

Supervised Learning Algorithm Comparison in Discharge Status Prediction of Trauma Patients: Empirical Evaluation

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ABSTRACT

Background: By analyzing information from trauma centers, hospitals can identify crucial performance indicators that affect budgets and present growth opportunities, potentially leading to lower mortality rates and improved health status indicators.

Objective: This study aims to determine the best-supervised algorithm for diagnosing the discharge status of trauma patients.

Material and Methods: This retrospective study used the data, collected by the Kashan Trauma Registry from March 2018 to February 2019. Several supervised algorithms, including Naive Bayes, Logistic Regression, Support Vector Machine, Random Forest, and K-Nearest Neighbors, have been evaluated for predicting the discharge status of trauma patients. The performance metrics of accuracy, precision, recall, and F-measure were used. The hold-out technique was applied to train the data.

Results: The Random Forest algorithm had the best performance among the other algorithms. The best accuracy, precision, recall, and F-measure for Gini index were 84.2%, 79.7%, 78.3%, and 76.4%, and for information gain were 84.6%, 79.6%, 76.8%, and 76.20%, respectively.

Conclusion: The results of this research showed that the supervised algorithms, with proper parameter settings, can help diagnose the discharge status of trauma patients. In addition, data balancing can help improve the performance of the algorithms. However, this claim cannot be generalized because it depends on the type of algorithm and the values of the parameters.

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Keywords

Artificial Intelligence; Supervised Machine Learning; Trauma; Trauma Centers

Introduction

The term “Trauma” is employed to characterize injuries that result in substantial physical and psychological harm [1]. Injuries can result from various causes, such as car accidents, falls, drowning, burns, self-harm, or violence toward oneself or others [1] that some of them (29%) were associated with road incidents [2]. Road fatalities in low-income and developing nations have consistently exceeded those in developed countries, as highlighted in the 2018 global status report on road safety [3].

The variation in mortality rates across different locations and countries also corresponds to disparities in the demographics of individuals most

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affected while traveling on roads. Globally, pedestrian and cyclist fatalities contribute to 26% of all deaths, while motorized two- and three-wheeled vehicle-related fatalities account for an additional 28%. Car occupants make up 29% of the fatalities, while the remaining 17% are attributed to unidentified road users. In Africa, pedestrians and cyclists constitute the largest proportion of fatalities, accounting for a significant 44% of all deaths. In SouthEast Asia and the Western Pacific, motorized two- and three-wheeled vehicle riders account for the majority of fatalities, comprising 43% and 36% respectively [4].

Conversely, the discharge outcomes of trauma patients involve various factors, including the length of hospitalization, rates of mortality, rates of readmission, and the distinction between discharge to home and discharge to healthcare facilities [5-8].

Through a research investigation conducted in the United States, an examination was made into the discharge practices at trauma centers, revealing the factors that influence post-hospital disposition. The study revealed that patient characteristics, such as race, insurance status, and injury severity, played a predictive role in determining the type of care received after hospitalization. Notably, individuals with self-pay status and Black patients exhibited a diminished likelihood of being discharged to secondary care facilities [6]. In another study, the relationship between discharge destination and the 30-day readmission rate among elderly trauma patients was explored. The findings indicated that being discharged to extended care and inpatient rehabilitation facilities independently posed risk factors for hospital readmissions within this demographic [8].

In 2009, the World Health Organization (WHO) published a comprehensive guide aimed at improving the quality of trauma treatment. The primary objective of this guide was to reduce the mortality rate resulting from trauma in low- and middle-income countries, while drawing inspiration from successful

strategies implemented in other regions [9]. Emphasized within this document was the necessity to establish hospital trauma care systems and implement quality assessment programs to ensure the provision of high-quality care. Among the various instruments utilized for quality assessment, the trauma registry was identified as the most crucial [9]. For several decades, trauma registries have played a pivotal role in the trauma systems of high-income countries, with substantial evidence supporting their numerous benefits. These registries have significantly enhanced the methods of record-keeping and are commonly utilized to demonstrate the advantages associated with trauma systems [10].

Machine Learning (ML) plays a crucial role in the healthcare industry, enabling the discovery of new knowledge and the identification of patterns to inform decision-making. This cutting-edge field aims to extract valuable and essential information from vast datasets. Analytical methods are necessary to identify crucial information for decision-making in healthcare data. The application of ML offers several benefits, including disease detection, management, and prevention, as well as cost reduction in medical care. It also assists in formulating efficient healthcare policies, developing patient recommendation systems, and creating health profiles. The healthcare industry generates significant amounts of data, so maintaining accurate patient diagnosis and treatment requires effective database management [11].

The complexity and volume of healthcare data make it challenging to extract meaningful insights about patients' health status. This data encompasses various aspects such as therapy costs, hospitals, medical claims, patients, physicians, and medical history. ML techniques are crucial for analyzing and drawing conclusions from such complex data to improve patient care and management. ML can aid in the classification of patients' disorders, assist in treatment and management, predict

hospital admission duration, and maintain accurate management information systems. Current technologies and ML approaches are helping reduce costs and identify factors contributing to diseases [12]. ML techniques have found extensive applications in the healthcare field, including predicting the development of type 2 diabetes [13], diagnosing breast cancer [14], indicating chronic diseases [15], solving multi-object fusion detection problems in e-healthcare [16], analyzing COVID-19 through clustering algorithms [17], evaluating healthcare facility performance [18], and enhancing mutual privacy in healthcare IoT systems through clustering strategies [19].

ML has also been extensively utilized in the field of trauma and injury. For example, Bruschetta et al. conducted a study comparing different ML algorithms and a classical linear regression model to evaluate traumatic brain injury patients at different time points [20].

Kuo et al. aimed to develop and validate ML models for predicting the mortality of hospitalized motorcycle riders using Logistic Regression (LR), Support Vector Machine (SVM), and Decision Tree (DT) analyses [21]. Feng et al. compared the predictive abilities of twenty-two ML models with a LR model, using performance measures such as Receiver Operating Characteristic (ROC), Area Under the Curve (AUC), accuracy, F-score, precision, recall, and decision curve analysis [22]. Another research focused on evaluating diagnostic accuracy for traumatic brain injury in elderly patients using various ML algorithms [23]. Rau et al. predicted patient deaths using LR, SVM, DT, Naive Bayes (NB), and artificial neural network models [24].

ML has diverse applications in trauma registry systems, encompassing patient classification, predictive modeling, data analysis, and system integration. For instance, ML models have demonstrated high prognostic performance and medical validity in predicting recovery post-trauma [25]. These models have also been utilized to anticipate blood product

transfusion needs in pediatric patients undergoing craniofacial surgery [26]. Furthermore, ML has been applied to identify geospatial and structural factors influencing youth violence [27] and predict the risk of prolonged mechanical ventilation for patients with traumatic brain injury [28]. Finally, ML has been applied to surgical imaging for diagnosing and treating spine disorders [29].

Research indicates that supervised algorithms are increasingly being used in trauma treatment; despite these studies, no conclusive evidence has been found.

The algorithms that showed acceptable performance were LR, SVM, and Random Forest (RF). This study focused on supervised methods to diagnose the discharge status of trauma patients because Kashan Trauma Registry data are local, and ML has not been applied to them.

The current study will address these questions at the conclusion of this study:

Among the different algorithms used to classify trauma patients, which one performed better at predicting their discharge status? How does data balancing affect algorithm performance? Which of the following indicators of accuracy, precision, recall, and F-measure is most influenced by data balancing?

Material and Methods

It is a retrospective study of patients who have received trauma treatment at the Kashan Trauma Center. A specific time frame of patient treatment at the Kashan Trauma Center is scrutinized in this study. In order to improve trauma care, supervised algorithms are employed to analyze the discharging status of trauma patients, distinguishing between those who have improved and those who haven't.

Dataset

Data from the Kashan Trauma Registry was collected between March 2018 and February 2019. We removed noisy data and outliers after data collection. We excluded missing

data, split the data, and then balanced these classes based on Synthetic Minority Over-sampling Technique (SMOTE) (Figure 1). A total of 3,930 records were obtained after preprocessing the data. We categorized features numerically and categorically (Table 1). The class label was based on the patient's discharge status, which was either improved (2,642) or non-improved (1,288).

Algorithm selection

During the learning step, a classification

model is built, followed by the classification step, a two-part procedure for classifying data (using the model to predict class labels). In the first stage, a classifier is built to describe a preset set of data classes or concepts. During the training phase of the learning stage, a classification algorithm creates the classifier by “learning from” a training set of database tuples and their associated class labels. Since each training tuple has a class label, this process is also known as supervised learning; As a result, the classifier's learning is “supervised”

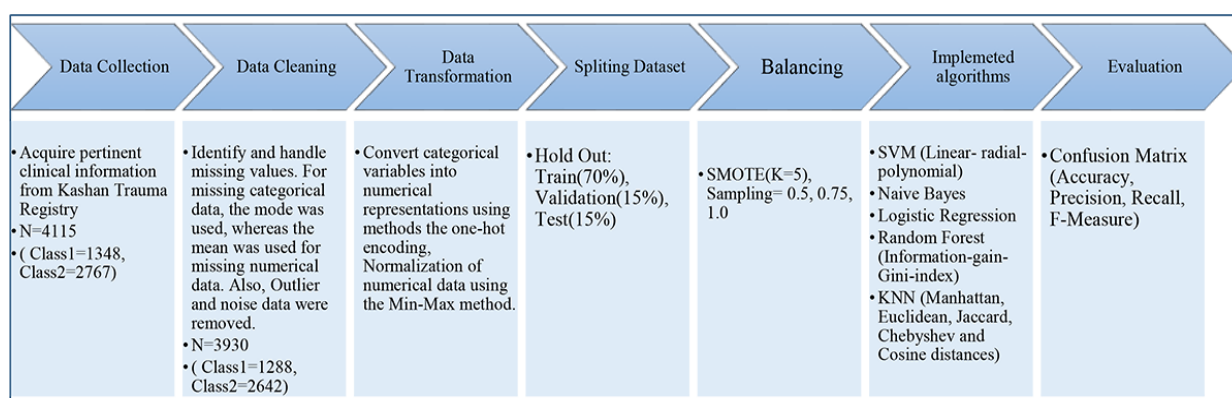


Figure 1: Implementation Framework (SMOTE: Synthetic Minority Over-sampling Technique, SVM: Support Vector Machine, KNN: K-Nearest Neighbors)

Table 1: Trauma dataset features after preprocessing

Numerical variables	<ul style="list-style-type: none"> - Age - Total expenditures - The number of days admitted - Place birth - Type of insurance - Sex - Occupation
Categorical variables	<ul style="list-style-type: none"> - Education - Type of conveyance carrying to emergency - ICD-injuries - ICD-external causes - State of discharge

ICD: International Classification of Diseases

since it knows to which class each training tuple belongs [30, 31]. The following are some descriptions of supervised algorithms used in this article.

1. SVM

SVM is a supervised ML model that can be utilized for both regression and classification tasks. A key advantage of SVMs is their use of kernels, mathematical functions that project input data into higher-dimensional feature spaces to facilitate separation between classes [32-34]. This projection into hyperspace enables SVM to construct optimal separating hyperplanes between data points of different class labels, improving generalizability and classification accuracy. By effectively separating complex and nonlinear data, SVMs can generate robust predictive models.

2. KNN

The K-Nearest Neighbors (KNN) algorithm is a nonparametric, supervised ML technique used for both classification and regression predictive modeling. Unlike parametric algorithms, KNN does not make assumptions about the underlying statistical distribution of the data. A key hyperparameter, k , must be predefined to specify the number of neighbors examined during prediction. To determine neighbors, KNN utilizes distance metrics to quantify the similarity between data points, with common choices being Euclidean distance, Manhattan distance, cosine similarity, and Jaccard distance [33, 35]. A key advantage of KNN is that it adapts to the local structure of the data, classifying new points based on their proximity to points in the training set.

3. Naive Bayes

The NB classifier is a probabilistic ML algorithm for categorical data predicated on Bayes' theorem. It relies on the simplifying assumption that predictor variables are conditionally independent given the class label - the "naive" conditional independence assumption. Despite this oversimplification, NB has demonstrated high predictive performance, especially when dealing with high-dimensional feature spaces [34, 36]. As it requires relatively few training data to estimate parameters, NB is an efficient and effective supervised learning technique for multivariate classification tasks. The algorithm calculates posterior probabilities for each class and assigns new data points to the most probable class. Though naive, this Bayesian approach has proven surprisingly robust and applicable across multiple domains.

4. Logistic Regression

LR is a statistical technique for modeling the relationship between a categorical dependent variable and one or more independent predictor variables, which may be continuous or categorical [37, 38]. It estimates the probability of particular outcomes, most often binary, based on logistic functions of the linear

predictor. LR facilitates explanatory modeling and prediction of categorical response variables.

5. Random Forest

RF is an ensemble ML algorithm that can be utilized for both regression and classification tasks. It operates by constructing a multitude of DT during training and aggregating their individual predictions, thereby improving predictive performance and reducing overfitting compared to single DT models [34, 39, 40]. To determine the optimal feature split at each node when building individual trees, RF employs metrics such as information gain, Gini impurity, and gain ratio. By training each tree on a random subset of features and data points, the resulting forest model incorporates diversity while capitalizing on averaging to enhance generalization capability. The algorithm's combination of bagging and random feature selection yields robust and accurate predictions.

6. SMOTE

SMOTE is a data preprocessing approach that handles class imbalance in ML datasets where one class is underrepresented compared to others [41, 42]. Algorithms can struggle to adequately learn patterns and properties of the minority class due to insufficient instances. To mitigate this, SMOTE synthetically generates new minority class examples by interpolating between existing minority data points in feature space [42, 43]. Augmenting the minority class via oversampling improves class balance and enhances model performance on the rare class. By compensating for skewed class distributions, SMOTE facilitates more robust learning from imbalanced data.

Implemented framework

Various supervised ML models were implemented for binary patient diagnosis, including SVM with linear, Radial Basis Function (RBF), and polynomial kernels; KNN algorithm with Manhattan, Euclidean, Jaccard, Chebyshev, and cosine distance metrics and

varying k values; NB; LR; and RF with information gain, gain ratio, and Gini impurity criteria. Algorithms were implemented using Python and Jupyter Notebook.

The dataset was partitioned into 70% training, 15% testing, and 15% validation sets using the hold-out method to enable robust model development, rigorous evaluation, and reliable performance validation. To address the class imbalance in the training data, the SMOTE was applied at sampling rates of 0.5, 0.75, and 1.0 to synthetically generate additional minority class instances.

Evaluation

A confusion matrix is a summarizing the performance of a classification ML model by tabulating its True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) predictions [44, 45]. The confusion matrix facilitates the evaluation of key classification metrics including accuracy, precision, recall, and F1-score.

The four confusion matrix categories are [44, 45]:

TP: Correctly predicted non-improved instances

TN: Correctly predicted improved instances

FP: Incorrectly predicted as non-improved when improved

FN: Incorrectly predicted as improved when non-improved

By condensing results into a confusion matrix, model performance on binary classification tasks can be visualized and quantified.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

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

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

$$F - \text{measure} = \frac{(2 \times \text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

A confusion matrix with high accuracy

indicates the model correctly classified a substantial proportion of samples [34, 44, 45]. However, accuracy alone can be misleading, especially with imbalanced datasets where one class predominates. While high accuracy is desirable in a confusion matrix, additional metrics should be examined for comprehensive model evaluation. High recall signifies the model correctly identified most actual positives, while high precision indicates few false positives were produced. A high F1 score demonstrates proficiency in both precision and recall, balanced by the F1 measure. Consequently, accuracy, precision, recall, and F1 score were calculated to evaluate the performance of the implemented algorithms. Though accuracy provides an overall measure of correct predictions, precision, and recall offer deeper insight into positive and negative classification capabilities on imbalanced data. The F1 score synthesizes precision and recall into a singular metric, facilitating model selection and performance benchmarking.

Therefore, we calculated the algorithms' accuracy, precision, recall, and F-measure.

Results

Table 2 presents the dataset partition sizes for training, validation, and testing based on the 70/15/15 hold-out split. This allocated 2,751 records for training, 589 for validation, and 590 for testing. After SMOTE oversampling of the training set at rates of 50%, 75%, and 100%, the validation and testing partitions remained unchanged while the training set increased in size as shown in Table 2. Oversampling enabled compensation for class imbalance in the training data only, while preserving untouched validation and test sets for unbiased model evaluation.

The results of executing the algorithms on the test and validation data using SMOTE are shown in Tables 3 and 4. Among the KNN models, $K=10$ yielded the best performance.

The validation data (Table 3) showed SVM achieved a maximum accuracy of 81.5% with

the linear kernel and SMOTE 100%. The linear kernel with SMOTE 75% also yielded the highest precision of 81.5%. Additionally, the linear kernel coupled with SMOTE 100% produced the top recall of 64.8% and the F1 score of 68.4%.

For KNN, Euclidean and Manhattan distances attained a peak accuracy of 80% without SMOTE. Manhattan distance without SMOTE also achieved the highest precision of 79.1%. SMOTE 100% enabled the maximum recall of 78% based on the Jaccard index. An F1 value of 63.6% was obtained using Manhattan distance and SMOTE 75%.

With NB, the best accuracy of 65.9% and precision of 46.2% resulted from no SMOTE and SMOTE 50%. SMOTE 100% generated the highest recall of 78% and F1 score of 62.1%.

LR achieved its maximum accuracy of 81% using SMOTE 50%. The same configuration yielded the top precision of 79.3%. SMOTE 100% produced the highest recall of 76.4% and F1 of 67.4%.

RF attained its best accuracy of 86.2% and precision of 82.2% with the Gini index and SMOTE 50%. Top recall of 76.4% was seen with SMOTE 100% and 75% for Gini and Information indexes. The maximum F1 of 77% occurred using the Information index and SMOTE 75%.

The test data results (Table 4) showed SVM achieved its highest accuracy of 80.8%, recall

of 67.2%, and F1 of 70.2% using the linear kernel and SMOTE 100%. The linear kernel with SMOTE 50% yielded the maximum precision of 85.8%.

In KNN, cosine distance with SMOTE 50% produced the top accuracy of 79.2%. The highest precision was 74.5% without SMOTE for Euclidean distance and with SMOTE 50% for Manhattan distance. SMOTE 100% enabled the maximum recall of 77.3% per the Jaccard index. Cosine distance with SMOTE 50% achieved the highest F1 of 65.2%.

With NB, no SMOTE yielded the best accuracy of 64.7% and precision of 48.2%. SMOTE 100% generated a peak recall of 75.8% and F1 of 57.3%.

For LR, SMOTE 75% achieved the maximum accuracy of 78.8%. SMOTE 50% yielded the highest precision of 73%. Top recall of 71.7% and F1 of 68.1% resulted from SMOTE 100%.

In RF, an equal high accuracy of 84.6% occurred with and without SMOTE 50% using the information gain index. The Gini index attained its best precision of 79.7% with SMOTE 50%. Additionally, SMOTE 100% enabled the maximum recall of 78.3% and F1 of 76.4% for the Gini index.

Discussion

Trauma and injury registration encompasses the collection of prehospital data and demographic information pertaining to the

Table 2: Partitioning of data before and after balancing

Balancing	Split dataset	The number of class 1 records	The number of class 2 records
Before Balancing	Train	908	1843
	Validation	182	407
	Test	198	392
After Balancing	Train_resampled (100%)	1843	1843
	Train_resampled (75%)	1382	1843
	Train_resampled (50%)	921	1843

Table 3: Performance of algorithms based on the Confusion matrix criteria for different balances (Validation dataset)

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Criteria	Balancing (%)	SVM					KNN			NB (%)	LR (%)	RF	
		Linear (%)	Polynomial (%)	RBF (%)	Euclidean (%)	Manhattan (%)	Chebyshev (%)	Cosine (%)	Jaccard (%)			Gini (%)	Information-Gain (%)
Accuracy	SMOTE (100)	81/5	72/5	70/3	73/9	74/5	72/0	72/8	70/6	64/2	78/6	84/4	85/6
	SMOTE (75)	83/0	72/0	71/5	76/9	77/4	72/3	75/9	73/2	64/7	78/8	85/6	85/9
	SMOTE (50)	80/0	73/3	73/5	79/6	79/6	72/2	78/6	74/2	65/9	81/0	86/2	85/6
	SOMTE (0)	79/3	73/3	73/3	80/0	80/0	72/2	78/8	72/5	65/9	80/6	85/6	85/9
	SMOTE (100)	72/4	55/4	51/7	55/9	57/0	59/6	54/7	51/6	45/3	63/7	73/9	77/1
Precision	SMOTE (75)	81/5	55/1	54/4	62/1	63/4	63/0	60/3	55/7	45/4	65/7	78/0	77/7
	SMOTE (50)	81/4	59/8	60/8	76/7	77/7	70/5	72/6	59/3	46/2	79/2	82/2	81/7
	SOMTE (0)	80/6	59/8	60/7	78/1	79/1	70/5	73/2	57/5	46/2	79/3	79/8	81/9
	SMOTE (100)	64/8	56/6	57/7	73/1	71/4	29/1	70/3	78/0	76/4	71/4	76/4	75/8
	SMOTE (75)	58/2	50/5	47/3	64/8	63/7	25/3	64/3	64/8	70/9	65/4	74/2	76/4
Recall	SMOTE (50)	45/6	41/8	40/1	48/9	47/8	17/0	49/5	52/7	63/7	52/2	70/9	68/7
	SOMTE (0)	43/4	41/8	39/0	48/9	47/8	17/0	49/5	42/3	63/7	50/5	71/4	69/8
	SMOTE (100)	68/4	56/0	54/5	63/3	63/4	39/1	61/5	62/1	56/9	67/4	75/1	76/5
	SMOTE (75)	67/9	52/7	50/6	63/4	63/6	36/1	62/2	59/9	55/4	65/6	76/1	77/0
	SMOTE (50)	58/5	49/2	48/3	59/7	59/2	27/4	58/8	55/8	53/6	62/9	76/1	74/6
F-Measure	SOMTE (0)	56/4	49/2	47/5	60/1	59/6	27/4	59/0	48/7	53/6	61/7	75/4	75/4
SVM: Support Vector Machine, KNN: K-Nearest Neighbors, NB: Naive Bayes, LR: Logistic Regression, RF: Random Forest, SMOTE: Synthetic Minority Over-sampling Technique, RBF: Radial Basis Function													

SVM: Support Vector Machine, KNN: K-Nearest Neighbors, NB: Naive Bayes, LR: Logistic Regression, RF: Random Forest, SMOTE: Synthetic Minority Over-sampling Technique, RBF: Radial Basis Function

Table 4: Performance of algorithms based on the Confusion matrix criteria for different balances (Test dataset)

Criteria	Balancing (%)	SVM					KNN			NB (%)	LR (%)	Gini (%)	RF Information-Gain (%)
		Linear (%)	Polynomial (%)	RBF (%)	Euclidean (%)	Manhattan (%)	Chebyshev (%)	Cosine (%)	Jaccard (%)				
Accuracy	SMOTE (100)	80/8	72/2	71/9	73/2	73/6	71/7	72/5	70/2	62/0	77/5	83/7	82/4
	SMOTE (75)	80/0	72/2	71/5	75/9	76/3	72/5	75/9	70/7	62/9	78/8	83/9	83/4
	SMOTE (50)	80/2	71/5	72/2	78/3	78/5	71/5	79/2	73/6	64/4	77/5	84/2	84/6
	SOMTE (0)	79/8	72/0	72/0	78/5	78/6	71/5	78/8	72/4	64/7	77/3	84/2	84/6
	SMOTE (100)	73/5	57/5	57/3	58/5	58/8	66/7	57/6	53/9	46/0	64/8	74/5	72/4
Precision	SMOTE (75)	77/0	58/7	58/1	64/0	64/5	73/1	63/9	55/4	46/6	68/9	77/0	75/5
	SMOTE (50)	85/8	60/0	62/3	74/0	74/5	74/2	74/2	60/5	47/9	73/0	79/7	78/9
	SOMTE (0)	85/6	61/1	62/0	74/5	75/0	74/2	73/9	60/9	48/2	72/9	79/7	79/6
	SMOTE (100)	67/2	66/2	63/6	69/7	70/7	31/3	68/7	77/3	75/8	71/7	78/3	76/8
	SMOTE (75)	57/6	58/1	54/5	64/6	65/2	28/8	65/2	65/2	72/7	67/2	74/2	74/7
Recall	SMOTE (50)	49/0	45/5	43/4	54/5	54/5	23/2	58/1	61/1	67/7	52/0	71/2	73/7
	SOMTE (0)	48/0	46/0	42/9	54/5	54/5	23/2	57/1	49/5	67/7	51/5	71/2	72/7
	SMOTE (100)	70/2	61/5	60/3	63/6	64/2	42/6	62/7	63/5	57/3	68/1	76/4	74/5
	SMOTE (75)	65/9	58/4	56/3	64/3	64/8	41/3	64/5	59/9	56/8	68/0	75/6	75/1
	SMOTE (50)	62/4	51/7	51/2	62/8	63/0	35/4	65/2	60/8	56/1	60/8	75/2	76/2
F-Measure	SOMTE (0)	61/5	52/4	50/7	63/0	63/2	35/4	64/4	54/6	56/3	60/4	75/2	76/0

SVM: Support Vector Machine, KNN: K-Nearest Neighbors, NB: Naive Bayes, LR: Logistic Regression, RF: Random Forest, SMOTE: Synthetic Minority Over-sampling Technique, RBF: Radial Basis Function

occurrence of the injury. The WHO has recommended the utilization of this data for the purpose of effectively managing these patients and enhancing the standard of care provided to them [9]. The quantity of data in our progressively digitalized world is experiencing exponential growth, and big data analytics represents both a burgeoning trend and a prominent area of study. The algorithms employed in ML grant access to analyses, enabling the detection and prediction of disease existence, as well as aiding medical professionals in decision-making by facilitating early disease identification and appropriate therapy selection.

Based on the outcome of the present study, the optimal outcomes were observed with SVM, RF (depth=10), and KNN algorithms in which linear kernels were used, along with the Gini index and Information Gain, as well as the Euclidean and Manhattan distances with k set to 10.

In the majority of algorithms, SMOTE with a 50% oversampling rate yielded higher accuracy compared to SMOTE with a 75% oversampling rate and SMOTAE with a 100% oversampling rate. The precision metric showed suboptimal performance with SMOTAE (75%) and SMOTE (100%) in most algorithms. Furthermore, recall, and F-score exhibited an upward trend across most algorithms as the number of balanced records increased.

Nevertheless, it cannot be definitively concluded that SMOTE had a uniformly positive or negative impact on all indicators simultaneously. In certain algorithms, the application of SMOTE appeared to be necessary, while in others, better results were achieved without utilizing SMOTE.

A notable finding in our study was that NB was the algorithm with the weakest performance, whereas RF was the algorithm with the best performance.

In the study conducted by Bruschetta et al. [20] the performance of SVM, KNN, NB, DT algorithms, and an ensemble ML approach

was compared individually. The results indicated that the NB algorithm exhibited the poorest performance when a two-class outcome (positive or negative) was employed. Similarly, in the current study, NB was also among the algorithms that demonstrated relatively inferior performance.

The ML techniques can be utilized to predict the mortality of motorcycle riders with a reasonable level of accuracy [21]. By integrating a ML model, particularly the SVM algorithm, into the trauma system, it may be possible to identify high-risk patients and guide clinical staff towards the most suitable interventions. In the current study, the SVM algorithm with the linear kernel exhibited satisfactory performance.

In the study conducted by Feng et al. it was found that the twenty-two ML models selected for outcome prediction in patients with Severe Traumatic Brain Injury (STBI) exhibited capabilities comparable to the traditional LR model. Notably, the cubic SVM, quadratic SVM, and linear SVM models outperformed LR in terms of performance [22]. In the present study, SVM with a linear kernel was identified as the SVM algorithm with the highest performance. However, the RF algorithm (using the Gini-Index) demonstrated the best overall performance among all the algorithms tested, although the results obtained with LR were also deemed acceptable.

According to the findings of Abujaber et al. [46], the performance of the SVM algorithm surpassed that of traditional classical models employing conventional multivariate analytical approaches when predicting mortality in patients with Traumatic Brain Injury (TBI). In the current study, although the SVM (linear) algorithm exhibited relatively good performance, it was not the top-performing algorithm.

Similar to the present study, the RF algorithm showed the best performance, and LR yielded acceptable results. In a study by Wang et al. [23], it was reported that

prognostication tools utilizing Adaboost, RF, and LR algorithms proved beneficial for physicians in assessing the risk of poor outcomes in geriatric patients with TBI and in guiding the selection of personalized therapeutic options.

According to the findings of Matsuo et al. [47], both the RF and Ridge Regression algorithms demonstrated the highest performance in predicting poor in-hospital outcomes and mortality in cases of TBI. Their research indicates that modern ML techniques can effectively predict the occurrence of TBI. Similarly, in the current study, the RF algorithm was identified as the best-performing algorithm among the ones tested.

According to the conclusions drawn from this study, equalizing class features can effectively improve the performance of ML algorithms. However, it is important to note that the choice of algorithm, its parameters, and the quantity of added samples can directly impact the algorithm's performance. Therefore, relying solely on accuracy values in scenarios with imbalanced data may not be feasible. The findings of this research suggest the potential use of supervised algorithms for predicting the discharge status of trauma patients.

Despite the advantages of this study, there are some limitations to consider. First, the data used in the study is retrospective, and it was not possible to access the paper records to verify the quality of the electronic data. Additionally, in future research, alternative classification methods with different parameters, ensemble learning techniques, and clustering approaches could be explored to improve the diagnosis of discharge status for trauma patients.

Conclusion

The registration of health data in health systems can benefit from the application of ML techniques, which can help health stakeholders uncover hidden knowledge in the

data and support them in decision-making and health prediction. While supervised algorithms are valuable in diagnosing the discharge status of trauma patients, the impact of data balancing on accuracy measures such as Precision, Recall, and F-measure varies across different algorithms. These measures do not consistently show a trend of increase or decrease. Therefore, optimizing the performance of algorithms requires appropriate parameter settings. Balancing imbalanced data may improve algorithmic performance, but it is important to note that the effectiveness of this approach depends on the specific algorithm and the parameter values assigned to it. In summary, the success of data balancing in enhancing algorithmic performance hinges on carefully considering algorithm characteristics and configuring parameters accordingly.

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Authors' Contribution

AM. Nickfarjam, ZA. Kohzadi, M. Mahdian conceived and designed the analysis, collected the data, and contributed to the revision. AM. Nickfarjam, ZA. Kohzadi, ZE. Kohzadi conceived and designed the analysis, contributed data or analysis tools, performed the analysis, wrote, revised, and edited the manuscript, and was involved in the investigation and methodology. AM. Nickfarjam, ZA. Kohzadi, ZE. Kohzadi, F. Holl, L. Shokrizadeh Arani, and M. Mahdian collectively conducted a review of related works in the field of trauma and contributed to writing, editing, and revision tasks. All authors participated in the review and approval of the article.

Ethical Approval

This article is based on a research project that received support from the Kashan University of Medical Sciences, with research approval code 401098 and ethics code IR.KAUMS.NUHEPM.REC.1401.056. The methods employed in this study were carried out in accordance with the applicable guidelines and regulations of the ethical committee at Kashan University of Medical Sciences.

Conflict of Interest

None

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