https://doi.org/10.3311/PPtr.21203

Periodica Polytechnica Transportation Engineering, 51(4), pp. 329–337, 2023

Accident Prediction Modeling for Indian Metro Cities

Villuri Mahalakshmi Naidu[1*], Phaniteja Kunisetti[1], Vavilapalli Chetan Babu[1], Chekuri Siva Rama Krishna Prasad[2]

[1] Department of Civil Engineering, Gayatri Vidya Parishad College of Engineering (Autonomous), Madhurawada, Visakhapatnam 530048, India
[2] Department of Civil Engineering, National Institute of Technology Warangal, National Institute of Technology Campus, Hanamkonda, Telengana 506004, India
[*] Corresponding author, e-mail: naidun@gvpce.ac.in

Received: 19 September 2022, Accepted: 21 June 2023, Published online: 27 July 2023

Abstract

Road accidents are one of the biggest concerns to the road safety of developing nations. In India, around 150,000 fatal accidents occur annually. Road accident prediction models help in accessing the factors responsible for and those that contribute more to accidents. Most of the prediction models focus on the parameters like road characteristics, traffic characteristics, driver characteristics, and road geometrics. In this study, we considered socio-economic and land-use parameters as input data for accident prediction modeling. The socio-economic and land-use variables data of 20 Indian metro cities were collected. The data were collected for a period of 5 years ranging from 2016 to 2020. A multiple linear regression model was developed between the total number of accidents that happened in the 20 metro cities and the socio-economic and land-use variables. ANN model was also developed to check its applicability to this study and the results obtained are satisfactory.

Keywords

CAVR (city accident vulnerability rate %), principal components, MCA (metro city area), MCP (metro city population), ANN (artificial neural network)

1 Introduction

On the 19th and 20th of February, 2020, the third Global Ministerial Conference on Road Safety took place in Stockholm, Sweden. At the summit, all of the participants, including India, reaffirmed their strong commitment to attaining the goals of decreasing road accident-related deaths by half by 2025. By 2030, at least 50% will be achieved. According to the Global Status Report on Road Safety 2018, road traffic continues to be a major developmental issue, a public health concern, and a leading cause of death and injury worldwide, killing more than 1.35 million people, with 90 percent of these fatalities occurring in developing countries. Every year, almost 150,000 people are killed in road accidents in India. As a result, India is responsible for over 11% of all accident-related deaths worldwide. Due to population expansion and large-scale socio-economic activity, most Indian metropolitan cities are seeing an ever-increasing surge in automobile traffic. As a result, there are serious traffic difficulties on the highways, as well as a high number of road accidents.

Accident prediction models help in accessing the parameters responsible for the mishap. Most of the researchers developed prediction models considering parameters like traffic volume, AADT, Vehicular density on the road, road geometrics, road characteristics like the curvature of the road, type of junction, number of potholes, construction activities on the road, etc.

To access the vulnerability of metro cities to accidents we introduced the new term CAVR (%) (City accident vulnerability rate, it is the ratio between the average annual accidents in the metro cities and the average annual accidents in the entire country in terms of percentage). The primary goal of this study was to establish a link between socio-economic and land-use characteristics and CAVR (percent) and to construct accident prediction models using linear regression and principal component analysis.

$$\text{CAVR}(\%) = \frac{\begin{array}{c}\text{Average annual accidents}\\ \text{in the metro city}\end{array}}{\begin{array}{c}\text{Average annual accidents}\\ \text{in the country}\end{array}} \times 10$$

Cite this article as: Naidu, V. M., Kunisetti, P., Babu, V. C., Prasad, C. S. R. K. (2023) "Accident Prediction Modeling for Indian Metro Cities", Periodica Polytechnica Transportation Engineering, 51(4), pp. 329–337. https://doi.org/10.3311/PPtr.21203

2 Literature review and methodology

Detailed study of the literature on accidents, regression models was carried out (Adanu and Jones, 2017; Afework and Sipos, 2020; Alkheder et al., 2017; Basu and Saha, 2017; Jovanis and Chang, 1986; Kumar and Jain, 2021; Roy et al., 2017; Sipos et al., 2021; Valli et al., 2005). Along with regression models, principal component analysis and artificial neural network was also studied (Alqatawna et al., 2021; Aworemi et al., 2010; McFadden et al., 2001; Xue and Weng, 2014; Yeole et al., 2022; Yuan et al., 2020; Zheng and Meng, 2011). Traffic safety plays a vital role in accident prediction (Božović et al., 2022; Todosijević et al., 2022). The flow chart of the methodology of this study is presented in Fig. 1. Various input variables like socio-economic and land use were taken for modelling. The concept of linear regression, principal component analysis and artificial neural network was used for modelling.

3 Data collection

The socio-economic parameters are, e.g. population, city area, population density, per capita income, and male (%), female (%) population from the world's largest cities' demographics and registered vehicles, city buses data from the office of state road transport commissioners/ UT administrations. Land-use data were collected from

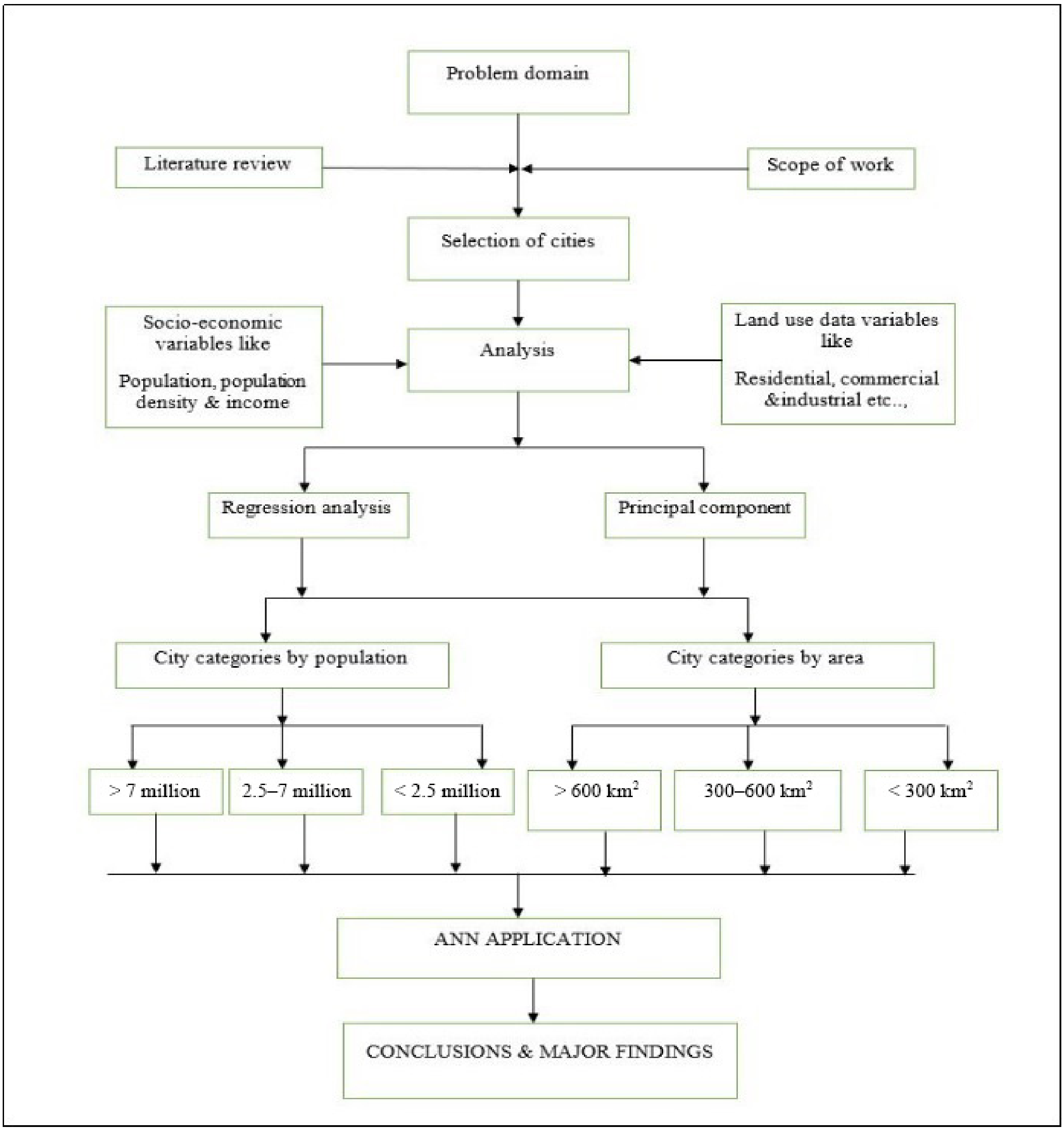

Fig. 1 Flow chart of the methodology

the comprehensive city development plan. Accident data were collected from the ministry of road transport and highway (MORTH) annual reports.

3.1 Selected cities

Throughout history, India has been largely rural, yet several urban areas have thrived from time to time. The country is rapidly expanding, with 35 percent of the people living in urban areas, which is anticipated to rise to 70 percent by 2050 (World Urbanization Prospects). Urbanization occurs as more and more people move to cities for employment, education, and medical assistance leading to a rise in the number of motorized vehicles. As the fraction of the people living in cities grows, so does the number of motorized vehicles. With their better wealth and current level of living, they possess vehicles (cars, trucks, two-wheelers, etc.). Cars, for example, are frequently viewed as emblems of prosperity and luxury. Urbanization directly encourages the expansion of trade, commerce, and services. In the current study, many cities in India are examined for research purposes, as stated in Table 1, which shows the population and area details for the selected cities.

3.2 Socio-economic and land use variables

Parameters considered in the study is provided in Table 2. The study only includes cities with reliable data availability. Cities have been divided into three groups because different-sized cities exhibit diverse behaviors. The first group (given in Table 3) consists of the cities identified by MCP1 with a population of more than 7 million. The next one contains the cities identified by MCP2 with populations between 2.5 and 7 million. Lastly, cities with a population fewer than 2.5 million are identified by MCP3.

Cities expand spatially over time. Table 4 consists of cities group based on area. The area's alterations will affect how the city's traffic behaves. Based on their size or scope, cities are further divided into three categories/classes. Small cities are first identified by MCA1 and have an area of more than 600 km^2. The MCA2 code designates medium-sized cities, which have an area between 300 and 600 km^2. Finally, cities with an area less than 300 km^2 are designated by the MCA3 code.

4 Results and discussions

4.1 Model development

The intention of this study is to develop an accident prediction model for the future prediction of accidents in Indian metro cities. For this, accident data from 2016 to

Table 1 Selected cities and their demographics

No	City name	Area (km^2)	Population (in millions)
1	Delhi	1434	16.32
2	Mumbai	603	18.41
3	Kolkata	206	14.11
4	Bangalore	709	8.5
5	Chennai	426	8.7
6	Hyderabad	650	7.75
7	Ahmedabad	505	6.35
8	Pune	516	5.05
9	Surat	474	4.59
10	Kochi	95	2.12
11	Kanpur	3155	2.92
12	Indore	525	2.17
13	Jaipur	709	3.07
14	Madurai	148	1.46
15	Bhopal	463	1.88
16	Patna	250	2.05
17	Nagpur	394	2.5
18	Agra	121	1.75
19	Varanasi	82	1.44
20	Amritsar	139	1.18

Table 2 Parameters considered for the study

No	Parameter type	Parameter	Units
1	Socio-economic	Population	Numbers (in millions)
2		Area	km^2
3		Population density	Numbers/km^2
4		Male	%
5		Female	%
6		Per capita income	Rs
7		City buses	Numbers
8		Road density	km/km^2
9		Registered vehicles	Numbers (in millions)
10	Land use	Residential	%
11		Commercial	%
12		Industrial	%
13		Public area	%
14		Recreational	%
15		Transport	%
16		Agriculture	%
17		Waterbodies	%
18		Open space	%
19		Other land use	%

Table 3 Metro cities categorization based on population

City category	Population (in millions)
MCP1	> 7
MCP2	2.5–7
MCP3	< 2.5

Table 4 Metro cities categorized based on area

City category	Area (km²)
MCA1	> 600
MCA2	300–600
MCA3	< 300

2020 was collected, and linear regression and ANN models were developed. The dataset was divided into 3 parts 70% for training, 15% of the dataset for validation, and 15% of the dataset for testing. The results obtained from linear regression and ANN models are presented below.

4.1.1 Multiple linear regression

ANOVA analysis was carried out with a 90% confidence interval and the parameters having a p-value less than 0.10 were considered sensitive parameters to the CAVR (%). From Table 5 for all city data, city buses (No), registered vehicles (in millions), and industrial area (%) parameters are significant. For the MCP1 category city's population (in millions), registered vehicles (in millions), and industrial area (%) are significant. For the MCP2 category city's population (in millions), and industrial area (%) are significant. The regression equations developed from the multiple regression analysis are given in Eqs. (1)–(7).

$$\begin{aligned}&\text{CAVR\%}(\text{All cities}) = -0.047 + 4\times10^{-5}\\&\times\text{City buses}(\text{No}) + 0.0006\times\text{Reg. vehicles}(\text{in millions})\\&+17.85\times\text{Industrial area}(\%)\end{aligned} \quad (1)$$

$$\begin{aligned}&\text{CAVR\%}(\text{MCP1 cities}) = -0.04 - 0.34\times10^{-6}\\&\times\text{Population}(\text{in millions}) + 0.0007\\&\times\text{Reg. vehicles}(\text{in millions})\\&+22.63\times\text{Industrial area}(\%)\end{aligned} \quad (2)$$

$$\begin{aligned}&\text{CAVR\%}(\text{MCP2 cities}) = 1.19 - 0.1\times10^{-4}\\&\times\text{Population}(\text{in millions}) + 9.34\times\text{Industrial area}(\%)\end{aligned} \quad (3)$$

$$\begin{aligned}&\text{CAVR\%}(\text{MCP3 cities}) = 0.057 + 0.0031\\&\times\text{Population}(\text{in millions})\\&+0.27\times\text{Population density}(\text{No})\end{aligned} \quad (4)$$

$$\begin{aligned}&\text{CAVR\%}(\text{MCA1 cities}) = -0.007 + 0.0008\\&\times\text{Reg. vehicles}(\text{in millions})\\&+17.06\times\text{Industrial area}(\%)\end{aligned} \quad (5)$$

$$\begin{aligned}&\text{CAVR\%}(\text{MCA2 cities}) = 0.72 - 0.01\\&\times\text{Population}(\text{in millions}) + 7.6\times10^{-4}\times\text{City buses}(\text{No})\\&+0.01\times\text{Reg. vehicles}(\text{in millions})\\&+10.30\times\text{Industrial area}(\%)\end{aligned} \quad (6)$$

Table 5 Significant parameters for CAVR (%)

		Models of CAVR of various city categories						
	Co-efficient (t-stat)	All cities	MCP1	MCP2	MCP3	MCA1	MCA2	MCA3
V	Population (in millions)	–	-0.34×10^{-6} (0.06)	-0.10×10^{-4} (5.94)	0.0031 (0.182)	–	−0.01 (−0.404)	–
	Population density (No)	–	–	–	0.27 (1.13)	–	–	–
	City buses (No)	4.0×10^{-5} (1.22)	–	–	–	–	7.6×10^{-4} (4.15)	3.5×10^{-5} (0.90)
	Registered vehicles (in millions)	0.0006 (2.29)	0.0007 (1.01)	–	–	0.0008 (4.82)	0.01 (3.68)	−0.002 (−1.22)
	Industrial (%)	17.85 (3.68)	22.63 (2.59)	9.34 (5.94)	–	17.06 (2.77)	10.30 (1.40)	–
	Intercept	−0.047 (−0.52)	−0.04 (−0.03)	1.19 (12.53)	0.057 (0.13)	−0.007 (−0.06)	0.72 (3.93)	0.50 (1.63)
F	Sample size	20	6	6	8	6	7	7
	R^2	0.75	0.89	0.98	0.74	0.94	0.97	0.56
	F-test (table)	16.50 (4.0×10^{-5})	5.82 (0.14)	107.82 (0.001)	7.39 (0.03)	23.65 (0.01)	17.33 (0.05)	2.59 (0.09)

Note: V indicates variables and F indicates sample size, R^2, F-test values

$$\text{CAVR\%}(\text{MCA3 cities}) = 0.50 + 3.5\times10^{-5} \times \text{City buses}(\text{No}) - 0.002\times\text{Reg. vehicles}(\text{in millions}) \quad (7)$$

4.1.2 Principal component analysis

It is observed that CAVR (%) mostly affecting 5 parameters out of 19 parameters that are considered for the study, therefore the principal component analysis was performed to identify a smaller number of uncorrelated variables from a large set of data. The goal was to explain the maximum variance within the fewest number of principal components (to explain maximum variance in the data, with the fewer number of variables).

A total of 19 variables were considered to find the principal components, from 19 variables 13 were shown in a screen plot; these 13 variables explain 99% variability from the given data. The first 5 principal components explain 85% variability of the given data. Squared cosines of the variables whose factors are greater than 0.5 were considered significant. Table 6 explains the variables correlated in each principal component (the variables having a squared cosine factor greater than 0.5).

Similarly, the principal component analysis was also carried out for MCP1, MCP2, MCP3, MCA1, MCA2, and MCA3 category cities. Regression models were developed for the principal components and the results are mentioned in Table 7. ANOVA analysis was carried out for the principal components with a 90% confidence interval and principal components with a p-value less than 0.1 were considered significant. The significant principal components are mentioned in Table 8.

The regression models developed between the principal components and CAVR (%) are given in Eqs. (8)–(14).

$$\text{CAVR\%}(\text{All cities}) = 0.464 + 0.129\times\text{PC1} \quad (8)$$

$$\text{CAVR\%}(\text{MCP1 cities}) = 0.883 - 0.17\times\text{PC2} \quad (9)$$

Table 6 Correlated variables of principal component

Principal component	Variability explained (%)	Variables correlated (significant)
PC1	27.05%	Residential area, Registered vehicles, Road density, Industrial area
PC2	21.95%	Population, Population density, Per capita income
PC3	16.70%	Commercial area, transport area, others
PC4	12.90%	Total city area
PC5	6.40%	Agriculture

$$\text{CAVR\%}(\text{MCP2 cities}) = 0.31 + 0.044\times\text{PC1} \quad (10)$$

$$\text{CAVR\%}(\text{MCP3 cities}) = 0.261 - 0.125\times\text{PC3} \quad (11)$$

$$\text{CAVR\%}(\text{MCA1 cities}) = 0.67 - 0.107\times\text{PC1} \quad (12)$$

$$\text{CAVR\%}(\text{MCA2 cities}) = 0.53 + 0.14\times\text{PC1} \quad (13)$$

$$\text{CAVR\%}(\text{MCA3 cities}) = 0.21 - 0.08\times\text{PC3} \quad (14)$$

4.1.3 Artificial neural network (ANN)

Nineteen neurons make up the input layer of the two-layer feed-forward network that was chosen. In the buried layer, 19 neurons were chosen for further processing. The CAVR (%) of the chosen city was set as the one neuron in the output layer. Input data was divided into 3 parts 70% of the dataset as training data, 15% of the dataset as testing data, and 15% of the dataset as validation data. As an activation function, the sigmoid function was employed. The division of the dataset is given in Table 9. The neural network architecture is given in Fig. 2.

The network output was matched with the intended output for each set of input that was applied to the network. The mean square error is given in Eq. (15). The disparity between these two is regarded as the error. Equation (15) was used to determine the mean square error.

$$\text{MSE} = \frac{1}{i}\sum_{j=1}^{i} e(j)^2 = \frac{1}{i}\sum_{j=1}^{i}\{v(j) - u(j)\}^2 \quad (15)$$

Where Q = number of observations; $v(j)$ = target output of j^{th} observation; $u(j)$ = Network output of j^{th} observation; $e(j)$ = difference of target output and network output of j^{th} observation.

Fig. 3 displays the network's training, validation, and testing results with total inputs and the CAVR (%) as the output of all cities with original data.

4.1.4 Principal components – ANN application

Fig. 4 depicts the network design utilizing principal components. A two-layer feed-forward network with a back propagation algorithm makes up the chosen network. Five neurons make up the input layer, which receives the principal component data.

That was acquired by doing a principal component analysis on the complete set of data. Given that they account for 85% of the original data, the first five main principal components were taken into account. Five neurons have been added to the hidden layer. TRANSIG was

Table 7 Principal component analysis results

	Models of CAVR (%) of various city categories						
Co-efficient (*t*-stat)	All cities	MCP1	MCP2	MCP3	MCA1	MCA2	MCA3
PC1	0.129 (3.57)	−0.05 (−0.61)	0.044 (1.66)	0.002 (0.078)	−0.107 (−2.22)	0.14 (2.71)	0.007 (−0.24)
PC2	0.033 (0.671)	−0.17 (−2.63)	0.031 (0.85)	0.007 (0.177)	0.057 (0.62)	0.044 (0.45)	−0.04 (−1.16)
PC3	0.087 (1.74)	0.007 (0.048)	−0.011 (−0.217)	−0.125 (−4.54)	0.078 (0.75)	0.038 (0.315)	−0.08 (−2.56)
PC4	0.040 (0.61)	−0.150 (0.455)	0.056 (0.78)	−0.05 (−0.75)	0.162 (1.05)	−0.17 (−1.28)	0.047 (0.81)
PC5	−0.049 (−0.52)	0.237 (0.784)	−0.086 (−1.27)	0.006 (0.05)	−0.064 (−0.24)	0.03 (0.14)	0.030 (0.19)
Intercept	0.464 (5.85)	0.883 (3.60)	0.31 (4.26)	0.261 (2.80)	0.67 (4.78)	0.53 (3.71)	0.21 (3.65)
Sample size	20	6	6	8	6	7	7
R^2	0.64	0.63	0.41	0.77	0.55	0.595	0.56

Table 8 Significant principal components

	Models of CAVR (%) of various city categories						
Co-efficient (*t*-stat)	All cities	MCP1	MCP2	MCP3	MCA1	MCA2	MCA3
PC1	0.129 (3.57)	–	0.044 (1.66)	–	−0.107 (−2.22)	0.14 (2.71)	–
PC2	–	−0.17 (−2.63)	–	–	–	–	–
PC3	–	–	–	−0.125 (−4.54)	–	–	−0.08 (−2.56)
PC4	–	–	–	–	–	–	–
PC5	–	–	–	–	–	–	–
Intercept	0.464 (5.85)	0.883 (3.60)	0.31 (4.26)	0.261 (2.80)	0.67 (4.78)	0.53 (3.71)	0.21 (3.65)
Sample size	20	6	6	8	6	7	7
R^2	0.64	0.63	0.41	0.77	0.55	0.595	0.56

Table 9 ANN Data set description

Input data size	Training set (70%)	Validation set (15%)	Testing set (15%)
20 × 19	14 × 15	3 × 2	3 × 2

the activation function employed for the job. With all of the neurons processing the data forward, this network is fully linked.

Fig. 5 displays the network's training, validation, and testing results with total inputs and the CAVR (%) as the output of all cities with principal components data. Training results like *R*-value and Mean Square Error (MSE) of all cities, MCP1, MCP2, MCP3, MCA1, MCA2, and MCA3 categorized cites are given in Table 10.

5 Conclusions

When compared to the original data, principal components have resulted in the development of superior CAVR models (R^2 (All data-ANN) = 0.70, R^2 (All data-ANN-PC) = 0.84).

ANN-based CAVR was shown to have higher explanatory power in comparison to regression models (R^2 (All data-regression) = 0.65, R^2 (All data-ANN) = 0.70).

The city population, registered vehicles, and industrial area (%) are discovered to be the important variables in regression analysis describing the CAVR (city accident vulnerability rate).

Cities were classified according to their size or location. The city area has not generated any results for the creation of improved models. This might be because each category had a modest sample size.

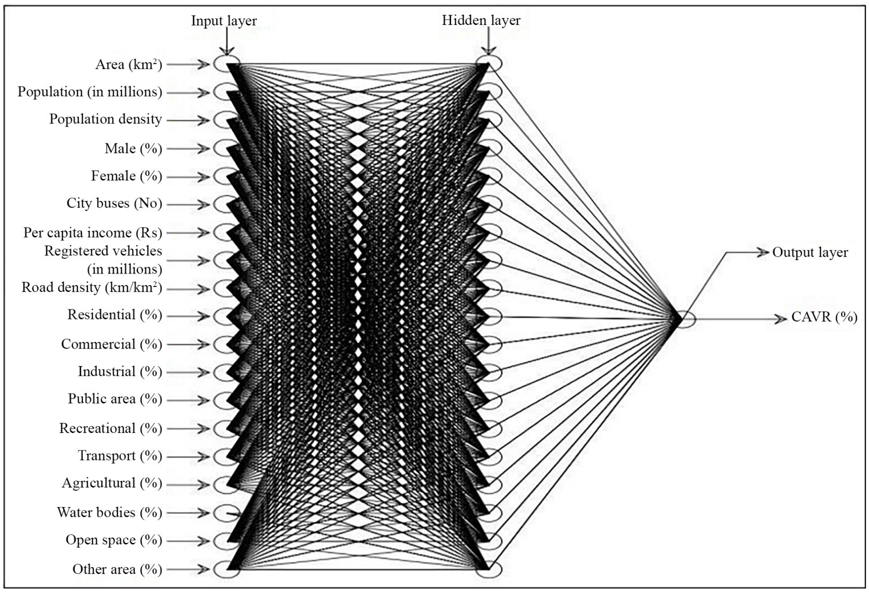

Fig 2 Neural network architecture

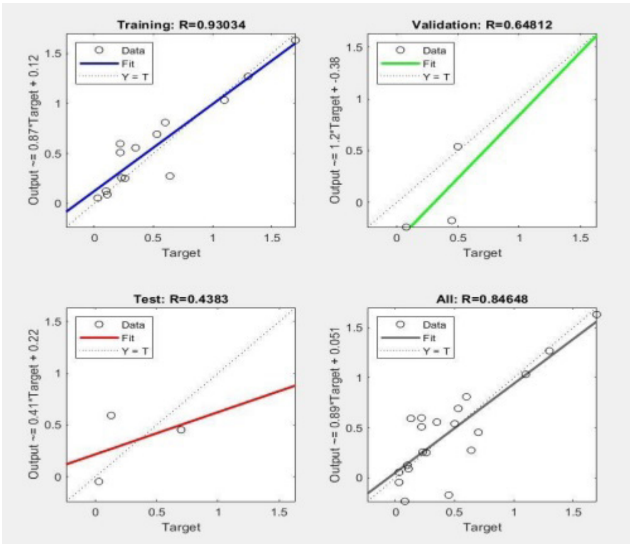

Fig. 3 Performance of ANN (with total input) – for CAVR (%)

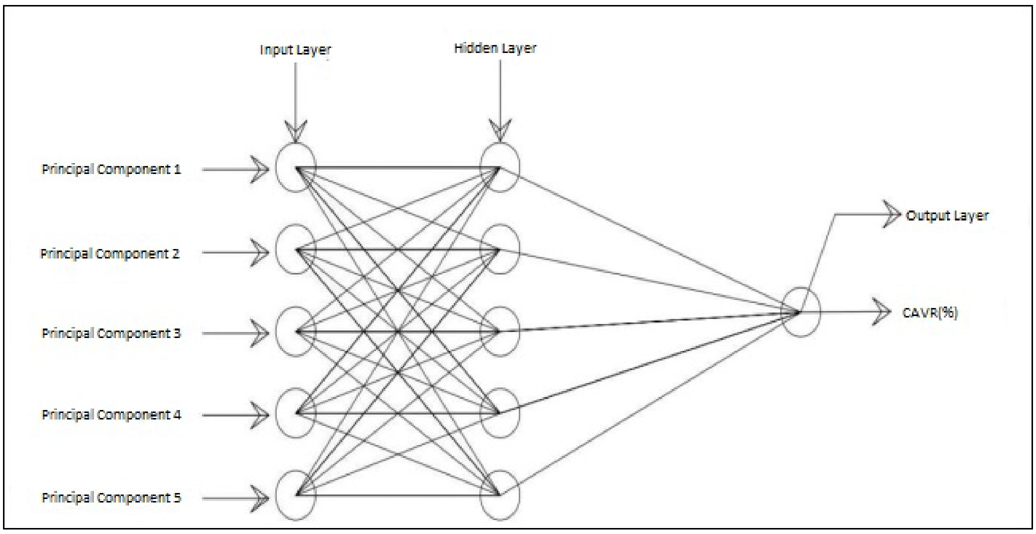

Fig. 4 Principal component neural network architecture

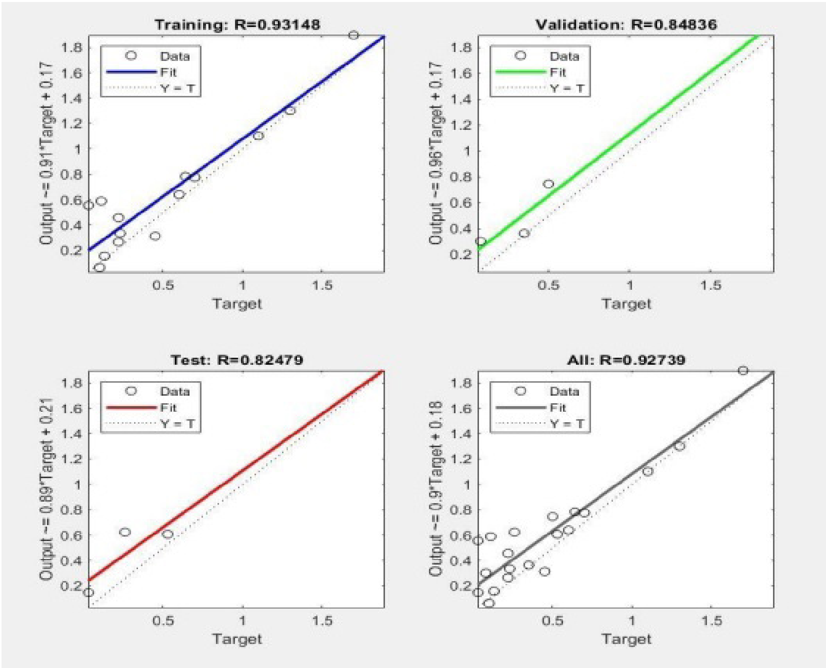

Fig. 5 Performance of ANN (with principal components) – for CAVR (%)

Table 10 Results of ANN original data and PC data

Category	Original data as input in ANN			PC data as input in ANN		
	Network structure	*R*-value	MSE	Network structure	*R*-value	MSE
			Data of all cities			
All	19:19:1	0.84	0.16	5:5:1	0.92	0.03
			City data categorized based on the city population			
MCP1	19:19:1	1.00	0.00	5:5:1	1.00	0.00
MCP2	19:19:1	0.99	0.02	5:5:1	1.00	0.00
MCP3	19:19:1	0.99	0.003	5:5:1	0.99	0.002
			City data categorized based on the city area			
MCA1	19:19:1	0.99	0.02	5:5:1	1.00	0.00
MCA2	19:19:1	0.64	1.2	5:5:1	1.00	0.00
MCA3	19:19:1	1.00	0.00	5:5:1	1.00	0.00

References

Adanu, E. K., Jones, S. (2017) "Effects of human-centered factors on crash injury severities", Journal of Advanced Transportation, 2017, 1208170.
https://doi.org/10.1155/2017/1208170

Afework, A., Sipos, T. (2020) "Modelling of accidents for four lane non-urban highways using artificial neural networks technique", In: 2020 IEEE 14th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, pp. 000047–000052. ISBN 978-1-7281-7378-8
http://doi.org/10.1109/SACI49304.2020.9118819

Alqatawna, A., Rivas Álvarez, A. M., García-Moreno, S. S.-C. (2021) "Comparison of multivariate regression models and artificial neural networks for prediction highway traffic accidents in Spain: A case study", Transportation Research Procedia, 58, pp. 277–284.
https://doi.org/10.1016/j.trpro.2021.11.038

Alkheder, S., Taamneh, M., Taamneh, S. (2017) "Severity prediction of traffic accident using an artificial neural network", Journal of Forecasting, 36(1), pp. 100–108.
https://doi.org/10.1002/for.2425

Aworemi, J. R., Abdul-Azeez, I. A., Olabode, S. O. (2010) "Analytical Study of the Causal Factors of Road Traffic Crashes in Southwestern Nigeria", [pdf] Educational Research, 1(4), pp. 118–124. Available at: https://www.interesjournals.org/articles/analytical-study-of-the-causal-factors-of-road-trafficcrashes-in-southwestern-nigeria.pdf [Accessed: 18 September 2022]

Basu, S., Saha, P. (2017) "Regression models of highway traffic crashes: A review of recent research and future research needs", Procedia Engineering, 187, pp. 59–66.
https://doi.org/10.1016/j.proeng.2017.04.350

Božović, M., Pešić, D., Davidović, J., Antić, B., Simeunović, M. (2022) "Traffic Safety Impact Factors Related to Changing the Vehicles Among Drivers in Closed Systems", Promet – Traffic & Transportation, 34(3), pp. 421–430.
https://doi.org/10.7307/ptt.v34i3.4062

Jovanis, P. P., Chang, H.-L. (1986) "Modeling the Relationship of Accidents to Miles Traveled", [pdf] Transportation Research Record, 1068, pp. 42–51. Available at: https://onlinepubs.trb.org/Onlinepubs/trr/1986/1068/1068-005.pdf [Accessed: 18 September 2022]

Kumar, P., Jain, J. K. (2021) "Accident Prediction Modeling for Yamuna Expressway", [pdf] In: Ray, K., Roy, K. C., Toshnival, S. K., Sharma, H., Bandyopadhyay, A. (eds.) Proceedings of International Conference on Data Science and Applications, Springer, Singapore, Singapore, pp. 241–248. ISBN 978-981-15-7560-0
https://doi.org/10.1007/978-981-15-7561-7_19

McFadden, J., Yang, W.-T., Durrans, S. (2001) "Application of artificial neural networks to predict speeds on two-lane rural highways", Transportation Research Record, 1751(1), pp. 9–17.
https://doi.org/10.3141/1751-02

Roy, N., Roy, R., Talukdar, H., Saha, P. (2017) "Effect of mixed traffic on capacity of two-lane roads: Case study on Indian highways", Procedia Engineering, 187, pp. 53–58.
https://doi.org/10.1016/j.proeng.2017.04.349

Sipos, T., Afework Mekonnen, A., Szabó, Z. (2021) "Spatial Econometric Analysis of Road Traffic Crashes", Sustainability, 13(5), 2492.
http://doi.org/10.3390/su13052492

Todosijević, B., Pešić, D., Antić, B., Lipovac, K., Filipović, F. (2022) "Combining Traffic Safety Exposure Indicators in a Composite Exposure Index", Promet – Traffic & Transportation, 34(2), pp. 211–221.
https://doi.org/10.7307/ptt.v34i2.3928

Valli, P. P. (2005) "Road accident models for large metropolitan cities of India", IATSS Research, 29(1), pp. 57–65.
https://doi.org/10.1016/S0386-1112(14)60119-9

Xue, S., Weng, J. (2014) "Analysis of uncertainty associated with response time in work zone traffic accidents", In: CICTP 2014: Safe, Smart, and Sustainable Multimodal Transportation Systems, Changsha, China, pp. 3710–3722. ISBN 9780784413623
https://doi.org/10.1061/9780784413623.355

Yeole, M., Jain, R. K., Menon, R. (2022) "Prediction of Road Accident Using Artificial Neural Network", International Journal of Engineering Trends and Technology, 70(3), pp. 151–161.
https://doi.org/10.14445/22315381/IJETT-V70I2P217

Yuan, Z., Huang, D., Tong, W., Liu Z. (2020) "Characteristic analysis and prediction of traffic accidents in the multiethnic plateau mountain area", Journal of Transportation Engineering, Part A: Systems, 146(8), 04020068.
https://doi.org/10.1061/JTEPBS.0000398

Zheng, L., Meng, X. (2011) "An Approach to Predict Road Accident Frequencies: Application of Fuzzy Neural Network", [pdf] presented at 3rd International Conference on Road Safety and Simulation, Indianapolis, IN, USA, Sep. 14-16. Available at: http://onlinepubs.trb.org/onlinepubs/conferences/2011/RSS/2/Zheng,L.pdf [Accessed: 18 September 2022]