Mortality Prediction from Hospital-Acquired Infections in Trauma Patients Using an Unbalanced Dataset

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Objectives: Machine learning has been widely used to predict diseases, and it is used to derive impressive knowledge in the healthcare domain. Our objective was to predict in-hospital mortality from hospital-acquired infections in trauma patients on an unbalanced dataset. Methods: Our study was a cross-sectional analysis on trauma patients with hospital-acquired infections who were admitted to Shiraz Trauma Hospital from March 20, 2017, to March 21, 2018. The study data was obtained from the surveillance hospital infection database. The data included sex, age, mechanism of injury, body region injured, severity score, type of intervention, infection day after admission, and microorganism causes of infections. We developed our mortality prediction model by random under-sampling, random over-sampling, clustering (k-mean)-C5.0, SMOTE-C5.0, ADASYN-C5.5, SMOTE-SVM, ADASYN-SVM, SMOTE-ANN, and ADASYN-ANN among hospital-acquired infections in trauma patients. All mortality predictions were conducted by IBM SPSS Modeler 18. Results: We studied 549 individuals with hospital-acquired infections in a trauma hospital in Shiraz during 2017 and 2018. Prediction accuracy before balancing of the dataset was 86.16%. In contrast, the prediction accuracy for the balanced dataset achieved by random under-sampling, random over-sampling, clustering (k-mean)-C5.0, SMOTE-C5.0, ADASYN-C5.5, and SMOTE-SVM was 70.69%, 94.74%, 93.02%, 93.66%, 90.93%, and 100%, respectively. Conclusions: Our findings demonstrate that cleaning an unbalanced dataset increases the accuracy of the classification model. Also, predicting mortality by a clustered under-sampling approach was more precise in comparison to random under-sampling and random over-sampling methods.

Keywords: Machine Learning, Mortality, Injuries, Healthcare Associated Infections, Data Mining, Decision Tree, C5.0

Submitted: January 17, 2020, Revised: 1st, March 30, 2020; 2nd, June 11, 2020; 3rd, September 17, 2020, Accepted: October 23, 2020

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I. Introduction

Healthcare data mining has been widely used to help predict diseases and extract impressive knowledge [1], and it is commonly applied to detect early progress of diseases. These techniques can be applied to detect cancer, Alzheimer disease, transient ischemic attacks, lung nodules, coating on the tongue, diabetes, hepatitis, traumatic events, polyps, acute pediatric conditions, and Parkinson’s disease [2]. Typically, the prediction variable is unbalanced, which means that one class does not have as many records as the other. The largest class is called the majority, and the smallest class is called the minority [3]. Prediction models using unbalanced data are intricate, as long as balanced training sets are required for standard classifiers learning, such as logistic regression, decision tree, support vector machine (SVM), neural networks, and deep learning. Models often underestimate rare classes in terms of unbalanced data, while the overlapping between two classes will happen.

There are many methods to deal with unbalanced learning, such as data level, algorithm-level, and hybrid methods. In data-level methods, researchers modify the training dataset to make it appropriate for a classifier algorithm. For balance distribution, they might generate new objects for the minority group (over-sampling) and remove instances from majority groups (under-sampling). In algorithm-level methods, they tune existing learners to decrease their bias toward the majority groups, while the cost-sensitive approach is the most commonly used algorithm-level method [4]. Our aim is to predict death by applying various methods of balancing to data on hospital-acquired infection among trauma patients. In medical datasets, records in minority classes are often more vital than those of the control class. Hence, it is critical to handle unbalanced data to improve recognition rates, while it is remarkable that the balancing method depends on the context.

Trauma is a leading cause of death worldwide, while these injured patients usually acquire infections during hospitalization [5]. These infections are the principal cause of mortality and extended hospitalization for trauma patients [6]. Moreover, these types of mortality are among the top five causes of death throughout the world [7]. Trauma patients with hospital-acquired infections have a significantly increased risk of mortality, longer stays in the hospital, and increased cost of equipment or services [8,9], resulting in the nosocomial cause of 80% of in-hospital mortality [10].

Although numerous studies have been done on balancing, there has been little research on the prediction of mortality from hospital-acquired infections in trauma patients using a balanced dataset. On the other hand, context, environment, and predictor variables (such as injury severity score and injury body region) affect the prognostic model. A previous study in Shiraz Trauma Center showed that the accuracy of the traditional scoring system for predicting mortality in trauma patients is under 91% [11]. This research is one of the first works on this topic that handles unbalanced data. We compared various method of data balancing to predict death related to hospital-acquired infections in trauma patients based on a real dataset gathered in a tertiary-care teaching trauma hospital in Shiraz, Iran. This study tries to determine the best method to precisely predict the death rate for hospital-acquired infections in trauma patients. Accurate prediction models can provide useful information for decision making to manage hospital-acquired infections as a priority in terms of patient treatment.

The objectives of this study were the following:

1. Predicting death from hospital-acquired infections in trauma patients in the absence of a balanced dataset (C5.0 and CHAID);
2. Predicting death from hospital-acquired infection in the trauma patients using a balanced dataset by sampling methods (reduced data set) (C5.0 and CHAID);
3. Clustering hospital-acquired infections in trauma patients by k-means algorithms;
4. Predicting death from hospital-acquired infections in trauma patients in each cluster (C5.0 and CHAID);
5. Predicting death from hospital-acquired infections in trauma patients with SMOTE-C5.0 and ADASYN-C5.0;
6. Predicting death from hospital-acquired infections in the trauma patients with SMOTE-SVM, ADASYN-SVM, SMOTE-ANN, and ADASYN-ANN.

Many previous studies have attempted to handle unbalanced data [12-14] by adopting various approaches, such as using the right evaluation metrics, resampling the training set (under-sampling, and over-sampling), using K-fold cross-validation appropriately, ensemble different resampled datasets, resampling different ratios, and clustering the frequent class. However, no best model for these problems has been identified, while this strongly relates to techniques, models, and subjects used [2].

In 2013, Roumani et al. [15] indicated that the C5 and SVM algorithms have the highest recall and specificity, respectively, to predict death in an extremely unbalanced ICU dataset. In 2017, Gu et al. [2] reviewed class unbalanced data and provided techniques to balance data, such as data pre-
Finally, records of a total of 549 trauma patients with hos-
ital-acquired infections were selected. The values (sex, age, 
mechanism of injury, body region injured, severity score, 
type of intervention, infection day after admission, microor-
ganism causes of infections, and outcome) were chosen from 
this hospital-acquired infection management database.

This substantial clinical database tends to be incomplete, 
dirty, inaccurate, and inconsistent. Hence, for the prepara-
tion step, we removed duplicate records, found missing 
values, eliminated outliers, and revised inconsistency in the 
database. We randomly split data into training (70%), testing 
(20%), and validation (10%) sets. Moreover, on building the 
decision tree model (CHAID), we stopped when the mini-
imum records in the parent and child branches became 2% 
and 1%, respectively. In the CHAID algorithm, a $p$-value of 
at least 0.05 was considered significant.

All data were transformed to an appropriate format for 
the IBM SPSS Modeler software (IBM, Armonk, NY, USA). 
Some new features were also derived using other fields. For 
example, age was calculated by the expiring date and the 
birthdate. Next, we divided the participants into three age 
groups based on a previous study: between 15 and 45, be-
tween 46 and 64, and above 65 years [18]. Table 1 presents 
other categorized variables used.

Furthermore, we applied a decision-tree model for clas-
ification considering the study of Alonso et al. [19], which 
showed that decision-tree models are the conventional tech-
niques in mental health. Hence, the C5.0 and CHAID algo-
ritms were applied for classification. For the CHAID algo-
rum, we also used a chi-square test to decide the condition 
for splitting [20]. The following objectives were carried out 
by using the C5.0 and CHAID algorithms:

1. To predict the death rate from hospital-acquired infec-
tions in trauma patients in the absence of a balanced 
dataset (using C5.0 and CHAID);
2. To predict the death rate from hospital-acquired infec-
tions in trauma patients using a balanced dataset by 
using sampling methods (reduced dataset, C5.0, and 
CHAID);
3. To cluster hospital-acquired infections in trauma pa-
tients by k-means algorithm;
4. To predict the death rate from hospital-acquired infec-
tions in trauma patients regarding each cluster (C5.0 
and CHAID);
5. To predict death from hospital-acquired infections in 
trauma patients by using SMOTE-C5.0 and ADASYN-
C5.0;
6. To predict death from hospital-acquired infections in 
trauma patients by using SMOTE-SVM, ADASYN-
### Table 1. Detailed information about dataset used in this study

| Data variable name | Measurement Level | Data variable categories or values | Role | Definition of the data variable |
|--------------------|-------------------|-----------------------------------|------|---------------------------------|
| 1 Sex              | Nominal           | 0 = Female 1 = Male               | Input| The patient’s gender           |
| 2 Age category     | Ordinal           | 1 = "15–45" 2 = "46–64" 3 = ">=65"| Input| The patient’s age at the time of injury |
| 3 Mechanism of injury | Nominal       | 1 = Car accident 2 = Motorcycle accident 3 = Pedestrian 4 = Assault 5 = falling 6 = Struck by objects | Input| The mechanism (or multiple injury factor) that caused the injury event |
| 4 Injured body region | Nominal     | 1 = Head and neck 2 = Face 3 = Thorax 4 = Abdomen 5 = Extremities 6 = Multiple injuries | Input| ISS body region |
| 5 Injury Severity Score (ISS) category | Ordinal      | 1 = "1–8" 2 = "9–15" 3 = ">=16" | Input| ISS was calculated based on the Baker formula. The ISS severity score that reflects the patient's injuries. |
| 6 Ward             | Nominal           | 1 = ICU 2 = General or surgical ward | Input| Ward where detect nosocomial infection |
| 7 Type of invasive intervention | Nominal | 1 = Catheter vein 2 = Urinary catheter 3 = Medical ventilator 4 = Tracheostomy 5 = Trachea intubation 6 = Arterial line 7 = Surgery | Input| Type of invasive intervention performed |
| 8 Infected day     | Nominal           | 1 = Infection is less than 21 day 2 = Infection is higher than 22 day | Input| Substation detect infection date from admission date |
| 9 Hospital-acquired infected | Nominal | 1 = upper respiratory infection 2 = Urinary tract infection - other UTI 3 = Surgical site infection - SKIN 4 = Bloodstream infection 5 = Pneumonia 6 = Upper respiratory infection - symptomatic UTI 7 = Central nervous system - meningitis 8 = Surgical site infection - surgery took place | Input| Type of hospital-acquired infections |
| 10 Survival status | Nominal          | 0 = Non-survivors 1 = Survivors | Target| Survival status when patients discharge |

ICU: intensive care unit, UTI: urinary tract infection.
Table 2. Bivariate analysis of mortality predictors

|                        | Survivors (n = 464) | Non-survivors (n = 85) | Total (n = 549) | p-value |
|------------------------|---------------------|------------------------|-----------------|---------|
| Sex                    |                     |                        |                 |         |
| Male                   | 386 (85.6)          | 65 (14.4)              | 451 (100)       | 0.137   |
| Female                 | 78 (79.6)           | 20 (20.4)              | 98 (100)        |         |
| Age (yr)               |                     |                        |                 | <0.05   |
| 15–45                  | 318 (89.8)          | 36 (10.2)              | 354 (100)       |         |
| 46–64                  | 84 (81.6)           | 19 (18.4)              | 103 (100)       |         |
| >65                    | 62 (67.4)           | 30 (32.6)              | 92 (100)        |         |
| Mechanism of injury    |                     |                        |                 | <0.05   |
| Car accident           | 188 (86.2)          | 30 (13.8)              | 218 (100)       |         |
| Motorcycle accident    | 117 (88.6)          | 15 (11.4)              | 132 (100)       |         |
| Pedestrian             | 61 (82.4)           | 13 (17.6)              | 74 (100)        |         |
| Gunshot                | 8 (66.7)            | 4 (33.3)               | 12 (100)        |         |
| Falling                | 65 (74.7)           | 22 (25.3)              | 87 (100)        |         |
| Assault                | 13 (100)            | 0 (0)                  | 13 (100)        |         |
| Struck by objects      | 13 (100)            | 0 (0)                  | 13 (100)        |         |
| Injured body region    |                     |                        |                 | 0.38    |
| Head and neck          | 183 (84.7)          | 33 (15.3)              | 216 (100)       |         |
| Face                   | 17 (81)             | 4 (19)                 | 21 (100)        |         |
| Thorax                 | 54 (84.4)           | 10 (15.6)              | 64 (100)        |         |
| Abdomen                | 16 (94.1)           | 1 (5.9)                | 17 (100)        |         |
| Extremities            | 107 (88.4)          | 14 (11.6)              | 121 (100)       |         |
| Multiple Injuries      | 87 (79.1)           | 23 (20.9)              | 110 (100)       |         |
| Injury Severity Score  |                     |                        |                 | 0.18    |
| (n = 492)              |                     |                        |                 |         |
| 1–8                    | 157 (89.2)          | 19 (10.8)              | 176 (100)       |         |
| 9–15                   | 170 (82.5)          | 36 (17.5)              | 206 (100)       |         |
| ≥16                    | 94 (85.5)           | 16 (14.5)              | 110 (100)       |         |
| Ward                   |                     |                        |                 | <0.05   |
| ICU                    | 312 (80.4)          | 76 (19.6)              | 388 (100)       |         |
| General or surgical ward | 152 (94.4)    | 9 (5.6)                | 161 (100)       |         |
| Type of invasive intervention |                   |                        |                 |         |
| Catheter vein (yes)    | 86 (89.6)           | 10 (10.4)              | 96 (100)        | 0.13    |
| Urinary catheter (yes) | 113 (90.4)          | 12 (9.6)               | 125 (100)       | <0.05   |
| Medical ventilator (yes) | 102 (75)   | 34 (25)                | 136 (100)       | <0.05   |
| Tracheostomy (yes)     | 74 (87.1)           | 11 (12.9)              | 85 (100)        | 0.48    |
| Trachea intubation (yes) | 14 (70)   | 6 (30)                 | 20 (100)        | 0.06    |
| Arterial line (yes)    | 2 (100)             | 0 (0)                  | 2 (100)         | 0.54    |
| Surgery (yes)          | 74 (88.1)           | 10 (11.9)              | 84 (100)        | 0.32    |
| Infected day           |                     |                        |                 | 0.51    |
| Infected in less than 21 days after admission | 415 (84.9) | 74 (15.1) | 489 (100) |         |
| Infected in more than 22 days after admission | 49 (81.7)  | 11 (18.3) | 60 (100)  |         |
In this study, a death prediction model was applied to unbalanced hospital-acquired infection datasets. Mortality was significantly associated with age, gender, ward, urinary catheter, medical ventilator (yes), and central nervous system - meningitis (yes) (all $p < 0.05$). Table 2 depicts the detailed bivariate analysis of mortality predictors of the studied individuals.

We predicted death rates related to hospital-acquired infections for trauma patients based on the C5.0 and CHAID algorithms. The prediction accuracy of C5.0 was 70.69%, and that for the CHAID algorithm was 61.24%, as shown in Table 4. After we boosted the dataset for oversampling by C5.0 and CHAID, the accuracy reached 94.74% for C5.0; however, it remained relatively low at 79.47% for CHAID (Table 5).

In terms of clustering, we first used k-mean algorithms by setting 5 as the k value. We set the number of clusters (i.e., $k = 5$) equal to the number of principal infection diagnoses for the majority class (survivor class). Then mortality was predicted separately for each cluster. After all, the mortality prediction accuracy of this model on the clustered data was higher than the previous methods assessed in this study. Table 6 presents the findings in detail.

### III. Results

There were 549 individuals who acquired hospital infections in this trauma hospital during the study period from March 2017 to March 2018. In the studied population, 82.1% were male, and 17.9% were female; 64.5% were aged between 15 to 45 years. The total number of patients with hospital-acquired infections who passed away in the hospital was 85 (15.5%), while the remaining 464 (84.5%) survived. Table 2 shows the demographic characteristic of the studied individuals.

SVM, SMOTE-ANN, and ADASYN-ANN. The following tools were used in this study: IBM SPSS Modeler, MS Excel, SPSS, and Python (for running SMOTE and ADASYN).

We calculated the accuracy, precision, and recall for each classifier algorithm to evaluate each model separately. Previous studies found that these metrics were commonly used to assess the performance of prognostic models [21,22]. In addition, the receiver operating characteristic curve is a standard technique for evaluating classifier performance, and the area under the curve (AUC) is another typical metric for a ROC curve. Hence, we measured the AUC in this study [21].

Accuracy $= \frac{TP + TN}{TP + TN + FP + FN} \times 100$ (1)

Precision $= \frac{TP}{TP + FP}$ (2)

Recall $= \frac{TP}{TP + FN}$ (3)

### Table 2. Continued

| Hospital-acquired infected                              | Survivors (n = 464) | Non-survivors (n = 85) | Total (n = 549) | p-value |
|---------------------------------------------------------|---------------------|------------------------|-----------------|---------|
| Upper respiratory infection (yes)                       | 252 (83.7)          | 49 (16.3)              | 301 (100)       | 0.57    |
| Urinary tract infection - other UTI (yes)              | 90 (85.7)           | 15 (14.3)              | 105 (100)       | 0.70    |
| Surgical site infection - SKIN (yes)                   | 92 (85.2)           | 16 (14.8)              | 108 (100)       | 0.83    |
| Bloodstream infection (yes)                            | 82 (80.4)           | 20 (19.6)              | 102 (100)       | 0.20    |
| Pneumonia (yes)                                        | 34 (85)             | 6 (15)                 | 40 (100)        | 0.93    |
| Upper respiratory infection - symptomatic UTI (yes)    | 14 (87.5)           | 2 (12.5)               | 16 (100)        | 0.73    |
| Central nervous system - meningitis (yes)              | 17 (70.8)           | 7 (29.2)               | 24 (100)        | <0.05   |
| Surgical site infection - surgery took place (yes)     | 1 (50)              | 1 (50)                 | 2 (100)         | 0.17    |

Values are presented as number (%).

ICU: intensive care unit, UTI: urinary tract infection.

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Further, we applied SMOTE-C5.0, ADASYN-C5.0, SMOTE-SVM, ADASYN-SVM, SMOTE-ANN, and ADASYN-ANN, while the AUC for death classification using SMOTE-SVM was 1.00 and 0.99 for the ADASYN-SVM algorithm. Table 7 represents the details of calibration of SVM and the ANN algorithm shown in Supplementary Table S1.

To validate the results, we split the data into training (70%), testing (20%), and validation (10%) sets. Table 8 shows the details for the AUC and the accuracy of each approach. The highest validation accuracy was obtained by the k-means algorithm in the clustering approach, followed by the C5.0 algorithm in classification.

IV. Discussion

This research developed models to predict mortality sustained by hospital-acquired infection data set (dead vs. survived) by various methods like over-sampling, under-sampling, and clustered data set using k-means. Next, death predicted by CHAID, C5.0, SMOTE-C5-0, ADASYN-C5.0, SMOTE-SVM, ADASYN-SVM, SMOTE-ANN, and ADASYN-ANN algorithms while each one run separately. Comparing all, the prediction process by clustering method on imbalanced hospital-acquired infection was better than under-sampling and over-sampling methods.

As a part of this study, the best prediction accuracy for mortality from hospital-acquired infection based on an unbalanced dataset was achieved by using the cluster-based algorithm. Alongside our research, regarding cluster-based under-sampling methods, Yen and Lee [23] found that k-means reduces imbalance distribution, and Rahman and Davis [24] noted its significantly better performance on unbalanced cardiovascular data. Likewise, Onan [25] reported the more reliable predictive performance of clustering-based under-sampling methods.

Additionally, our results showed that random over-sampling led to significantly better prediction performance. These results are similar to the findings of Chawla et al. [21], which showed accuracy improvement after the application of a random over-sampling approach to classify a minority class. Nevertheless, random over-sampling approaches are
### Table 6. Performance evaluation for death models on the clustered dataset

| Model               | Cluster number                                      | AUC | Accuracy (%) | Class      | Precision (%) | Recall (%) |
|---------------------|-----------------------------------------------------|-----|--------------|------------|---------------|------------|
| CHAID tree          | Cluster 1 with alive data and dead data set         | 0.862 | 79.19        | Survivors  | 96.40         | 74.19      |
|                     |                                                     |     |              | Non-survivors | 57.25         | 92.59      |
|                     | Cluster 2 with alive data and dead data set         | 0.961 | 89.34        | Survivors  | 100           | 82.64      |
|                     |                                                     |     |              | Non-survivors | 78.35         | 100        |
|                     | Cluster 3 with alive data and dead data set         | 0.987 | 94.74        | Survivors  | 94.66         | 94.66      |
|                     |                                                     |     |              | Non-survivors | 95.87         | 95.87      |
|                     | Cluster 4 with alive data and dead data set         | 0.993 | 97.60        | Survivors  | 97.06         | 94.28      |
|                     |                                                     |     |              | Non-survivors | 97.89         | 98.88      |
|                     | Cluster 5 with alive data and dead data set         | 0.982 | 95.05        | Survivors  | 96.59         | 93.40      |
|                     |                                                     |     |              | Non-survivors | 93.62         | 96.70      |
| Overall             | -                                                   | 0.962 | 91.30        | Survivors  | 96.98         | 83.35      |
|                     |                                                     |     |              | Non-survivors | 82.56         | 96.78      |
| C5.0 tree           | Cluster 1 with alive data and dead data set         | 0.899 | 87.25        | Survivors  | 95.80         | 83.77      |
|                     |                                                     |     |              | Non-survivors | 76.34         | 93.46      |
|                     | Cluster 2 with alive data and dead data set         | 0.944 | 92.89        | Survivors  | 96.00         | 90.57      |
|                     |                                                     |     |              | Non-survivors | 89.69         | 95.60      |
|                     | Cluster 3 with alive data and dead data set         | 0.962 | 94.77        | Survivors  | 96.00         | 91.14      |
|                     |                                                     |     |              | Non-survivors | 93.81         | 96.81      |
|                     | Cluster 4 with alive data and dead data set         | 0.981 | 97.60        | Survivors  | 91.18         | 100        |
|                     |                                                     |     |              | Non-survivors | 100           | 96.80      |
|                     | Cluster 5 with alive data and dead data set         | 0.999 | 97.80        | Survivors  | 97.72         | 97.72      |
|                     |                                                     |     |              | Non-survivors | 97.87         | 97.87      |
| Overall             | -                                                   | 0.965 | 93.02        | Survivors  | 93.88         | 88.29      |
|                     |                                                     |     |              | Non-survivors | 90.39         | 96.04      |

AUC: area under the curve.

### Table 7. Performance evaluation for death models with SMOTE-C5.0 and ADASYN-C5.0

| Model               | AUC | Accuracy (%) | Class      | Precision (%) | Recall (%) |
|---------------------|-----|--------------|------------|---------------|------------|
| SMOTE-C5.0          | 0.97 | 93.66        | Survivors  | 96.35         | 90.95      |
|                     |     |              | Non-survivors | 91.15         | 96.43      |
| ADASYN-C5.0         | 0.95 | 90.93        | Survivors  | 89.60         | 92.89      |
|                     |     |              | Non-survivors | 92.40         | 88.91      |
| SMOTE-SVM           | 1.00 | 100          | Survivors  | 100           | 100        |
|                     |     |              | Non-survivors | 100           | 100        |
| ADASYN-SVM          | 0.99 | 98.57        | Survivors  | 98.74         | 98.39      |
|                     |     |              | Non-survivors | 98.43         | 98.71      |
| SMOTE-ANN           | 0.92 | 91.48        | Survivors  | 86.54         | 95.74      |
|                     |     |              | Non-survivors | 96.27         | 98.41      |
| ADASYN-ANN          | 0.97 | 97.46        | Survivors  | 96.86         | 98.09      |
|                     |     |              | Non-survivors | 98.08         | 96.83      |

SVM: support vector machine, ANN: artificial neural network, AUC: area under the curve.
Table 8. Evaluation metrics in training, testing, and validation sets

| Model | Evaluation metrics | Training | Testing | Validation |
|-------|--------------------|----------|---------|------------|
| Classification without the balanced data set (with CHAID) | AUC | 0.77 | 0.81 | 0.76 |
| | Accuracy (%) | 82.34 | 85.57 | 92.54 |
| Classification without the balanced data set (with C5.0) | AUC | 0.59 | 0.75 | 0.60 |
| | Accuracy (%) | 84.68 | 88.66 | 91.04 |
| Classification with balance data set (boost) with CHAID | AUC | 0.89 | 0.87 | 0.88 |
| | Accuracy (%) | 79.11 | 76.72 | 82.42 |
| Classification with balance data set (boost) with C5.0 | AUC | 0.97 | 0.97 | 0.97 |
| | Accuracy (%) | 92.65 | 94.71 | 91.21 |
| Classification with the balanced data set (random under-sampling) with CHAID | AUC | 0.64 | 0.53 | 0.74 |
| | Accuracy (%) | 59.50 | 48.28 | 53.57 |
| Classification with the balanced data set (random under-sampling) with C5.0 | AUC | 0.78 | 0.80 | 0.84 |
| | Accuracy (%) | 72.07 | 76.92 | 73.08 |
| Cluster 1 with alive data and dead data set and classification with C5.5 | AUC | 0.91 | 0.82 | 0.91 |
| | Accuracy (%) | 88.29 | 81.82 | 87.76 |
| Cluster 2 with alive data and dead data set and classification with C5.5 | AUC | 0.95 | 0.91 | 0.96 |
| | Accuracy (%) | 93.94 | 90.91 | 90.62 |
| Cluster 3 with alive data and dead data set and classification with C5.5 | AUC | 0.96 | 0.95 | 0.96 |
| | Accuracy (%) | 95.76 | 96.30 | 88.46 |
| Cluster 4 with alive data and dead data set and classification with C5.5 | AUC | 0.98 | 0.98 | 1.00 |
| | Accuracy (%) | 98.86 | 94.74 | 94.44 |
| Cluster 5 with alive data and dead data set and classification with C5.5 | AUC | 0.99 | 0.99 | 1.00 |
| | Accuracy (%) | 97.54 | 98.88 | 100 |
| Cluster 1 with alive data and dead data set and classification with CHAID | AUC | 0.88 | 0.759 | 0.872 |
| | Accuracy (%) | 81.46 | 72.73 | 75.51 |
| Cluster 2 with alive data and dead data set and classification with CHAID | AUC | 0.955 | 0.981 | 0.954 |
| | Accuracy (%) | 89.39 | 93.94 | 84.38 |
| Cluster 3 with alive data and dead data set and classification with CHAID | AUC | 0.982 | 1.00 | 0.99 |
| | Accuracy (%) | 94.07 | 96.30 | 96.15 |
| Cluster 4 with alive data and dead data set and classification with CHAID | AUC | 0.99 | 1.0 | 1.0 |
| | Accuracy (%) | 96.59 | 100 | 100 |
| Cluster 5 with alive data and dead data set and classification with CHAID | AUC | 0.99 | 0.95 | 0.95 |
| | Accuracy (%) | 98.36 | 87.50 | 86.66 |
| SMOTE-C5.0 | AUC | 0.98 | 0.84 | 0.89 |
| | Accuracy (%) | 93.69 | 79.69 | 86.52 |
| ADASYN-C5.0 | AUC | 0.90 | 0.77 | 0.69 |
| | Accuracy (%) | 86.37 | 77.16 | 75.86 |
| SMOTE-SVM | AUC | 1.00 | 0.989 | 0.98 |
| | Accuracy (%) | 100 | 92.71 | 94.38 |
| ADASYN-SVM | AUC | 0.99 | 0.89 | 0.87 |
| | Accuracy (%) | 98.57 | 81.73 | 80.46 |
sometimes inefficient because it can take a long time to prepare unbalanced data [26].

Notably, we compared these three methods for unbalanced data on a hospital-acquired infection dataset; practicing the same methods as future studies on different healthcare data will be valuable. We were interested in doing this comparison; however, the time and resources of the project were limited. Further, external validation using an alternative dataset could improve the assurance of the model; hence, we consider it a limitation in our study.

Original datasets are unclean and sparse. Therefore, the preparation steps for healthcare data take a long time. A further subject to study could be a systematic review of the handling of unbalanced data in healthcare, which is imperative to provide evidence-based approaches.

The results of this study examined two aspects of unbalanced data elaborately, the prognosis of patients with hospital-acquired infection and the need for pre-processing these types of data.

Interestingly, various balancing approaches were applied to handle the imbalance issue for hospital-acquired infection data in the trauma hospital. What stands out in these types of data is that clustered under-sampling performed better than random over-sampling and under-sampling. Overall, the issue of unbalanced data in healthcare remains from prevention to prognosis and follow-up. Hence, we suggest methods for handling unbalanced data in the healthcare domain.

### Conflict of Interest

No potential conflict of interest relevant to this article was reported.

### Acknowledgments

The authors would like to acknowledge Tiffany Armstrong from Laurentian University of Canada for proofreading and improving the language. The authors also appreciate the contribution of Trauma Research Center members affiliated with the Shiraz University of Medical Science and nosocomial supervising of Shiraz Trauma Hospital and their colleagues for data collection.

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### Supplementary Materials

Supplementary materials can be found via https://doi.org/10.4258/hir.2020.26.4.284.

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