Prediction of Mortality in Trauma Patients with Insufficient Training Data Using Deep Learning

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Abstract: The trauma victim is in an emergency phase and needs immediate help. This phase is very sensitive to time, considering that the most common trauma is bleeding. The patient will die if the help is not given immediately. Trauma is comprehended as a degree of severity. Medical treatment is given based on this degree. However, methods to measure the degree currently used require quite some time, which risks the patient's life. This study proposes a standardized measurement of the degree of trauma and predicts patient mortality based on selected features. We select and discard medical data that does not affect the degree of trauma. The data becomes simple. The primary trauma dataset was collected from the emergency room at Hasan Sadikin Hospital in Bandung, Indonesia. The data has 19 features and two prediction classes for mortality, namely death and life. Data mining techniques were carried out to provide a sufficient dataset so that the algorithm could work optimally. This study performs several steps of data pre-processing as follows: cleaning, correcting, and augmenting the dataset in order to obtain significant results. Then reduce some features in light of the fact that some have overlapped. We implement a long-short-term memory deep learning algorithm to build a mortality prediction model. Although there were inconsistencies in the data and an insufficient amount, the result was promising. Features become concise and comprehensive. It was accurate up to 92% of the time and took less time than the other methods.

Keywords: Inadequate; severity; LSTM; mortality; patient; trauma

1. Introduction

Medical informatics trauma is rarely a result of research, even though the outcome of this field can help medical personnel analyze various medical cases. The medical trauma dataset is unique, structured, and varied. The number of them increases progressively since trauma happens almost every day. Most trauma cases are caused by traffic accidents (70%) [1].

Traffic accidents involving motor vehicles, bicycles, pedestrians, and recreational vehicles account for 49% of all the TBI [2]. In addition, the use of firearms, sports, and other recreational activities are other causes of traumatic injury [3]. According to the World Health Organization (WHO), at least 5 million people die from trauma each year [4] [5] [6] [7], with 90% of these deaths occurring in developing countries. Traumatic injuries are more common in young men (75%), which will eventually cause a burden to society or the government because

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they will suffer from disability for the rest of their lives. Trauma patients (50-60%) die before reaching the hospital [8]. In patients suffering from severe multiple trauma injuries, their level of mental and physical health and quality of life will decline post-injury [9] [10]. Head injuries and Injury Severity Scores (ISS) are known to be independent predictors of higher mortality in some trauma patients [11, 12].

Chest trauma is one of the most common traumas. Approximately one-third of some trauma patients develop a chest contusion complication [13]. In 20% of patients with trauma, chest injury or concomitant other injuries, approximately 25% of cases lead to death [14]. Falls, drowning, and burns cause the second, third, and fourth major causes of death [15]. As well, trauma also occurs in the pelvic ring. Disruption of the pelvic ring occurs due to blunt force injuries. It is often found in patients with multisystem trauma.

Patients with pelvic injuries need immediate help because this part is closely related to the hinge movement. There is excruciating pain when this part is accidentally moved. The severity of hip fractures in trauma victims was determined based on a full-body CT scan and AO/OTA section classification. The classification results are useful for the interpretation of the radiologist in analyzing the fracture and the severity of the trauma. Several studies detected different hip fractures on CT scans with high specificity using the Faster-RCNN model [16]. It is then interpreted using a structural model from clinical best practice to infer severity. The implementation of the machine learning algorithm is used to determine the possibility of cracks that occur.

In many cases of trauma, the health worker is hardly able to save the patient's life, even though the treatment taken must be in accordance with the degree of trauma [17]. It takes a long time to find out the degree of trauma. Some guidance is needed, such as ISS (Injury Severty Score), injury mechanism, RTS (Revised Trauma Score), and so forth [18]. The certainty of facts, diagnoses, and solutions are explored from manual calculations and health workers' experiences. In order to save time and increase accuracy, it is important to standardize the measurement (scoring) of trauma.

Most of medical informatics research uses Neural Network algorithms to answer medical problems. The Neural Network is one of the best machine learning algorithms and has been tried in various fields of research. This algorithm is capable of imitating the way the human brain works. Thus, it is frequently implemented in various fields of science. The Neural Network Algorithm can solve difficult cases, such as analyzing the patient's heart rate [19], measuring the ability of human brain function based on ECG data [20], and detecting the condition of the baby in the fetus [21].

Predicting the risk of adverse events in trauma patients has so far been limited to cross-sectional and static models, including rare side effects such as nonaccidental trauma (NAT), as well as identifying optimal points for intervention in the ED. The development of an iterative neural network model of the patient's trajectory through the "diagnostic space" using long short-term memory cells (LSTM) [22]. Explicitly modeling the sequence of patient diagnoses over time, and "attention" mechanisms to identify prognostically significant events in the patient's trajectory.

A new feature of neural networks, called Deep Learning, which makes this algorithm learn deeper, is currently being developed. One of the most popular algorithms in deep learning is Long Short Term Memory (LSTM). LSTM has a memory gate and a delete gate that are capable of solving problems for numerous data and high dimensional features. This algorithm can memorize which pieces of data can be deleted and retained. One of the important LSTM parameters is the sequence length, or window size. LSTM can extract abstract features from long sequences of data. The strong point of LSTMs is the ability to remember long term sequences, which is difficult to achieve with traditional feature techniques. For example, data is processed with graduality according to the window size. Therefore, the data could lead to a loss of information by describing values over a long period of time. On the other hand, using all values as input could give better results. LSTM can use a larger data size and use all the data as input. Then LSTM builds a deep network. The first layer is the number of units, followed by another layer with the same number of units (hidden layer). This study predicts the mortality of patients in emergency and critical conditions. The goal is to give an immediate recommendation to a health worker on the degree of trauma severity. Medical treatment could be gotten faster by doing so. People who read the literature say that more than half of the deaths can be prevented if they get an early diagnosis and get the right treatment [23].

2. Related Works

Prior research in Senegal [1] investigated the causes of trauma at a hospital. Its data comprised patients who had a major complaint related to a traumatic injury. Features included in data abstraction were date of incident, time of arrival, time of injury, age, sex, mechanism of injury, injury suffered, and disposition. Approximately 105 trauma datasets were obtained from the data. Another study used machine learning methods to predict mortality. The instance is brain trauma where the person is in an emergency condition [24]. The characteristics are gender, age, pupil reactivity at presentation to the emergency room, Glasgow Coma Scale (GCS), presence of hypoxia and hypotension, computed tomography findings, trauma severity score, and laboratory results. Mortality was predicted to occur over a period of 14 days with an accuracy of 0.906. GCS on arrival, GCS before going to the hospital, age, and pupillary reactions were the most important predictors.

Other studies have tried to compare the machine learning algorithm with other algorithms to find the best performance to detect and classify brain injury data (EEG) [25], [26], [27]. They used decision trees, random forests, rule-based, K-Nearest Neighbor, neural networks, and deep learning convolution neural networks (CNN). CNN showed a best precision value of 0.868. The experiment was conducted again with the regression algorithm, but the precision fell to 0.72.

In the case of trauma, medical professionals need to know how long the patient can survive according to his medical characteristics, McGonigal et al. [28] predicted the likelihood of survival in trauma patients. They discussed further how to build a neural network architecture that could do more work in assessing the survival of existing trauma scoring methods (Characterization of Trauma Severity, TRISS, and Trauma and Injury Severity Score). The goal was to cut down on deaths and make better use of resources, as shown by studies that predicted a wide range of conditions, such as hemorrhagic shock, sepsis, and the need for intervention to save a patient's life (LSI).

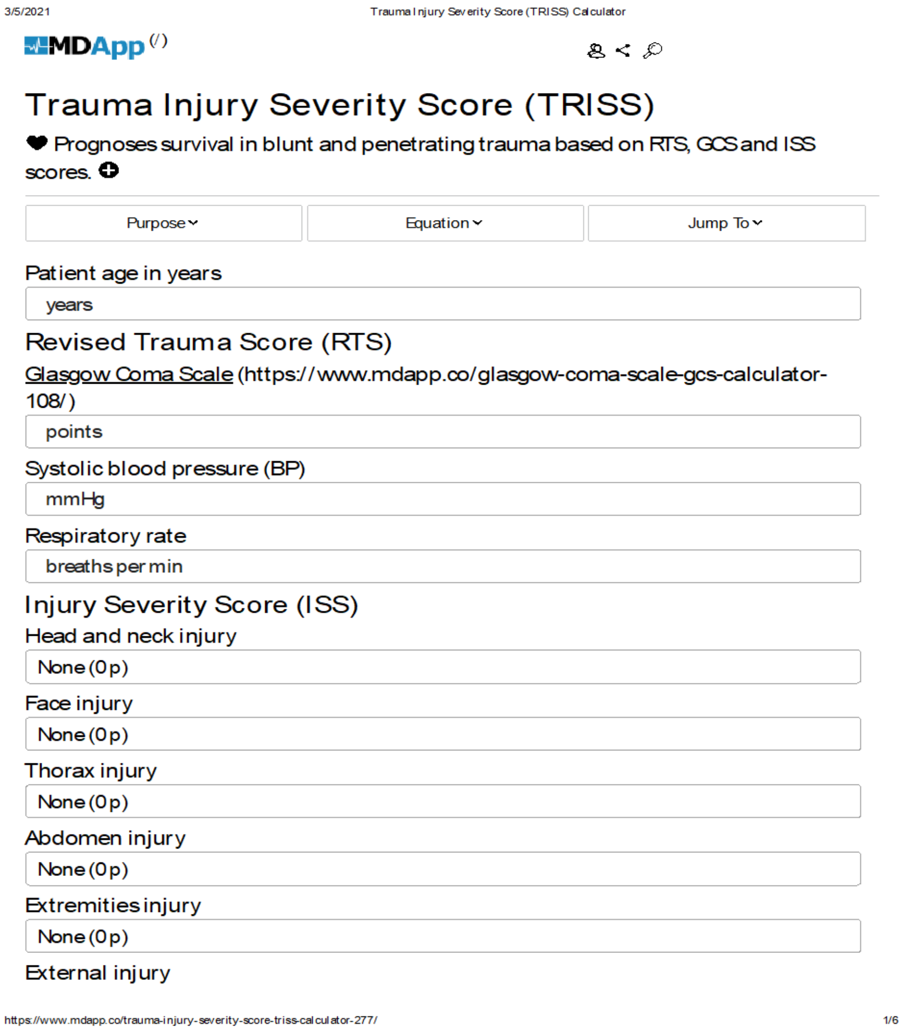
The Trauma Severity Score is an international assessment method for traumatic injury patients. A brief synopsis of the ISS follows:
The body is divided into 6 regions:

1. Head / Neck: (Cerebral contusion, Single NFS, Internal carotid artery, complete transection) ,
2. Face (Fractured tooth),
3. Chest (Rib fractures left side, ribs 3-4),
4. Abdomen (GR III splenic laceration 3),
5. Extremities (Fractured tibial shaft; open), and
6. Outside (Overall abrasions).

While Abbreviated Trauma Scale scores from 1 to 6 are given for each injury, 1 = minor, 2 = moderate, 3 = serious, 4 = severe, 5 = critical, 6 = maximum. In this study, the score is simplified to be two classes because the data collected does not provide a class that matches the recommendations above. As trauma cases are increasing, many models have been developed to predict trauma risk. To help people deal with traumas in the past and future, they used it as a risk assessment tool [29, 30], [31]. In recent years, deep learning has become very useful for making more accurate prediction models. This is because technology has been getting better, there is more data available, and we need to process and analyze a lot of data.

Two methods for measuring are used by medical workers nowadays. However, each of them has limitations and incomplete variables. One of the current methods is to fill out the manual form. The form can be seen in Figure 1. Figure 1 is the application form for the trauma severity score. The application works like a calculator. A health worker fills out the form:

- Age
- RTS (Revised Trauma Score)
- Systolic Blood Pressure (BP)
- Respitatory Rate
- Injury Symptoms Scorre (Face, Thorax, Abdomen, Extremities, External Injury).


3/5/2021 Trauma Injury Severity Score (TRISS) Calculator

MDApp (/)

Trauma Injury Severity Score (TRISS)

Prognoses survival in blunt and penetrating trauma based on RTS, GCS and ISS scores.

Purpose | Equation | Jump To

Patient age in years

years

Revised Trauma Score (RTS)

Glasgow Coma Scale (https://www.mdapp.co/glasgow-coma-scale-gcs-calculator-108/)

points

Systolic blood pressure (BP)

mmHg

Respiratory rate

breaths per min

Injury Severity Score (ISS)

Head and neck injury

None (0 p)

Face injury

None (0 p)

Thorax injury

None (0 p)

Abdomen injury

None (0 p)

Extremities injury

None (0 p)

External injury

https://www.mdapp.co/trauma-injury-severity-score-triss-calculator-277/ 1/6

Figure 1. The Trauma Injury Severity Score (TRISS) calculator (https://www.mdapp.co/trauma-injury-severity-score-triss-calculator-277/)

Some important values are not present in this application, like hemoglobin, erythrosyt TDS, GCS, etc. On the other hand, the application works but does not consider the previous data. Another measuring tool is a form that is filled out manually. Medical workers calculate using a calculator or by feeling. To some extent, it is true to say that the feeling can be right if done by an experienced doctor. If there is no doctor available, it will be a big problem because the patient requires appropriate care immediately.

This study proposes a standardized measurement of mortality in trauma patients using the LSTM deep learning algorithm. We use a prediction method adapted to the dataset.

3. Method

During the COVID-19 pandemic, which began in March 2020 and ended in September 2020, primary trauma data was collected in the Hasan Sadikin hospital emergency room (ER). During this period, the emergency room installation was exclusive for COVID-19 treatment, so it was difficult to collect trauma data. Thus, this study utilized data mining technology to manage and process limited data [32]. Data mining is also used to normalize inconsistencies and missing values. The stages of the data mining preprocessing were carried out in this study.

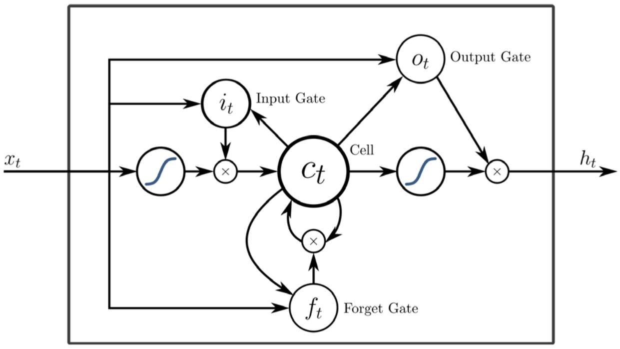


Figure 2. The architecture of Deep Learning Long Short Term Memory (https://subscription.packtpub.com/book/big_data_and_business_intelligence/9781788992596/5/ch05lvl1sec33/long-short-term-memory)

At the end of preprocessing, the data is trained using the Long Short Term Memory algorithm. Figure 2 shows the sequential input of the LSTM. Therefore, the training process is highly influenced by time. The last stage, takes a long time for the next output. LSTM can overcome this by learning when to remember and when to forget, through memory gates and forget gates. For example, if the forgotten gate has a value of 0.8, in 3 time units this value becomes: $0.5^3 = 0.512$, or 50% of the information is forgotten.

Mortality prediction research is not limited to trauma patients. In the intensive care unit, there are many patients who are critically ill and in danger of dying. Patients with other infectious diseases and those who have been hurt [33] can predict who will die, which is helpful for figuring out the order in which ICU patients are treated.

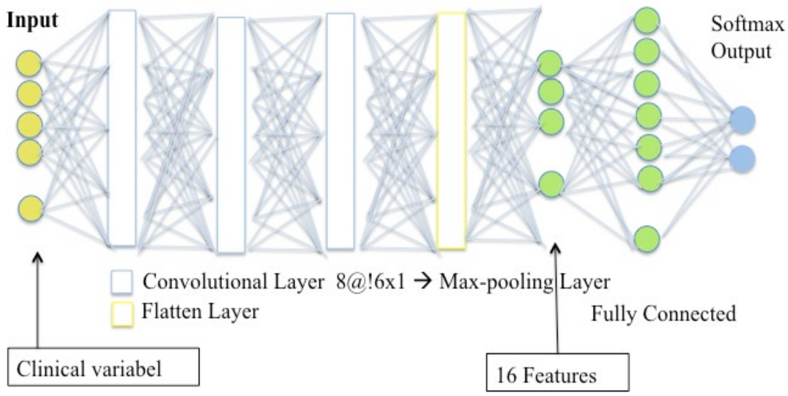


Figure 3. Architecture of Convolutional Neural Network for Mortality Prediction of Septic Patients in the Emergency Department [33]

A deep learning (LSTM) architecture was developed for the prediction of mortality in sepsis patients and compared with several machine learning algorithms and two sepsis screening tools: Systemic Inflammatory Response Syndrome (SIRS) and rapid sepsis-associated organ failure assessment (qSOFA).

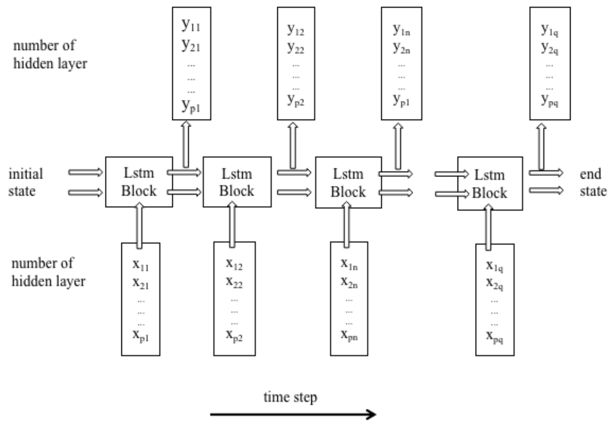


Figure 4. The architecture of LSTM for predicting mortality Trauma Patient

There were 53 clinical variables achieved by Convolutional NN, The architecture of Convolutional NN is shown in Figure 3. There were three convolutional layers in the architecture, and each convolutional layer had eight filters at a size of 16 × 1. The activation function of the convolutional layers is the ReLU.

This study uses long and short-term memory. We use 100 block LSTM, a 0.005 learning rate, and 10 epochs for 15.943 clinical data points. The configuration as seen in Figure 4.

A. *Mining for Medical*

The trauma data in this study consist of 12 features as shown below:

1. Abbreviated Injury Scale
2. Injury Severity Score,
3. The static component of trauma.
4. Trauma Score
5. Revised Trauma Score simplification of TS.
6. Mangled Extremity Severity Score
7. Glasgow Coma Score.
8. CRAMS
9. Pediatric Trauma
10. Trauma Score-Injury Severity Score
11. Severity Characterization of Trauma
12. MGAP/ GAP is another simple trauma scoring system.

This research is close to the Triss method. We use the Triss scoring method because Triss adopts most of the important trauma values.

The number of primary data records collected was 3.600, with 18 features, and two classes, namely dead and alive. The number of data deaths is 637, while the number of live data is 2.963. As mentioned earlier, collected data is very limited. Classification tasks in unbalanced datasets are defined when the amount of data is not evenly distributed among the available classes. Data mining algorithms that have large amounts of data, force data mining algorithms to lean their performance in that direction. Overcoming unbalanced dataset classification includes common problems with Big Data classification. It is necessary to carry out experimental analysis to study the behavior of the unbalanced dataset preprocessing technique and to carry out discussion about the related scenarios to be carried out. In general, the algorithm only looks at simple accuracy when it comes to the percentage of data that is classified into the correct or incorrect class.

Table 1. The snippet primary data of patient trauma in Hasan Sadikin Hospital

No	Feature	Number of Data						
		1	2	3	4	5	6	..
1.	Age	63	30	53	33			…
2	HR	95	90	-	92	92	90	…
3	T	120/80	110/70	-	120	120/70	110/70	…
4	Leukosit	13 K	18.6	15.5	42.5	42.5	17.9	…
5	Eritrosit	-	-	-	-	-	-	…
6	HB	36	16.5	-	13.2	13.2	13.4	…
7	Trombosit	206	279	204	354	300	254	…
8	INR	-	-	0.94	1.01	1.01	0.92	…
9	GDS	232	-	125	195	180	175	…
10	Na	133	-	125	195	134	138	…
11	K	3.3	-	4.1	2.9	2.0	3.8	…
12	Cr	0.74	-	0.67	0.07	1.06	0.95	…
13	SGOT	29	-	17	117	110	49	…
14	SGPT	49	-	13	81	71	30	…
15	GCS	15	15	15	11	11	14	…
16	ISS	-	-	-	59	49	21	…
17	RTS	-	-	-	6.9	-	-	…

In the case study of skewed distributions, the minority class has the minimum effect on the overall accuracy. As a result, the performance of the majority class can dominate the performance of the minority class. For example, if given a dataset having a ratio of 98:2, which is commonly found in the real world, then the accuracy can reach 98%. Therefore, the dataset had to be augmented by multiplies in order to get a good prediction model. Table 1 shows the snippets of trauma clinical data taken from the emergency room of Hasan Sadikin Hospital.

1) Data Cleaning

Primary data is not always ready to be processed, and so is trauma data. Data defects such as missing values and inconsistencies were found in the dataset. Medical staff used their experience to fix the missing values and inconsistencies in the data. Table 1 is an example of primary data collected with its features and classes.

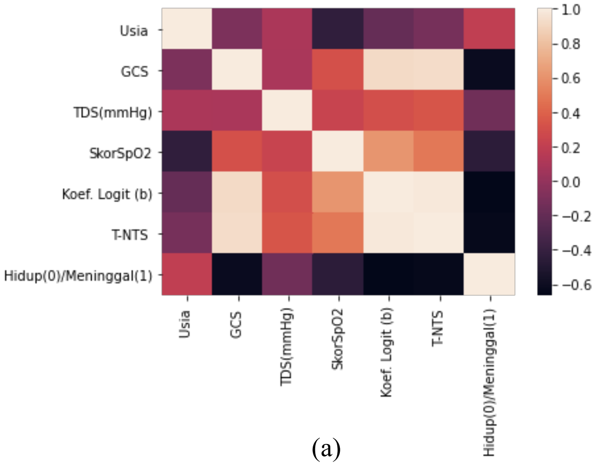
In Table 2 are the features and feature values of trauma data to measure the mortality of trauma patients. The medical history of the trauma patient was not considered in this research. Whether patients with comorbidities or medical conditions were excluded from the cohort is unknown. These include pregnancy, coronary heart disease, atrial fibrillation, history of stenting, thrombocytopenia, liver sclerosis, hypohepatia, and others. Using data preprocessing techniques, patients with incomplete baseline data (feature) when they came to the ER were fixed.

Table 2. Variants features and trauma collected from several research sources

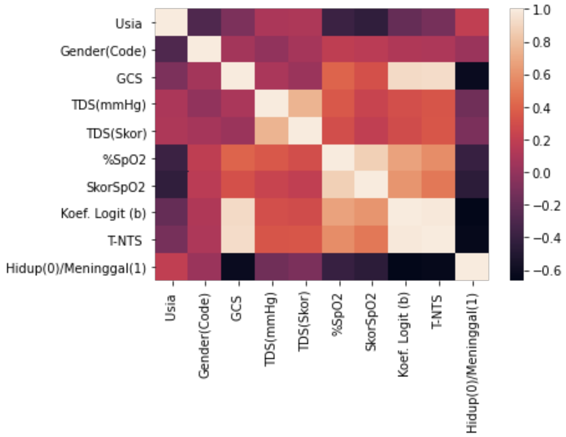
Abbr	Description	Value
AIS	Injury Severity Score, simplification of AIS, to measure motor vehicle accident trauma. The ISS summarizes the severity of the condition in six areas: head and neck, thorax, abdomen (including pelvic organs), locomotion (including pelvic bones), and body surfaces. Each trauma was recorded, and given the highest boot in the area of concern. AIS score of 6 is equivalent to the value of ISS 7.Major trauma if the ISS is ≥15, is associated with a mortality of more than 10% (Burd, Ouyang and Madigan, 2008).	0 - 6
ISS	Score of 6 is equivalent to the value of ISS 7.Major trauma if the ISS is ≥15, is associated with a mortality of more than 10% (Burd, Ouyang and Madigan, 2008).	6 - 15
AP	AP is the anatomical value assessing the static component of trauma, the physiological value assessing the acute dynamic component.	'String'
TS	Trauma Score, has a TS value range ranging from 1 (poor prognosis) to 16 (good prognosis). The TS was revised to a Revised trauma score (RTSRibas et al., 2011).	1 - 16
RTS	Revised Trauma Score (RTS) simplification of TS by eliminating the assessment of respiration expansion and capillary content time because it is difficult to assess, especially at night. This method is most widely used.	1- 16
MESS	The Mangled Extremity Severity Score (MESS) is a scoring instrument designed to predict the survival / survival of a traumatized limb. A value ≥7 predicts the need for amputation.	>= 7
GCS	Glasgow Coma Score (GCS). The GCS variables were eye opening, verbal, and motor responses. Calculations of GCS are quick and simple, and can inform patient progress or deterioration but are subjective in some cases.	'String'
CRAMS	CRAMS measures five components, including circulation, respiration, abdominal trauma, and motor and speech responses. A score of ≥9 is considered minor trauma and a value of ≤8 is considered major trauma. The CRAMS scale has a sensitivity of 92% and a specificity of 98%.	≥ 9 ≤ 7
PTS	Pediatric Trauma Score, developed into six components. Mortality increases up to 30% for patients with PTS ≤8. The PTS triage guide suggests10 children with PTS ≤8 should be sent to a trauma center. PTS is a good scoring system but not better than RTS.	≤ 8
TRISS	Trauma Score-Injury Severity Score, combined scoring systems are used to address weaknesses in the anatomic and physiological systems. This system combines age, ISS, trauma mechanisms, and the RTS component of the study to calculate the probability of survival (Ps / Probability of survival). Ps are only statistical figures and are not accurate predictions of impact, but they can provide a basis for calculating the probability of life.	1 - 4
SCOTT	Severity Characterization of Trauma (ASCOT) is a combined scoring system that uses GCS, AIS, age, systolic blood pressure, and respiration rate to estimate the probability of survival. ASCOT was introduced to reduce the weakness of TRISS. ASCOT menggunakan AP menggantikan ISS dan menggolongkan usia ke dalam bilangan decimal.	23 - 29
MGAP	The MGAP/GAP is another simple trauma scoring system, introducing the trauma mechanism, GCS, age, and arterial pressure (MGAP) scoring system. MGAP divides risk groups into three, namely low (23-29 points), moderate (18-22 points), and high.	18-22

2) Feature Selection

Feature selection was used to select the feature that does not affect the degree of trauma. The step of feature selection combined and replaced several features with other features repeatedly. The best combination is retained as a feature. The results were age, gender, GCS, TDS (mmHg), TDS (Score), %SpO2, SpO2 (Score), Koef.Logit (b), T-NTS as shown in Figure 5.



(a)



(b)

Figure 5. The visualization of feature selection (a) before (b) after

3) Augmented Data

There are several techniques in data mining that can be used to expand the data. This research expanded the data by using a randomization technique. Referring to each feature value and considering the upper and lower limits of the feature value, a random number was generated. As in the TDS column, the feature values moved from 70 to 170, then the scoring technique was carried out by dividing them into three groups.

Table 3. Meta data of Trauma based on its features

No	Age	Sex	CGS	TDS (mmHG)	TDS (Score)	%SpO2	%SpO2 (Score)	Coef.Logit .b	T-NTS	Label
1.	18	0	15	110	4	97	4	4145	23	0
2.	33	1	14	120	4	93	3	2874	21	0
3.	35	0	15	140	4	99	4	4145	23	0
4.	57	1	14	130	4	97	4	3745	22	0
5.	20	0	14	110	4	96	4	470	22	0
6.	58	0	8	130	4	89	3	45	15	1
7.	19	0	15	110	4	97	4	41	223	0
8.	50	1	13	110	4	95	4	3344	21	1
9.	21	1	5	130	4	90	3	732	12	1
10	28	1	14	105	2	93	3	2277	19	1
..	..	..	..	..	..	..	..	..	..	..

Group 1 represented a value range greater than 140, Group 2 a value between 100 and 139, and Group 3 a value of 100.From the scoring results in the corresponding group, random numbers were generated. Likewise, for other features. This research generated 15.943 datasets, with a proportion of 6.000 for the living class and 9.943 for the dead class. Feature selection and data expansion were carried out afterwards. Finally, the meta data could be generated after the data cleaning process, as shown in Table 3.

Table 4. LSTM parameter for Mortality prediction Model: 'sequential_2"

Layer (type)	**Output Shape**	**Param #**
dense_10 (Dense)	(None, 6)	42
dense_11 (Dense)	(None, 100)	700
dense_6 (Dropout)	(None, 100)	0
dense_12 (Dense)	(None, 100)	10100
dense_7 (Dropout)	(None, 100)	0
dense_13 (Dense)	(None, 50)	5050
dense_8 (Dropout)	(None, 50)	0
dense_14 (Dense)	(None, 1)	51
Total param: 15,943		
Trainable params: 15,943		
Nontrainable params: 0		

Building the LSTM architecture is an important part of this research. The right LSTM architecture will give the best results. This study tried out a lot of different layer combinations and the parameter values that made the best prediction model. It came up with the combination shown in Table 4.

1. *Experiment Result*

The biggest challenge is preparing the dataset. The emergency room at Hasan Sadikin Hospital is exclusively for COVID-19 patients during data collection. Finally, the dataset is generated and then trained using the LSTM algorithm to obtain the best model. Data testing is primary data that is collected and then the cleaning process for the data. Data classes for both the dead and the living were tested. There were 59 data classes for the death class and 61 for the living class. Data prediction is done by using a model from the training dataset. The prediction from the model resulted in two data points that did not belong to the proper class. Figure 4 shows the experimental results of the loss and accuracy graphs of the experiments carried out. In Table 5, you can see the two data points that don't belong to their classes.

The features that may be useful for developing future ML-based prediction models and algorithms. This research suggests that a common set of deep learning features may be determined for predicting outcomes in trauma. It's possible to use these features for both the assessment and triage of the patient, as well as to improve trauma systems after the fact.

Table 5. Experimental result for missing class

No.	Age	GCS	TDSm	Sp02	TDSa	Logit	T-NTS	Outcome	Predicted
1.	33	42.0	9.0	120	4.0	1742	17	00	1
2.	86	26.0	15.0	110	4.0	4145	23	00	1

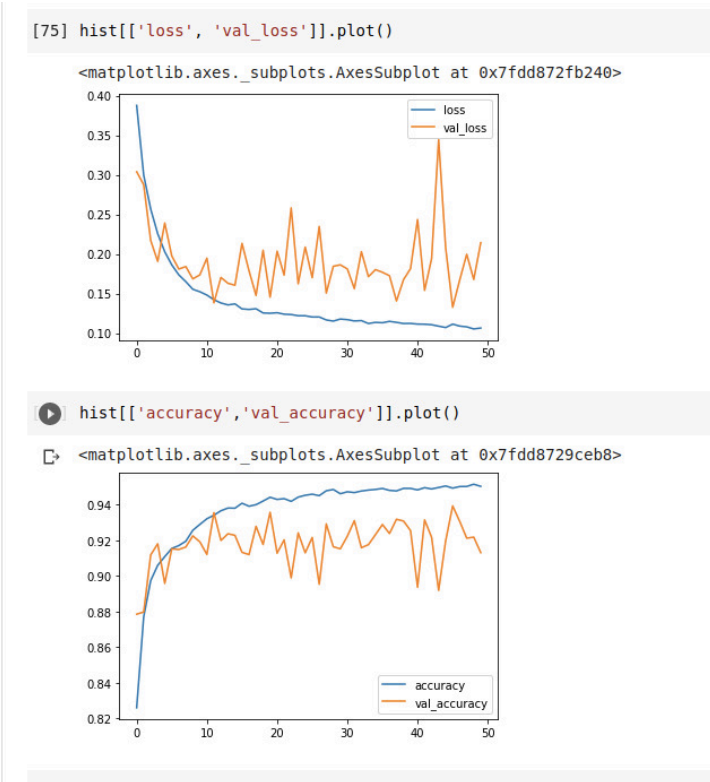


Figure 6. The chart of loss function (above) and accuracy (bottom)

4. Discussion

Trauma is the leading cause of death. The burden of trauma has led to many risk prediction models, not only retrospectively, but also prospectively for triage/ risk methods. Unfortunately, data collection is difficult during pandemic COVID-19. In general, the primary data is rarely perfect. Data preprocessing is needed before carrying out the training process. This research used data mining techniques to solve the aforementioned problems. Limited data, missing values, incomplete data, and inconsistency of data are very common obstacles in developing a model. To reach the goals of the research, an overview of the topic of not having enough data and a classification of data imbalances were done.

First, focusing on the solution to the problem of lacking datasets, we use a data mining preprocessing technique by generating data according to the characteristics of the column and its value. And then handling the problem of high data inconsistency contained in the primary data that we collect. At the same time, normalizing the data to fit the range of types of each characteristic column then, they used deep learning to figure out how likely it was that trauma patients would die, which is the goal of this study.

Despite this, machine learning continues to outperform in prediction problems.This research proved that the degree of trauma is serious and predictable using deep learning algorithms and data mining to preprocess datasets. The result of our model is 0.92 (92%). In addition, the number of published medical informatics studies focused on machine learning has been increasing from time to time. Building the LSTM architecture is an important part of this research. The right LSTM architecture will give the best results. This study tried out different layer combinations and the parameter values that made the best prediction model in order to find the best combination.

5. Acknowledgment

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