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Project Submission Sheet – 2020/2021

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Predicting Customer Lifetime Value (CLV) of an Automobile Insurance Company using Various Customer Demographics

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***Abstract*—With the growing number of churning consumers in the insurance industries, it is crucial for insurance provider companies to seek for new and robust customer retention models. Customer Lifetime Value is a reliable and a valid metric which can aid in evaluating different customers based on their buying behaviour. This will help the companies analyse the customers more coherently on the basis of different segments and hence devise business strategies to retain these consumers. In this study, we analysed the marketing campaign data collected by an automobile insurance company, both quantitatively and qualitatively and build a predictive model to determine the lifetime value of individual customers based on their demographics and purchase history. A critical review of the existing literature has been done for the selection of suitable technique. The results obtained were analysed both qualitatively and quantitatively. The qualitative analysis of the results was performed with the help of various visualisations and the quantitative analysis was done by evaluating the results of the implemented machine learning algorithm. The implemented technique is based on the random forest regressor model. The model was evaluated on the basis of R^2, adjusted R^2 and the mean absolute percentage error (MAPE). The implemented model was able to achieve an R^2 value of 0.987 for the train set and 0.910 for the test set. the adjusted R^2 value comes out to be 0.908. It was also able to achieve an excellent MAPE value of just 0.98%.**

***keywords*—Customer Lifetime Value, Random Forest, Customer Churn, F-1 Score, Precision**

I. Introduction

The recent increase in the amount of churning customers in the automobile insurance industry has lead to insurers looking for various new strategies for customer retention to keep their revenues from declining and engaging their current customers. The studies have shown that for an enterprise, retaining current customers costs way less than acquiring new consumers. Major enterprises in every industry today are working on different approaches that helps them in retaining the existing customers. One such approach involves measuring the value of the customer and determine which of the customer relationships with the company will increase or decrease in revenue over the period of their association with the company. The Customer Lifetime Value (CLV) is an important and a valid metric which is used for efficient measurement of a customer's total worth to a business. The idea behind CLV is that the consumers should be judged based on their profitability for an organization [1]. CLV is used widely by almost every company today, even the companies operating an online store, as a basis for their decision-making strategies for marketing management [2]. For framing efficient strategies to compete in the market, companies choose the CLV models that are best suited for their kind of business. The main objective of analysing CLV is the identification of potentially valuable consumers for a company. In general, the CLV can be calculated by subtracting the total costs of the customer service, sales from the total revenue generated by the customer.

$$\text{CLV} = \sum_{t=1}^{T} \frac{\text{Revenue}}{(1+d)^t} - \sum_{i=1}^{T} \frac{\text{cost}}{(1+d)^t} \tag{1}$$

One of the major advantages of using CLV as a metric is that it enables the companies to segment their customers [3] and thus allowing them to spend their capital and resources for potentially profitable customers only. The ongoing research for CLV focuses on the two main methodologies for determining CLV:

- *Numerical/Model Based Methodologies*: These types of methodologies mainly focus on proposing a simple formula or model suitable for the enterprise and then calculate the CLV using different numerical methods [4] and/or conventional arithmetic calculations.
- *Data Mining Based Methodologies*: These methodologies use different data mining techniques and build predictive models to predict CLV. These kinds of studies require a substantial amount of data (like customer's history, transactional data, etc.) in order to make precise predictions [5].

Studies reveal that both of these approaches are practical and applicable in the real world scenarios. However, using machine learning based methodologies enable us to get results faster than numerical based methodologies, allow us to uncover hidden patterns in the data which may be of practical use for the enterprise and aids in the customer segmentation to manage marketing efforts aimed at customers.

To determine the lifetime value of a customer of an insurance provider company, the following aspects need to be incorporated into the models:

- Calculation of the present value of the customer.

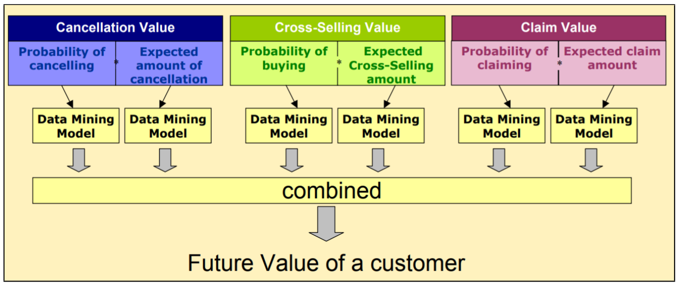


Fig. 1. Predicting customer lifetime value for an insurance provider company

- Measurement of the customer potential by taking into account the following components:
  - Value of claim
  - Value of cancellation
  - Value of cross-selling

These aspects are summarized in figure 1.

In this study, our aim is to build a predictive model that can predict the Customer Lifetime Value based on the different customer demographics and buying behaviour. Here, we use the both quantitative and qualitative data from the marketing campaign of an automobile insurance company to build a predictive model for determining CLV and improve customer retention.

II. Related Works

Customer Lifetime Value is not a new concept for enterprises. Researchers have been studying this for several years for improving the customer retention models for their business. In order to understand the current state of research, we have to critically review the peer-reviewed researches in the domain.

In one of the recent studies done by Stouthuysen et. al [6], the customer churn is predicted using various machine learning algorithms like random forest and decision trees, and from those results, the lifetime value for individual customers is analysed for a Belgium based telecommunications start-up called Eurotel. Their objective was to analyse which groups or segments of customers are most profitable to the company and then strategically target those particular segments.

Predicting the customer churn is another alternate way of analysing the customer lifetime value. Churn rate has an enormous influence on the CLV since it affects the overall revenue of the enterprise and also the length of the service provided. In this regard, Kavitha et. al [7] have used machine learning algorithms like Decision tree, Random Forest and XGBoost to predict the churning customer. Random forest model was able to outperform the other two achieving an accuracy of 80%.

Powerful classifier methods like random forest, decision trees have also been used for predicting the customer class for building a successful customer relationship management(CRM) strategies. In the light of this Win and Bo [8] carried out a study in which they used the CLV in order to predict the categories of customer class for the coming year. They used the random forest algorithm and the random search tuning technique to achieve the best predictive accuracy. With hyperparameter tuning, they were able to achieve the accuracy of 84.27%. They also used Adaboost model, which was able to achieve an overall accuracy of 78.21%.

In a similar study of classification of customers in social CRM [9], Lamrhari et. al were able to achieve state-of-the-art results using Random Forest algorithm. They achieved an accuracy of 98.46%. Moreover, they compared their results with several state-of-the-art classifier models like ANN, SVM and kNN. The different classes in their data were '*Satisfied Customer*', '*Unsatisfied Customer*' and '*Prospect*'.

Scriney et. al [10] conducted a research in which they predicted the customer churn using the data from an insurance company. In this study, the authors essentially lay a foundation for calculating CLV. Since CLV calculation requires the data for customer history of every client, there are instances where the data isn't just available. To solve this issue, they proposed an approach for imputing some of the missing parameters in the CLV data. They used the artificial neural networks and two decision trees algorithms for generating one of the key parameters employed in CLV calculations called *retention*. Their evaluation results showed that the artificial neural network achieved the highest accuracy and F1 score followed by the two decision tree algorithms.

The RFM(Recency, Frequency Monetary) value is a tool used in marketing analysis to evaluate the best customers of an organization using three quantitative measures:

- *Recency*: How recent is a purchase made by a customer.
- *Frequency*: How frequent is a purchase.
- *Monetary*: How much money is spent by a customer on purchases.

keeping these three measures in mind, a consumer is ranked on a scale of 1-5 and the higher the number, the more value a consumer has. Several studies have been conducted over the years using RFM as a metric to evaluate consumers on the basis of their buying behaviour [11].

LRFM (Length, Recency, Frequency, Monetary) is an extension of the RFM model containing an additional measure *length* which takes into account the no. of days since the last purchase is made by a customer. Using this model, Pramono et. al [3] build a customer segmentation model using k-means clustering algorithm. They used a two-stage clustering method using Ward's method to choose the initial number of clusters and the k-means algorithm for performing clustering analysis. They used two different approaches LRFM and LRFM-AI (Average Item) for customer segmentation. They later ranked the customer segments on the basis of their CLV values and also assigned the weights to the 4 measures in the LRFM model namely Length, Recency, Frequency and Monetary.

In 2019, Desirena et. al [12] conducted a study in which they proposed a novel recommender system using a 2 stage stacked neural network system in order to maximize the customer lifetime value. The first stage neural network used the attention mechanism to generate recommendations of products and the second stage neural network used survival analysis to deduce the insurance product recommendations that generates the maximum customer lifetime. They tested their proposed model on an Australian Insurance company data.

The probabilistic models have produced state-of-the-art results in different prediction and segmentation tasks in the domain of online shopping. In light of this, Jasek et. al [13] studied the different probabilistic models for customer lifetime value prediction in online purchasing. They carried out a statistical analysis on a selected group of probabilistic models that show promising results in online retail purchasing environment. They chose 11 different probabilistic models and tested them on the datasets of online stores in Central and Eastern Europe regions. In general, all of the chosen models were able to achieve good results on the datasets. The BG/NBD model was able to outperform the other models in the customer base value prediction, achieving an average of 100.44% profits and a standard deviation of 19%. Another research for modelling CLV in online retail was conducted by the same team of authors, a year ago in which they used three different models: Markov Chain model, EP/NBD and the status quo model [2]. They chose six different online retail stores with high revenues to check the applicability of their models. In this case, EP/NBM model was able to outperform the other two models on the basis of the majority of evaluation metrics.

Wang et. al [14] used a deep probabilistic model for CLV prediction. They used the combination of two types of distributions- zero point mass and the lognormal distribution to model the lifetime value. The advantage of using the combination is that it is able to account for the churn probability and the skewed nature of the CLV values. The highly skewed nature of the customer LTV can be owed to the fact that, however small, but there is a fraction of consumers who never come back after the first purchase. They designed a custom deep neural network that was able to capture the above features. They demonstrated their proposed model on two different real world datasets.

A. Conclusion

After critically reviewing the existing literature, we can conclude that the classifier machine learning algorithms like random forests, decision trees and the support vector machines (SVM) have produced state-of-the-art results in the customer lifetime value and customer segmentation and classification tasks. However, in online retail, the probabilistic models still stand out in comparison to other machine learning algorithms, in terms of the performance. Random forest algorithm in particular has been used most frequently and has produced results comparable to or in some cases, even better than the state-of-the-art. Therefore after critical evaluation of the existing methods and analyzing our data requirements, we will be employing the random forest algorithm for the prediction of customer lifetime value based on different customer demographics.

Column_Name	Type	Description
Customer Lifetime Value	String	Customer's total worth to business over lifetime of the relationship
State	String	State of residence or business of the customer
Customer	Float	Customer ID No.
Response	String	Yes or No response to a renewal offer
Coverage	String	Type of Policy (Basic, Extended, Premium)
Education	String	Level of education of customer (High School or less, College, BA, MA, PhD)
Effective To Date	Date-time	Date on which the policy expires
EmploymentStatus	String	Employment Status of Customer (Employed, Unemployed, Retired, Disabled, Medical Leave)
Gender	String	Gender of customer (Male or Female)
Income	Integer	Customer's annual income
Location Code	String	Location type of customer (Urban, Rural, Suburban)
Marital Status	String	Marital Status of the customer (Married, Single, Divorced)
Monthly Premium Auto	Integer	Amount of customer's monthly insurance payments
Months Since Last Claim	Integer	Number of months between customer's last reported insurance claim
Months Since Policy Inception	Integer	Number of months since customer began an insurance policy
Number of Open Complaints	Integer	Number of unresolved customer complaints
Number of Policies	Integer	Number of policies customer currently owns
Policy Type	String	Type of policy (Corporate auto, Personal auto, Special auto)
Policy	String	3 levels (L1, L2, L3) as per policy type (Corporate, Personal, Special)
Renew Offer Type	String	4 types of renewal offers (Offer 1, Offer 2, Offer 3, Offer 4)
Sales Channel	String	Channels to purchase a policy (Agent, Branch, Call center, Web)
Total Claim Amount	Float	Cummulative amount of claims since policy inception
Vehicle Class	String	Type of vehicle (4-Door, Luxury, Luxury SUV, Sports car, SUV, 2-Door)
Vehicle Size	String	Size of vehicle (Large, Midsize, Small)

Fig. 2. Data Description for IBM Watson Customer Value Dataset

III. IMPLEMENTATION OF THE TECHNIQUES

For the successful implementation of the selected technique, the following methodology steps were followed:

A. Data Understanding and Resources

The data used in this study has been acquired from the IBM Watson analytics data repository. The IBM has open sourced their analytics data and therefore the data is also available on kaggle (Data Repository Link). The dataset contains the marketing campaign results conducted by an automobile insurance company in order to improve their customer retention policies and keep the rate of churning customers to a low. The company offered four different policy renewal proposals to the customers with expiring policies. But unfortunately, most of their customers denied to the proposals offered and hence the purchase response rate has been low. The aim of this study is to improve the customer retention by building a predictive model for determining the CLV for each of the customers.

B. Data Description

The data dictionary for the dataset used is shown in the figure 2. The data contains both continuous and the categorical variables. A thorough analysis of both types of variables is explained in next subsection.

C. Data Pre-Processing

- *Exploring Continuous and Categorical Variables*: The data contains both continuous and the categorical variables. Both types of variables need to be treated differently while analysing the data and implementing models. Therefore, it is important to segregate the two types beforehand so that model implementation is performed correctly. The continuous variables are given below and the categorical variables are summarized in table.
  - **Continuous Variables**:
    - Customer Lifetime Value
    - Income
    - Monthly Premium Auto
    - Months Since Last Claim
    - Months Since Policy Inception

* Number of Open Complaints
* Number of Policies
* Total Claim Amount

– **Categorical Variables**: The categorical variables in our data and their respective classes are shown in the table I.

Variable	Categories/Classes
State	'Washington', 'Arizona', 'Nevada', 'California', 'Oregon'
Response	'Yes', 'No'
Coverage	'Basic', 'Extended', 'Premium'
Education	'Bachelor', 'College', 'Master', 'High School or Below' 'Doctor'
Employment Status	'Employed', 'Unemployed', 'Medical Leave' 'Disabled', 'Retired'
Gender	'F', 'M'
Location Code	'Suburban,' 'Rural', 'Urban'
Marital Status	'Married', 'Single', 'Divorced'
Policy Type	'Corporate Auto', 'Personal Auto', 'Special Auto'
Policy	'Corporate L3', 'Personal L3', 'Corporate L2', 'Personal L1', 'Special L2', 'Corporate L1', 'Personal L2', 'Special L1,' 'Special L3'
Renew Offer Type	'Offer1', 'Offer3', 'Offer2', 'Offer4'
Sales Channel	'Agent', 'Call Center', 'Web', 'Branch'
Vehicle Class	'Two-Door Car', 'Four-Door Car', 'SUV', 'Luxury SUV', 'Sports Car', 'Luxury Car'
Vehicle Size	'Medsize', 'Small', 'Large'

TABLE I
DESCRIPTION OF CATEGORICAL VARIABLES IN THE DATA

* *Feature Transformation and Engineering*:
  – Our data has a lot of features/independent variables in it. Therefore we have to filter out the features that do not affect the target variable, that have strong correlations with one of the other variables or which violate any of the assumptions of a regression analysis. These variables will be removed in the final model implementation.
  – The target variable in our data is skewed with a skewness of 3.03(figure 3) which indicates presence of outliers in the data. Therefore, we apply log transformation to our target variable to reduce skewness within tolerable limits.
* *Dealing with the Outliers*: The outliers in the data cause the results to be biased. Therefore, it is important to identify the outliers in the data and remove them before the model implementation. Figure 3 shows the outliers in the target variable Customer Lifetime Value and their distribution with the variables Response and Renew Offer Type. We can infer from the figure that there are quite a few outliers in the target variable and hence these should be removed from the data to avoid biased results. Therefore, every value that is greater than 1.5 times the *interquartile range* will be removed (refer to figure 4).

Fig. 3. Log Transformation on the data.

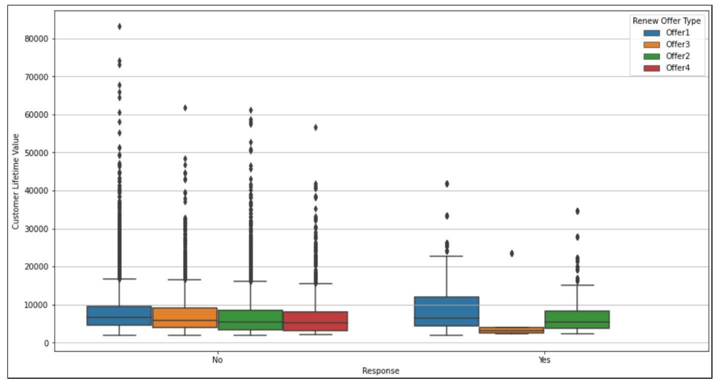


Fig. 4. Outlier Detection in the data

* *Correlation between Continuous Variables*: It is crucial to identify the variable shaving high correlation between them so that only those variables are left in the final model statistically significant contribution in the dependent or the target variable. Figure 5 shows the correlation heat map f the different continuous variables in the data.

D. Model Implementation

Random Forest is the model chosen for implementation part of the study i.e the prediction of the customer lifetime

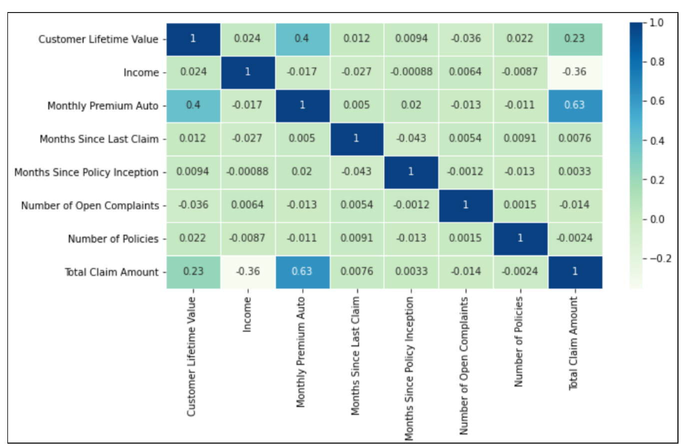


Fig. 5. Pearson correlation heatmap of the continuous variables

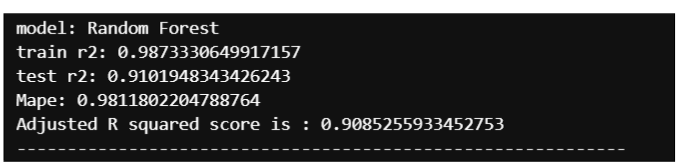
value. The random forest algorithm can be used for both the classification as well as regression based tasks. Since, CLV prediction is a regression task, we will be employing the random forest regressor algorithm. The reason for the choice of the model has been highlighted in the subsection II-A. The primary reason is that the random forest model has been used predominantly in the customer segmentation, classification and regression based tasks. The choice for the model is also dependent upon the given computational resources, training time, nature and sophistication of the data chosen and last but not the least, the desired accuracy of the predicted values. The qualitative and the quantitative results of the study are highlighted in the next section.

IV. Analysis of the Results

A. Quantitative Analysis

The quantitative analysis of the techniques implemented involves the analysis and evaluation of the results obtained after the model implementation. In our study, the quantitative analysis will be done on the basis of R^2, Adjusted R^2 and the mean absolute percentage error (MAPE). We implemented the random forest model with 432 as no of estimators.The summary of results is shown in figure 6.

- R^2: The R^2 value tells how much of the variation in the dependent variable is explained by the independent variables in the model. The closer the value is to 1, the better is the variation explained and hence the better is the model. The R^2 value for the train set comes out to be 0.987 and for the test set it is 0.910. Hence, we can safely say that these values are optimum.
- *Adjusted* R^2: The adjusted R^2 tells us how well does terms fit a curve, adjusting for the no. of terms in the model. So, adding more variables to the model which contribute very little or nothing in the variation of the dependent variable will actually decrease the adjusted R^2. In our case, the adjusted R^2 for the random forest model is 0.908. Hence, the choices of variables in our models are correct and are justified.
- *Mean Absolute Percentage Error (MAPE)*: The MAPE measures the accuracy of a forecast system as percentage. The MAPE for our model comes out to be 0.9810%. This value can be considered as excellent according to the defined norms in statistics.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model: Random Forest
train r2: 0.9873330649917157
test r2: 0.9101948343426243
Mape: 0.9811802204788764
Adjusted R squared score is : 0.9085255933452753
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Fig. 6. Results of the quantitative analysis

B. Qualitative Analysis

In order to analyse our implemented technique in terms of its business impacts, it is crucial to qualitatively analyse the findings of our study and draw inferences from them to further improve the current business models of the company. The qualitative analysis of the results is presented in form of different visualisations of the data. The inferences drawn from the different visualisations shown have been explained in the captions of the figures (figures to)

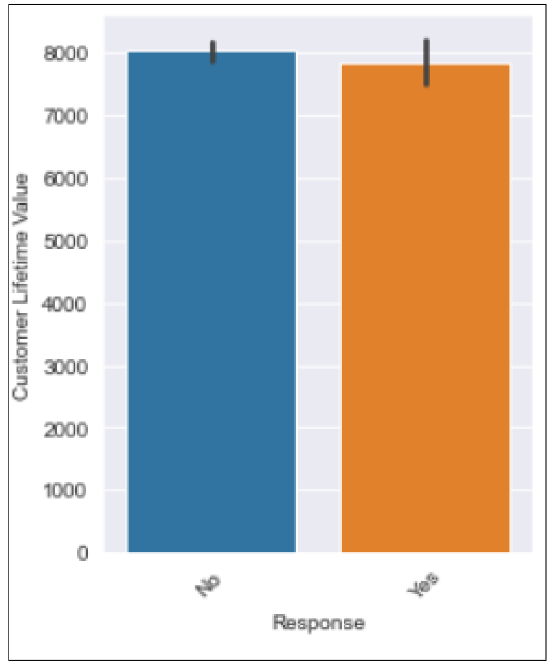

Fig. 7. This figure shows the CLV of customers according to the response of their policy renewal request. The consumers who denied to renew their policy have higher CLV than those agreed to continue with the company.

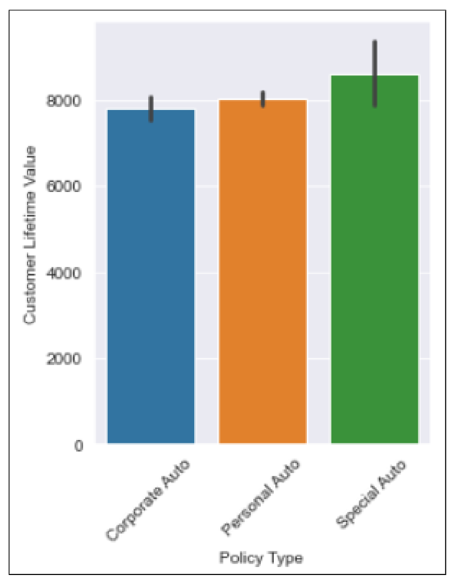

Fig. 8. Distribution of different types of policies and their cumulative CLVs. As we can clearly see, the customers with the policy *Special Auto* have the highest cumulative CLV. This means that the company should invest their resources more on this type of policy as it is preferred by large no. of their customers.

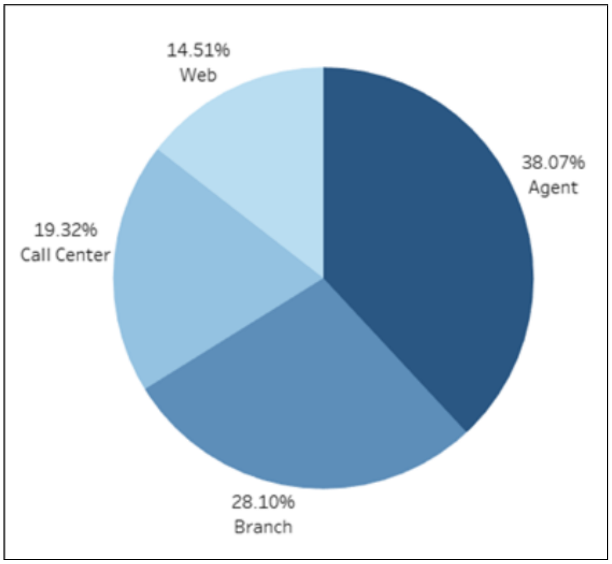

Fig. 9. This figure shows the different channels through which the customers were offered the policies who agreed to renew their current policy with the company. We can infer that most of the renewals were by the customers who were offered the policy by the agents.

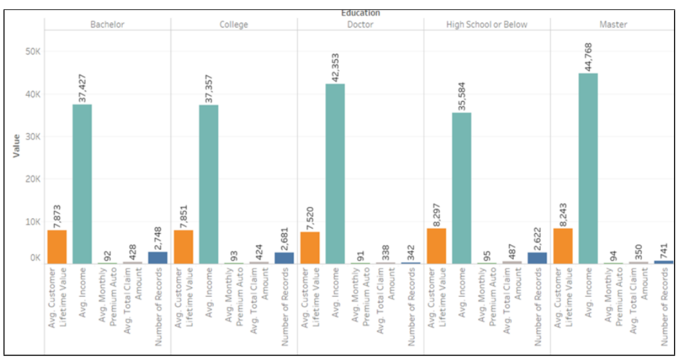

Fig. 10. This figure shows the average CLV, income, monthly premium auto and total claim amount by the different education level of the customers. The customers who have a masters degree or have a doctorate have very high LTV as compared to other categories. This shows that the company should target more educated customers as they are more likely to buy new insurance policies.

V. Conclusions

The aim of the study was to predict the customer lifetime value of the individual customers based on different customer demographics. A random forest regressor algorithm was implemented to achieve the stated objective. The data first preprocessed and then transformed to get rid of the outliers and the skewness present. The random forest regressor was then implemented which was able to achieve and R^2 of 0.98 for the train data and 0.91 for the test data. The adjusted R^2 value comes to be 0.908 which can be considered as an optimum value based on the given data. The model was able to achieve a mean absolute percentage error of just 0.98%. Overall, we can infer that our model has performed quite well to accomplish the given predictive analysis task.

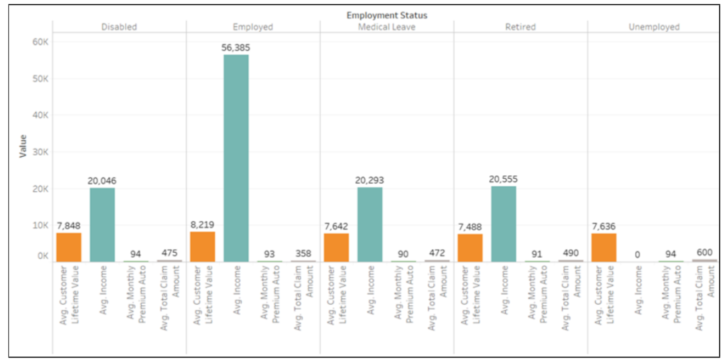

Fig. 11. This figure shows the average CLV, income, monthly premium auto and total claim amount by the employment status of the customers. We can see that the employed customers have highest average CLV. The average CLV for other categories is not too less either. Therefore, it can be inferred that the employment status can not be used as a viable metric to judge whether the customer is valuable to the enterprise or not.

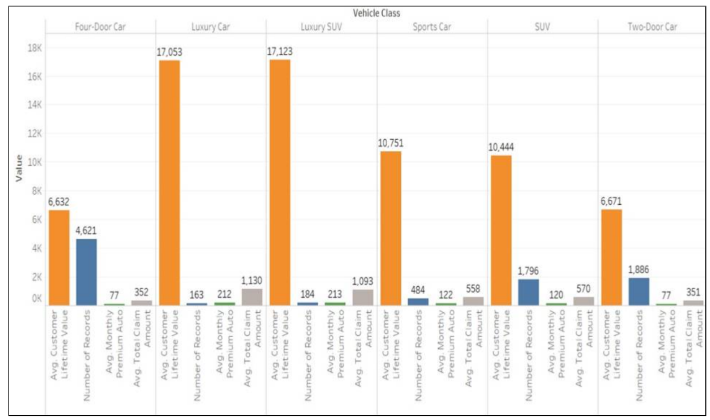

Fig. 12. This figure shows the average CLV, income, monthly premium auto and total claim amount by the type pf vehicle owned by the customer. It can be readily inferred from the distribution that customers with luxury cars and SUV are more likely to buy the automobile insurance than those who own average four door and two door cars. Therefore the company should target more the former kinds of consumers in order to increase their revenue.

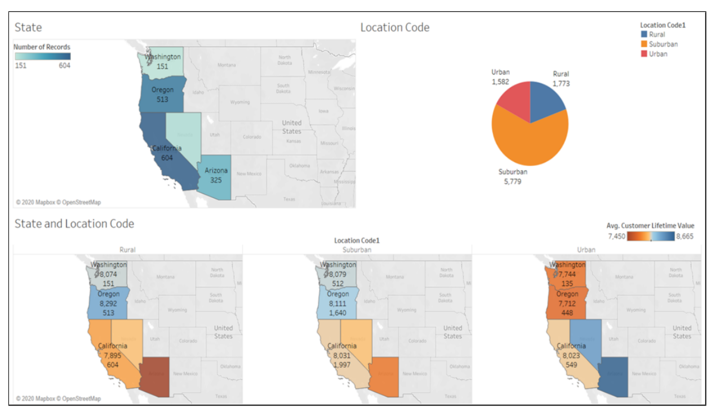

Fig. 13. This picture shows the distribution of the variable in different states and location(rural, urban or suburban) where the campaign was held. We can see that California and Oregon have the highest share of the total CLV. This kind of analysis will help the company decide where is most of their revenue coming from and accordingly make strategies to cover the larger market in the longer run.

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