Traffic Accident Prediction Methods Based on Multi-factor Models

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Abstract. Road traffic accident prediction has always been a complex problem for intelligent transportation since it is affected by many factors. However, to simplify the calculation complexity, most of the current research considers the impact of a few key factors and ignores multiple factors' impact in reality. To address this problem, we propose traffic accident prediction methods based on multi-factor models. The model introduces information including the severity of the traffic accident, the weather in which the accident occurred, and the external geographic environment to construct a multiple factors model to improve the prediction accuracy. Also, we can use more factors to construct the multi-factor model with the enrichment of data information. The multi-factor model can overcome the shortcomings of existing models in filtering data fluctuations and achieve more accurate predictions by extracting time-periodic features in time series. Furthermore, we combine the multi-factor models with different deep learning models to propose multiple traffic accident prediction methods to explore multi-factor models' effects in traffic accident prediction. The experimental results on the 2004–2018 Connecticut Crash Date Repository data of the University of Connecticut show that the $C(T) + R + W + RC$ multi-factor model has better prediction performance than other multi-factor models. Moreover, Multi Factors $(C(T) + R + W + RC)$ Based Bi-LSTM-Attention Method for Traffic Accident Prediction achieved the best performance on this data set.

Keywords: Road traffic safety · Traffic accident prediction · Time series · Multi-factor model · Bi-LSTM-attention

1 Introduction

Nowadays, Traffic safety is one of the focal problems in the realization of intelligent transportation [1]. The World Health Organization report shows that about 20–50 million people are injured in traffic accidents, and 1.35 million people die of road traffic accidents every year [2,3]. For instance, an estimated 6.74 million police-reported motor vehicle traffic crashes in the United States resulted in 36,096 fatalities and 2.74 million people injured in 2019 [5]. So, it is necessary

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to build an accurate early warning system with the accurate prediction of traffic accidents under the specific situation to ensure road traffic safety and prevent road traffic accidents. The authority can reasonably allocate public resources such as traffic police and medical personnel based on the prediction results, and maximize the usage of rescue resources. Also, rescuers can respond accurately to the accident, minimizing the property damage and casualties [4].

Complex and diverse climate and weather conditions often lead to traffic accidents [6–8], which significantly affects the periodicity of the time series of traffic accidents. Many studies have shown a strong connection between weather and road condition factors and the formation of road traffic accidents [6,8]. Also, traffic accidents' crash results are closely related to weather and road environment [9,10]. Besides the common factors, traffic accidents are also susceptible to emergencies and low-probability events, such as sudden breakdowns of vehicles or sudden diseases of drivers [7,11].

In a word, traffic accidents are affected by multiple factors, including amounts of abnormal data, and have a certain periodicity in the macroscopic view. Moreover, based on this, many researchers have done much valuable work. For example, Wang et al. estimated the crashes by type and severity using the Integrated Nested Laplace Approximation (INLA) Multivariate Poisson Lognormal (MVPLN) model [12]. Naik et al. used Random parameters ordinal and multinomial regression to find the relationship between traffic accident injuries and detailed weather conditions [10]. Li et al. also used mixed logit and latent class models to investigate the relationship between traffic accidents and rainfall in rural areas [13]. Yuan proposes a Hetero-Conv-LSTM framework to address the spatial heterogeneity challenge in the data, which involves several factors [14].

Although there is research on the screening and analyzing traffic accident data based on the severity of traffic accidents, weather conditions, rainfall conditions, and road conditions, the researchers often focus on a single factor. However, the data's periodicity is determined by the collective impact of multiple factors. The analysis of a single factor often has problems in capturing the actual periodic characteristics of the data. Therefore, we conduct a comprehensive analysis of multiple factors to explore their effects on the data sequence.

This paper proposes multi-factor models, which have excellent effects in filtering outliers in the data and capturing local characteristics and periodic changes of accident time series. The prediction method with the multi-factor model can effectively learn the local characteristics and the periodic changes of time series. Factors can participate in the construction of the prediction model in the form of parameters. With the multi-factor model, we can build a specific prediction model based on specific information, making the prediction model more realistic. For example, "rain', "highway", and "injury" can be used as parameters to construct a predictive model to predict the number of traffic accidents in which people are injured on the highway on a rainy day. After comparing with the other models, we eventually proposed the multi-factor-based Bi-LSTM-Attention method for traffic accident prediction.

The main contributions of this paper can be summarized as follows:

1) A method of extracting accident features based on different factors to build multi-factor models is proposed to improve the accuracy of the prediction.
2) Combined with the multi-factor model, we proposed the multi-factor-based Bi-LSTM-Attention method for traffic accident prediction. It has the best performance on the data set and significantly reduces the MAE of the predicted accidents to 0.91.

The structure of this paper is as follows: We summarize related research in Sect. 2, introduces the construction of the multi-factor model and the Bi-LSTM-Attention prediction method based on multi-factor models in Sect. 3. Furthermore, in Sect. 4, we summarize the experimental results and make a discussion. Finally, we give a conclusion in Sect. 5.

2 Related Works

Researchers have proposed many studies about the relationship between traffic accidents and different factors. For instance, Mussone et al. focused on analyzing road and weather factors in urban traffic accidents [15]. Lin et al. use FP trees to select features that are more helpful for the prediction [16]. Wang et al. employ a copula-based multivariate temporal ordered probit model to simultaneously estimate the four common intersection crash consequence metrics: driver error, crash type, vehicle damage, and injury severity [17].

Given the accident result factor, weather factor, and other factors, researchers launched many studies aim at the influence of the result factors on traffic accidents. Sharaf et al. divided the road risk into four levels, i.e., minor, moderate, severe, death, and used the K-means algorithm to improve the performance of the ANN model [18]. Biswajeet and Maher model traffic accident severity using neural networks and support vector machines to find out determining factors that significantly affect the severity of driver injuries caused by traffic accidents [19]. Mondal et al. comprehensively considered the weather factors that are most closely related to traffic accidents [20]. Wenqi et al. combined traffic flow, weather, and light factors to build a TAP-CNN model for highway traffic accident prediction [21].

In order to handle complex and periodic traffic accident time series and make accurate predictions, Zhou et al. used the Attention mechanism to predict traffic accidents [22].

3 Methodology

3.1 Single-Factor Model ($C(T)$)

The traditional traffic accident prediction mehtod can be further formulated as the Eq. 1.

$$\begin{cases} f\left(x_1\right)=m \\ f\left(x_i\right)=F\left(f\left(x_1\right), f\left(x_2\right), \cdots, f\left(x_{i-1}\right)\right)(i=2,3, \cdots, n) \end{cases} \tag{1}$$

In the Eq. 1, $f(x_1)$ is the num of accidents on the first day. $f(x_i)$ is the function that calculates the number of accidents on the i day based on a series of daily accidents on previous $i-1$ days.

We called Eq. 1 as $C(T)$ model, which is based on the time series of traffic accidents. Traffic accidents will be affected by many factors, such as the environment and road conditions. Due to insufficient information, prediction only based on the time factor of the series will result in low-performance prediction results. So we introduce more factors to the $C(T)$ model to construct a multi-factor model for improving the prediction.

3.2 Multi-factor Model

We propose traffic accident prediction methods based on multi-factor models, using various information for accurate predictions.

We take the $C(T)$ model as the baseline to propose a novel multi-factor model combining different factors. The multi-factor model can act as a filter by checking all traffic accident data during a day and then selecting a series of data that can meet the requirements of the factors.

The multi-factor model can be further formulated as the Eq. 2.

$$\begin{cases} h(f_i) = \begin{cases} 1 \\ 0 \end{cases} (i = 1, 2, 3, \cdots, m) \\ V = [h(r_i), h(w_i), h(rc_i), \cdots] \\ f(x_j) = t_j * \sum_{i=1}^{m} V/dim(V) \\ T_n = [f(x_1), f(x_2), \cdots, f(x_{n-1})] \\ f(x_n) = F(T_{n-1}) \end{cases} \tag{2}$$

In the Eq. 2, $h(f_i)$ is the factor selected to build the multi-factor model. V is a feature vector formed by selected factors. Vector V determines whether a traffic accident can be used in the prediction method based on the information it carries. $f(x_j)$ is the function that calculates the number of accidents on the j day and m is the number of total accidents. We use the $f(x_j)$ function to multiply the time vector by the feature vector and then sum them up. After the normalization, we calculate the number of accidents that occurred on the day j based on the time factor. Furthermore, we serialize $f(x)$ and build the time series of traffic accidents T, and use the time series of past $n-1$ days as the input to calculate $f(x_n)$, which is the number of accidents that occurred on the day n under the selected situation.

As described in Eq. 2, this paper improves the traditional traffic accident prediction methods by combining multiple factors, such as the accident results factor(R), weather factor (W), and road condition factor (RC) of traffic accidents. Based on the $C(T)$ model and those factors, the data features are extracted to construct the three multi-factor models, i.e., $C(T)+R$, $C(T)+R+W$ and $C(T)+R+W+RC$, these three multi-factor models, to explore the contribution of multi-factor models to traffic accident prediction. By combining traffic accident data variables to extract features of accident time series in advance, we can build a multi-factor model. The prediction method based on the multi-factor model can obtain more accident information and carry out machine learning targets on data features to make more accurate predictions (Fig. 1).

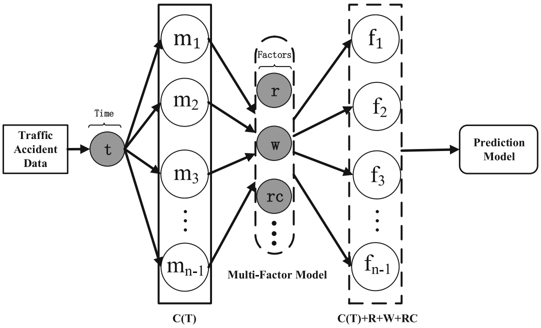

Fig. 1. Multi-factor model, where the m_i stands for accident data on the i day and the f_i stands for the output result of the multi-factor model, which is used to form the time series to build the prediction model.

Accident Results Factor. Generally, the accident result (R) is divided into three categories which are "Property Damage Only", "Injury of any type (Serious, Minor, Possible)" and "Fatal (Kill)", by the injury situation of the passengers and drivers. We found significant differences in the periodicity of traffic accidents of different results by analyzing traffic accidents [17]. However, most of the traditional methods ignore the impact of the accident result factor.

To address this problem, we extract the R from traffic accidents to establish a $C(T) + R$ multi-factor model based on the $C(T)$ model.

Weather Factor. On the other hand, the statistical results between weather conditions and traffic accidents show a strong correlation. Bad weather conditions (such as snow or fog) will reduce road visibility and traffic capacity, increasing traffic accidents. Although the research on the impact of the weather factor on traffic accidents has achieved outstanding results [7], most researchers ignore the joint impact of the weather factors and other factors on traffic accidents. Therefore, it is necessary to extract the weather factor (W) from the data feature and integrate it into the multi-factor model.

Road Condition Factor. The incidence of traffic accidents varies significantly in different road conditions(such as Interstate and Route). Besides the R and W, with the road condition factor added to the multi-factor model, the prediction of traffic accidents will be more accurate. In order to determine the collective impact of various factors on traffic accidents, we extract the road condition factor (RC) from the data feature and integrate it into the multi-factor model.

We can also get other multi-factor models by extracting features from the data. Furthermore, We propose deep learning methods based on the multi-factor model to make traffic accident predictions. The multi-factor model delivers the data as an input vector to the prediction method and eventually improves the prediction accuracy.

3.3 Proposed Bi-LSTM-Attention Method Based on Multi-factor Model

We propose a Bi-LSTM-Attention model based on the multi-factor model to predict traffic accidents. This method consists of 5 components: convolutional layer, bidirectional LSTM layer(Bi-LSTM layer), attention layer, and dense layer.

The multi-factor model extracts the features of the traffic accidents based on the factors to form the input vector. Furthermore, it then passes the data with apparent features to the prediction method:

1. The convolutional layer receives the input vector.
2. The convolutional layer passes the data to the Bi-LSTM layer.
3. The attention layer accepts the data delivered from the Bi-LSTM layer and learn key features scattered in the series.
4. Dense layers receive the data and flatten it to output the prediction result.

The Convolutional Neural Network (CNN) can filter the abnormal data caused by random factors and capture the local features of the data that came from the multi-factor model [23]. At the same time, traffic accident data is affected by long-term factors such as climate and weather during a short period. Hence, we can assume that all accident data in this period are related to each other. Consequently, we use the self-attention mechanism [24] to enable the model to assign the importance of traffic accidents so that the model can focus on learning the critical features scattered in the time series. Combining the advantages of the attention mechanism, Bi-LSTM can specifically learn the multiple periodicities of traffic accident time series due to the bidirectional learning mechanism [25]. It further overcomes the week learning effect in capturing the multiple periodicities of varying strengths under multiple factors.

Because of the joint action of CNN, Bi-LSTM, and the attention mechanism, the model can capture the periodicity of traffic accident time series despite multiple factors and abnormal data. In conclusion, the model's ability to capture the periodicity of time series is greatly enhanced, which solves the critical problem of traffic accident prediction (Fig. 2).

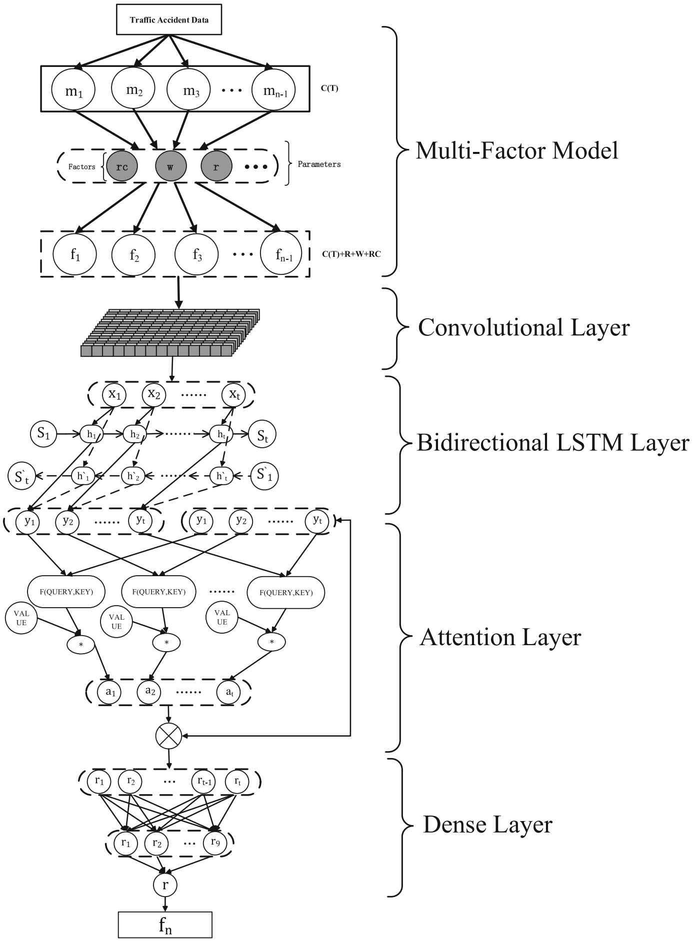

Fig. 2. The framework of Bi-LSTM-attention method based on multi-factor model

4 Experiments

4.1 Experiments Settings

Data Preparation. To verify the effectiveness of our proposed model, we use Connecticut traffic data from 2004 to 2018 from Connecticut Crash Data Repositor (CTCDR) as the data set. In this paper, the variables are set as $R =$ "Injury of any type (Serious, Minor, Possible)", $W =$ "Rain", $RC =$ "State" (State Highways), to construct a multi-factor model, and combine the comparison models to make predictions. We divide the entire data set (5479 days) into two groups. The first 13 years (5114 days) are used as the training set, and data of 2017 (365 days) is used as the verification set. The last year (365 days) is used as the test set.

Evaluation Metrics. This article uses the following methods to evaluate the accuracy of the model: mean absolute error(MAE), mean squared error (MSE), root mean square error (RMSE).

Parameter Configurations. We set the window size to 90 and batch size to 365. We compile the model with the mean squared error loss function and the stochastic gradient descent optimizer with the settings: lr=1$e-5$, $momentum$=0.9.

4.2 Comparison Models

We compare our proposed framework with the following baseline models:

(1) Prophet model [26]. This model is built using the Prophet framework.
(2) DNN [27]. This model consists of a convolutional layer with 64 filters, and four DNN layers, which have 64, 32, 10 and 1 units respectively.
(3) LSTM [28,29]. This model consists of a convolutional layer with 64 filters, a 16-unit LSTM layer, and three DNN layers.
(4) Bi-LSTM [30]. This model consists of a convolutional layer with 64 filters, a 64-unit Bi-LSTM layer, and three DNN layers.
(5) Bi-LSTM-Attention. This model consists of a convolutional layer with 16 filters, a 64-unit Bi-LSTM layer, a Self-Attention layer, and three DNN layers.

4.3 Experiment Result and Discussion

This experiment aims to verify the effectiveness of the multi-factor model for improving the traffic accident prediction method and test the prediction effect of the proposed Bi-LSTM-Att model. We choose to reflect the prediction results and model effects by predicting the number of daily traffic accidents in Connecticut during 2018. Through the comparison between comparison models, we test the effectiveness of the multi-factor model.

To determine the impact of factors on the prediction, we use three multi-factor models: $C(T)+R$, $C(T)+R+W$, $C(T)+R+W+RC$. We combined the multi-factor model with different prediction methods to predict the traffic accidents in Connecticut during 2018 and measured the MAE, MSE, RMSE of the prediction results. The results are summarized in Table 1. The performance of the multi-factor models is shown in Fig. 3.

Based on the experimental results, we can first find that, in general, with the addition of a multi-factor model, the prediction model's performance is greatly improved. After combining the multi-factor model, the Mean-MAE of the $C(T)$ model has been dramatically reduced from 44.32 to 8.276 for the $C(T)+R$ model. At the same time, we found that as the factor increases, the accuracy of the prediction increases. Compared with the $C(T)+R$ model, with the addition of weather factor, the Mean-MAE of $C(T)+R+W$ model reduces to 7.04.

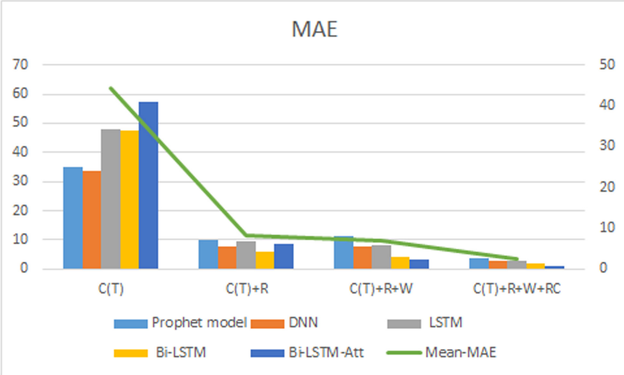

Fig. 3. The performance of different multi-factor models

Table 1. RESULTS of Multi-factor MODEL

Multi-factor modle	Method	MAE	MSE	RMSE
$C(T)$	Prophet	35.13	2929.09	54.12
	DNN	33.59	2394.23	48.93
	LSTM	47.92	4716.45	68.68
	Bi-LSTM	47.48	4775.38	69.10
	Bi-LSTM-Att	57.47	6310.34	79.44
$C(T)+R$	Prophet	9.88	166.28	12.89
	DNN	7.64	95.05	9.75
	LSTM	9.40	147.82	12.16
	Bi-LSTM	5.87	65.33	8.08
	Bi-LSTM-Attention	8.59	222.79	14.93
$C(T)+R+W$	Prophet	11.42	287.43	16.95
	DNN	7.90	265.60	16.30
	LSTM	8.38	301.20	17.36
	Bi-LSTM	4.36	109.49	10.46
	Bi-LSTM-Attention	3.13	44.28	6.65
$C(T)+R+W+RC$	Prophet	3.90	37.96	6.16
	DNN	2.60	34.71	5.89
	LSTM	2.62	34.82	5.90
	Bi-LSTM	1.70	14.79	3.84
	Bi-LSTM-Attention	**0.91**	**4.00**	**2.00**

Moreover, the $C(T)+R+W+RC$ model has the best effect on improving the prediction model's predictive ability. It reduces the Mean-MAE to 2.35. As factors increase, the ability of prediction models to capture the periodicity of time series has been enhanced. The addition of a multi-factor model allows the prediction model to obtain more traffic accident information and targeted learning data features while ensuring training speed and efficiency and eventually achieving accurate prediction of the number of traffic accidents. It can be concluded that the multi-factor model can more significantly highlight the data feature affected by the factors and can pass more explicit information about data feature to the prediction model for machine learning.

Among comparison models, DNN and LSTM models have similar poor performance. Because the information in the LSTM network is a one-way transmission, which can only use past information, there is no obvious manifestation when dealing with traffic accident prediction. However, many factors still exist after the accident, which are not immediate but continuous. These effects will be reflected in the time series as data changes over a period, which means future traffic accident data can also reflect past traffic accidents. Thus, the effect of Bi-LSTM has reflected in the experimental results that the Bi-LSTM model obtains far better performance than DNN and LSTM. The Bi-LSTM-Attention model based on the $C(T) + R + W + RC$ model reaches the best performance and reduces the MAE to 0.91, shown in Fig. 4.

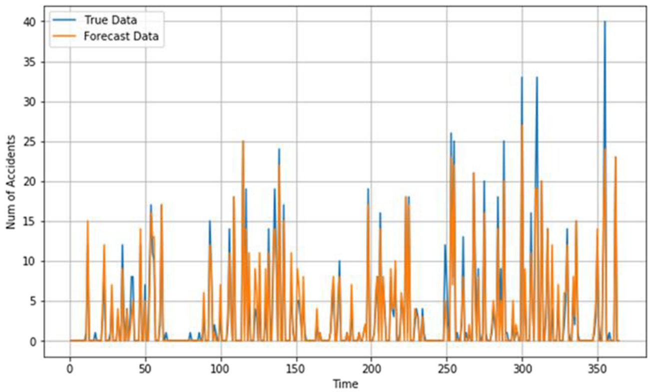

Fig. 4. The prediction result of the Bi-LSTM-Attention combined with C(T)+R+W+RC model, and the x-axis represents time, 0 represents January 1, 2018, and y represents the number of traffic accidents that occurred that day.

Interestingly, combined with the $C(T) + R + W$ and $C(T) + R + W + RC$ multi-factor model, the Bi-LSTM-Attention model reduces the MAE to 3.13 and 0.91, respectively, and achieves the best performance. Nevertheless, the performance of the Bi-LSTM-Attention model on the $C(T)$ and $C(T) + R$ model is poor. The attention mechanism can ignore irrelevant information and amplify the functional characteristics of the required information. However, because the key data features scattered in the time series are affected by many factors, the information conveyed by the $C(T) + R$ and $C(T)$ model is unclear, making the critical information mixed, even covered by each other.

5 Conclusion

This paper studies the method of traffic accident prediction based on the multi-factor model. Traffic accidents are affected by multiple factors, under the influence of which the accident time series presents complex periodicity. Hence, we propose the multi-factor model. Combined with the multi-factor model, the prediction model will have the ability to filter abnormal data in the time series, capture local features of the series, and recognize the pattern which shows strong periodicity in traffic accident time series. The experimental results show that the participation of the multi-factor model dramatically improves the accuracy of the prediction, and as the factor increase, the accuracy of the prediction also increases. The Bi-LSTM-Attention method based on the $C(T) + R + W + RC$ model has the best performance and reduces the MAE value of prediction to 0.91. The multi-factor model has specific research value in predicting events involving multiple factors, and it is a promising solution.

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