Cost Prediction of Health Insurance

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***Abstract*—In comparison to other nations, India's government allocates only 1.5% of its annual GDP to public healthcare. On the other hand, over the past 20 years, worldwide public health spending has nearly doubled along with inflation, reaching US $8.5 trillion in 2019, or 9.8% of global GDP. Around 60% of comprehensive medical procedures and 70% of outpatient care are provided by multinational multi-private sectors, who charge people exorbitant prices. Health insurance is becoming into a necessity for everyone due to the rising cost of high-quality healthcare, rising life expectancy, and the epidemiological shift toward non-communicable diseases. In the previous ten years, there has been a significant increase in insurance data, and carriers now have access to it. To improve outcomes, the health insurance system looks into predictive modelling.**

Keywords— Machine Learning, Regression Models, Ridge Regression, Linear Regression, Multiple Linear Regression and Polynomial Regression.

I. INTRODUCTION

We live on a planet that is full of dangers and ambiguity. people, Families, businesses, real estate, and other assets are exposed to various risk kinds. and there are different risk levels. These Risks of mortality, ill health, and property loss are among the dangers.

The most important aspects of people's lives are life and wellbeing.

However, hazards may seldom be eliminated, therefore the realm of Finance has created a variety of protective products. Protecting people and organisations from these dangers. Financial resources to pay them back. Insurance is a result.

Policy that lowers or eliminates loss expenses that are paid by different dangers[1], regarding the importance of insurance in people's lives of people, it becomes crucial for the businesses of insurance to be accurate enough to quantify or assess the sum covered information. Instead of exposing the data itself, the nature of the data stored is disclosed. Gestures can be identified by examining photo metadata and content information. Feature extraction and classification are combined in one operation.

The cost of insurance premiums depends on a number of factors. the result is Costs for insurance are continuous quantities. The best is regression available options to meet our needs. We employ many linear Since there are numerous independent variables in this analysis, regression variables utilised in the target (dependent) variable's calculation. For The dataset for health insurance premium costs is utilised in this study [2].

First, the dataset underwent preprocessing. next, we practiced evaluation of regression models using training data based on testing results for these models.

II. LITERATURE SURVEY

Several research projects on calculating medical costs have been published in many health-related contexts. Many likely assumptions underlie machine learning, however, the performance of it depends on using a virtually accurate method. pertaining to the mentioned problem domain and using the acceptable methods to create, train, and use the model.

Moran and coworkers "used a thorough linear the cost of an item using the regression method ICU using patient profile information and DRGs The amount of time spent in the groups (diagnosis-related) a hospital, and other characteristics."

The model Sushmita et al. "presented was based on Using a person's medical history and previous spending patterns, future medical expenses expected costs for each quarter.

Machine learning (ML) algorithms for predicting health insurance premiums are continuously being researched and developed in the healthcare industry. A computational intelligence method for calculating healthcare insurance costs using a variety of machine learning approaches was proposed in the work of [2]. One piece [3] started out by considering the possible effects of employing predictive algorithms to determine insurance rates. Would this put the concept of risk mutualization in jeopardy, leading to new forms of bias and insurance exclusion? The second part of the study examined how the insured's realisation that the corporation had a wealth of continuously updated information about her actual behaviour affected their relationship.

Van den Broek-Altenburg and Atherly's study [4] aimed to ascertain consumers' opinions about medical insurance by monitoring their Twitter activity. The purpose was to use sentiment categorization to learn how individuals feel about doctors and health insurance.

The authors used an Application Program Interface (API) to gather tweets on Twitter that contained the terms "health insurance" or "health plan" throughout the 2016–2017 healthcare insurance registration period in the United States. Insurance is a strategy that lowers or eliminates the expenses of losses brought on by various risks. The price of insurance is affected by a number of [5] factors. These factors have an effect on how insurance policies are created.

III Methodology

The statistical techniques known as regression procedures are used to determine the relationship between a target or dependent variable and a group of independent or predictor variables.

It is assumed that there is some sort of correlation between the target and predictor variables and that both have numerical values. The models we're using to solve our problem are detailed more below.

A. Model Choice:

Simple Linear Regression: In simple linear regression [16], the model develops a linear connection between the target variable (Y) and a single independent variable (X).

The dependent(y) and independent(X) variables are independent, and the linear regression model aims to fit the regressor line between them.

Y = a + bX is the equation for the line (1)

where "a" is the value of the Y intercept that the line makes when X is equal to zero and "b" is the slope that denotes the change in Y with the change in X. These model parameters are referred to as regression coefficients. A greater value of "b" indicates that, in both directions, a little change in X results in a substantial change in Y. The Ordinary Least Squares method can be used to determine the values of "a" and "b."

There will always be some discrepancy between the values predicted in linear regression models, therefore we add an error term to the original equation (1) to account for the difference and help in prediction.

Y = a + bX + (2)

Linear Regression Assumptions

• The sample size of data should be greater than the number of

• The regression can only be valid across a specific set of data, and the error term is normally distributed.

• This also implies that the mean of the error has an expected value of zero.

Multiple Linear Regression: Multiple regression [17] is a statistical method that assesses the strength of the relationship between a number of independent variables and a dependent variable.

In basic linear regression, there is just one independent variable and one dependent variable; however, in multiple linear regression, there are many predictor variables, and the value of the dependent variable (Y) is now determined based on the values of the predictor variables. It is assumed that the predictor variables are independent of one another. Assume that the regressor fits the regression line in an N-dimensional space if the goal value depends on "n" independent variables. The regressor line equation is now written as Y = a + b1X1 + b2X2 + b3X3 +..... + bnXn + (3), where "a" represents the value of the Y-intercept, "b1, "b2, "b3,..., "bn" > are the regression coefficients connected to the n independent variables, and "is the error term."

Another unique kind of linear regression is polynomial regression, which is described in [18]. The goal of linear regression is to fit a straight line between the independent and dependent variables. In situations where there isn't a linear relationship between the goal and predictor variable, a curve is fitted against the two variables rather than a straight line. This is done by establishing a curvilinear link between the dependent and independent variables using a polynomial equation of degree n that is fitted to the non-linear data. The requirement that the independent variables be independent of one another is not necessary in polynomial regression. Thus, the line's equation becomes Y = a + b1X 1 + b2X 2 + b3X 3 +... + bnX n

Applying polynomial regression has a number of advantages, including the following:

• Polynomial Regression provides the most accurate estimate of

• Higher degree polynomials typically offer a strong fit on the dataset in terms of the relationship between the dependent and independent variables.

• The main idea behind polynomial regression is to fit a variety of curves to the dataset.

Polynomial regression has the following drawbacks:

• These are overly sensitive to the presence of outliers in the dataset, as outliers increase the variance of the model.

• The model performs poorly when it encounters an unidentified piece of data.

B. Dataset Description:

For the purpose of creating the ML Health Insurance Prediction System, we collected our dataset from the Kaggle website [21]. (MLHIPS). The acquired data set consists of 1338 rows and seven properties or features, three of which have category values and the remaining four have numerical values. After that, the data set is split in half.

The first part is known as training data, while the second part is known as test data. The model will be more accurate when making predictions based on unobserved data the more data that is provided to the model during its training phase. When splitting data for testing and training, the average ratio is 80:20

There were blank values in certain fields of the dataset.

The distributions were examined, and it was determined to replace the Adding new characteristics to missing variables suggests that there are gaps in the data. [9]. This is only conceivable if the data is lost entirely at random, thus it is necessary to first design the missing data mechanism, which chooses the most efficient way to analyse the data. [10] [11]. Medical data have hidden linkages and multilevel structures [12]. It is crucial to uncover these underlying patterns using a variety of available fundamental analysis approaches combined.

This is the rationale behind the widespread usage of various ensemble Machine Learning models in the study of medical data.

The subject of price prediction has also been addressed by researchers using hierarchical regression analysis. Many of them have employed various ensemble learning methodologies.

C. Data Pre-processing:

As can be seen in the table above, there are seven variables in the dataset. The values of the remaining six variables are taken into account while determining the cost of a customer's charges, which is our goal variable. The data is examined, correctly recreated, and properly incorporated into machine learning algorithms during this phase. First, we looked for any missing values in the dataset.

The bmi and charges columns in the dataset were discovered to be empty.

The mean values of the corresponding attribute values were used to impute the missing values.

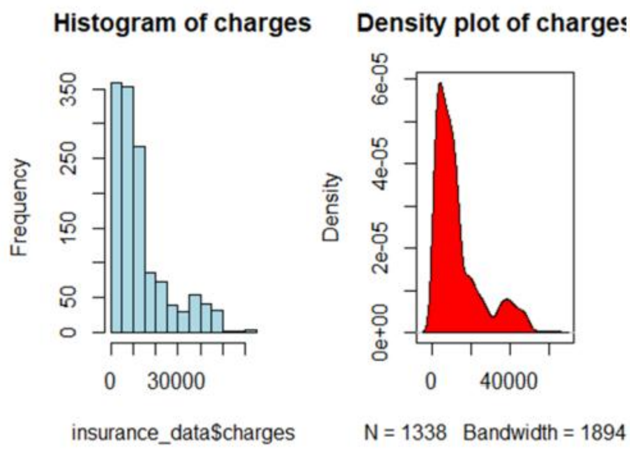
The sex, smoker, and region columns in our example were categorical columns that were turned into numerical values using label encoding because regression models only accept numerical data.

TABLE I
DATASET

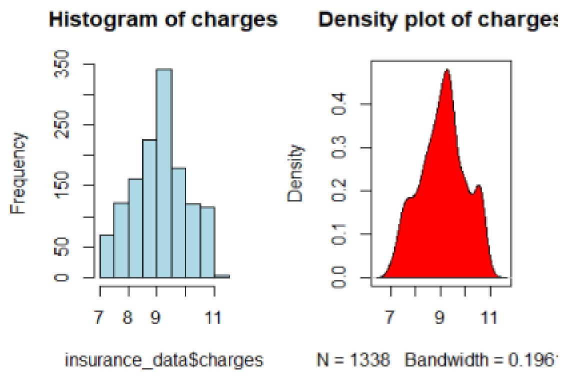
Name	Description
Age	Customer's Age
BMI	Body mass index of the customer
Number of kids	Number of kids of the customer
Gender	Male / Female
Smoker	Whether the customer is smoker or not.
Region	Where the customer lives: southwest, southeast, northeast, northwest
Charges (target variable)	Medical fee the customer has to pay

Additionally, severely skewed data in regression scenarios may lead to an unsatisfactory model fit. And in this situation, severely skewed data can frequently be normalised using the log (natural logarithm) transformation.

Therefore, the log transfer is employed to normalise the expenses of health insurance. Additionally, the following graph displays the increased cost of health insurance.



Histogram or density plot for the dependent variable (charges) shows the medical insurance costs distributed have been skewed to the right.

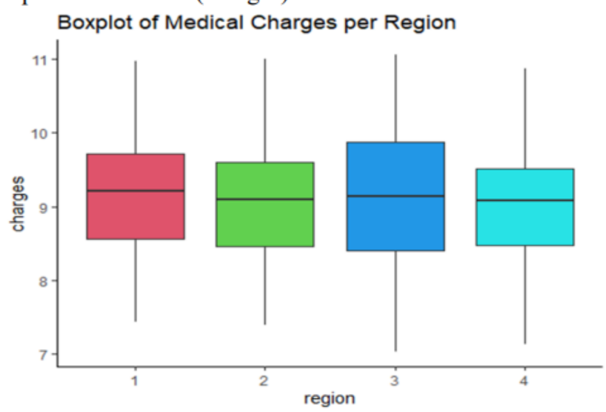


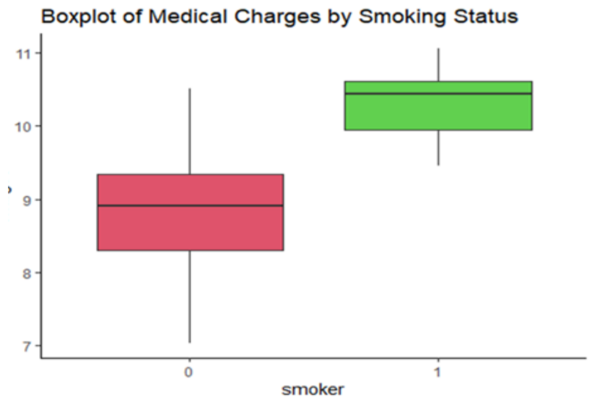
The categorical variables are then converted to numeric or binary values that can either represent 0 or 1. For instance, the "Male" variable would be true (1) if the subject is a man instead of "SEX" with males or females. "Female" would also be (0)

The data can now be applied to all regression models used in this investigation, as shown in the table.

name	Description
age	Age of the client
BMI	body mass index
The Number of Kids	number of children the client have
gender	Male / Female 1=Male 0=Female
smoker	whether a client is a smoker or not 1=yes 0=no
region	where the client lives 1= southwest 2= southeast 3= northwest 4= northeast
Charges(target variable)	Medical Cost the client pay

Now we examine the other independent variables with the dependent variable (charges).





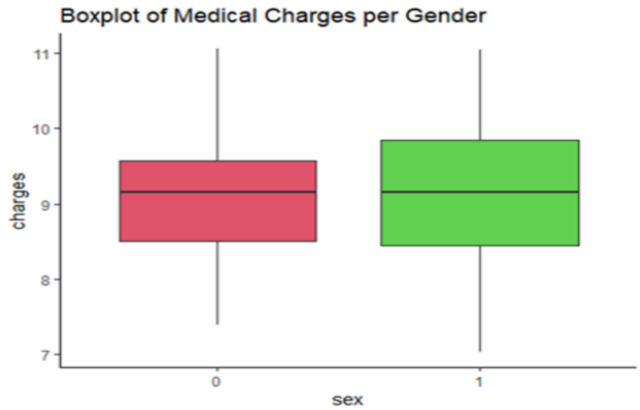
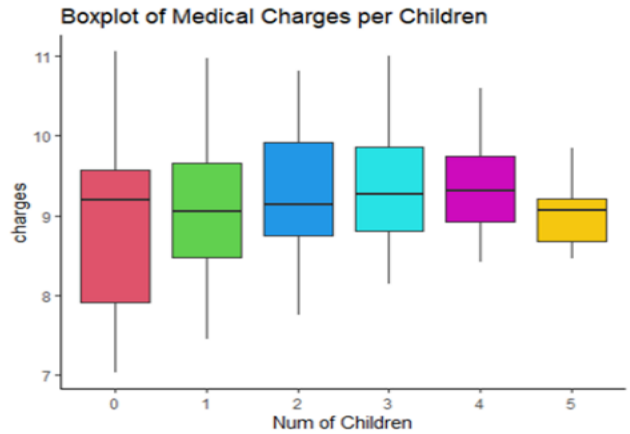


Figure V



IV RESULTS

The following metrics are used to gauge the effectiveness of the regression model.

Root Mean Square Error (R2 Score) (RMSE)

R2 Score: R-Squared is a useful metric for assessing the model's fitness. The range of the R-squared value is 0 to 1 (0% to 100%). A higher value indicates a better fit.

SSE (Squared Sum of Error) is the sum of the squared residuals, which are the squared deviations of each observation from the value predicted.

$$R^2 = 1 - \frac{SSE}{SST}$$

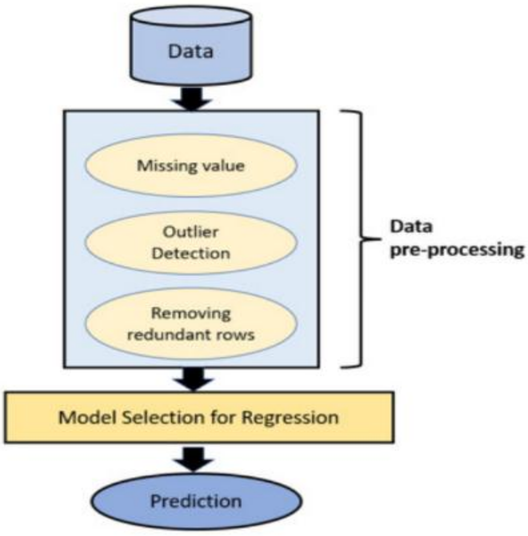
SST (Sum of Squared Total): squared deviations between each observation and the mean value as a whole.

The Root Mean Square Error, or RMSE, is a frequent

a process for determining a model's prediction error, which shows how closely the observed data points are

The predicted values demonstrate the model's perfect fit to the observed data. Lower RMSE values suggest a better match.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - y^*)^2}{n}}$$



V OBSERVATIONS

As can be seen from the calculations above, Polynomial Regression performs better than other models for the proposed MLHIPS, with an accuracy of 80.97%.

In contrast to other models, polynomial regression fits a curve to the dataset, which raises the model's variance and lowers the residual error. When employing Polynomial Regression, the model produces better results, with an RMSE of 5100.53 and an R2 value of 0.80. Polynomial regression eventually yields superior results if the target and collection of predictor variables have a nonlinear connection. In addition, MLHIPS' Polynomial Regression Ridge and Lasso Regression have each obtained accuracy values of 75.82% and 75.86%.

The six independent factors have strong correlations with one another, which is why lasso regression and ridge regression yield comparable findings. The accuracy of the MLHIPS multiple linear regression model is 75.66%. In contrast, simple linear regression had the lowest accuracy of all, at 62.86%. The dataset is divided in the aforementioned situation in an 80-20 ratio for training and testing purposes.

The accuracy of the polynomial regression falls from its prior value of 80.97% to 80.54% in the dataset of the 70:30 ratio, which is inconsequential. The accuracy values of the other models have similarly decreased.

Additionally, it was observed that the accuracy increased from the previous value of 80.97% to 83.62% when the degree of polynomial regression was changed from n=2 to n=3. though later on, raising the degree even further to 4 and greater values accuracy decreased for degrees n=4 and n=5, from 83.62% to 68.06% and 51.98%, respectively. Therefore, the polynomial regression gives us a decent level of accuracy in forecasting the charges with degree n=3.

VI. FUTURE WORK

For our proposed problem statement, we reviewed some standard regression models in this study. Moving forward, however, certain new techniques, such as Support Vector Machine (SVM), XGBoost, Decision Tree (CART), Random Forest Classifier, and Stochastic Gradient Boosting, need to be addressed. On top of model evaluation, a variety of optimization methods, including the Genetic Algorithm and the Gradient Descent Algorithm, may be used.

Before training our model, we can also use certain feature selection strategies on our dataset to improve accuracy since some features could be missed when predicting charges.

VII. CONCLUSION

A properly balanced dataset with a higher number of observations is also necessary for a model to perform well. This will lower the variability of the model and enable the model to be trained effectively in the future if more data become available.

The old method of calculating health insurance costs is a difficult undertaking for insurance firms. Human interaction in the process can occasionally result in flawed or inaccurate conclusions, and as the amount of data grows, it takes longer for humans to calculate. The organisation can benefit greatly from the use of machine learning models in situations like these. In this study, a number of machine learning regression models are employed to forecast the price of health insurance using data from the dataset's unique attribute values. Table II provides a summary of the outcomes. Polynomial Regression is the most effective, with an accuracy of 80.97%, an R2 of 0.80, and an RMSE of 5100.53.

For insurance companies, using the outdated way of figuring health insurance prices is a challenging task. As the amount of data increases, human computation becomes more time-consuming and occasionally leads to erroneous or misleading results. Machine learning models can be used in instances like these to the organization's great advantage. This study uses data from the distinct attribute values of the dataset to anticipate the cost of health insurance using a variety of machine learning regression models. The results are summarised in Table II. The most efficient model is polynomial regression, which has an accuracy of 80.97%, an R2 of 0.80, and an RMSE of 5100.53.

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