Support Vector Machine algorithm yields the lowest MAE, MAPE, RMSE and MSE values (0.984, 0.968, 0.740, 0.953, respectively) and has highest R square. The R^2 number shows how much of the entire variance in the independent variable E-CRM, CL, can be attributed. 0.2% of the data in this scenario may be explained, which is extremely little, and Fig.8 confirming these results. The same results can be concluded from Fig.9 and Fig.10.

Table 6: Predictive accuracy procedure of CL~E-CRM

	RMSE	MSE	MAE	MAPE	R. Square
ANN	1.01297	1.026108	0.757916	1.00064	3.46E-05
LRM	1.018766	1.037884	0.782307	1.122763	0.00045
RF	1.02501	1.050646	0.804004	1.270528	0.007996
SVM	**0.984038**	**0.968332**	**0.740771**	**0.953061**	**0.023099**
DT	1.035455	1.072168	0.778295	1.157231	0.000108
K-NN	1.013134	1.02644	0.777938	1.188128	0.007906

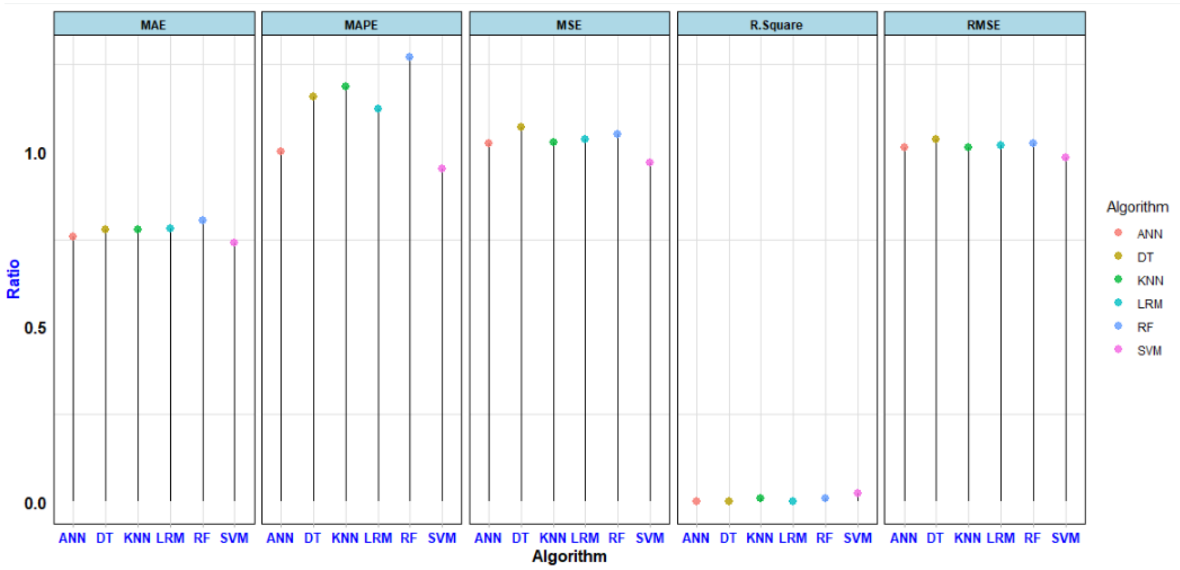

Fig.8: Result of Evaluation of Performance for Different Algorithms.

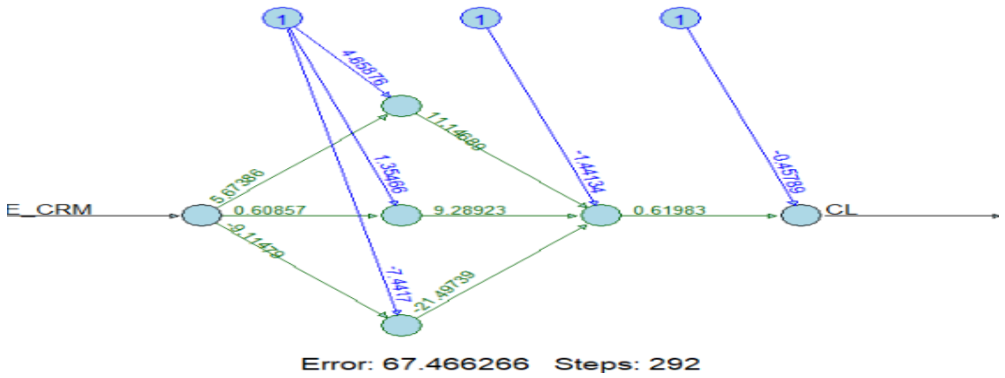

Fig.9: Artificial Neural Networks for Customer Loyalty~ E-CRM

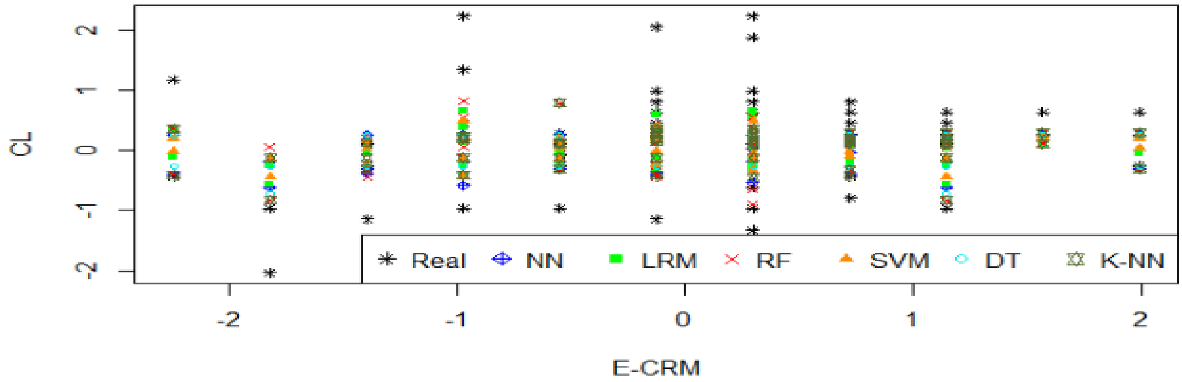

Fig.10: Real vs predicted for Customer Loyalty~ E-CRM

3.4.2 Result of E-CRM on Service Quality

The dataset is categorized, and Table 7 compares the classification metrics of algorithms. The MSE rates of SVM, DT, KNN, LRM, and RF are determined to be in the range of 0.603 to 0.719. In our dataset, the performance parameter measurement in Table 7 yields a very positive result. This method achieves MSE of 0.603% and R Square of 0.30. How much of the entire variance in the dependent variable, SQ, can be accounted for by the independent variable, E-CRM, is shown by the R2 value. 0.29% in this situation can be explained. Which is moderate, and Fig.11 confirming these results. The same results can be concluded from Fig.12 and Fig.13.

Table 7: Predictive accuracy procedure of SQ~E-CRM

	RMSE	MSE	MAE	MAPE	R. Square
ANN	0.84838	0.719749	0.67167	1.125185	0.159694
LRM	0.846713	0.716923	0.654955	1.132679	0.232984
RF	0.833609	0.694904	0.634246	1.139871	0.245655
SVM	**0.776979**	**0.603697**	**0.621889**	**1.20651**	**0.297764**
DT	0.814984	0.664199	0.628007	1.110972	0.243355
K-NN	0.813023	0.661006	0.61618	1.099947	0.266843

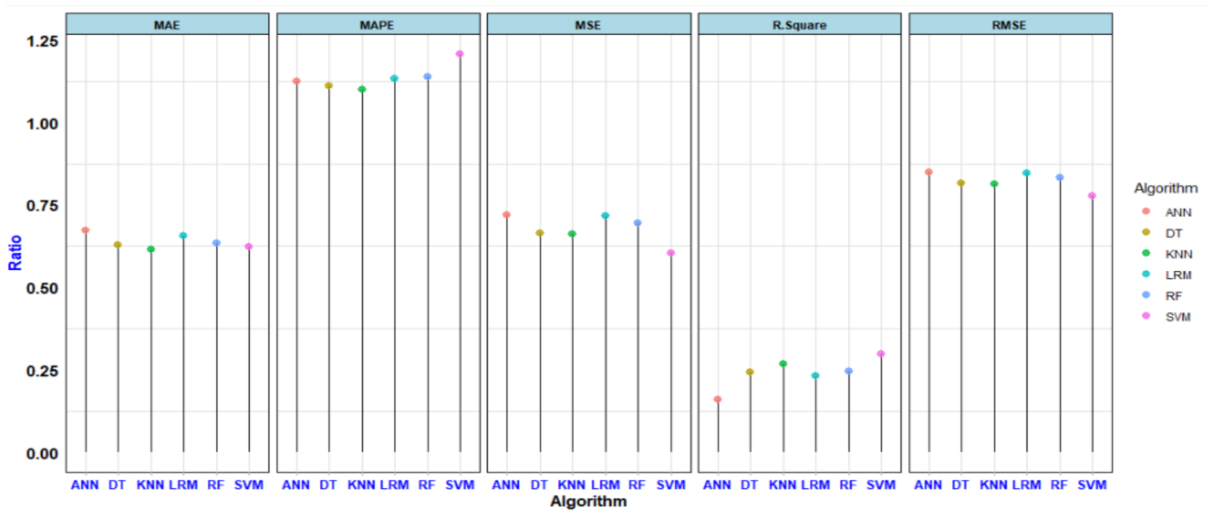

Fig.11: Result of Evaluation of Performance for Different Algorithms for SQ~ E-CRM.

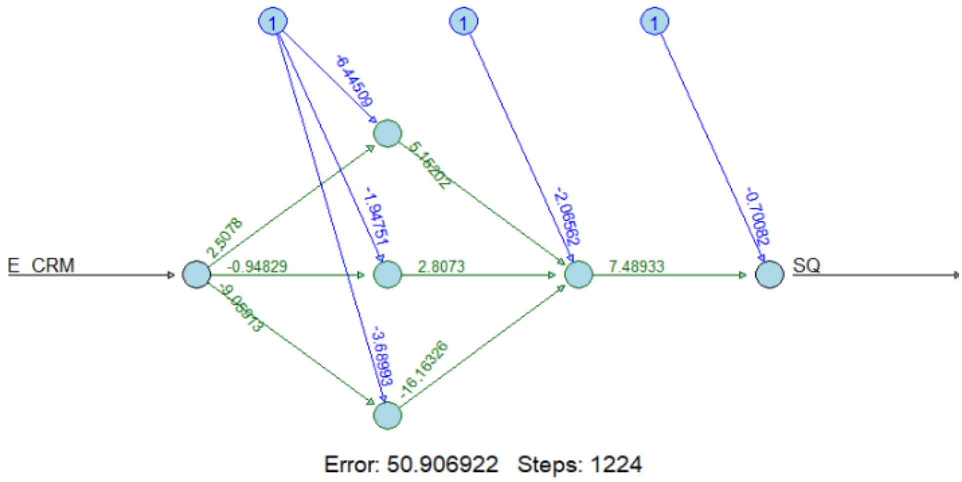

Fig.12: Artificial Neural Networks for Service Quality~ E-CRM

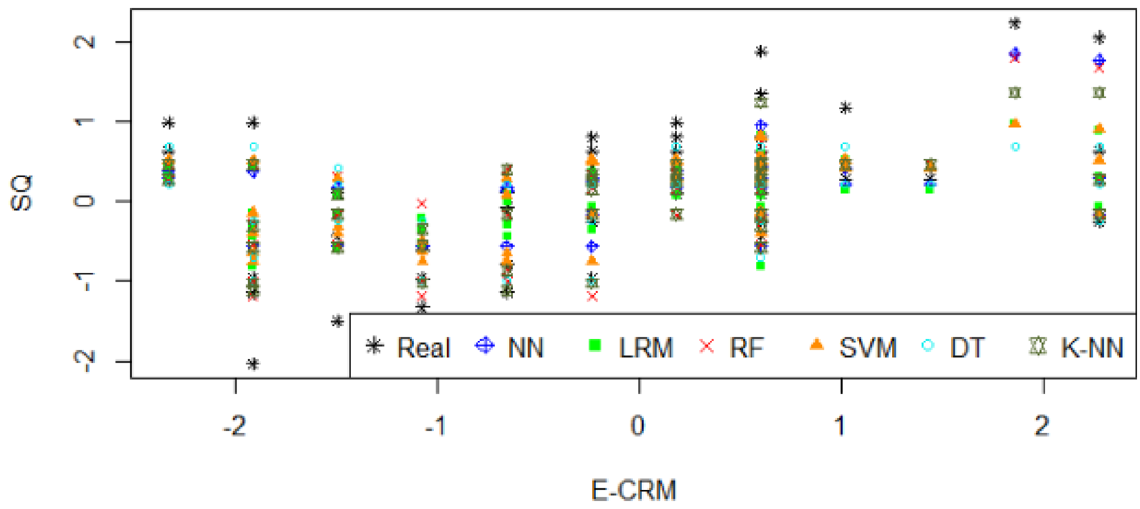

Fig.13: Real vs predicted for SQ~ E-CRM

3.4.3 Result of E-CRM on Customer Satisfaction

The Decision Tree Machine algorithm yields the lowest RMSE and MSE values (0.758, 0.574, respectively) and has the highest R square 0.44 in Table 8. The amount of variance in the dependent variable, CS, that can be accounted for by the independent variable, E-CRM, is shown by the R2 value. In this instance, 0.44% is explicable. Which is high moderate, and Fig.14 confirming these results. The same results can be concluded from Fig.15 and Fig.16.

Table 8: Predictive accuracy procedure of CS~E-CRM

	RMSE	MSE	MAE	MAPE	R. Square
ANN	0.811722	0.658892	0.642391	1.225886	0.364051
LRM	0.784171	0.614924	0.605026	1.379971	0.413189
RF	0.805699	0.64915	0.64108	1.423392	0.388451
SVM	0.789857	0.623874	0.615044	1.390449	0.412262
DT	**0.758279**	**0.574986**	**0.612486**	**1.639953**	**0.440618**
K-NN	0.770075	0.593016	0.605947	1.366862	0.42567

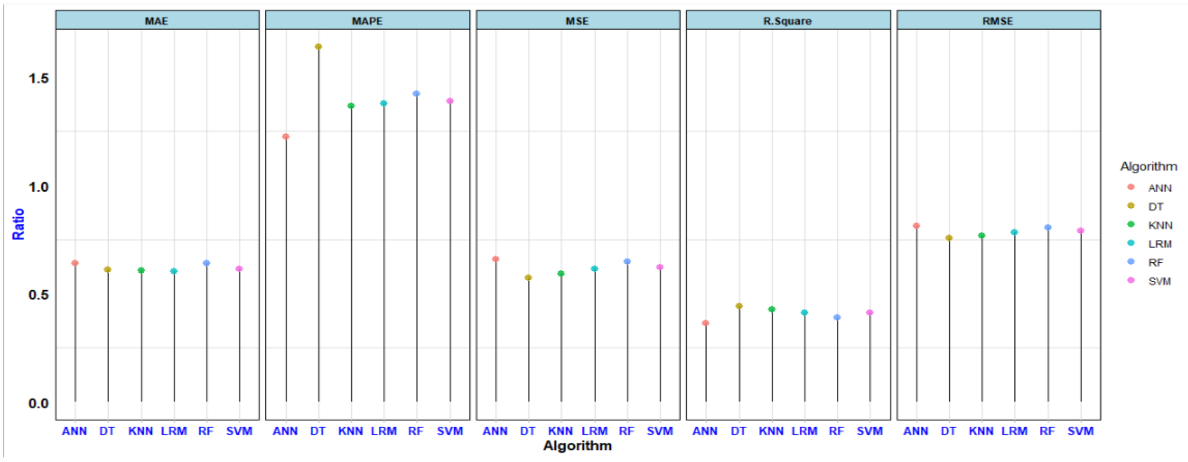

Fig.14: Result of Evaluation of Performance for Different Algorithms for CS~ E-CRM

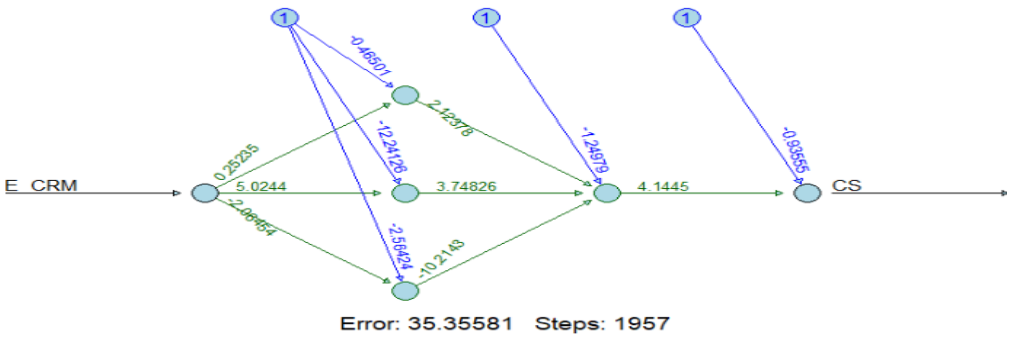

Fig.15: Artificial Neural Networks for Customer Satisfaction~ E-CRM

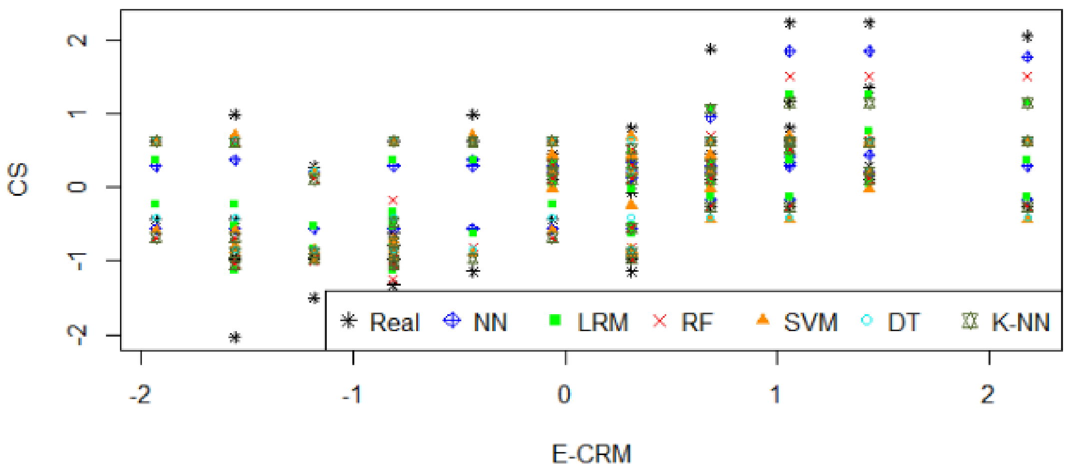

Fig.16: Real vs predicted for CS~ E-CRM

3.4.4 Result of E-CRM on Trust

The Linear regression algorithm yields the lowest RMSE, MSE and MAE values (0.877 0.770 and 0.681, respectively) and has highest R square 0.275 in Table 9. The R2 value is the percentage of total variance in the independent variable E-CRM that can be accounted for by the dependent variable TR. In this instance, 0.27% is explicable., which is moderate, and Fig.17 confirming these results. The same results can be concluded from Fig.18 and Fig.19.

Table 9: Predictive accuracy procedure of TR~E-CRM

	RMSE	MSE	MAE	MAPE	R. Square
ANN	0.898869	0.807965	0.700511	0.898679	0.270957
LRM	**0.877721**	**0.770394**	**0.681759**	0.946603	**0.275096**
RF	0.954159	0.910419	0.751298	1.102685	0.135338
SVM	0.906353	0.821476	0.734644	1.011098	0.221457
DT	0.885873	0.78477	0.724493	1.068279	0.254273
K-NN	0.924298	0.854326	0.721551	1.006915	0.173699

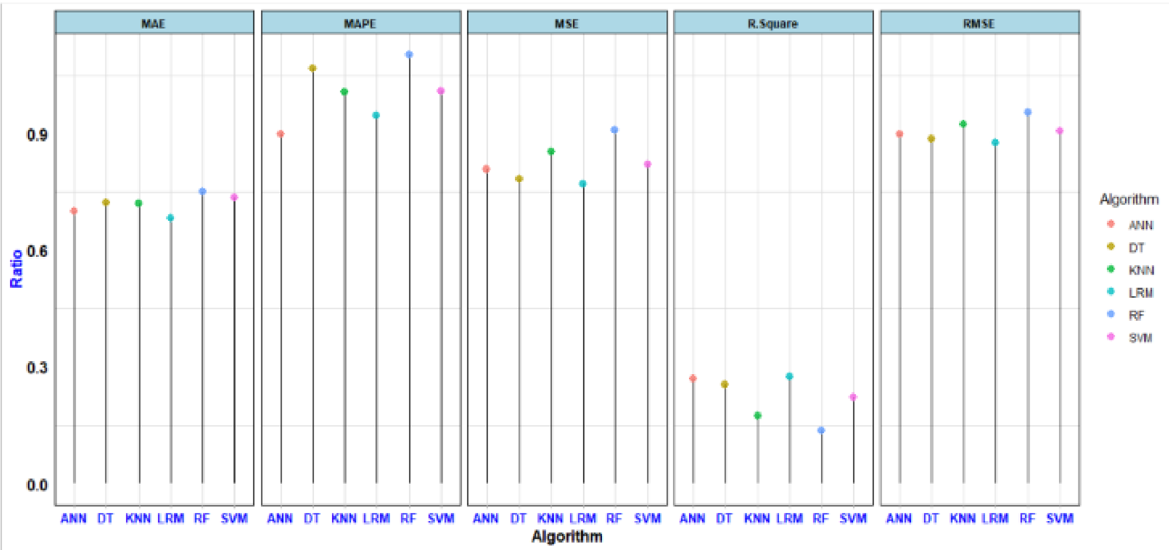

Fig.17: Result of Evaluation of Performance for Different Algorithms for Trust~ E-CRM.

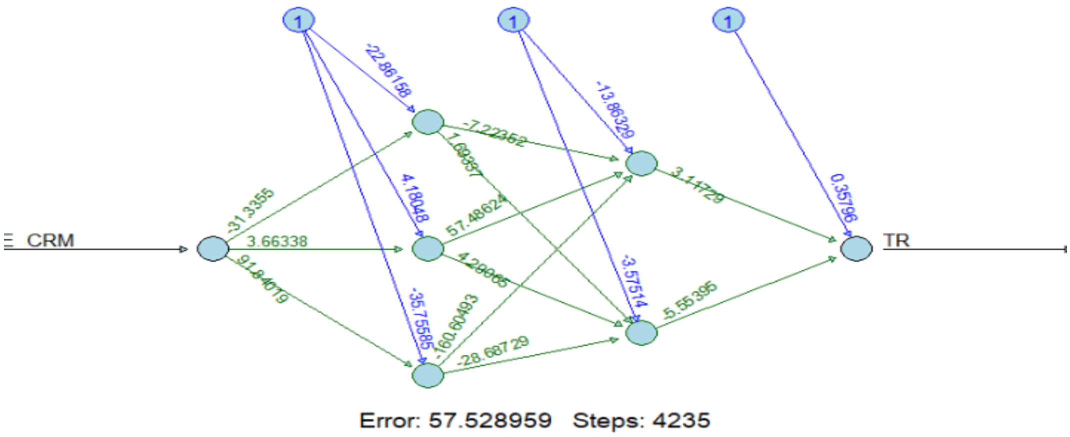

Fig.18: Artificial Neural Networks for Trust~ E-CRM

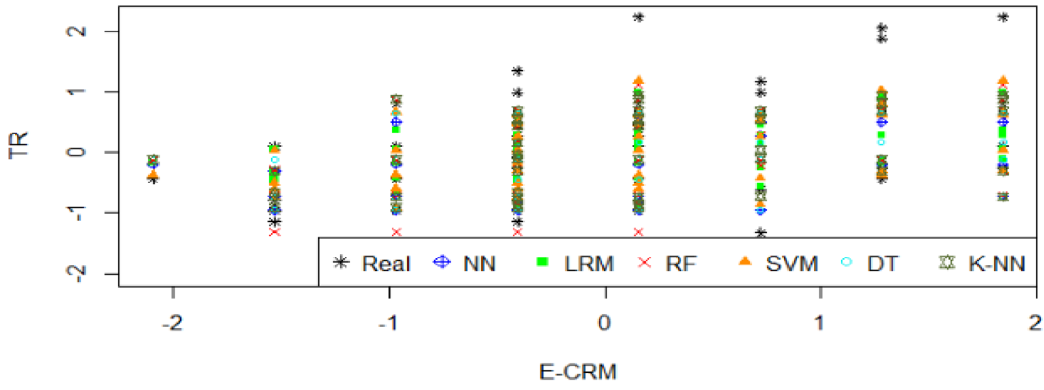

Fig.19: Real vs predicted for Trust~ E-CRM

Results from machine learning models displayed in the table The following. table10, provides clarification after presenting the findings for machine learning models and the impact of E-CRM on the variables (service quality, customer satisfaction, customer loyalty, and trust).

Table 10: Results of effects

Effect	R^2	Best machine learning model
CL~E-CRM	0.023099	SVM
SQ~E-CRM	0.297764	SVM
CS~E-CRM	0.440618	DT
TR~E-CRM	0.275096	LRM

4. CONCLUSION

Customers hold the most sway in the competitive business landscape of today. It is therefore imperative that companies and marketers realize this and make every effort to increase their network of devoted clients. E-CRM may be viewed as the unambiguous answer for both customers and enterprises. This study aimed to investigate the effects of E-CRM on customer satisfaction, trust, service quality, and loyalty. The performance of each algorithm varies based on the dataset and parameter choices. SVM technique has provided the best results for clarifying the relationship between E-CRM and customer loyalty as well as the relationship between E-CRM and service quality. DT technique has provided the best results for explaining the relationship between E-CRM and customer satisfaction, and LRM technique has provided the best results for clarifying the relationship between E-CRM and trust. We conclude that these techniques are the best ones for enhancing E-CRM.

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