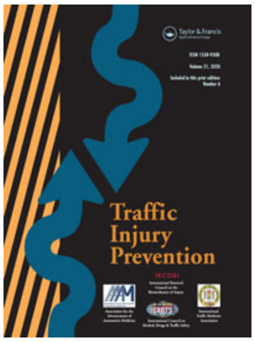

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Forecasting deaths of road traffic injuries in China using an artificial neural network

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ABSTRACT

Objectives: This study was conducted to estimate road traffic deaths and to forecast short-term road traffic deaths in China using the Elman recurrent neural network (ERNN) model.

Methods: An ERNN model was developed using reported police data of road traffic deaths in China from 2000 to 2017. Different numbers of neurons of the hidden layer were tested and different combinations of subgroup datasets have been used to develop the optimal ERNN model after normalization. The mean absolute error (MAE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE) were measures of the deviation between predicted and observed values. Predicted road traffic deaths from the ERNN model and the seasonal autoregressive integrated moving average (SARIMA) model were compared using the MAPE.

Results: By comparing the MAE, RMSE and MAPE of different numbers of hidden neurons and different ERNN models, the ERNN model provided the best result when the input neurons were set to 3 and hidden neurons were set to 10. The best validated neural model (3:10:1) was further applied to make predictions for the latest 12 months of deaths (MAPE = 4.83). The best SARIMA $(0, 1, 1)\ (0, 1, 1)_{12}$ model was selected from various candidate models (MAPE = 5.04). The fitted road traffic deaths using the two selected models matched closely with the observed deaths from 2000 to 2016. The ERNN models performed better than the SARIMA model in terms of prediction of 2017 deaths.

Conclusions: Our results suggest that the ERNN model could be utilized to model and forecast the short-term trends accurately and to evaluate the impact of traffic safety programs when applied to historical road traffic deaths data. Forecasting traffic crash deaths will provide useful information to measure burden of road traffic injuries in China.

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Elman recurrent neural network; artificial neural network; road traffic death; forecast; China

Introduction

As the largest developing country, China has been affected by the expansion of the highway network and the rapid growth of private car ownership, which has had a profound impact on China's public health (Wang et al. 2018). With the motorization rate increasing from 0.023 vehicles per person to 0.188 vehicles per person in the most recent two decades, China is facing enormous challenges in improving road safety and reducing road traffic casualties (Wang et al. 2018). In 2009, approximately 80% of road traffic deaths in China occurred among productive populations aged 21 to 65, which could have devastating effects on the potential economic and human capital (Zhang, Yao et al. 2013). Although the number of non-fatal injuries and deaths caused by RTIs has gradually decreased since 2011 as a result of the implementation of effective interventions and a new national road traffic safety law (Zhang et al. 2015), there were still more than 200,000 injuries and about 60,000 deaths in the 203,049 road traffic crashes in 2017 (Bureau of Traffic Management of the Ministry of Public Security of People's Republic of China 2018). The rapid growth of motor vehicle ownership has put tremendous pressure on the traffic environment. To achieve global and national road safety goals, priority should be given to RTIs to reduce the high rates of road traffic mortality around the world, particularly in developing countries. Therefore, a short-term modeling approach is needed to provide an early estimate of future road traffic deaths based on historical time series data for decision makers to facilitate their assessment of effects of the potential policies implemented.

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People in China have suffered greatly from serious consequences of road traffic nonfatal injuries and deaths. This leading public health challenge calls for more effective interventions. Road safety policies and interventions should be based on an accurate assessment of the burden of RTIs and projections of future trends, which are often affected by data quality, correct estimation parameters and correct modeling methods (Dogan and Akgungor 2011). In-depth analysis and surveillance of road traffic deaths and predictions are of great significance in understanding road safety and disparities in road traffic deaths in China. Modeling and forecasting road traffic deaths based on historical data are of national significance (Dogan and Akgungor 2011). In previous studies, various conventional methodologies have been applied to estimate and predict Chinese road traffic deaths, including time series models (Zhang et al. 2015), regression models (Wang et al. 2018) and so on. However, conventional methods could not handle nonlinear trends effectively and the assumption of linearity in many time series analyses might have not been met (Zhang, Liu et al. 2013; Wu et al. 2019). Artificial neural network (ANN) modeling has been successfully applied in forecasting trends due to its ability to map complex nonlinear patterns and non-intuitive relationships between variables (García et al. 2018). When capturing the nonlinearity in a dataset, ANN is considered a better model choice than conventional methods (Zhang, Liu et al. 2013; Fattah et al. 2018). When it comes to ANN models, different structures of ANN models have been proposed including single-layer feedforward neural networks, multilayer feedforward neural networks, and recurrent neural networks. In feedforward neural network models, all input signals flow in the input-output direction and static mapping is performed between input and output spaces. In comparison with feedforward neural networks, recurrent neural networks can reintegrate the output feedback to the model, behaving more powerfully and rationally in computing and being more suitable for modeling sequences (Sameen and Pradhan 2017). Elman recurrent neural network (ERNN), as a typical dynamic recurrent neural network, is specially designed to remember internal states and map dynamic features (Zhang et al. 2019). ERNN has the ability to store a large amount of information in the past efficiently and its outputs not only reflect the current input, but also previous inputs and outputs (Zhang, Liu et al. 2013). However, no previous study has used ERNN models to examine road traffic deaths in China although other structural types of ANN models have been applied in other areas of public health in many countries (Zhang, Liu et al. 2013; García et al. 2018; Umar and Gokcekus 2019; Zheng et al. 2019).

This study was conducted to develop an ERNN model to estimate road traffic deaths and to compare the estimated deaths with observed historic road traffic deaths in China. Then, the model was used to forecast short-term road traffic deaths in order to assess the feasibility and usefulness of the ERNN model in predicting road traffic deaths for planning purposes. Theoretical and practical features of the ERNN model and conventional time series model were then discussed in the context of road traffic injuries and the implications for policy making and intervention planning.

Methods

Data source

This study used surveillance data of road traffic deaths in China from 2000 to 2017 collected by the Bureau of Traffic Management at Ministry of Public Security of the People's Republic of China (Bureau of Traffic Management of the Ministry of Public Security of People's Republic of China 2018). The historical monthly road traffic deaths between 2000 and 2016 were used as the training sample to fit the ERNN model and observed road traffic deaths from January 2017 to December 2017 were used as the testing sample for assessing model's prediction capability. The seasonal autoregressive integrated moving average (SARIMA) model was developed with the same dataset and predicted road traffic deaths in 2017.

Road traffic related injuries were identified as all injuries or deaths caused by road traffic crashes, including injuries suffered by drivers, motorcyclists, cyclists, passengers, pedestrians and so on in the Chinese road traffic surveillance system (Zhang et al. 2015). Road traffic deaths were defined as deaths that occurred within 7 days of any traffic crash (Zhang et al. 2015).

ERNN model development

A typical ERNN consists of an input layer, a recurrent layer that provides state information, a hidden layer, and an output layer (Wang et al. 2016). The topology of ERNN model could be seen in Figure A1 (see Appendix, online supplement). The nonlinear state space expression could be depicted as follows:

$$\mathrm{y(t)} = \mathrm{g}(\omega_1 \cdot x(\mathrm{t})) \tag{1}$$

$$x(\mathrm{t}) = \mathrm{f}[\omega_1 \cdot x_c(\mathrm{t})] + [\omega_2 \cdot \mathrm{u}(\mathrm{t}-1)]) \tag{2}$$

$$x_c(t) = x(t-1) \tag{3}$$

where y, x, u, x_c are the output node vector, hidden layer node vector, input layer vector and feedback state vector, respectively. The ω_1 and ω_2 are the corresponding weights.

To evaluate road traffic deaths and to forecast short-term road traffic deaths in China, we developed ERNN models with road traffic deaths data from 2000 to 2016. First, dimensions of input neurons and output neurons were determined according to the observed data. In this study, different combinations of datasets have been tested. Different input and output variables were used in different ANN models due to dataset divisions. Road traffic deaths data were divided into two parts: data from 2000 to 2016 were used for training the models; data from January 2017 to December 2017 were used for forecasting traffic crash deaths to provide an independent measure of network performance during and after training the models.

Second, normalization was an important step in the establishment of a neural network. To avoid different

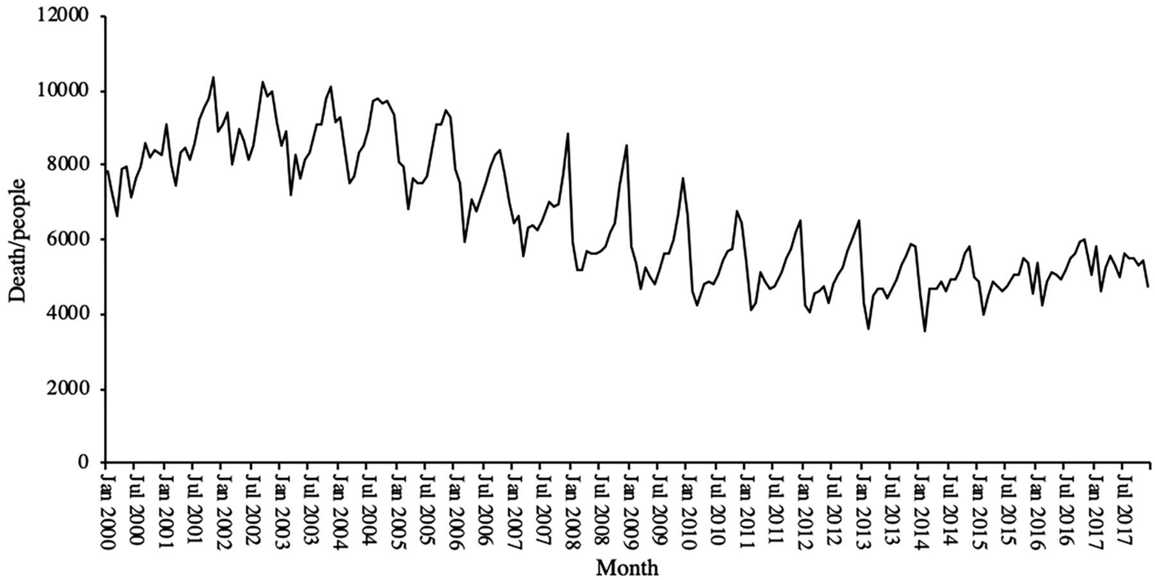

Figure 1. Temporal distribution of monthly road traffic deaths in China, 2000-2017.

training processes which could lead to algorithm convergence problems, we adapted the min-max method to obtain normalized data (Wu et al. 2019).

$$x_{norm} = [(x - X_{min})/(X_{max} - X_{min})] \cdot (U - L) + L \qquad (4)$$

where U and L are the upper and lower values of the normalization range.

Third, we developed the ERNN models. The maximum training iterations number was 4,000 and the minimum validation error was 10^{-4}. All the connection weights were initialized randomly in the range [-1,1], and connection weights were adjusted iteratively by a process of minimizing the forecast errors. The optimum weights ($\omega 1$ and $\omega 2$) were selected by updating the weight vector to minimize the error between the target output and the network output. In this ERNN model, various network architectures were tested by selecting different numbers of neurons in the hidden layer to obtain the convenient model architectures and to find the best topology for the neural model. The best structure was selected from tested models according to the minimization of the deviation between the values of the training samples and the corresponding observations in the raw samples.

Fourth, different models were compared to find the best model. The performance of ERNN models were evaluated by the mean absolute error (MAE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE). Due to the fact that MAE, RMSE and MAPE are measures of the deviation between predicted and actual values, the prediction would be better when the values of these evaluation criteria approach 0 (Wang et al. 2016). When the results are inconsistent among these criteria, MAPE is often chosen as the benchmark due to its stability.

SARIMA model development

As a conventional time-series model, a SARIMA model was conducted using the same data that the ERNN models were based. The structure of a SARIMA model is often denoted as SARIMA (p, d, q) (P, D, Q), where p is the autoregressive order, d is the number of differencing operations and the q is moving average order. The corresponding seasonal orders are P, D, Q. The autocorrelation function (ACF) and the partial autocorrelation function (PACF) of residuals of time series were used to determine the order and parameter of SARIMA models. Then, after parametric test and the Ljunge-Box test, differences between the developed SARIMA models were evaluated by Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and MAPE to select the best SARIMA model from the developed models.

Finally, both the selected ERNN model and the selected SARIMA model were applied to predict road traffic deaths between January 2017 and December 2017. The prediction accuracy of the two models was compared by MAPE.

The data analysis and the modeling of ERNN were performed using Matlab2018a and the modeling of SARIMA was performed using SPSS 11.0 (SPSS Inc, Chicago, IL).

Results

The number of road traffic deaths in China from 2000 to 2017 is presented in Figure 1. According to the monthly death surveillance data, road traffic deaths in China had an obvious seasonal fluctuation; more deaths occurred in autumn and winter. Over the past 18 years, the annual road traffic deaths varied greatly in China from a low of 58,022 in 2015 to a high of 109,381 in 2002. Since 2004, the number of road traffic deaths has decreased year by year, but the number of deaths in 2016-2017 increased again.

ERNN model results

Results from different ERNN models are reported in Table 1. Monthly road traffic deaths data from January 2000 to December 2016 were coded chronologically as X_1, $X_2 \ldots X_i$ and a total of six models were developed with different dataset divisions. Net 1: predicted road traffic deaths in the next

Table 1. ERNN models with different dataset dividing methods.

Number	Input layer	Output layer
Net 1	X_i, X_{i+1}, X_{i+2}	X_{i+3}
Net 2	X_i, X_{i+1}, X_{i+2}, X_{i+3}, X_{i+4}, X_{i+5}	X_{i+6}
Net 3	X_i, X_{i+1}, $X_{i+2} \ldots X_{i+11}$	X_{i+12}
Net 4	X_i, X_{i+12}, X_{i+24}	X_{i+36}
Net 5	X_i, X_{i+12}, X_{i+24}, X_{i+36}	X_{i+48}
Net 6	X_i, X_{i+12}, X_{i+24}, X_{i+36}, X_{i+48}	X_{i+60}

month using the deaths in the first 3 months, Net 2: predicted road traffic deaths in the next month using the deaths in the first 6 months, Net 3: predicted road traffic deaths in the next month using the deaths in the first 12 months, Net 4: predicted road traffic deaths in the current month using the deaths in the same period of the previous 3 years, Net 5: predicted road traffic deaths in the current month using the deaths in the same period of the previous 4 years, Net 6: predicted road traffic deaths in the current month using the deaths in the same period of the previous 5 years.

As presented in Figure A2 (see Appendix, online supplement), different numbers of the hidden layer neurons were tested in the models from 5 to 15 with an increment of 1 to develop the optimal ERNN model after normalization. By comparing the MAE, RMSE and MAPE of different numbers of hidden neurons, our results showed that the model provided the best result when the hidden neurons were set to 10.

Performance of different models is reported in Table 2. The performance of the Net 4 was more accurate and reasonable than other models. Therefore, the best validated neural model (3:10:1) was chosen from the six models to make predictions of the traffic crash deaths in 2017.

SARIMA model results

The seasonal variation and a nonstationary mean of road traffic deaths were found from January 2000 to December 2017 in China (Figure 1). After first-order difference and the first-order seasonal difference, the time series showed no apparent pattern of noise and looked relatively stationary (Figure A3, see Appendix, online supplement). After comparing AIC values, BIC values and MAPE for the different SARIMA models, the best time series model was SARIMA (0,1,1) $(0,1,1)_{12}$, among several candidate SARIMA models (Table 3). Ljung-Box test indicated that the residuals were white noise ($Q = 12.45$, $P = 0.30$).

Prediction results

Developed models (ERNN model and SARIMA model) were then used to predict trends. The predicted monthly road traffic deaths with the chosen models from January to December of 2017 are graphed in Figure 2. The dynamic trend of predicted traffic crash deaths was consistent with the observed traffic crash deaths. However, ERNN model prediction showed higher accuracy (ERNN MAPE = 4.83, SARIMA MAPE = 5.04).

Table 2. Performance of artificial neural network models with different dataset dividing methods in predicting monthly road traffic deaths in 2017.

		Predicted deaths					
Month	Observed deaths	Net1	Net2	Net3	Net4	Net5	Net6
January	5840	5105	4920	4920	5503	5311	5143
February	4639	5667	5742	5742	4408	4555	4370
March	5241	4837	4472	4472	5002	4917	4743
April	5602	5218	5440	5440	5258	5097	5038
May	5318	5514	5511	5511	5141	5020	4917
June	4999	5303	5250	5250	5088	4974	4837
July	5607	5059	5094	5094	5294	5148	4976
August	5516	5502	5504	5504	5576	5385	5275
September	5503	5445	5397	5397	5593	5416	5293
October	5342	5426	5521	5521	5745	5671	5533
November	5419	5311	5251	5251	5773	5663	5473
December	4746	5366	5311	5311	5171	5069	4847
MAPE (%)		7.23	7.95	6.81	4.83	5.15	6.19
MAE		374	412	372	255	278	335
RMSE		478	535	484	283	322	394

Table 3. AIC values, BIC values, and MAPE for different SARIMA models.

Model	AIC	Normalized BIC	MAPE
(0, 1, 0) (0, 1, 0)	2958.80	12.75	6.24
(0, 1, 1) (0, 1, 1)	2894.41	12.42	5.04
(2, 1, 0) (0, 1, 1)	2907.53	12.53	5.35
(2, 1, 0) (1, 1, 0)	2907.14	12.57	5.45
(1, 1, 1) (0, 1, 0)	2904.74	12.48	5.32

Discussion

Our results showed strong seasonality of monthly road traffic deaths from 2000 to 2017 in China. According to Sivak (2009), the possible explanation for the seasonal variation could be the joint influence of the various factors such as darkness duration, alcohol consumption, amount of recreational driving and potential inclement weather in different seasons.

RTIs can be viewed as a time series of data and many previous studies have been conducted to predict road traffic deaths utilizing this feature (Zhang et al. 2015; García et al. 2018). Time series forecasting models use mathematical techniques based on the assumption that the future is an extension of the past (Fattah et al. 2018). The early recognition of road traffic deaths is significantly important when assessing the impact of strategies to prevent deaths and improve road safety (Zhang et al. 2015). Different methods, such as auto-regressive integrated moving average (Shin 2019), SARIMA (Zhang et al. 2015), and exponential smoothing (Jomnonkwao et al. 2020) have been used to model time series of traffic crash deaths. Unfortunately, few studies focus on road traffic death time series forecasting using ERNN models. Accurate forecasts of road traffic deaths are particularly important in the regions and countries with heavy road traffic death burdens such as in China. To the best of our knowledge, this was the first study to apply ERNN to fit and forecast the monthly road traffic deaths in China. Our results found a seasonality of monthly road traffic deaths and suggested the capability of this methodology to analyze the temporal dynamic of traffic crashes deaths. As there are many models for predicting time series, more and more attention has been paid to the issue of comparison of models and selection of the best models. In this

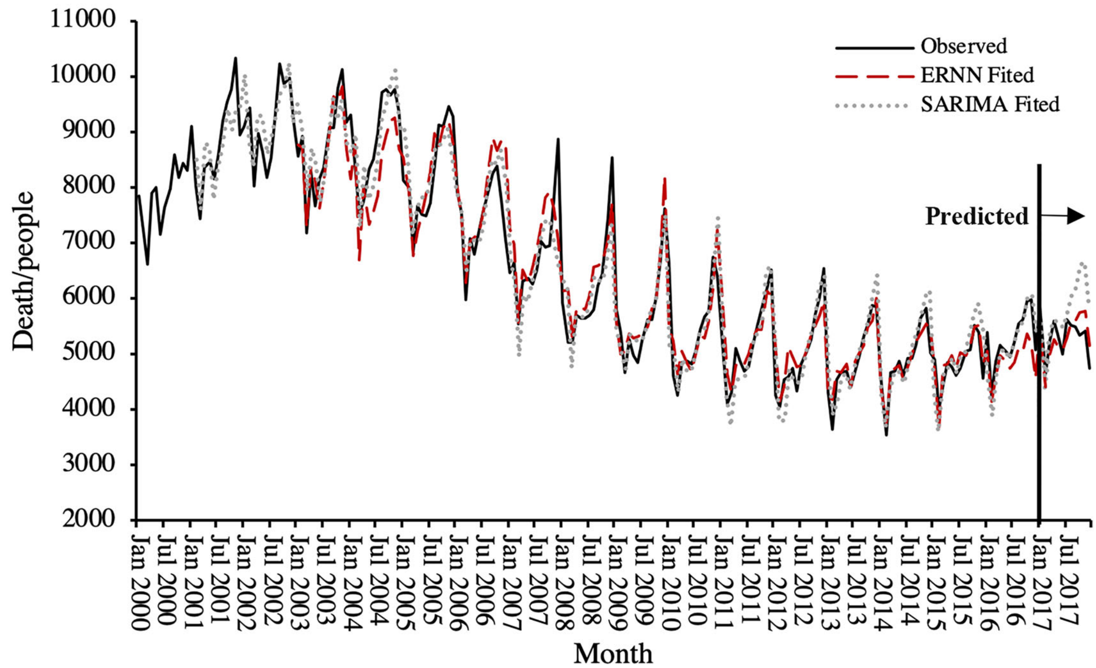

Figure 2. Fitted and actual number of monthly road traffic deaths in China, 2000-2017.

study, comparison of final selected SARIMA model and ERNN model was conducted.

In principle, when compared to auto-regressive integrated moving average models and exponential smoothing models, SARIMA model often shows its effectiveness and advantages in capturing the linear trends of the seasonal series and can be easily developed by many data analysis software programs (Zhang, Liu et al. 2013). SARIMA is one of the most effective linear models for predicting seasonal time series (Zhang et al. 2015). However, the disadvantages of SARIMA models are also obvious. When producing a stationary time series, it is often necessary to preprocess a large amount of longitudinal data with appropriate transformation techniques such as differencing and transformation to stabilize the variance prior to fitting the model (Zhang et al. 2015). The transformation to remove the inherent seasonal effect from a time series may lead to loss of information. In contrast, ERNN model, one of ANN models, can fit the complex nonlinear functions of real-world data to approximate to any desired degree of accuracy. Indeed, ERNN model can map input vectors in the empirical data to the corresponding random output vectors and then make predictions even without a prior assumption about the complex data (García et al. 2018).

With regard to practical application, difference, autoregression, moving average and seasonal functions should be taken into consideration to determine orders and parameters when applying the SARIMA models. Although SARIMA model could capture the linear trend of seasonal time series, it might fail to forecast road traffic deaths accurately due to the nonlinearity of the data and variety of influencing factors related to road traffic deaths. With the characteristic of a recurrent layer to model the spatial and temporal dependencies between the input and output sequences, the ERNN model often shows more tolerance to data than conventional time series prediction models (Zhang, Liu et al. 2013). For example, epidemiology models of human brucellosis established by Wu et al. showed that the RMSE, MAE, and MAPE of SARIMA model were much higher than those of the ERNN model (2019). We applied both the SARIMA models and the ERNN models to analyze monthly road traffic deaths data during 2000 to 2017. In terms of the prediction results, compared with the developed SARIMA model, the ERNN model developed in our research performed better in forecasting time series with strong seasonal patterns and the ERNN model could forecast trends of 2017 road traffic deaths in China more accurately. This study suggests that the ERNN model could be a reliable statistical model to predict the fluctuations in RTIs by utilizing the continuously collected and updated road traffic deaths surveillance data.

Some limitations in this study should be noted when interpreting the results. The data in this paper were collected from police traffic crash records and it is well known that under-reporting is ubiquitous in official statistics. Thus, underreporting bias might be a main limitation that might contribute to inaccurate estimation of the true number of road traffic deaths. Second, the definition of road traffic deaths in China includes all traffic-deaths within 7 days of the traffic crash event while the international definition includes road fatalities occurs within 30 days of the traffic crash (Zhang et al. 2015). The differences between these two traffic crash death definitions might lead to an underestimation of road traffic deaths in China when compared with other countries. Third, shortcomings of the neural network's prediction method would also reduce the accuracy of the prediction. Further research on accurate prediction of road traffic deaths with improved ANN models should be conducted and more advanced prediction techniques should be tested. Fourth, due to the vast territory and huge geographic variations, the economic development of different regions in

China varies greatly. The distribution of RTIs has been reported to be significantly affected by geographic region and economic development. Because data are not available, RTIs in different regions in China could not be analyzed in this study.

In China, deaths caused by RTIs pose a significant threat to public health. It is necessary to monitor and forecast the trends of RTIs in order to develop interventions and implement strategic safety policies. Results of this study indicate that the ERNN model shows its superiority when compared with conventional time series models when both were used to fit historical road traffic deaths data and to predict short-term mortality cases. Predicting road traffic deaths accurately has the potential to provide evidence for future burden of RTIs as well as for evaluating the impact of traffic safety programs and policies.

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Data availability

The datasets generated during and analyzed during the current study are available from the corresponding author on reasonable request.

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