Accident Severity Prediction in Big Data Using Auto-Machine Learning

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Abstract

Estimating the severity of a traffic accident is a problem in motor vehicle traffic because it affects saving human life. If the severity value can be predicted before the accident, all the emergency teams needed could be sent to the area to provide faster first aid. With this aim, we studied a big data set for accidents in the USA between 2016 and 2020, almost 2.25×10^6 rows long. First, the data is preprocessed by removing unnecessary variables. Then rows with blank cells are removed. Finally, about 1.7×10^6 rows length data are left for the prediction process. A machine learning algorithm has been used to classify the severity based on 16 input parameters. Binary-to-decimal count conversation has been used as a novel preprocessing method. As a result, the model has been built with a total accuracy of 0.816. The test results are also validated with precision, recall, and f1-score values. An auto-machine learning model has been developed and trained to predict the severity of a possible traffic accident based on the weather and road conditions. Thus it will be possible to direct emergency units to areas with high accident severity, and preventing a fatality.

Keywords: big data, machine learning, classification, traffic accident, severity

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1. Introduction

Accidents are unplanned and uncontrolled events caused by people, situations, environmental factors, or combinations [1]. Road traffic accidents have become the primary source of property damage, health problems, permanent disability, and death. Traffic accidents are a noteworthy public health drawback worldwide, causing 1.35 million deaths and between 20 and 50 million injuries annually [2]. Every day there are 3,000 deaths from traffic accidents worldwide. The number of injured is almost ten times the number of dead, with around 240,000 cases per year. These high rates and high passenger volume imply the need for a comprehensive passenger safety study [3]. Traffic accidents are among the causes of death and injury worldwide [4]. Therefore, it is imperative to predict traffic accidents accurately. Studies on predicting the severity of traffic accidents utilizing artificial intelligence can be found in the literature. Some of these use genetic algorithms (GA) [5], some with artificial neural networks [6-8], some with the Bayesian network [9], some with machine learning (ML) [10-15], some with deep learning (DL) methods [16-17] estimated traffic accident severity.

Angarita-Zapataa et al. (2021) used the Auto- Machine Learning (Auto-ML) model to estimate traffic accident severity using data covering injury accidents and property damage accidents from approximately 220,000 data between 2014 and 2018 in Medellin, Colombia [18]. Alnami et al. (2021) used data mining and machine learning algorithms using the 633372 traffic accident dataset to predict traffic accident severity in Florida [19]. Theofilatos et al. (2019) Compared ML and Deep Learning DL methods to predict real-time accident occurrence [20]. Hashmienejad et al. (2017) estimated traffic accident severity in the Tehran province of Iran over five years (2008-2013) with the data set containing 14211 accidents and the Non-Dominated Sorting Genetic Algorithm (NSGA-II) method. When they evaluated the estimation results, they stated that the NSGA-II method gave an accuracy of 88.2% [5].

Alkheder et al. (2017) used an artificial neural network (ANN) to evaluate the injury severity of traffic accidents based on 5973 traffic accident records between 2008 and 2013 in Abu Dhabi. For each accident record, they collected 48 different characteristics at the time of the accident, and after data preprocessing, the data were reduced to 16 factors and four injury severity classes. They said that ANN classifiers could accurately forecast accident severity [6]. Sameen and Pradhan (2017) developed a DL model using the Recurrent Neural Network (RNN) to calculate the injury severity of traffic accidents based on 1130 accident records between 2009 and 2015 on the North-South Highway (NSE) in Malaysia to estimate [8].

In addition, there are studies on big data and risk management in the literature.

Zhang et al. (2022) used the big data analytics method to assess the risk of ship grounding in operational conditions [21]. Zhang et al. (2021) are used extensively in evaluating ship values [22]. Kaffash et al. (2021) aimed to provide a comprehensive review of the Intelligent Transportation System (ITS) implementation and a review of the best-known models with big data used in ITS. For this, 586 articles were examined between 1997-2019 [23]. Terzi and Erten (2020) examined sustainable transportation and big data examples. They made inferences about how these data will be used in the transportation sector [24].

Based on the literature, although there are accident severity analysis studies based on artificial intelligence methods, as explained above, accident severity estimation based on AutoML using big data is limited. This study proposes an AutoML framework that can be used as a decision support system to direct emergency units before traffic accidents occur. Data on 2.25 million accidents between February 2016 and December 2020 in 49 United States (USA) states were examined for this. These data are State, Temperature, Wind Chill, Humidity, Pressure, Visibility, Wind Speed, Precipitation, Weather Condition, Year, Month, point of interest (POI – amenity, bump, crossing, give way, Junction, no exit, railway, roundabout, traffic calming, traffic signal, and turning loop), Sunrise Number (Sunrise Sunset, Civil Twilight, Nautical Twilight, and Astronomical Twilight), Weekday and hour. Data of missing details are eliminated. Thus, 1.7 million accident data are used to develop the AutoML model. POIs have been converted to numbers for simplification and ease of model analysis. POI numbers were assigned using the binary count system, and AutoML models were developed. No studies have been found in the literature on assigning POI numbers to data with similar characteristics to the binary count system. Model results were validated with accuracy, acuity, recall, and F1-score.

The following section is about the theory of the model, where the AutoML and binary count system, which has been used to convert the POI parameters into numbers, have been specified. Afterward, detailed information about the dataset, such as the source and the content, is given as the practical application. In the fourth section, the analysis findings have been given and discussed. In the last section, a summary of the study has been presented.

2. Theory of the Model

2.1. Auto Machine Learning (Auto-ML)

The ML technique uses various probabilistic, statistical, and optimization algorithms to learn from experience and recognizes valuable patterns of large, unstructured, and complex datasets [25]. ML is a subclass of artificial intelligence that creates a mathematical model based on sample data (training data).ML learns first with the training set and then evaluates the performance of the regressor or classifier with the test set. It then aims to create a regressor or classifier [26]. The problem with Auto-ML is to make a trained process line $\mathrm{M:XY}$, which is hyper parameterized and minimizes the generalization error by automatically generating estimates for samples taken from

$$\mathrm{Pd:GE}\left(\mathrm{M}_{\lambda}\right)=\int\mathcal{L}\left(\mathrm{M}_{\lambda}\left(\mathrm{x}\right),\mathrm{y}\right)\mathrm{P}_{\mathrm{d}}\left(\mathrm{x},\mathrm{y}\right)\mathrm{dxdy} \tag{1}$$

Since a dataset can only be described through a set of n independent observations $D_d = \{(x_1, y_1), ..., (x_n, y_n)\} \sim P_d$, we can only empirically approximate the generalization error experimentally using example data:

$$GE(M_\lambda, D_d) = \frac{1}{|D_d|} \sum_{(x_i, y_i) \in D_d} \mathcal{L}(M_\lambda(x_i), y_i) \tag{2}$$

Auto-ML systems automatically search for the best $M\lambda*$:

$$M_\lambda * \in \underset{\lambda \in \Lambda}{\arg\min}\, GE(M_\lambda, D_{train}) \tag{3}$$

Moreover, estimate *GE*, e.g., by k-fold cross-validation:

$$GE_{CV}(M_\lambda, D_{train}) = \frac{1}{k} \sum_{i=1}^{k} GE\left(M_\lambda^{D_{train}^{(train,i)}}, D_{train}^{(val,i)} \right) \tag{4}$$

Where $M_\lambda^{D_{train}^{(train,i)}}$ mean that M_λ the training was carried out on the ith training fold $D_{train}^{(train,i)}$ [27].

Auto-learn: It uses Bayesian optimization, ensemble choice, and meta-learning to find a promising ML pipeline consisting of an AutoML method, preprocessing techniques, and an ML classifier [18].

2.2. Binary Count System

The point of interest (POI) and daylight status parameters are considered binary numbers in this study. If any POI or daylight status is present on the accident data, the corresponding number is 1, and 0, if not present. The binary number system only uses the values 0 and 1. In the binary number system, each parameter is represented as a power of 2. On the other hand, the decimal number system is used daily and shown using the digits 0 to 9 [28]. By converting the binary to the decimal system, the count of the parameters is decreased. Thus, the computational time needed to run the program can be reduced.

Conversion between binary and decimal counts has been done by multiplying the binary count with two raised to the power of the position of the POI. Here, the right-most POI variable's position starts with 0, and the position number increase by one for each variable standing left.

3. Practical Application

A traffic accident dataset has been applied practically to apply the above-explained theoretical method. The accident dataset comprises approximately $2.25x10^6$ traffic accidents in 49 states of the USA between February 2016 to December 2020 [29]. Figure 1 shows the frequency distribution of traffic accidents in the USA up to December 2020.

The following classifiers were applied in this study: Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GrB), Multilayer Perceptrons (MLP), k-Nearest Neighbors (kNN), Gaussian Naive Bayes (GB), Extra Trees, Adaptive Boosting, Latent Dirichlet Allocation (LDA) and Passive-Aggressive Classifiers.

The POI number has been calculated using a binary count system by combining 13 variables: Amenity, Bump, Crossing, Give Way, Junction, No Exit, Railway, Roundabout, Station, Stop, Traffic Calming, Traffic Signal, and Turning Loop (Figure 2). Also, the Sunrise Number has been calculated by combining four variables – Sunrise Sunset, Civil Twilight, Nautical Twilight, and Astronomical Twilight – using a binary count system.

4. Results and Discussion

$2.25x10^6$ data covering 49 states of the USA were filtered to 1.7x10^6 data to estimate traffic accident severity with AutoML. The data used are presented in Table 1. Here the severity levels could be thought of as "No effect accident," "Property Damage Accident," "Injury Accident," and "Fatal Accident" for levels 1 to 4, respectively.

State, Temperature(F), Wind Chill(F), Humidity (%), Pressure(in), Visibility(mi), Wind Speed(mph), Precipitation(in), Weather Condition, Year, Month, Day, POI Number, Sunrise Number, Weekday and Hour parameters were used as inputs in the Auto-ML model and severity was estimated. Statistical information about the data set is given in Table 2. The histograms of the dataset are presented in Figure 3.

In addition, a correlation matrix was created to examine the relationship between the variables used in the AutoML model. The correlation matrix is given in Figure 4.

When Figure 4 is examined, it is seen that the relationship between the input parameters and the output parameter is relatively low.

Auto-ML model uses RF, SVM, GrB, MLP, kNN, GB, Extra Trees, Adaptive Boosting, LDA, and Passive-Aggressive Classifiers algorithms. In order to develop Auto-ML models, the data set is divided into 75% training and 25% test set. The detail of the Auto-ML model is given in Figure 5. RF, with an accuracy value of 0.816, was selected as the most suitable AutoML model. The hyperparameters found as a result of the Auto-ML model are shown in Figure 6.

Accuracy, precision, recall, and f1 score were used to assess the model's performance developed usin precision, recall, and f1 value. The confusion matrix of the model is shown in Figure 7.

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{5}$$

$$\mathrm{Pr\,ecision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{6}$$

$$\mathrm{Re\,call} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{7}$$

$$\mathrm{F1Score} = 2 * \frac{\left(\mathrm{Re\,call} * \mathrm{Pr\,ecision}\right)}{\left(\mathrm{Re\,call} + \mathrm{Pr\,ecision}\right)} \tag{8}$$

Where; TP stands for True Positive, TN stands for True Negative, FP stands for False Positive, and FN stands for False Negative.

Figure 7 correctly predicts 3015 of 6955 accidents for severity 1, 317644 of 333055 accidents for severity 2, 24802 of 71625 accidents for severity 3, and 3545 of 15999 accidents for severity 4.

The Accuracy, Precision, Recall, and F1 scores calculated for each severity class are given in Table 3.

When Table 3 is examined, it is seen to give Severity 1 with 0.99 accuracies. According to the F1 score results, Severity 2 gave the best result with 0.89 and severity 1,3,4 with the order of other severity classes.

5. Conclusion

Between 2016 and 2020, more than 2.25 million traffic accidents occurred in the USA. In this study, real traffic and accident data for 49 states of the USA were used to estimate the severity of traffic accidents. Similar variables are combined with the Binary Count System. Auto-ML model was developed for traffic accident severity estimation. The correlation matrix determined the relations of each variable with the others. When the correlation matrix was examined, it was seen that each variable gave a low correlation between severity. The accuracy value was used to determine the best classifier. It has been determined that the best algorithm is RF, with an accuracy value of 0.816. Based on the literature studies, it has been seen that such a comprehensive study has yet to be carried out in almost whole states in the USA. In addition, the severity estimation made with approximately 1.7 million data yielded outstanding results. The severity estimation performed with such extensive data will be a source of inspiration for future studies. The developed Auto-ML model is suggested to be used as a decision support system to quickly direct the emergency units to the scene within a reasonable time according to the traffic accident severity.

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Figures and Tables Captions

Figure 1. Frequency Distribution of US-Accidents (2016-2020)

Figure 2. Schematic representation of the calculation of the POI number (*1 if true; 0 if false)

Figure 3. The histograms of the dataset.

Figure 4. Correlation matrix of the dataset

Figure 5. The detail of the Auto-ML model

Figure 6. Auto-ML model hyperparameters

Figure 7. Confusion matrix of the model

Table 1. Data used in accident analysis (These data were compiled by Moosavi et al., [27])

Table 2. The statistical information of the dataset

Table 3. Data on severity classes

Figures

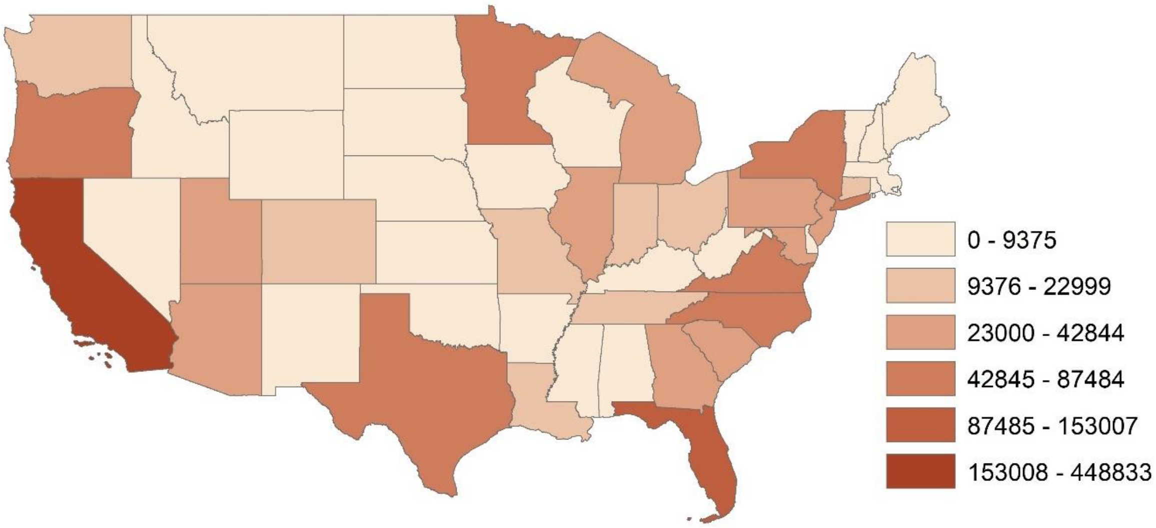


Figure 1. Frequency Distribution of US-Accidents (2016-2020)

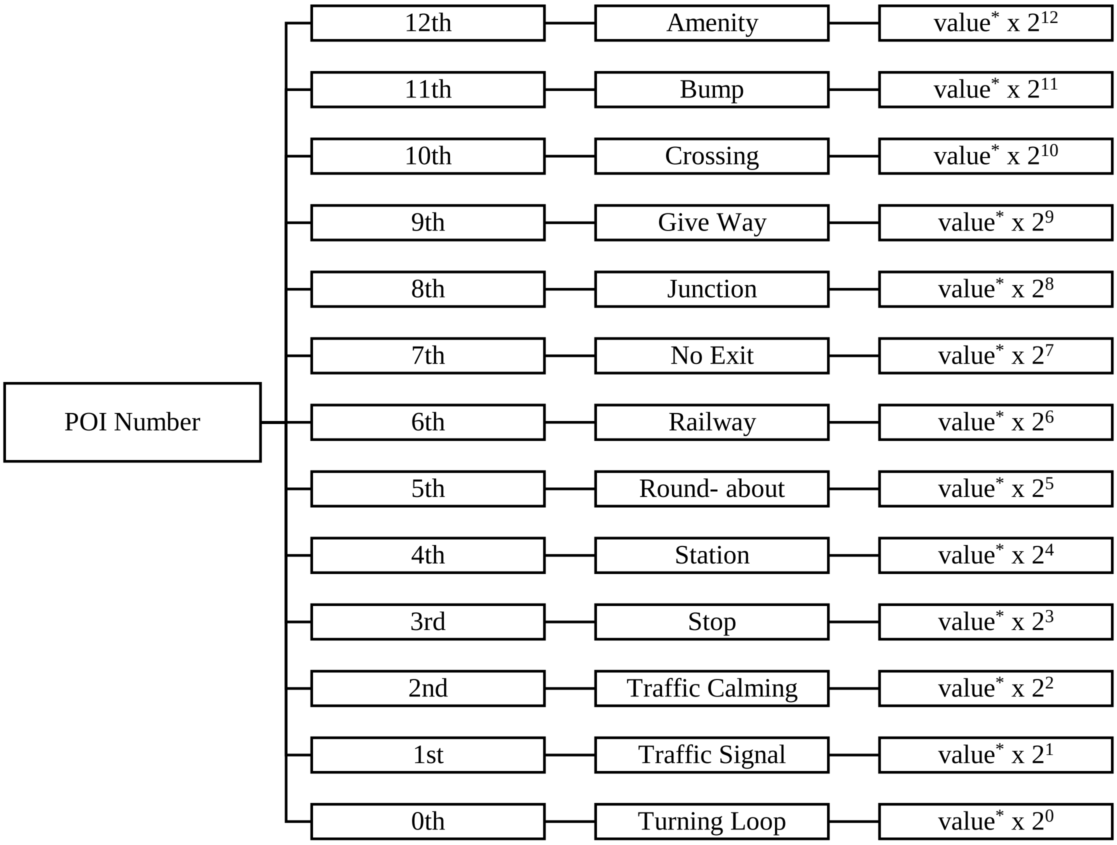


Figure 2. Schematic representation of the calculation of the POI number (*1 if true; 0 if false)

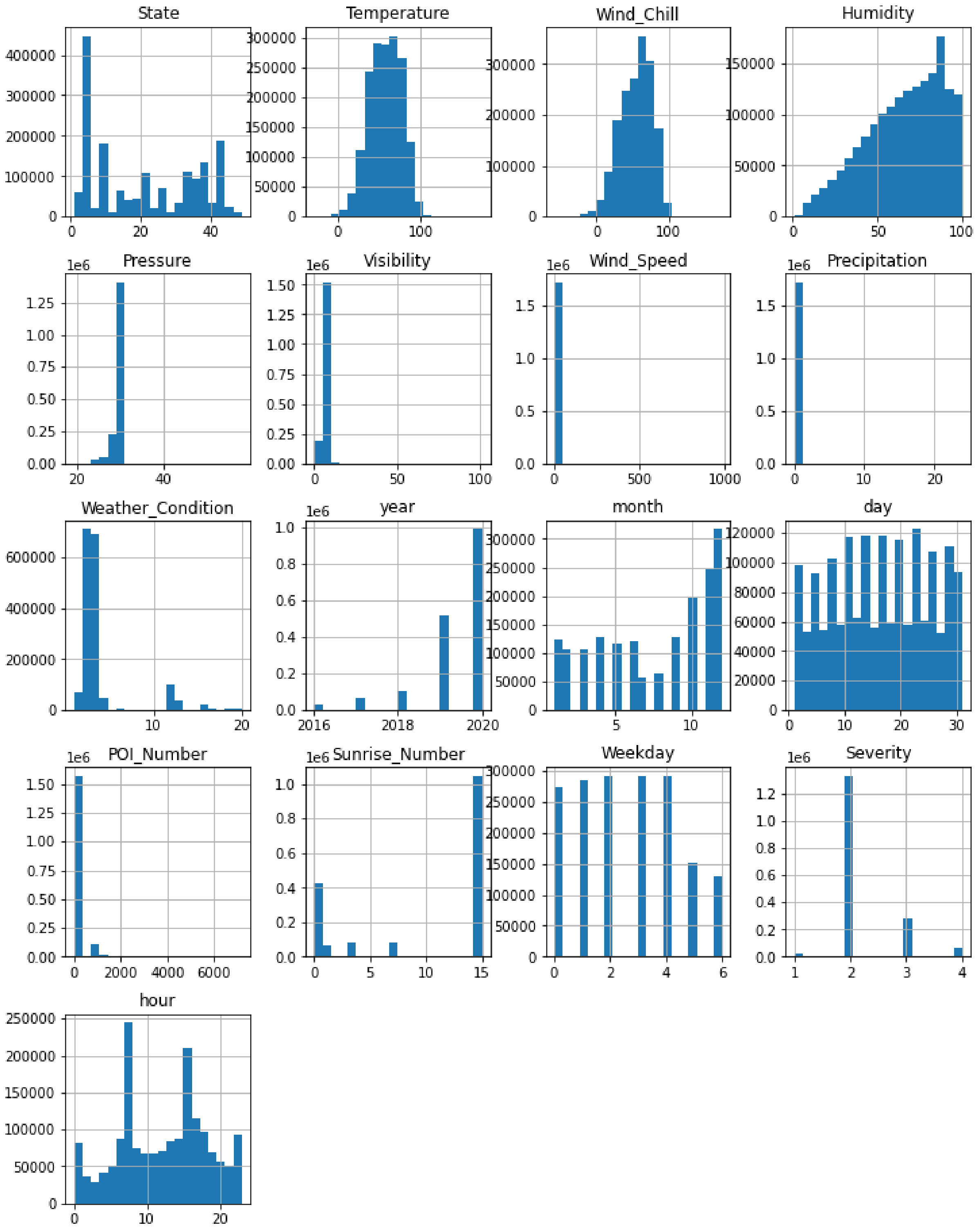
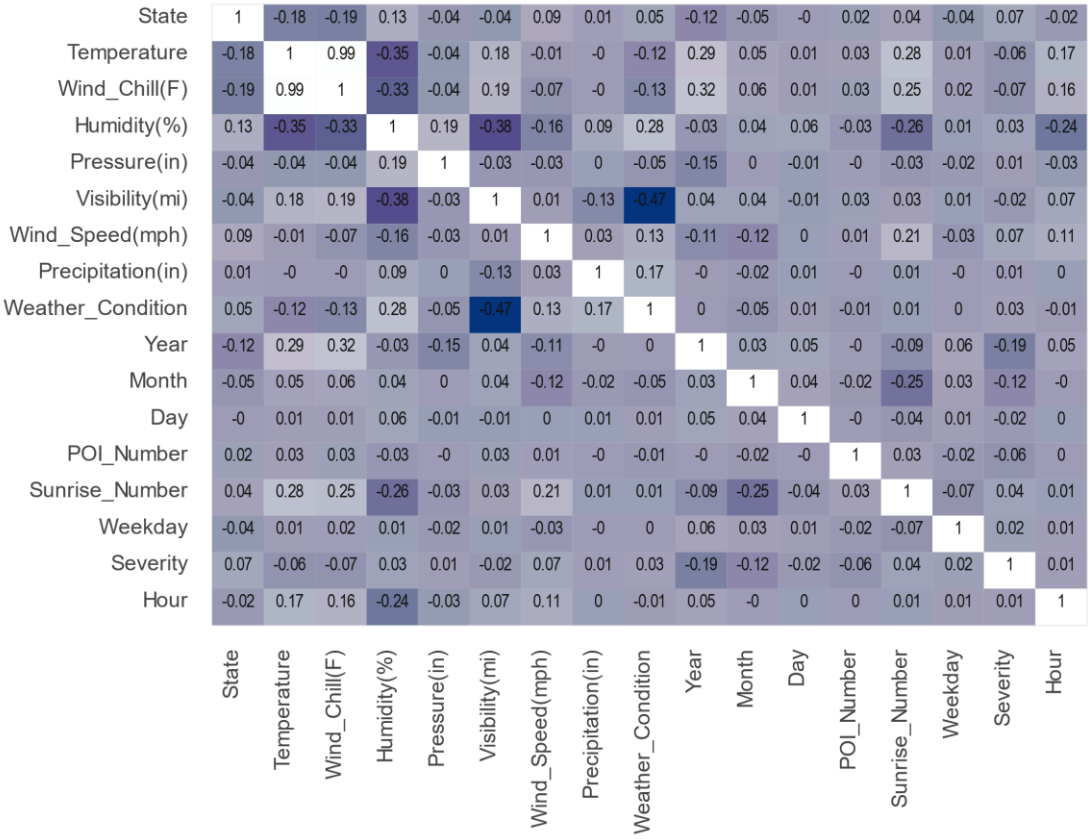


Figure 3. The histograms of the dataset.



	State	Temperature	Wind_Chill(F)	Humidity(%)	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Precipitation(in)	Weather_Condition	Year	Month	Day	POI_Number	Sunrise_Number	Weekday	Severity	Hour
State	1	-0.18	-0.19	0.13	-0.04	-0.04	0.09	0.01	0.05	-0.12	-0.05	-0	0.02	0.04	-0.04	0.07	-0.02
Temperature	-0.18	1	0.99	-0.35	-0.04	0.18	-0.01	-0	-0.12	0.29	0.05	0.01	0.03	0.28	0.01	-0.06	0.17
Wind_Chill(F)	-0.19	0.99	1	-0.33	-0.04	0.19	-0.07	-0	-0.13	0.32	0.06	0.01	0.03	0.25	0.02	-0.07	0.16
Humidity(%)	0.13	-0.35	-0.33	1	0.19	-0.38	-0.16	0.09	0.28	-0.03	0.04	0.06	-0.03	-0.26	0.01	0.03	-0.24
Pressure(in)	-0.04	-0.04	-0.04	0.19	1	-0.03	-0.03	0	-0.05	-0.15	0	-0.01	-0	-0.03	-0.02	0.01	-0.03
Visibility(mi)	-0.04	0.18	0.19	-0.38	-0.03	1	0.01	-0.13	-0.47	0.04	0.04	-0.01	0.03	0.03	0.01	-0.02	0.07
Wind_Speed(mph)	0.09	-0.01	-0.07	-0.16	-0.03	0.01	1	0.03	0.13	-0.11	-0.12	0	0.01	0.21	-0.03	0.07	0.11
Precipitation(in)	0.01	-0	-0	0.09	0	-0.13	0.03	1	0.17	-0	-0.02	0.01	-0	0.01	-0	0.01	0
Weather_Condition	0.05	-0.12	-0.13	0.28	-0.05	-0.47	0.13	0.17	1	0	-0.05	0.01	-0.01	0.01	0	0.03	-0.01
Year	-0.12	0.29	0.32	-0.03	-0.15	0.04	-0.11	-0	0	1	0.03	0.05	-0	-0.09	0.06	-0.19	0.05
Month	-0.05	0.05	0.06	0.04	0	0.04	-0.12	-0.02	-0.05	0.03	1	0.04	-0.02	-0.25	0.03	-0.12	-0
Day	-0	0.01	0.01	0.06	-0.01	-0.01	0	0.01	0.01	0.05	0.04	1	-0	-0.04	0.01	-0.02	0
POI_Number	0.02	0.03	0.03	-0.03	-0	0.03	0.01	-0	-0.01	-0	-0.02	-0	1	0.03	-0.02	-0.06	0
Sunrise_Number	0.04	0.28	0.25	-0.26	-0.03	0.03	0.21	0.01	0.01	-0.09	-0.25	-0.04	0.03	1	-0.07	0.04	0.01
Weekday	-0.04	0.01	0.02	0.01	-0.02	0.01	-0.03	-0	0	0.06	0.03	0.01	-0.02	-0.07	1	0.02	0.01
Severity	0.07	-0.06	-0.07	0.03	0.01	-0.02	0.07	0.01	0.03	-0.19	-0.12	-0.02	-0.06	0.04	0.02	1	0.01
Hour	-0.02	0.17	0.16	-0.24	-0.03	0.07	0.11	0	-0.01	0.05	-0	0	0	0.01	0.01	0.01	1

Figure 4. Correlation matrix of the dataset

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Figure 5. The detail of the Auto-ML model

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  'signed': False})),
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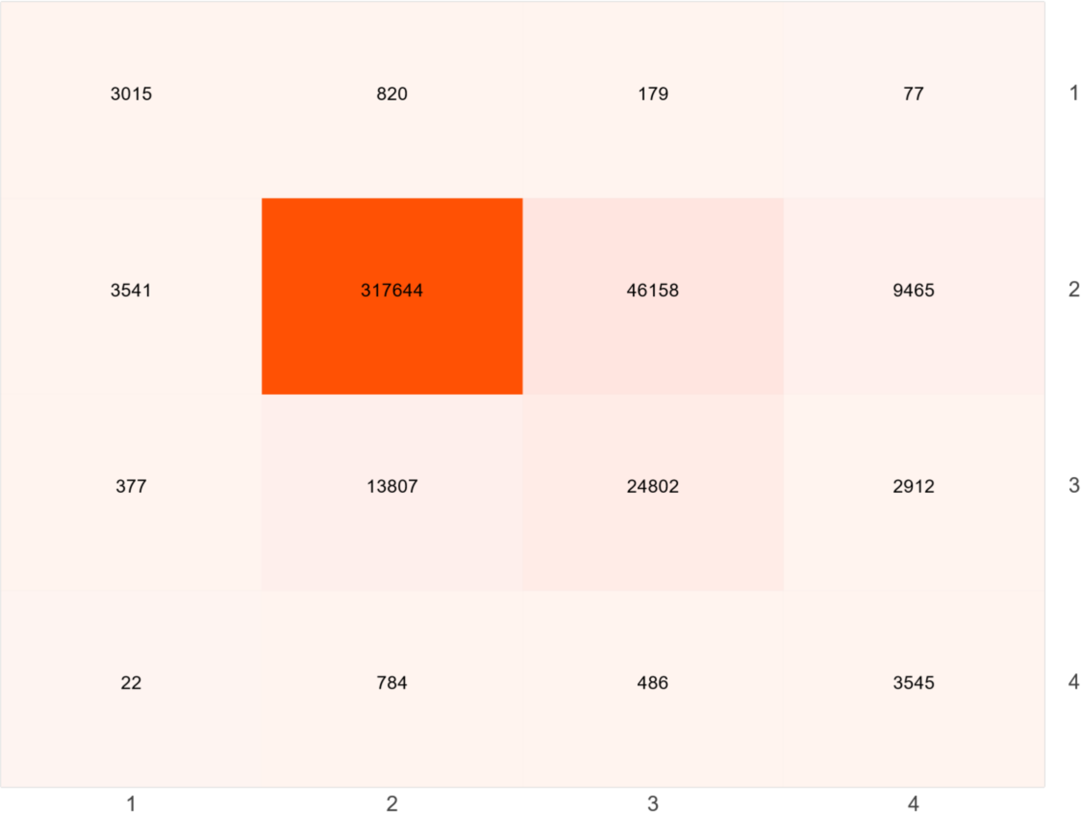
Figure 6. Auto-ML model hyperparameters



1	2	3	4	
3015	820	179	77	1
3541	317644	46158	9465	2
377	13807	24802	2912	3
22	784	486	3545	4

Figure 7. Confusion matrix of the model

Tables

Table 1. Data used in accident analysis (These data were compiled by Moosavi et al., [27])

Data	Definition
Severity	A number between 1 and 4 indicates the severity of the accident. Here, 1 indicates the most negligible impact on traffic, and 4 shows the most significant impact.
State	The state in the address field
Temperature(F)	Displays the temperature
Wind Chill(F)	Wind indicates cold
Humidity (%)	Displays humidity
Pressure(in)	Indicates air pressure
Visibility(mi)	Shows the visibility
Wind Speed(mph)	Shows wind speed
Precipitation(in)	Shows the amount of precipitation, if any
Weather Condition	Weather (rain, snow, storm, fog, etc.)
Year	Indicates the year in which the accident occurred.
Month	Indicates the month in which the accident occurred.
Day	Indicates the day the accident occurred.
POI Number	POI parameters are taken as position numbers to calculate the decimal number from the binary system. Thus, the 13 input parameters are clustered into 1 to improve the system's performance.
Sunrise Number	Day/night parameters are taken as position numbers to calculate the decimal number from the binary system. Thus, the four input parameters are clustered into 1 to improve the system's performance.
Weekday	Indicates the weekday on which the accident occurred.
Hour	Indicates the time when the accident occurred.

Table 2. The statistical information of the dataset

	count	mean	std	min	%25	%50	%75	max
State	1710535	20.79	15.19	1.00	4.00	19.00	36.00	49.00
Temperature(F)	1710535	56.98	19.45	-29.00	43.00	58.00	72.00	174.00
Wind Chill(F)	1710535	55.04	22.17	-59.00	39.00	58.00	72.00	174.00
Humidity (%)	1710535	65.94	22.79	1.00	50.00	69.00	85.00	100.00
Pressure(in)	1710535	29.43	1.09	19.37	29.22	29.76	30.00	58.04
Visibility(mi)	1710535	9.01	2.82	0.00	10.00	10.00	10.00	101.00
Wind Speed(mph)	1710535	7.36	5.54	0.00	3.00	7.00	10.00	984.00
Precipitation(in)	1710535	0.01	0.07	0.00	0.00	0.00	0.00	24.00
Weather Condition	1710535	3.64	3.43	1.00	2.00	3.00	3.00	20.00
year	1710535	2019.39	0.89	2016	2019	2020	2020	2020
month	1710535	7.61	3.75	1.00	4.00	9.00	11.00	12.00
day	1710535	16.14	8.65	1.00	9.00	16.00	23.00	31.00
POI Number	1710535	144.74	523.75	0.00	0.00	0.00	2.00	7180.00
Sunrise Number	1710535	9.70	6.82	0.00	0.00	15.00	15.00	15.00
Weekday	1710535	2.59	1.82	0.00	1.00	3.00	4.00	6.00
hour	1710535	12.15	6.01	0.00	7.00	13.00	17.00	23.00
Severity	1710535	2.23	0.53	1.00	2.00	2.00	2.00	4.00

Table 3. Data on severity classes

	Accuracy	Precision	Recall	F1 score
Severity 1	0.99	0.74	0.43	0.55
Severity 2	0.83	0.84	0.95	0.89
Severity 3	0.31	0.59	0.35	0.44
Severity 4	0.21	0.73	0.22	0.34

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S. Terzi

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