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Hospital capacity influencing factors at COVID-19 pandemic in the United States

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Abstract

We analyzed hospital capacity data from the Centers for Disease Control and Prevention in the U.S. using random forecast and regression trees to estimate the confidence intervals influencing hospital capacity. The results show that inpatient beds occupied by COVID-19 patients in California and Texas were the most influenced in the United States. The mean of their inpatient beds used in November and December in 2020 would be 7500 and 9000, respectively. Lower and higher limits of 95% confidence intervals. On the other hand, we simulated inpatient beds occupied and estimated that, if the inpatient bed occupied estimated is less than 261, 262.5 beds should be the pool of UL COVID-19 inpatients with a pool of less than 3,524 beds or range of 0 -1,500 beds or larger than or equal to 3,524 beds or a range of 1,500 – 16,000 beds. Upper and lower limits of 95% confidence intervals impacted hospital capacity and the population density could influence inpatient beds. they have significant relationship each other. Other variables of increased MSE, such as upper limit COVID-19 inpatients, total inpatient beds, and staffed adult ICU beds occupied by COVID-19 inpatients were relatively important influences.

1. Introduction

Hospital capacity in the United States during COVID-19 epidemic torture caused by severe acute respiratory syndrome coronavirus 2 (SARS-COV-2) has been used by over 90%. The critical need for inpatient beds has reached unprecedented levels. Many hospitals could not ensure adequate capacity of inpatient and intensive beds to be used. For example, Los Angeles Emergency Medical supplements have been shown to be saturated. Conservation of oxygen issues in COVID-19 patients has been severe. "Adults experiencing cardiac arrest should not be transported to the hospital if they cannot be resuscitated in the field, according to the other memo" (Hauck G., 2021).

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“Arizona now has the nation’s highest rate of coronavirus hospitalization. … nearly every major hospital is almost full, prompting state officials to reopen a field hospital for the third time, … the day after Thanksgiving, a team of researchers issued a dire warning in a memo to the Arizona Department of Health Services. Failure to issue a shelter-in-place order to stave off a crisis in hospitals…” (Nirappil F., et al, 2021). Inpatient beds occupied for all patients reached 50,4432, approximately 63% for 95% Cl; inpatient Page 1 of 12 Cambridge University Press Experimental Results for Open Peer Review Page 2 of 12 beds occupied by COVID-19 reached 64,496 and nearly 8% for 95% Cl; CIU beds occupied by all patients reached 75,257 and approximately 61% for Cl (NHSN, 2020). These problems exposed out the hospital capacity that hardly beard challenges when a severe epidemiological disease happens. The Department of Health and Human Services (HHS) reported that the facilities capacity and financial concerns to treat patients during COVID-19 confronted unexpected hardship: “Patients stayed in beds longer and experienced delays in transfers while they waited for tests and /or test results” (Janke A., et al, 2021). Hence, many hospitals looked for alternate facilities. For example, vacant college clinics, college dorms, and spaces for patient care (Janke A., et al, 2021. Hospitals became miserable with the increasing number of COVID-19 inpatients who must obtain specialty beds and even isolation areas so that they can obtain effective treatment and care. On the other hand, many hospitals complained of surge costs and dropping revenues because they could not control hospital finances. A clinic volume of 80% and primary care volume of 50% were reduced (Bredon S. C., et al, 2020). The workforce for most hospitals and their ability to handle COVID-19 inpatients describe being pale in comparison without mention of the routine patient. Therefore, we must test hospital capacity in all hospitals and medical settings. To estimate how hospital capacity is impacted by important factors, the author uses hospital capacity data from U.S. Department of Health and Human Services.

2. Materials and Methods

Dataset

This paper is used to analyze hospital capacity data from Health Human Service collected in November and December 2020 and includes 1612 observations and 29 variables with 50 states in the U.S. The variables have state, collection date, inpatient beds occupied estimated, (Lower Limits (LL) patient, Upper Limits (UL) patient, percentage of inpatient beds occupied, percentage LL, percentage Ul, total inpatient beds, total LL, total UL, inpatient beds occupied by COVID-19 patients, LL COVID-19 inpatient, UL COVID-19 inpatient. percentage of inpatient beds occupied by COVID-19 patients, percentage LL COVID-19 inpatient, percentage UL COVID-19 inpatient, total inpatient beds COVID-19 inpatient, total LL COVID-19 inpatients, total UL COVID-19 inpatients, staffed adult ICU beds occupied ICU, LL ICU, UL ICU, percentage of staffed adult ICU beds occupied ICU, percentage LL ICU, percentage UL ICU, total staffed adult ICU beds, total LL ICU, and total UL ICU (Kulm M., et al, 2013).

Model descriptions

Variable importance determination

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We use a gradient boosting algorithm to calculate variable importance. It is a machine learning technique to solve prediction models. Another author's work using Bayesian structural time series models revealed variable importance. The author used the flexibility of Bayesian structural time series to show the selection of modeling trends (Xie Liming, 2021). However, today the author considered different data set, therefore, applying the gradient boosting algorithm is appropriate for these data.

We assume that the variable *w* and vector of variable *v* are associated with one another and follow a certain distribution so that we can look for function *f*(*v*) to find the most accurate output variable and obtain the function minimizes the value after establishing the loss function such as $\lambda(w, f(v))$:

$\hat{F}$ =argmin $\theta_{w,v}[\lambda(w, f(v))]$. Suppose a value w and introduce function $\hat{F}(v)$ (approximate value) so that we obtain weight summation $\varphi_k\ (v)$ and it comes from certain weak leaners, that is,

$\hat{F}(v) = \sum_{k=1}^{M} \alpha_k \varphi_k\ (v)$ +constant value. (1)

When introducing a training set such $((w_1, v_1), (w_2, v_2), \ldots, (w_n, v_n))$, and an initial function $F_0\ (v)$exists in beginning a model, we have the following expression:

$F_0\ (v) = argmin_\delta\ \sum_{k=1}^{n} \varphi(w_k, \delta)$, and then we derive the following function:

$$F_n\ (v) = F_{n-1}\ (v) + argmin_{\beta_n}\, [\varphi(w_k, F_{n-1}\ (v_k) + \beta_n\ (v_k))] \quad (2)$$

When we use the functional gradient descent with continuous situations and then change the above functions by the corresponding terms to estimate the gradient for the loss function $\nabla_{F_{n-1}}$, we can obtain the following:

$$F_n\ (v) = F_{n-1}\ (v) - \alpha_k \sum_{k=1}^{n} \nabla_{F_{n-1}}\ \varphi(w_k, F_{n-1}\ (v_k)), \quad (3)$$

$$\alpha_k = argmin_\alpha \sum_{k=1}^{p} \varphi(w_k, F_{n-1}(v_k\ ) - \alpha \nabla_{F_{n-1}}\ \varphi(w_k, F_{n-1}\ (v_k))) \quad (8) \quad (4)$$

Importance feature algorithm

Typically, we use Gini impurity by computing the mean squared error. If there exists in node *n* and it has left and right child nodes, then for the reduction of impurity $R_n$we obtain the function of the impurity I_n through the computation: $R_n = I_n - (Q_a \times I_a + Q_b \times I_b)$, (5)

where Q_a is the weight of the left child node, I_a is the impurity of the left child node, Q_b is the weight of the right child node and I_b is the impurity of the right child node.

Therefore, we can obtain that, for project tree *c* with regression feature *s*, it adds to nodes $n \epsilon N_s^c$ to make a split for regression feature s while it is separated by the total impurity reduction:

$$T_s^c = \frac{\sum_{n\epsilon\ {}_s^c} R_n}{\sum_s \sum_{n\epsilon N_s^c} R_n}, \quad (6)$$

Hence, in terms of tree c of the random forest, the total importance of s for the total trees Z is:

$$\text{Feature\_importance}_{\ c} = \frac{1}{Z} \sum_{z=1}^{Z} T_s^c \quad (7)$$

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Bagging algorithm

This is the training computing of random forest using the technique of bagging to tree learnings. Assume a training set A=$a_1, a_2, \dots, a_n$. they have response set B=$b_1, b_2, \dots, b_n$. which is bagging many times by choosing a random sample. Then they could suit for these trees and samples. Therefore, we repeatedly define bagging a couple of times for m=1,2, …, q, and averaging the predictions for all the regression trees on unseen samples ρ could obtain these samples q, when training a regression tree r_q for a_q and b_q. Thus, we have the following function:

$$\hat{r} = \frac{1}{q}\sum_{m=1}^{q} r_q(\rho) \quad \text{(James, et al, 2013)} \tag{8}$$

In addition, for the regression tree of sample ρ there is an estimate of the prediction:

$$\sigma = \sqrt{\frac{\sum_{m=1}^{q}(r_m(\rho)-\hat{r})^2}{q-1}} \quad \text{(Kulm M., et al, 2013)} \tag{9}$$

We test the hospital capacity data by which the train defines 1 ratio half of the data, and the function is the object of the variable "Inpatient_Beds_Occupied_by_COVID_19_Patients".

Regression trees

If there is a dataset *f* with samples that include some classes such as *x*, then there exists a probability of the sample with class j, and then we can obtain the Gini impurity by the summation of this probability p_j. The function is:

$$\sum_{j\neq m}^{m} p_j = 1 - p_m, \tag{10}$$

In the training process of decision trees, the trees are often determined by split standards if samples could be selected at random. The Gini index and entropy are defined as this split criterion. If coefficient q is close to 1, the Gini impurity would be an expression that cannot evaluate decision trees. Because the entropy function is $S_q(y) = \frac{1}{1-q}\left(\sum_{j=1}^{k} p\left(y_j\right)^q - 1\right)$, (11)

where p (y_j) defines the probability sets and q is any real number. Therefore, when q=2, we should obtain the Gini impurity function:

$$S_q(y) = \frac{1}{1-q}\left(\sum_{j=1}^{k} p(y_j)^q - 1\right) = 1 - \sum_{j=1}^{k} p(y_j)^2) \quad \text{(McCabe R. et al, 2020)} \tag{12}$$

Pruning of regression trees

In this section we understand that pruning is to cut complexity pruning to simplify and speed it and avoid error as pruning process. Suppose that in dataset D there are tree set $x_0, x_1, \dots, x_n$. x_0 defines the initial tree and x_n defines the root. If there exists an *m* step of pruning, a subtree *m*-1 would substitute the trees and keep a leaf node after computing trees. That is:

We assume that for dataset D, there is an error rate for tree X; then we have error (X, D), and then we removed the following subtree until minimizing it:

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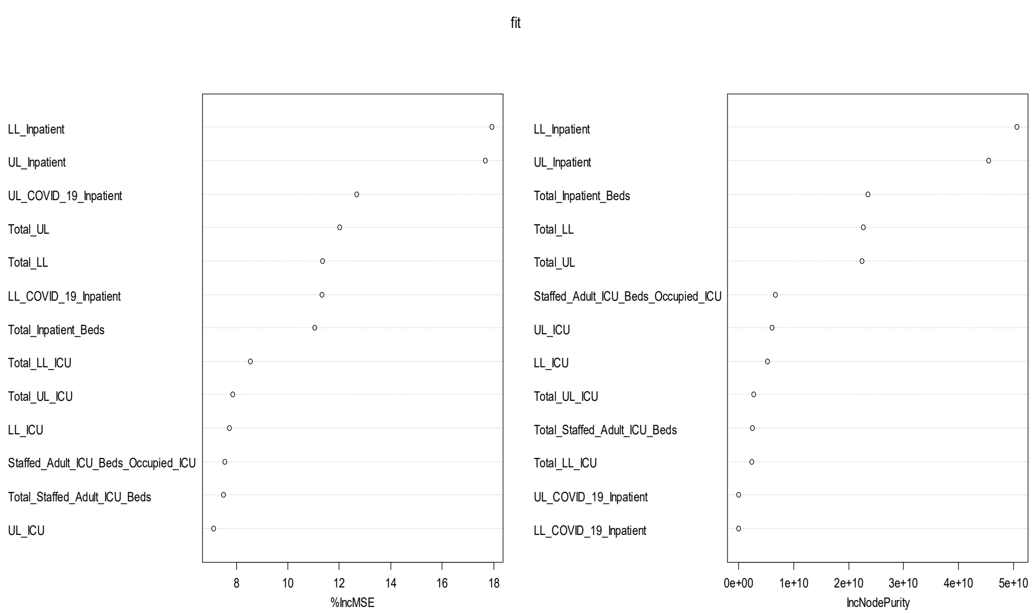
$\frac{\text{error (prune }(X,x),D)-\text{error }(X,D)}{leaves(X)-leaves(X,x))}$, where prune (X, x) is the tree that is removed by the subtree x for tree X. In general, the best tree creates the results after obtaining the series of trees and computed by cross validation. In terms of this algorithm, we test the data set hospital capacity and obtain the following regression trees.

3. Results

The relationship of hospital capacity with its variables

In this paper we would like to explore mutual relationships that some variables, such as LL inpatient (Estimated number of inpatient beds occupied by COVID-19 patients for the given state and date, lower limit, and 95% confidence interval) (Grasselli G., et al, 2020), UL inpatients (Estimated number of inpatient beds occupied by COVID-19 patients for the given state and date, upper limit, and 95% confidence interval), Percentage of LL, and the percentage of inpatient beds occupied, impact on the inpatient beds occupied by COVID-19 and inpatient beds occupied estimated. The random forest method revealed that LL patients, UL inpatients, UL COVID-19 inpatients, total UL (Schweigler, et al, 2009), total LL (U.S. DHHS, 2021), and LL COVID-19 inpatients strongly influenced the estimated number of inpatient beds or inpatient beds occupied by COVID-19 (Fig.1A and Fig.1B). Some researchers use time series methods to forecast short term emergency beds, providing some important results (Murray, Kadri, et al, 2014). Some research indicates that the ARIMAX timer series could exactly predict ICU bed utilization, with errors of 4% and 9% for 1-2 weeks (Goic M and et al, 2021).

(A)



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(B)

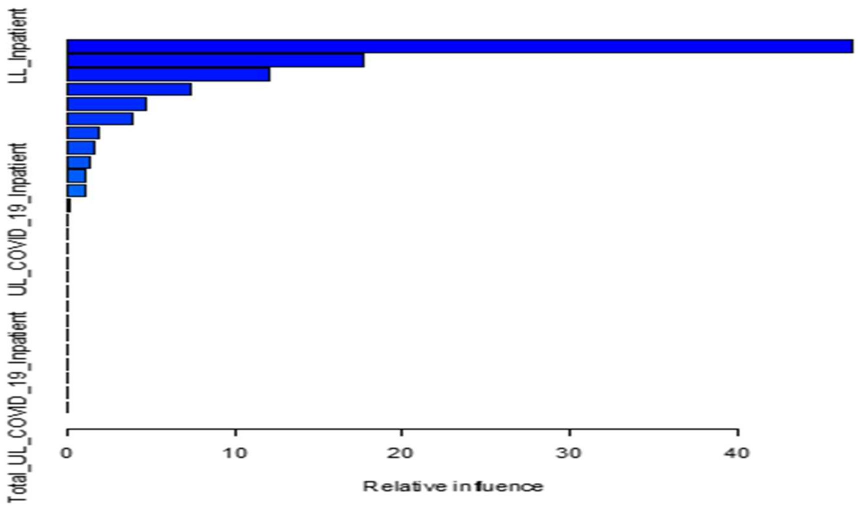

Fig. 1. The regimes of the important variables from raw data. (A) Random forecasting of statistical methods was used to select data variables. The results indicate the rank of all data variables. For %IncMSE that tests the prediction ability of mean square error for random permitted and how many MSE increase variables: top 6 are "LL_Inpatient", "UL_Inpatient", "UL_COVID_19 _Inpatient", "Total_UL", "Total_LL", "LL_COVID_19_Inpatient"; top 6 variables for IncNodePurity that assesses the variable importance by computing the splits in trees of data are "LL_Inpatient", "UL_Inpatient", "Total_Inpatient_Beds", "Total_LL", "Total_UL", "Staffed _Adult_ICU_Beds _Occupied _ ICU". %IncMSE selects variables by random permutation to compute the MSE increases. However, IncNodePurity uses Gini index to compute the splits. There is different ranking of variables. However, the former is better because it tests robust and informative assessment. **(B)** Choosing importance variables by creating a regression of generalized boosted models indicates that LL Inpatient is approximately 40% of relative influence, others are 12% of Staffed_Adult_ICU_Beds _Occupied_ICU, 12% LL_COVID _19_Inpatient, 8% Total_LL so on and so forth.

Regression trees of hospital capacity

We use tree regression to hospital capacity data. As shown in Fig.2A, the tree regression shows that, if we use inpatient beds estimated as a reference and have less than 261,262.5 beds occupied, then it influences fewer than 3,524 UL COVID-19 inpatients or more than or equal to 3,524. On the other hand, if the estimated number of inpatient beds occupied estimated is greater than or equal to 261,262.5 beds occupied, then it would influence LL COVID-19 inpatients to go to two

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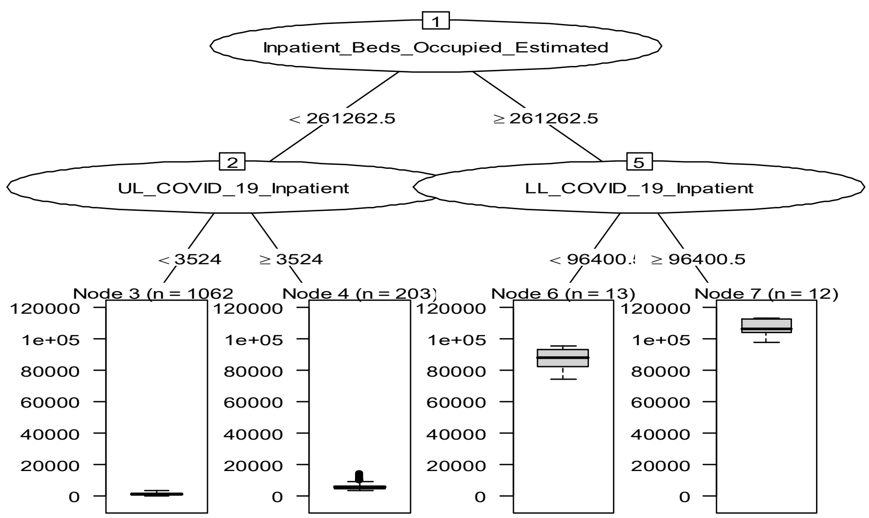
paths: first, it could be less than 96,400, or it could be greater than or equal to 96,400.5. Additionally, we could see out that some results were more detailed. If the number of UL inpatients is less than or equal to 48,994 and its p value is less than 0.001, then it would influence that UL inpatients would be less than 21,117 and p value would be smaller than 0.001, or go to another line, UL inpatient value is less than 21,117 and the p value <0.001. After that, this UL inpatient is probably to be two lines: first, it is likely to be larger than or equal to 9,526 and has p <0.001 and it influences LL inpatient smaller or equals to 4,467 or greater than 4,667… so on and so forth. Meanwhile, if UL inpatient is greater than 9,526 and p <0.001, then it splits a number of situations for LL inpatients or UL inpatients, so on and so forth (Fig.2 B). We may see out that, in Fig.2C, the characteristic in the heatmap should be the significant relationship for inpatient bed occupied by COVID-19. Also, some variables such as Total_inpatient_Beds_COVID_19 inpatients, and Total_LL_COVID_19 were impacted by Inpatient beds occupied by COVID-19.

(A)



(B)

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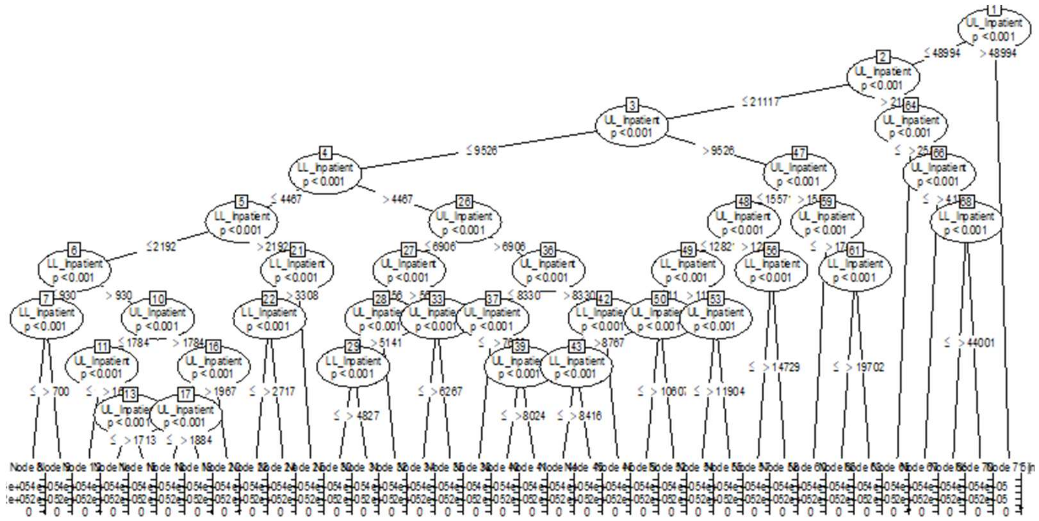

(C)

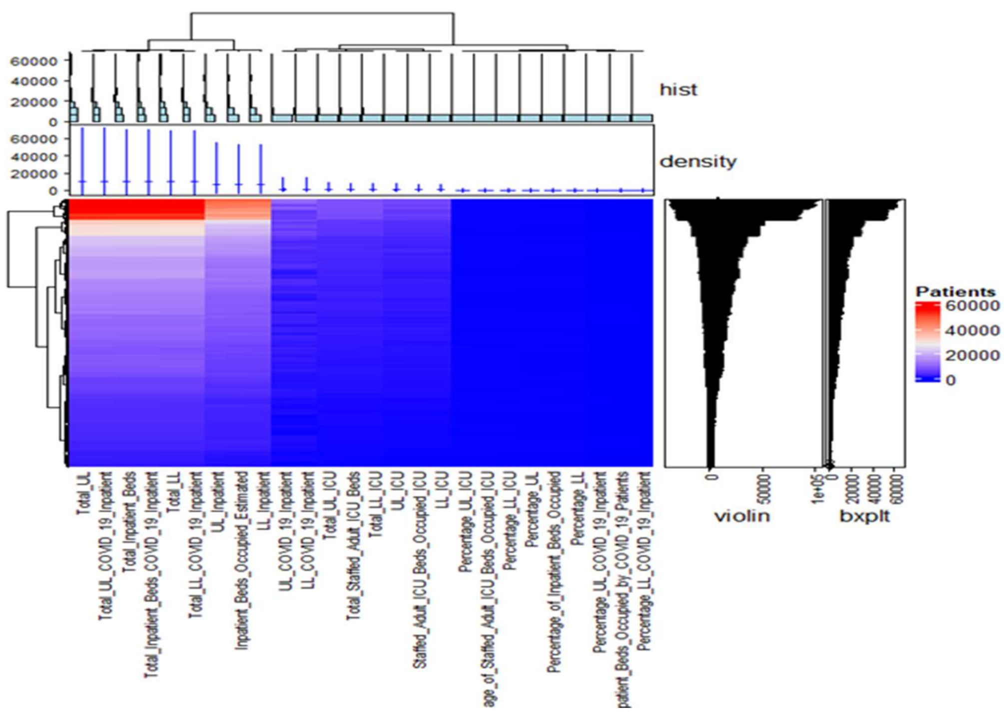

Fig.2. The regression trees of variable Inpatient_Beds_Occupied_by_COVID_19_Patients. (A) It is continuous decision trees. We could see that, when the inpatient bed occupied estimated is less than 261, 262.5 beds should be the pool of UL covid-19 inpatient with that it is less than 3,524 beds or the range of 0 -1,500; bigger than or equals to 3,524 beds or the range of 1,500 – 16,000. On the other hand, when the inpatient bed occupied estimated is bigger than or equals to 261, 262.5 beds, it should be the pool of UL one with the number of the beds < 96,400 or the range of 75,000 to 96, 000 and otherwise larger than/equals to 94,605 or the range of 100,000 to 110,000.

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(B) We continue to conduct analysis on a decision tree. For example, if the beds of UL patients with p value less than 0.001 is smaller than/equals to 47,594, it goes to two paths: one of them could be larger than 21,117 beds with p value < 0.001 that it is less than/equals to 36,678 and it is bigger than 36,678; one of them should be less than/equals to 21,117 beds with p value < 0.001, it is probably to be two cases of less than/equals to 7, 262 of UL inpatients with p values < 0.001, and then enters to LL inpatient with p values < 0.001 as smaller than/ equals to 2,053 beds and it is divided to two cases after that, so on so forth. (**C**) Heatmap of inpatient beds occupied by COVID-19 patients with other variables. It shows that 40,000-60,000 patients influence variables Total_LL,Total_LL_COVID_19_Inpatient, Total_Inpatient_Beds, Total_inpatient_Beds_COVID _19_Inpatient, and Total_LL, and Total_LL_COVID_19 _Inpatient.

4. Discussion

We explore some methods of hospital capacity data by random forests and machine learning methods. In histograms we find some states in the U.S. to have significant inpatient beds occupied. Some places are based on population densities such as CA, and TX where there is higher rate of infection. However, in some areas such as UT, inpatient beds are scarce if serious epidemiological diseases are suddenly outburst. They faced caseloads passing “20 per 10,000 population” (22). Additionally, we find that the estimated inpatient beds occupied have a significant relationship with the estimated number of inpatient beds occupied by COVID-19 patients for the lower limit, or upper limit within the 95% confidence interval. The lower limit with a 95% confidence interval has the highest relative influence on inpatient beds occupied. The Florida Department of Health reported that the mean age of patients was 69 years, and the range was 38-101 years if 67 patients were admitted to the COVID-19 unit (23). On the other hand, we also find that some variables, such as the percentage of LL COVID-19 inpatients and inpatient beds occupied by COVID-19 patients, LL inpatient and inpatient beds occupied estimated, total inpatient beds COVID-19 inpatient and total inpatient beds, and the percentage of inpatient beds occupied, and percentage of staffed adult ICU beds occupied have positively significant association. Approximately 98% of areas in the United States hospital capacity were lower than 75% on beds (24). Some countries such as Spain revealed that the lowest reduction of 1% in beds, with 299 beds per 10,0000 population (25). However, some organizations also reported that all hospital beds including adult ICUs occupied by the state were over 100% on May 1, 2020, and February 1, 2021(26).

5. Conclusion

The challenge for using machine learning techniques with hospital capacity is how to predict or forest the importance of related variables and then infer into some important factors influencing hospital capacity. Hence, the authors of this paper think it is necessary to explore machine learning methods to hospital capacity. We use random forests and regression trees to build prediction models and use a gradient boosting algorithm to calculate variable importance. This study indicates that some of their proposed variables, such as upper and lower limits of 95% confidence intervals, impacted hospital capacity.

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Author Contributions. LX, DG, and XL conceived and designed the study. LX executed statistical analysis that was verified by DG and XL. LX drafted the paper.

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