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Modeling Severity of Road Traffic Accident in Nigeria using Artificial Neural Network

(Pemodelan Kegentiran Kemalangan Jalan Raya di Nigeria Menggunakan Rangkaian Neural Buatan)

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ABSTRACT

In this study, an Artificial Neural Network (ANN) was used to model injury and fatality index in Nigeria with the aim to determine the effects of the number of GSM subscription (NGS) on the injury and fatality index in the country. Fifty-seven-year data from 1960-2016 comprising of Gross Domestic Product (GDP) per capita, population, NGS, the total number of traffic accidents, number of fatality and injury per year were used for developing the model. The result of the ANN implies that adding the NGS to the model has increased the model performance in both training and testing with a determination coefficient increasing by 18.7% and 2.5% in testing for fatality and injury index respectively. Comparing the performance of the ANN models and regression analysis shows the superiority of the ANN technique over the regression analysis for both injury and fatality index models. The goodness of fit of the model was further checked using t-test at 5% level of significance and the result proved the ANN approach as a powerful tool for modeling the severity of road traffic accident. Strict enforcement against the use of phone while driving will help reduce the accident severity caused as a result of phone usage while on wheels.

Keywords: Road traffic accident; Injury index; Fatality index; GSM subscription; Nigeria

INTRODUCTION

Every year road traffic accidents result in the death of about 1.3 million people and injured between 20-50 million more worldwide (WHO 2009). In 2015 road traffic accidents accounts for the death of about 1.36 million people and are projected to become the fourth leading cause of disability-adjusted life years (DALYs) lost by 2030 (Alam & Mahal 2016).

Road traffic accident is a socioeconomic problem with poor families been the most affected. Studies revealed that people from low-income settings are more vulnerable to road accidents than those from affluent families regardless of the country's economic status. For example in Australia, a disproportionate number of children from low economic background have been involved in a road accident than those from well to do families (Readings 2008). Another research conducted in India says mortality rate from a traffic accident in poor economic setting was found to be 13.1 and 48.1 per 100,000 in urban and rural areas respectively, compared to their affluent urban and rural counterpart having a death rate of 2.8 and 26.1 respectively (WHO 2009). African region has an average death rate of 24.1 per 100,000 populations as compared to the world average of 18.0 per 100,000 populations with Nigeria recording the highest number of fatal accidents in the region at an average death rate of 33.7 per 100,000 populations. Studies also revealed that, out of every four fatal accidents in Africa, one occurred on Nigeria's highway (WHO 2009).

Accidents occur on all the modes of transportation including railways, but none of these modes approaches the severity of the road traffic accident in the scale of deaths and injuries caused to vehicles occupants, pedestrians and other unprotected road users in Nigeria (Atubi 2010). In Nigeria, two-third of transportation of goods and persons are by road transport (Ali 2016). Impact assessment of road traffic accident on economy revealed that road traffic accidents have a negative impact on the growth of the economy in developing countries including Nigeria (Apparo et al. 2013; Ajibola, 2015). Ajibola (2015) further identifies the population, GDP, GDP per capita, total road network and government expenditure as some of the socio-economic determinants of road traffic accidents in Nigeria. The risk of recording a fatality in road traffic accident increases with mobile phone subscriptions for a study conducted in Malaysia (Danlami et al. 2017). Analysis of road traffic accident in Kano-Nigeria revealed that 19% of all traffic accidents occur while drivers were using mobile phones (Umar et al. 2017).

Artificial Intelligence (AI) techniques have been used to model complex non-linear relationship such as traffic accidents where empirical models do not provide satisfactory results. The AI approaches used to model traffic accidents includes the genetic algorithms (Kunt et al. 2011), fuzzy adaptive resonance theory MAP (Abdelwahab and Abdel-Aty

2002), artificial neural network (Jadaan et al. 2014), neuro-fuzzy and support vector machine (Aghayan et al. 2015). ANN is one of the most effective AI methods for modelling, prediction and function approximation of complex problems where the parameters are not linear (Vahid Nourani et al. 2019). Comparison between the Artificial Neural Network (ANN) model and a Genetic Algorithm (GA) model to estimate the number of accidents (A), fatalities (F) and injuries (I) in Ankara, Turkey by utilizing data obtained between 1986 and 2005 indicates better performance by the ANN model than that of the GA model (Akgüngör & Doğan 2009). Kunt et al., (2011) compared the performance of Genetic algorithm (GA), combined GA and PS, and the ANN approach in estimating traffic injury severity using twelve input parameters and three levels of injury severity, ANN provided the highest prediction accuracy with the R-value of 0.873 followed by the combination of the GA and PS with the R-value of 0.793 and lastly GA with R-value 0.792. ANN was used to predict the injury severity of traffic accidents based on 5973 traffic accident records occurred in Abu Dhabi over a 6-year period from 2008 to 2013. For each accident record, 48 different attributes had been collected at the time of the accident. After data pre-processing, the data were reduced to 16 attributes and four injury severity classes. The experimental results revealed that the developed ANN classifiers can predict accident severity with reasonable accuracy (Alkheder et al. 2016).

Despite the ability of ANN to model non-linear complex relationships, it has not been widely used to model road traffic accident in Nigeria. The objective of the research is to model the fatality index and injury index using the artificial neural network, and also to explore the significance of NGS on the fatality and injury index. Fatality index was defined in this research as the ratio of a number of fatalities to the total number of accidents in that year, and injury index is referred as the total number of injuries in a year to the yearly accident.

EXPERIMENTAL DESIGN

ARTIFICIAL NEURAL NETWORK ANN

ANNs are a class of flexible nonlinear models that can discover patterns adaptively from the data. Theoretically, it has shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and can estimate any complex functional relationship. Empirically, numerous successful applications have established their role for pattern recognition and forecasting (González & Zamarreño 2005; Murat & Ceylan 2006; Pao 2007). ANN is an information processing system which mimics the ability of a human brain to sort out patterns and learn from trial and error. It has the ability to extract relationships that exist within the data. Typically, ANN architecture consists of a series of processing elements called neurons. Neurons are arranged in layers namely the input layer, an output layer, and one or more hidden layers. Each layer is fully connected to the next layer by interconnection weights. Weights are first randomly assigned to all of the connections in the network. These initial values of weights are then corrected during a training (learning) process. The weights in the hidden and output layer neurons can be calculated using Equations. (1) and (2), respectively.

$$\mathrm{W}\ (\mathrm{N}+1) = w\ (N) - \eta\delta\phi \tag{1}$$

$$W\ (N+1) = w\ (N) + \eta x \sum_{q=1}^{r} \delta_q \tag{2}$$

where w is weight, N is a number of iterations, x is input value, η is learning weight, and ϕ is the output. In the equations above, δ is defined as $2\varepsilon_q\ \varepsilon\delta\ \phi/\delta$ I, where I is the sum of the weighted inputs, q is the neuron index of the output layer, and ε_q is the error signal. This training method is the standard backpropagation training algorithm wherein the estimated outputs are first compared to the known outputs, and then, the errors that occur are backpropagated to obtain the appropriate weight adjustments necessary in minimizing the errors (Patil & Deka 2017).

DATA DESCRIPTION

Fifty-seven-year data from 1960-2016 was used to model the severity (fatality and injury index) of traffic accident in Nigeria. The data includes the number traffic accidents, injury and fatality obtained from the federal Road safety corps (FRSC); population, gross domestic product (GDP) per capita, number of registered vehicles from the Nigeria Bureau of Statistics; and NGS obtained from the Nigeria communication commission (NCC). The data was summarized and presented in Table 1.

TABLE 1. Descriptive statistics of data

Variable	Mean	Standard Deviation	Kurtosis	Minimum	Maximum
GDP/Capita $	679.20	810.72	2.84	93.00	3,221.70
Population	98,271,483.34	41,356,925.11	-0.88	45,137,812.00	185,989,640.00
Registered Cars	2,300,280.70	2,723,218.14	1.89	0.00	10,600,000.00
GSM Subscription	19,664,193.47	42,905,255.92	3.39	0.00	154,380,000.00
Cases	19,658.93	8,092.76	-0.50	8,477.00	37,881.00
Fatality Index	0.34	0.15	-1.13	0.08	0.59
Injury Index	1.26	0.80	0.91	0.39	3.13

MODEL DEVELOPMENT

In the development of ANN models, the conventional feedforward neural network trained with Levenberg Marquart was employed. The data was divided into 70% was used for training and 30% testing. Two major models were developed to model the severity of road traffic accident in Nigeria, the first model has 4 input variables comprising of number of accidents, GDP/capita, number of registered vehicles, and population while the second model has 5 input variables number of accidents, GDP/capita, number of registered vehicles, population and NGS in the country. Both models have the fatality index and injury index as the output variables. The optimum ANN architecture was obtained by varying the number of hidden neurons from 2-14 as shown in Figure 1. MATLAB 2018a was used for the development of the model. The data were first normalized between 0.1 and 0.9 using equation 3 before inputting to the model.

$$X_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}(U - L) + L \quad (3)$$

in which x_{norm} is the normalized value, x is the original value, X_{max} and X_{min} are the maximum and minimum values of the original variables, and U and L are the upper and lower values of the normalization range. The normalizations prevent data with a large numerical range from overshadowing data in smaller ranges by bringing all dataset on to the same range. It also minimizes numerical difficulties in the model (Vahid Nourani et al. 2019).

The ANN architecture with the highest efficiency was selected for the model in both cases. The efficiency and performance of the model were evaluated using the Determination coefficient (R^2) and the root mean square error (RMSE). The RMSE and R^2 show the differences between the measured and computed value, both R^2 and RMSE value should be high in training and validation for best networks, the higher the R^2 the lower the RMSE under normal condition. Equations 4 and 5 were used in determining the parameters (V. Nourani & Sayyah 2012). The result was presented in Table 2.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_j \left|N_{obs} - N_{pre}\right|^2} \quad (4)$$

$$R^2 = 1 - \frac{\sum_j (N_{obs} - N_{pre})^2}{\sum_j (N_{obs} - \bar{N}_{obs})^2} \quad (5)$$

where n is the number of observations, $\bar{N}_{obs}$ is mean observed value, N_{obs} is the observed value, and N_{pre} is the predicted value.

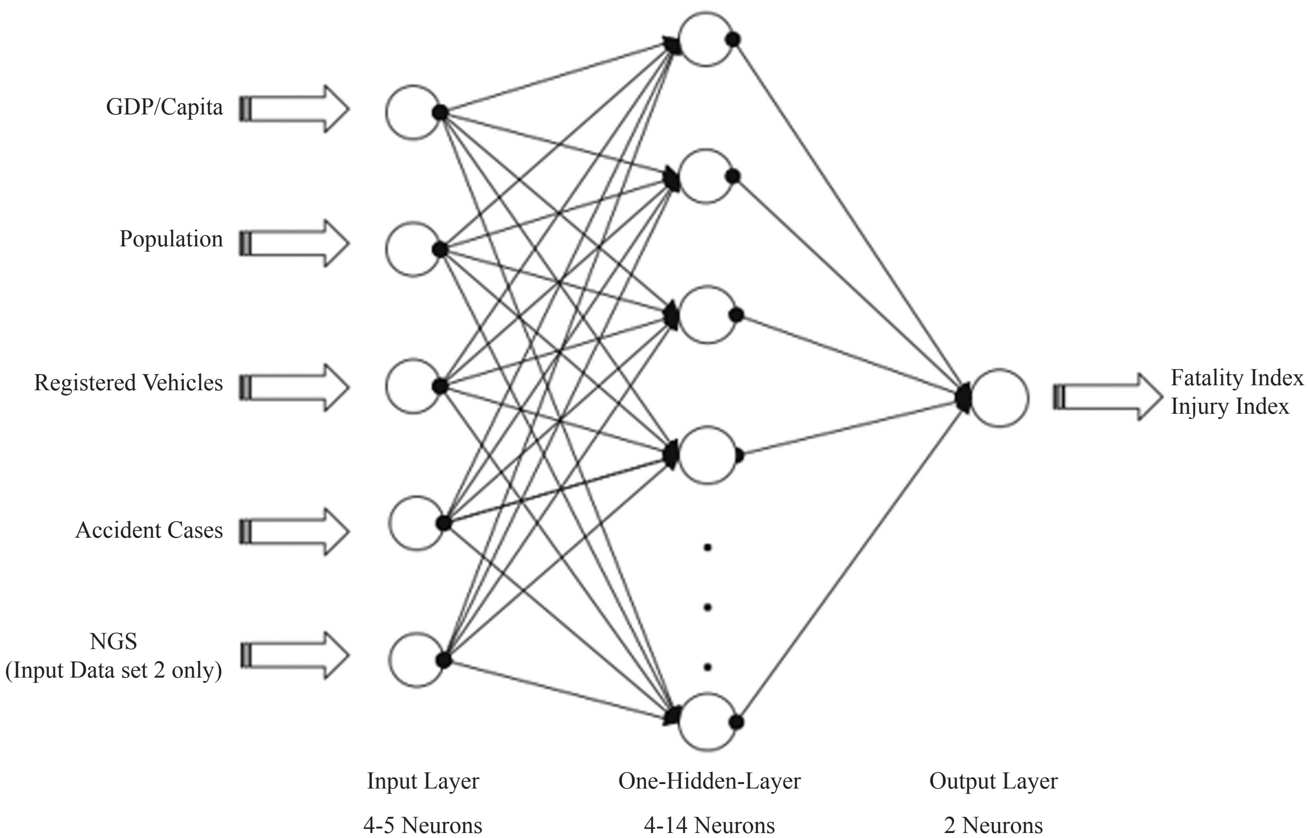

FIGURE 1. Architecture of the developed ANN models

TABLE 2. Performance result of ANN models

Models	Training				Testing			
	R^2		RMSE (normalized)		R^2		RMSE (normalized)	
	Fatality	Injury	Fatality	Injury	Fatality	Injury	Fatality	Injury
Model-1 = Without NGS								
4	0.9579	0.9710	0.0354	0.033	0.7726	0.4445	0.0384	0.0384
6	0.9429	0.961	0.0412	0.0329	0.5413	0.4739	0.0546	0.0443
8	0.9707	0.9652	0.0295	0.0301	0.2342	0.5585	0.0705	0.042
10	0.9581	0.9839	0.0353	0.0299	0.4221	0.5651	0.0613	0.0286
12	0.9568	0.9602	0.0359	0.0423	0.4088	0.1296	0.062	0.0449
14	**0.9652**	**0.9651**	**0.0322**	**0.0290**	**0.7727**	**0.5911**	**0.0384**	**0.0421**
Model-2 = With NGS								
4	0.9318	0.9755	0.0451	0.0367	0.2618	0.3471	0.0693	0.0353
6	0.9554	0.9870	0.0364	0.0313	0.2503	0.5231	0.0698	0.0257
8	0.9652	0.9802	0.0321	0.0331	0.1678	0.4692	0.0736	0.0316
10	0.9432	0.9737	0.0411	0.0331	-0.0216	0.4669	0.0815	0.0365
12	0.9661	**0.9919**	**0.0346**	**0.0281**	**0.9598**	**0.6167**	**0.0148**	**0.0201**
14	0.9559	0.9897	0.0362	0.0328	0.5855	0.4768	0.0519	0.0228

LINEAR REGRESSION

Linear regression analysis is a technique widely used in engineering sciences to model and analyses different variables. More specifically, regression analysis helps one understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed, and explores the complex interactions describing the relationship between these variables (Doğan & Akgüngör 2013). For evaluating the performance of the ANN model, multiple linear regression was used to model the relationship between the fatality index, Injury index and the observed data of population, GDP/capita, number of registered vehicles and the number of traffic accidents in Nigeria. The following relationships were obtained from the regression analysis.

$$\text{Fatality Index} = 0.42\text{-}0.19X_1 + 1.367X_2 - 0.326X_3 + 0.131X_4 \tag{6}$$

$$\text{Injury Index} = 0.141 - 0.622X_1 + 0.252X_2 + 0.136X_3 - 0.203X4 \tag{7}$$

where X_1 is the GDP/Capita, X_2 is the population, X_3 represents number of registered vehicles, and X_4 stands for the number of the traffic accident. The performance of the regression model was compared with that of the ANN model to determine the efficiency of the ANN model.

RESULTS AND DISCUSSION

The best model structure for the model without NGS is 4-14-2 having the optimum R^2 value and least RMSE value in testing and training and for the model with NGS, the best model architecture was 5-12-2 as summarized in Table 2. Comparing the ANN models without NGS and model with NGS shows that, incorporating the NGS into the ANN models has increased the performance of the model with R^2 value increasing from 0.9652 to 0.9661 for fatality index and 0.9651 to 0.9919 for injury index model in training as presented in Table 2. The value of the R^2 also increases by 8.7% for injury index and 2.5% for the injury index in testing. The RMSE also dropped by 11.98% for fatality index and 22.85% for injury index. This is a clear indication of the NGS contribution to the severity of traffic accidents in Nigeria. Comparing the performance of the ANN models with conventional regression analysis shows the superiority of ANN models over the linear regression models. The ANN model (without GSM) has increased the determination coefficient of the regression analysis by 60.5% for the fatality index and 21.8% for the injury index in testing as shown in Table 3. This tallies with previous research by Abdel-Aty and Abdelwahab, (2001); Kunt et al. (2011); Doğan and Akgüngör, (2013) indicating higher performance accuracy of the ANN models in predicting the severity of injury accidents than the regression analysis. The estimated result from the models was compared with the observed values and presented in Figure 1 and 2 for injury and fatality index respectively. It can be seen from the regression analysis, that GDP/capita and the number of registered vehicles have a significant contribution to the traffic accidents in Nigeria. This is logical because economic growth and increase in the number of the registered vehicles will increase traffic on the roads which have been identified as a significant factor contributing to a road traffic accident (Kononov et al. 2009). Traffic congestion which is considered one of the major problems in road network (Shaban et al. 2018) accumulates and increase chances of drivers involvement in traffic accident as a result of increase in traffic.

TABLE 3. Comparison between the regression, and ANN models in testing

Output Parameter	Regression Model		ANN Model without GSM		ANN Model with GSM	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
Fatality index	0.1677	0.0736	0.7727	0.0384	0.9598	0.0148
Injury index	0.3730	0.0726	0.5911	0.0421	0.6167	0.0201

TABLE 4. Results of t-test at 5% level of significance

Output Parameter	Regression Model		ANN Model without GSM		ANN Model with GSM	
	t-stat	t-critical	t-stat	t-critical	t-stat	t-critical
Fatality index	-0.0851	±2.0032	0.0594	±2.0032	0.2576	±2.0032
Injury index	0.0026	±2.0032	0.4932	±2.0032	-0.2388	±2.0032

The model's goodness of fits against the observed values for the two ANN models and a regression model was tested using t-test at 5% significance level and results indicate there is no significant difference between the predicted values and the actual values. Figure 4 also shows the model fitness against the observed values for both the injury index and fatality index.

The result in Figure 2 and 3 shows an increase in the severity of traffic accident in Nigeria from 1960 to 2016 despite reduction in total number of accidents which was similar to studies conducted by Ohakwe and Iwueze (2011); Sanusi et al. (2016) indicating increased injury from road traffic accident in Nigeria.

CONCLUSION

A total of 12 number ANN model were developed to predict the injury and fatality index in Nigeria. Two major models were selected where one includes NGS as an input parameter and the other did not include the NGS with an objective of determining the effect of NGS on the model performance. It was found that the addition of the NGS in the model has improved the performance of the model with high R^2 value and lower RMSE value hence indicating its effect on the severity of traffic accident in Nigeria. The goodness of fit of the model was further checked using t-test at 5% level of significance and the result proved ANN approach as a powerful tool for modeling the severity of road traffic accident. Strict enforcement against the use of the phone while driving will help reduce the accident severity caused as a result of phone usage while on wheels.

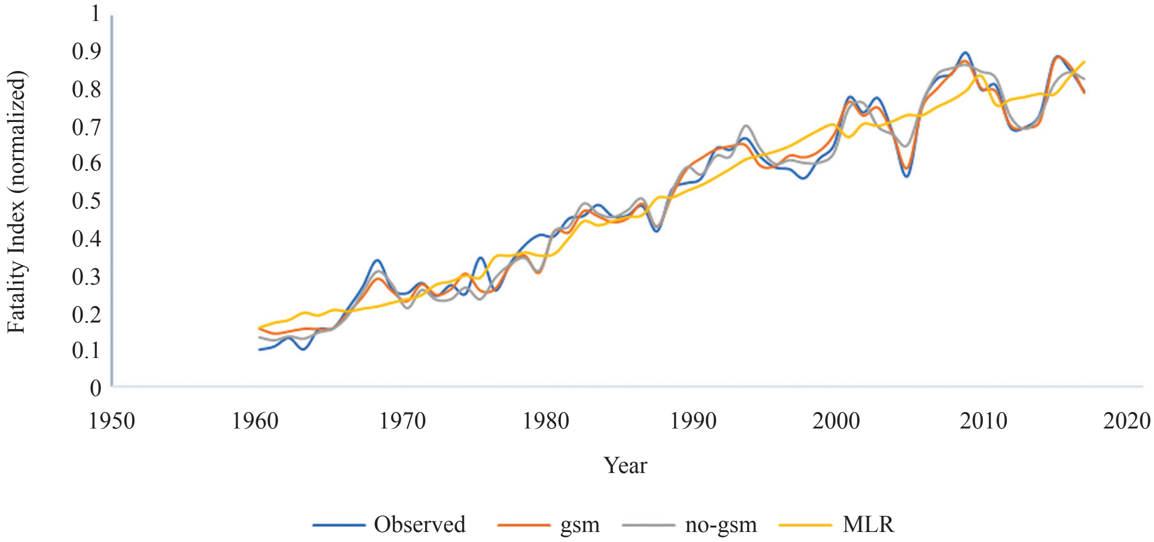

FIGURE 2. Comparison of the fatality index

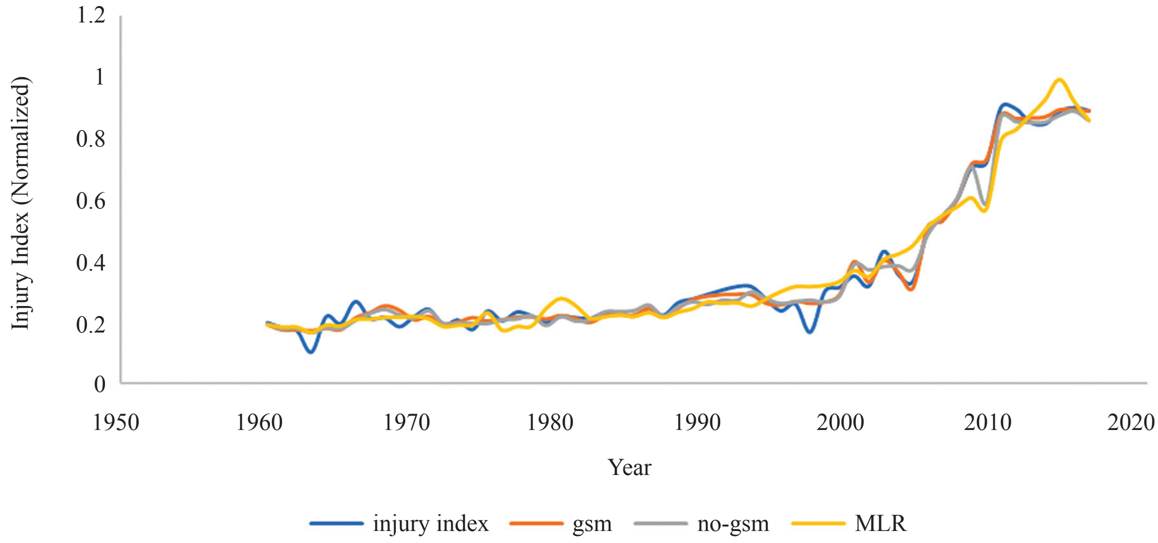

FIGURE 3. Comparison of injury index

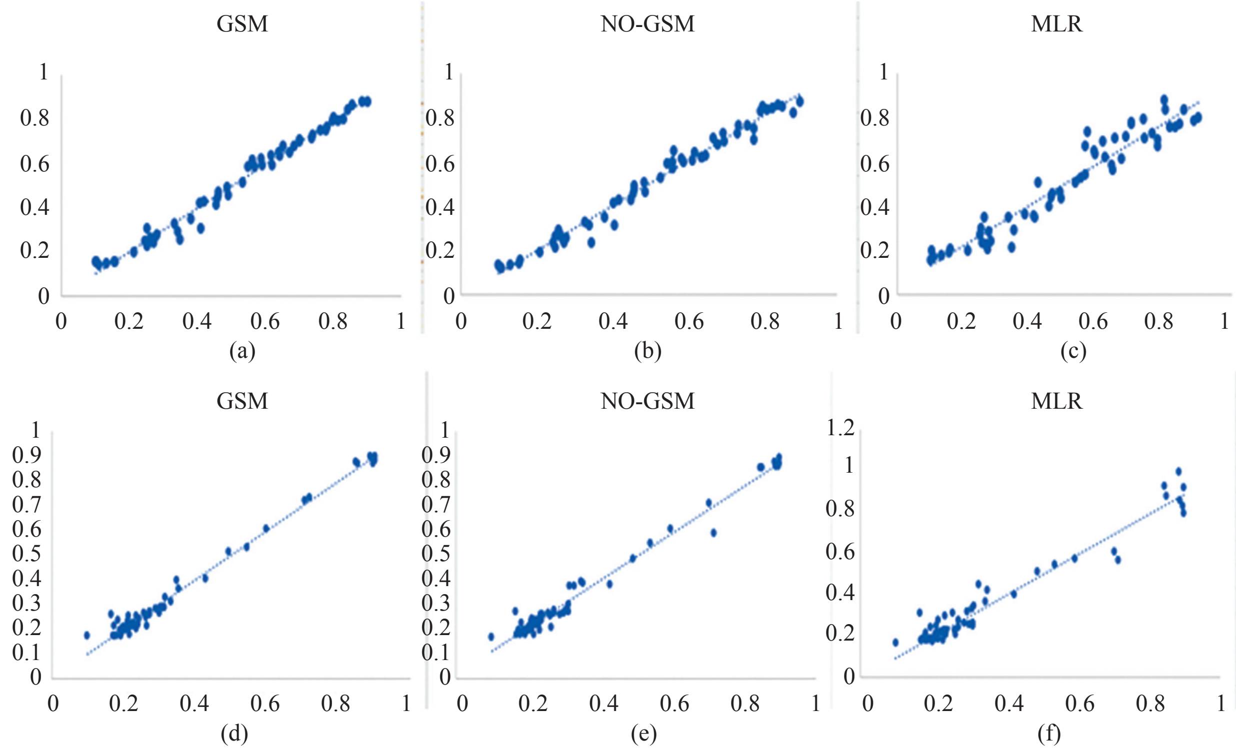

FIGURE 4. Model comparison for fatality and injury Index (a, b, c are fatality index plots for Model with GSM, without GSM and MLR model, and d, e, f are injury index plot for Model with GSM, without GSM and MLR model)

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