ANALYSIS OF PERFORMANCE OF THE HOSPITALS IN USA BASED ON CMS RATINGS

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1 ABSTRACT

This project focus on making the lives of general public in United States of America easier by suggesting them the best hospital in terms of quality near their place of living or the place near where they want to relocate. This project also gives insights to hospital management to improvise the influential quality factor to increase their star ranking on which CMS grades them. The dataset used for analysis is "General Hospital Information" taken from CMS database collected by HCAHPS. The hospitals in the country were compared based on the quality factors such as mortality rate, readmission rate, safety of care, Patient experience, Effectiveness of care, Timeliness of care, and Efficient use of medical imaging of the hospital with national average score provided by Center for Medicare and Medicaid Services (CMS) that of the respective quality factor. Star rating is provided by CMS to hospitals in the range of 5 on basis of taking all quality factors into consideration.

2 INTRODUCTION

In this volatile world, where nothing is permanent, people switch over places for better job, education, climatic conditions and lifestyle. While on a search for new place to move, looking for best health care system is one of the vital searches. This project also gives insights to hospital management to improvise the influential quality factor to increase their ranking among their competitors. In our project we focus on quality aspects of the hospitals. In general quality means a grade of excellence. Quality factors used here for grading hospitals are mortality rate, readmission rate, safety of care, Patient experience, Effectiveness of care, Timeliness of care, and Efficient use of medical imaging. The dataset used for our analysis and prediction is "General Hospital Information" taken from Center for Medicare and Medicaid Services (CMS) database collected by Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS). CMS compares the quality performance of hospitals through the score graded through quality predictors with its respective national average score and categorize them in three categories. Overall rating is provided to hospital in range from 1 to 5 by taking all quality factors into consideration. Most influencing predictor is predicted by fitting the built model with data and notified. These predictors influence on overall rating lies as a scale for improvement in quality service for hospital management and as a key factor to select hospital based on quality for patients.

3 LITERATURE REVIEW

Author Joseph Futoma analysed[1-3] the reason for readmission of patient in the hospital. Readmission is a subsequent inpatient admission to any acute care facility which occurs within 30 days of discharge. For predicting this, he has considered five different conditions. The data used for this journal is provided by New Zealand Hospital system[2]. The model used here is a binary classification model. He analysed his dataset using different models such as Logistic regression, Random Forest, Deep Neural Network (DNN) and found RF as the best approach since DNN is highly complex model for this dataset. The limitation of his study is the whole model is based on ICD codes which are not standardized and not reliable one. The five conditions he considered is not sufficient to predict readmission rate in the hospitals. We have considered readmission rate as one of the factors influencing the performance of the hospital and the general assumption is if the hospital has less readmission rate, then the hospital is considered to be better hospital. Author Justin B. Dimick has predicted the best performing hospital[11-14] by considering the surgical mortality for three kinds of surgeries in any particular hospital. So, the author analyzed the mortality rate[12] in three surgical procedures, Coronary Artery Bypass Grafting (CABG), Abdominal Aortic Aneurysm (AAA) and Repair and Panneatic Resection using random effect logistic regression. Author also implemented reliability adjustment method in his model to predict the mortality rate in hospital. Limitation of this model is the dataset he considered to analyze the best performing surgery hospital is narrow in scope since he analyzed only three kinds of surgeries. So, model, we have taken has mortality rate as one of the factors which does not rely only on surgery methods but also on the various other factors in the hospital. Author Stephen P. Schmaltz made a study[7-10] in ranking hospitals based on its performance. In this study, hospital performance is a measure of lack of national standardized data[8] for common disease. Performance data of Acute care and critical access hospitals from 2004 to 2008 is collected from CMS[1] and Joint commission[7]. Author assessed the relationship between hospital characteristic and performance of Joint commission accredited hospitals with that of hospitals that were not accredited by Joint commission using X2 test for categorical variable and t-test for continuous variable. So linear regression was used to estimate a five-year change in performance at each hospital. Major limitation of this study is, specification of standardized measure might change over a time due to acquisition of new clinical knowledge. Author has considered only critical access acute care hospitals for his model, whereas we have considered all the other kinds of hospitals too. Author Daniel C. McFarland has considered demographic factors and hospital size as two predictors to evaluate patient satisfaction variance[4-6]. HVBP (Hospital Value Based Purchasing) is a measure of quality performance where patient satisfaction score is directly proportional to payment made by patient. Main objective of the study is to determine the non-randomness in patient satisfaction as determined by HCAHPS. Multivariate regression model was performed for individual dimension performance for HCAHPS and aggregate scores. The author concludes that the hospital size and primary language as the predictors which contribute high variants in HCAHPS scores. Limitation of this study is data taken from each demographic location is approximated for each hospital in that particular designs, hence the specialty hospitals were excluded from the study. This leads to high bias in the model.

4 DATA COLLECTION AND DESCRIPTION

The Dataset collected by Center of Medicare and Medicaid Services (CMS) is used for this project. The dataset contains general information about all hospitals in the United States of America, that have been registered with Medicare, including their addresses, type of hospital and ownership structure. It also contains information about the quality of each hospital, in the form of an overall rating (1-5, where 5 is the best possible rating and 1 is the worst), and whether the hospital scored above, same as, or below the national average for a variety of measures.The names and data type of the columns present in the hospital is provided below.

VARIABLE NAME	VARIABLE DESCRIPTION
Hospital overall rating	The Overall rating of the Hospital
Mortality national comparison	Measure of number of deaths occurring at a period of time in a Hospital
Safety of care national comparison	Mortality is a measure of number of deaths occurring at period of time
Readmission national comparison	Measure of patient being readmitted within specific time
Patient experience national comparison	Measure of satisfaction of the patient
Effectiveness of care national comparison	quality of service provided by the hospital to its patients
Timeliness of care national comparison	Measure of how quick the hospital responds to the patient condition
Efficient use of medical imaging national comparison	Measure of effective usage of advanced equipment
Hospital Ownership	The Specific type of owner of the hospitals

Table 1: List of predictors and response

All the 8 predictors described in the table are comparative categorical values. They take only three values

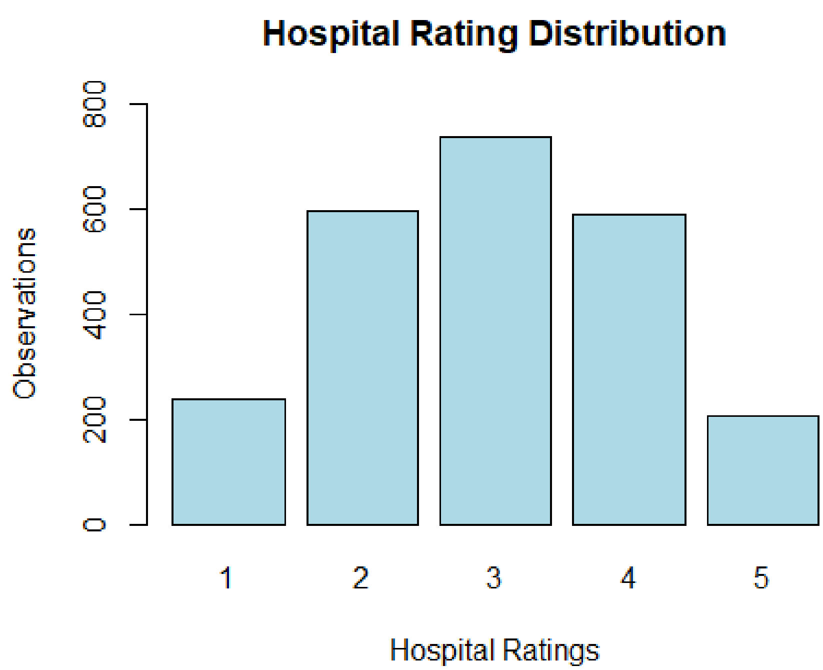
- Below the national average - 1
- Same as the national average - 2
- Above the national average - 3

All the categorical predictors have 3 levels and these 3 levels are encoded as 1, 2 and 3.
There are totally 5335 rows and 29 columns in the dataset and 2129 rows has no missing values in any of the columns.

4.1 DATA VISUALIZATION

4.1.1 DISTRIBUTION OF THE RESPONSE VARIABLE – HOSPITAL OVERALL RATING

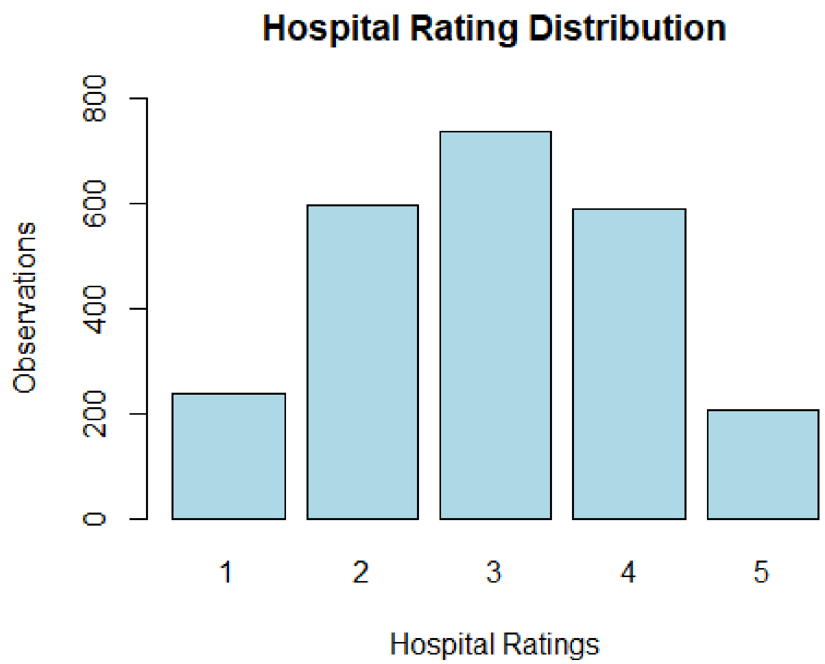
distribution.png



The results from the bar chart interprets the number of hospitals which comes under the category of 3 star is greater than the number of hospitals in other categories. The number of best performing hospital and the number of worst performing hospital based on overall rating is low when compared with the average performing hospital.

4.1.2 DISTRIBUTION OF THE RESPONSE VARIABLE – HOSPITAL OVERALL RATING

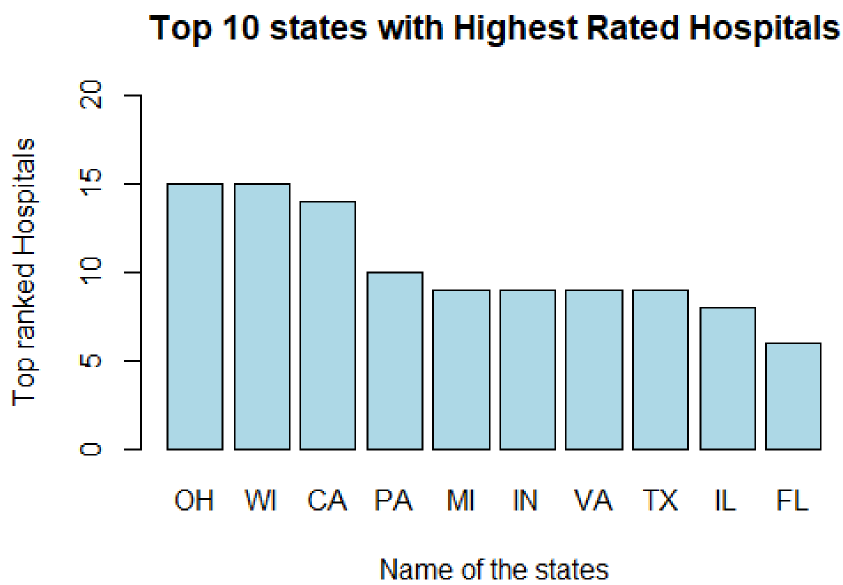
distribution.png



The Hospitals with more than 3-star rating are considered to be the best performing hospital and each state is counted with the best performing hospitals and the top 10 states with the high number of Best performing hospitals are plotted. The Texas state has 60 best performing hospitals and it is the best state in the United States of America with respect to highest number of best performing Hospitals.

4.1.3 TOP 10 STATES IN UNITED STATES WITH HIGH NUMBER OF BEST PERFORMING HOSPITALS

The Hospitals with 5-star rating are considered to be the best performing hospital and each state is counted with the best performing hospitals and the top 10 states with the high number of Best performing hospitals are plotted. The OHIO and WISCONSIN MADISON states has 15 best performing hospitals ranked hospitals.png

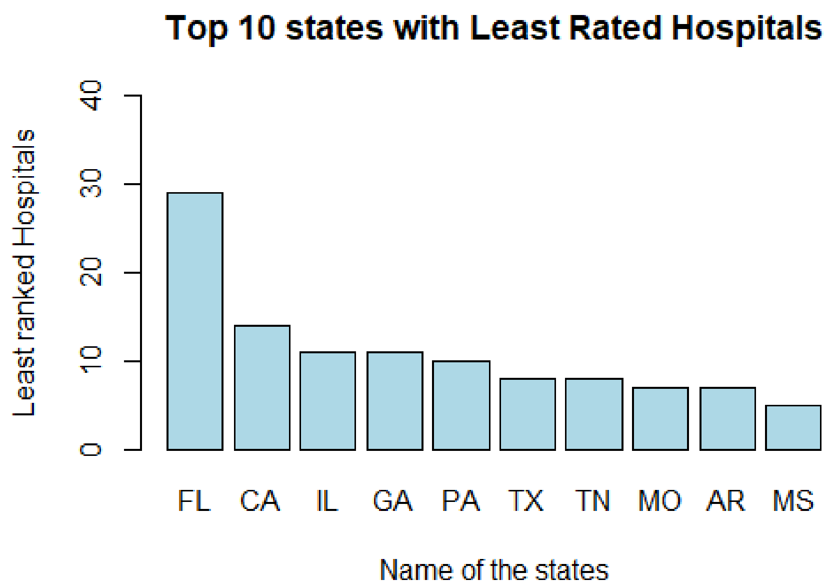


and those were the best states in the United States of America with respect to highest number of best performing Hospitals.

4.1.4 TOP 10 STATES IN UNITED STATES WITH HIGH NUMBER OF LEAST PERFORMING HOSPITALS

The Hospitals with 1-star rating are considered to be the least performing hospital and each state is counted with the least performing hospitals and the top 10 states with the high number of least performing hospitals are plotted. The FLORIDA state has 29 least performing hospitals and those were the poor states in the United States of America with respect to highest number of least performing Hospitals.

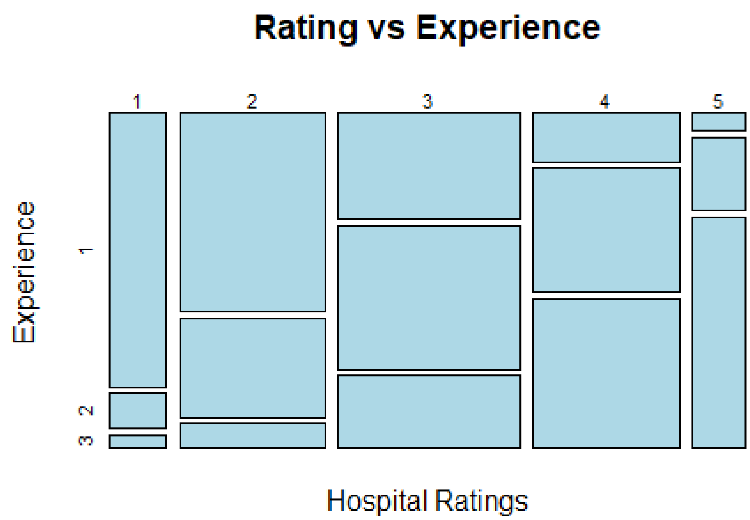
ranked hospitals.png



4.1.5 MOSAIC PLOT

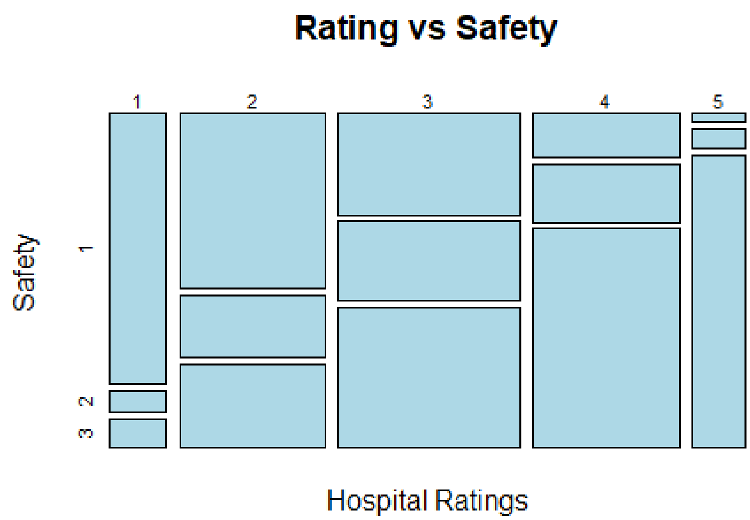
Mosaic plot is a representation of two-way frequency table where population or influence of predictors over response is clearly visualised. This plot also says whether the predictor has positive or negative influence over the response variable.
Here few of the influential factors with their response variable used are depicted using two-way frequency table.

vs Experience.png



The rating of the hospital is directly proportional to the patient experience. If the experience of the patient is good, then comparative score rated by CMS will be greater than national average (3), then there are high chance of getting high star rating (5). Similarly, if experience of the patient is bad, then CMS grade will be 1 and there are high chance of getting low star rating (1). Area occupied by the hospital rating under each grade, represents the population of hospital falling under that category.

vs Safety.png



The rating of the hospital is directly proportional to the Safety of care quality from patient feedback collected through HCAHPS data collection forms. If the Safety of care feedback of the patient is good, then comparative score rated by CMS will be greater than national average (3), then there are high chance of getting high star rating (5). Similarly, if Safety of care feedback given by the patient is bad, then CMS grade will be 1 and there are high chance of getting low star rating (1). Area occupied by the hospital rating under each grade, represents the population of hospital falling under that category respectively.

5 METHODOLOGY

The dataset we used here consists of categorical data, the general linear models however work well for continuous data, it has restriction for categorical data due to the following assumptions,

- Y range is restricted (e.g. binary, count)
- Y's variance depends on the mean

Since all general Linear Models were ruled out due to the assumption mentioned above, the Generalized Linear Model which extends its boundary beyond the restrictions mentioned in general Linear Models was considered for finding the best fit for the given categorical data. On the process of finding the best fit for the given categorical, it was found that one of the Generalized Linear Model, Logistic regression, deals with the categorical data.

5.1 LOGISTIC REGRESSION

Logistic regression is one of the generalized linear model that deals with categorical data containing binary valued response variable or otherwise called as dependent variables which are dichotomous in nature (0's/1's, True/False, Right/Wrong, Present/Absent,..).
As for as our response variable is considered, the categorical data that we have has discrete variables rather than just 0's and 1's. So, Logistic regression model was also ruled out.
However, there are other types of Logistic regression models which could fit our model in terms of discrete response variable, what we have in our data. A particular one which deals with such discrete response variables was Multinomial Logistic Regression (MLR) model.

5.2 MULTINOMIAL LOGISTIC REGRESSION

Multinomial logistic regression model can be used for response variables with multiple classes rather than dealing with only binomial class response variable. It fits for full-factorial model or user-specified model with more than two categories in response variable. These models works well in achieving a predictive model for the given categorical data and the predictor variables used can be continuous or discrete variables in order to make the required prediction for the obtained dataset. So, the multinomial logit model was included as a predictive model for the given dataset. In addition to multinomial logit model, tree-based methods also offer better model for the obtained dataset with both dependent and independent variable in categorical form.

5.3 TREE-BASED METHODS

Tree based methods looks like tree but in inverted form. It deals with both continuous and categorical variables. Based on the type of variable they were divided as follows,

- Classification trees.
- Regression trees.

These trees were commonly termed as Classification And Regression Trees (CART) model. They are commonly used when a decision has to be made out of the available predictors and response variable. The CART models are simpler models, with tree that could keep segregating or stratifying the predictors till the terminal node which will be mostly one observation at its terminal node. Residual Sum of Squares and Misclassification rate were some impurity measures used to determine the terminal nodes and splitting points. Since Regression tree deals with continuous data, we rule out that model and we approach Classification tree for the obtained dataset.

5.4 CLASSIFICATION TREE

In classification tree the recursive splitting is done by classification error rate, which is not sufficient enough to grow the tree and hence the following approaches were considered,

- Gini Index and Deviance.
- Cross Entropy.

The major advantage of using these trees were because of its interpretability and easy handling of qualitative data without the need of dummy variable. However, there are many models which were efficient enough to model the obtained data better than trees since these trees produces high variance along with the improved interpretability and reduced accuracy which should be avoided in order to predict better model. However, the high variance can be reduced by averaging the set of observations, which is not possible due to lack of access to all training dataset.
In order to reduce the high variance an approach named bagging can be carried out.
In-addition to normal classification tree recursive partitioning which was technically termed as RPART could also be used to obtain our predictive model for the obtained dataset.

5.5 BAGGING

Bagging/Bootstrap averaging is a method of averaging the observation on each node after sub setting single data into number of B different bootstrapped data. However, here on categorical observations each data split according to the class and the most occurring class is considered as overall prediction.

5.6 RANDOM FOREST

Random forest is the method similar to Bagging but instead of using the available predictors, for each split a fresh set of predictors were chosen from full predictors of the entire data. Typically, the number of predictors selected at each split is approximately equal to square root of actual number of predictors. Using this method, a number of trees were built and finally the average of the total trees formed gives the predicted response value.
This is one of optimal model for fitting the obtained data, since it can be used for prediction for both continuous and categorical data.

5.7 BOOSTING

Compared to Bagging model, Boosting deals with growing decision trees sequentially rather than fitting different copies of bootstrapped data to separate decision trees. Boosting grows tree from the information of the previously grown tree. In boosting model the following tuning parameters are used to improve the model accuracy,

- Number of trees B, too large B would over-fit the model, so cross validation was done to select appropriate B.
- Shrinkage parameter

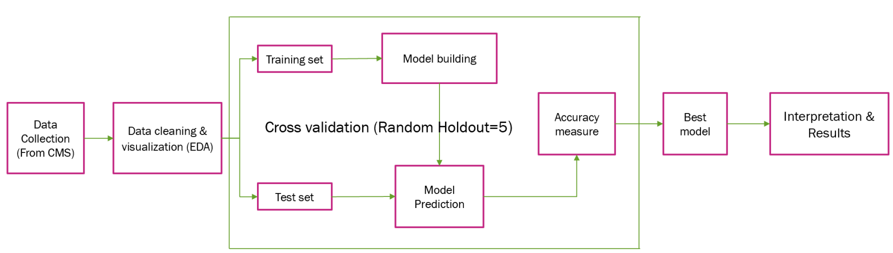
  $$\lambda$$

  , very small value of

  $$\lambda$$

  is used for very large value of B to get better performance of the model.
- Number of splits d, d=1 works well consisting of single split and resulting in an additive model.

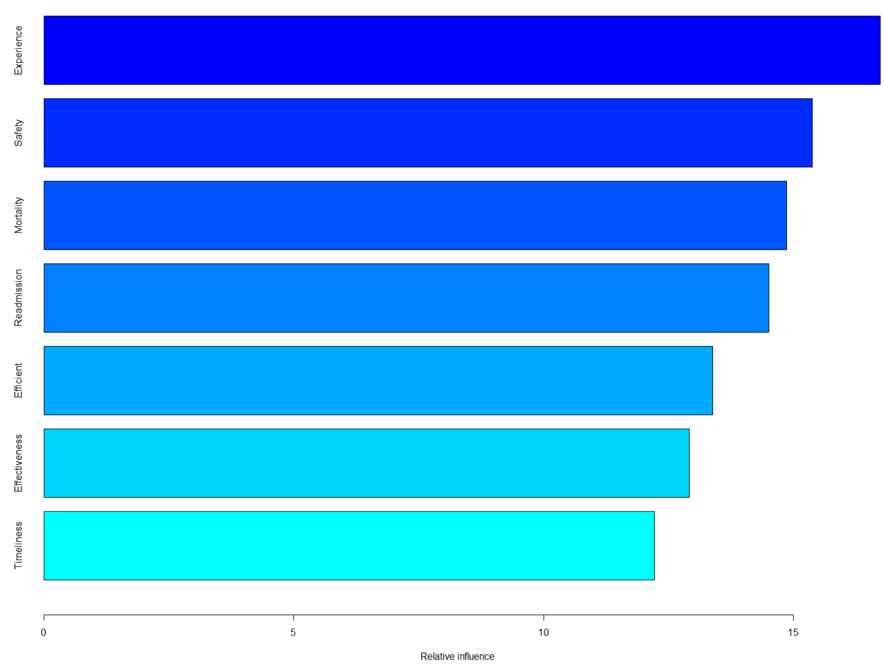
6 RESULT INTERPRETATION



ITERATION	NULL	MULTINOMIAL	CART-TREE	CART-RPART	BAGGING	RANDOM FOREST	G-BOOSTING
1	0.3150106	0.5898520	0.5602537	0.4799154	0.5729387	0.6025370	0.5856237
2	0.3382664	0.5898520	0.5306554	0.4926004	0.5517970	0.5949803	0.5940803
3	0.3213531	0.6321353	0.5348837	0.5369979	0.5602537	0.5644820	0.6321353
4	0.3150106	0.5835095	0.4926004	0.4630021	0.5750529	0.5771670	0.5940803
5	0.3128964	0.5919662	0.5295137	0.5264271	0.5391121	0.5433404	0.5919662
Average Accuracy	0.3205074	0.5974630	0.5255814	0.4997886	0.5598309	0.5763204	0.5995772

Table 2: ACCURACY TABLE

From the accuracy table, the model with highest prediction accuracy for the obtained dataset was Gradient Boosting model. In-addition to the Gradient Boosting predictive model, Multinomial logit model also provides accuracy closer to the Gradient Boosting predictive model. Gradient Boosting model provides out-of-sample accuracy of around 59.96%, which was the maximum predictive accuracy that can be acquired from the dataset obtained. The random holdout cross validation was carried out for 5 times. Predictive accuracy might be improved if the iteration count for random holdout cross validation was increased.



From the above relative influence plot from the Gradient Boosting model, the predictor of greater influence with the response variable was obtained. The graph states that the patient Experience predictor has the highest relative influence on the Hospital Overall Rating. From the relative influence plot, the second most influential predictor was Safety. Both Experience and Safety predictors plays the major role in providing the rating for the hospital. Hence the Hospital with 5-star rating will be the hospital providing the best patient

Experience and Highest Safety for the patient as per our prediction model.

7 CONCLUSION

The best model is the one with high accuracy, here for this dataset, Gradient Boosting serves the best prediction accuracy. The predictors influence on overall rating lies as a scale for improvement in quality service for hospital management and as a key factor to select hospital based on quality for patients are predicted from the model. From the relative influence graph, it is obvious that experience factor and Safety of care are the most influential predictors among the rest. In case of increasing the grade or ranking of hospitals, management should primarily look for improvising these two quality parameters.

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