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Development of a regional-based predictive model of incidence of traumatic spinal cord injury using machine learning algorithms

Seyed Behnam Jazayeri [a,b,1], Seyed Farzad Maroufi [b,c,1], Shaya Akbarinejad [d], Zahra Ghodsi [e,f], Vafa Rahimi-Movaghar [a,e,f,*]

[a] Sina Trauma and Surgery Research Center, Tehran University of Medical Sciences, Tehran, Iran
[b] Students' Scientific Research Center (SSRC), Tehran University of Medical Sciences (TUMS), Tehran, Iran
[c] Faculty of Medicine, Tehran University of Medical Sciences (TUMS), Tehran, Iran
[d] TRON - Translational Oncology at the University Medical Center of the Johannes Gutenberg University Mainz gGmbH, Mainz, Germany
[e] Brain and Spinal Cord Injury Research Center, Neuroscience Institute, Tehran University of Medical Sciences, Tehran, Iran
[f] Spine Program, University of Toronto, Toronto, Canada

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ABSTRACT

Objective: To develop a predictive model of incidence of traumatic spinal cord injury (TSCI).
Methods: The data for training the model included both the incidence data and the covariates. The incidence data were extracted from systematic reviews and the covariates were extracted from data available in the international road federation database. Then the feature processing measures were taken. First we defined a hyperparameter, missing-value threshold, in order to eliminate features that exceed this threshold. To tackle the problem of overfitting of model we determined the Pearson correlation of features and excluded those with more than 0.7 correlation. After feature selection three different models including simple linear regression, support vector regression, and multi-layer perceptron were examined to fit the purposes of this study. Finally, we evaluated the model based on three standard metrics: Mean Absolute Error, Root Mean Square Error, and R^2.
Results: Our machine-learning based model could predict the incidence rate of TSCI with the mean absolute error of 4.66. Our model found "Vehicles in use, Total vehicles/Km of roads", "Injury accidents/100 Million Veh-Km", "Vehicles in use, Vans, Pick-ups, Lorries, Road Tractors", "Inland surface Passengers Transport (Mio Passenger-Km), Rail", and "% paved" as top predictors of transport-related TSCI (TRTSCI).
Conclusions: Our model is proved to have a high accuracy to predict the incidence rate of TSCI for countries, especially where the main etiology of TSCI is related to road traffic injuries. Using this model, we can help the policymakers for resource allocation and evaluation of preventive measures.

1. Introduction

Traumatic spinal cord injury (TSCI) is a traumatic event that harms the normal sensory, motor, or autonomic functions of patients. TSCI poses significant health and social impact worldwide, with an incidence of between 10.4 and 59.0 injured individuals per million inhabitants per year.[1,2] The management of TSCIs requires substantial health care resources, with its annual health care costs being up to six times more expensive than that of other chronic diseases.[3] These costs are largely related to the need for a high-level acute care in the short term. TSCI associated long-term secondary complications further increase the cost for patients family and health system.[4]

The available information on the epidemiology of TSCI is very limited worldwide, especially in developing countries. A 2023 study by Jazayeri et al[5] on the worldwide epidemiology of spinal cord injury found that only 49 predominantly developed countries had data regarding the prevalence and incidence of TSCI, and there lies a huge gap in the epidemiology of TSCI in other countries. It's clear that such information is of great importance for government planning and financial resource allocating purposes. Developed countries are planning and reducing the number of casualties and its caused damage, while the rate of injuries and damage is increasing in developing countries.[6] On this

* Corresponding author. Sina Trauma and Surgery Research Center, Sina Hospital, Hassan Abad Square, Imam Khomeini Avenue, Tehran, Iran.
E-mail addresses: v_rahimi@sina.tums.ac.ir, v_rahimi@yahoo.com (V. Rahimi-Movaghar).
[1] Equal contribution.

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account, developing a valid model that is able to predict TSCI incidence could help countries to plan and allocate budgets to reduce the incidence of TSCI.

Predicting the incidence or prevalence of a disease based on the variables affecting it (covariates) is increasingly being done by machine learning methods. Machine learning models, computational algorithms that can identify hidden relationships between covariates and the outcome, hold many advantages against traditional methods which relied on predefined rules. Thus, unlike rule-based systems, machine learning automatically gives appropriate weight to predictors based on the observed pattern in data, and therefore it does not require prior knowledge of predictors' importance.[7,8] Also, certain machine learning models, such as support vector machines (SVMs), and artificial neural networks (ANNs), have the ability to extract complex non-linear relationships within the dataset and thus, provide better predictions compared to linear models.[9] These capacities to unveil intricate connections in data make machine learning particularly well-suited for the prediction and estimation of incidence and prevalence data. Herein, we aim to develop a regional-based predictive model of the incidence of traumatic spinal cord injury using machine learning algorithms.

2. Material and methods

2.1. Data collection and preprocessing

The data for covariates are extracted from International Road Federation (IRF) world road statistics millennium data for 2000–2015.[10] The IRF is a global not-for-profit organization that publishes annual reports regarding world road statistics utilizing multiple sources including national statistics, transport-related administrations and National Police reports on road traffic crashes.[11,12] The 2015 version of IRF contains 207 features pertaining road infrastructure and safety for 205 countries. We used the following indicators from IRF millennium data to train our model: (1) Country profiles: country name, income group and region, (2) Road network: Length of the road network in kilometer (Km) including motorways/highways, national roads, % paved and unpaved roads. (3) Road traffic: Traffic volume in million (Mio) Vehicle-Km unit. (4) Multimodal traffic comparisons in passenger-km unit. (5) Vehicles in use: total number of passenger cars, buses, motor coaches, vans and pick-ups, lorries and road Tractors, motorcycles & mopeds. (6) Road accidents: number of crashes with at least one person killed or injured, number of person injured, and number of persons killed/fatality. (7) Road expenditures: Expenditure on constructions/investments, maintenance, administrative costs, research and other recurrent costs and (8) CO2 emission as a measure of transport activities. In order to gather incidence data, we extracted data from two previously published systematic reviews.[13,14]

Before applying any model to the collected data, we needed to clean data, deal with the missing values, select the most important features to prevent over-fitting, and normalize them to speed up the convergence of the model.

All datapoints from different sources were aggregated in a single table with 168 rows (the number of instances), and 70 columns, where 68 of them were IRF indicators, one of them specified the year, and the other determined the name of the country. We added another column that represented the incidence rates we were trying to predict. In this study, we included national and sub-national incidences. For each entry in the table, we first searched for the national incidence rate, and only if there was no national incidence in our data sets, we put sub-national incidence in its corresponding row. It is important to note, that we excluded incidences that were the mean values across several years since we witnessed that including these incidences would distort the data, and worsen our final results.

Many of our features had undefined values in some rows; hence, we had to tackle the missing values problem to be able to run a model on the data. We defined a parameter, missing-value threshold, which ranged from 0 to 1. This parameter specified what percentage of a feature can be undefined at most, and still remain included. Those features with missing data percentages exceeding this threshold were removed. In our analysis, we set the missing-value threshold 0.4, as it had the best performance. It means that if more than 40% of values of a feature are missing, the feature is eliminated. Using this threshold, out of 68 indicators, 12 of them were removed, with a threshold of 0.4. For other missing values, we imputed them using the Python implementation of MICE.[15]

One common pitfall of applying machine learning to problems which have few datapoints but many features, is over-fitting. In short, over-fitting means that the model is so powerful that it captures not only the underlying pattern in data, but also noise and random fluctuations. As a rule of thumb, the number of training datapoints should be ~5–10x more than the number of features. As we had 168 datapoints and 56 features, we were also faced with over-fitting. To mitigate this, we removed highly correlated features. Concretely, we computed the Pearson correlation matrix of all 56 features, and among two features with a correlation more than a specific threshold (another hyper-parameter), only one got selected. In this study, this threshold was empirically chosen as 0.7. After this feature selection phase, 23 features remained.

Finally, as some features, e.g. total highways in Km, were several orders of magnitude larger than others, e.g. national currency per dollar, we needed to normalize features. We performed standard normalization so that each feature has a standard deviation of 1 and a mean of 0.

2.2. Models

In this paper, three different regression models have been proposed to predict the incidence rate based on the given features: simple linear regression, support vector regression (SVR), and multi-layer perceptron (MLP). Linear regression model has the advantage of being simple to implement and being easily interpretable, however its assumption that the covariates and target variable are linearly dependent can reduce its power. On the other hand, SVR can learn non-linear functions among features, but is less interpretable. In this paper we use ϵ-SVR which is more robust against noisy input. Finally, MLP is the most powerful model of the three which can learn highly complex patterns in the data, and can automatically discard irrelevant features. However, the downside of MLPs is being a black box, meaning that it is not trivial to interpret why a certain prediction was made. Here, we utilized an MLP with 3 hidden layers, containing 10, 20, and 10 nodes in each layer with the ReLU activation function. Fig. 1 depicts the architecture of the proposed neural network. All models were implemented by the Scikit-Learn package.[16] The details of each model are presented in Appendix 1.

2.3. Evaluation metrics

We evaluated the methods based on three standard metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2. MAE measures average magnitude of the errors in a set of predictions. We can interpret MAE as the average difference of predicted points to the actual values. RMSE is similar to MAE, however, RMSE gives more weight to higher errors and less weight to lower errors. Meanwhile, R^2 is intended to capture the proportion of variability in a dataset that is accounted for by the statistical model. It is always between 0 and 1. When $R^2 = 1$ it means that all of the variability in data is explained and the model can very closely predict the actual values. Contrary, if $R^2 = 0$ it means non of the variability is explained, and there is no relation between the predicted values and actual values. You can find the details of each metric in Appendix 1.

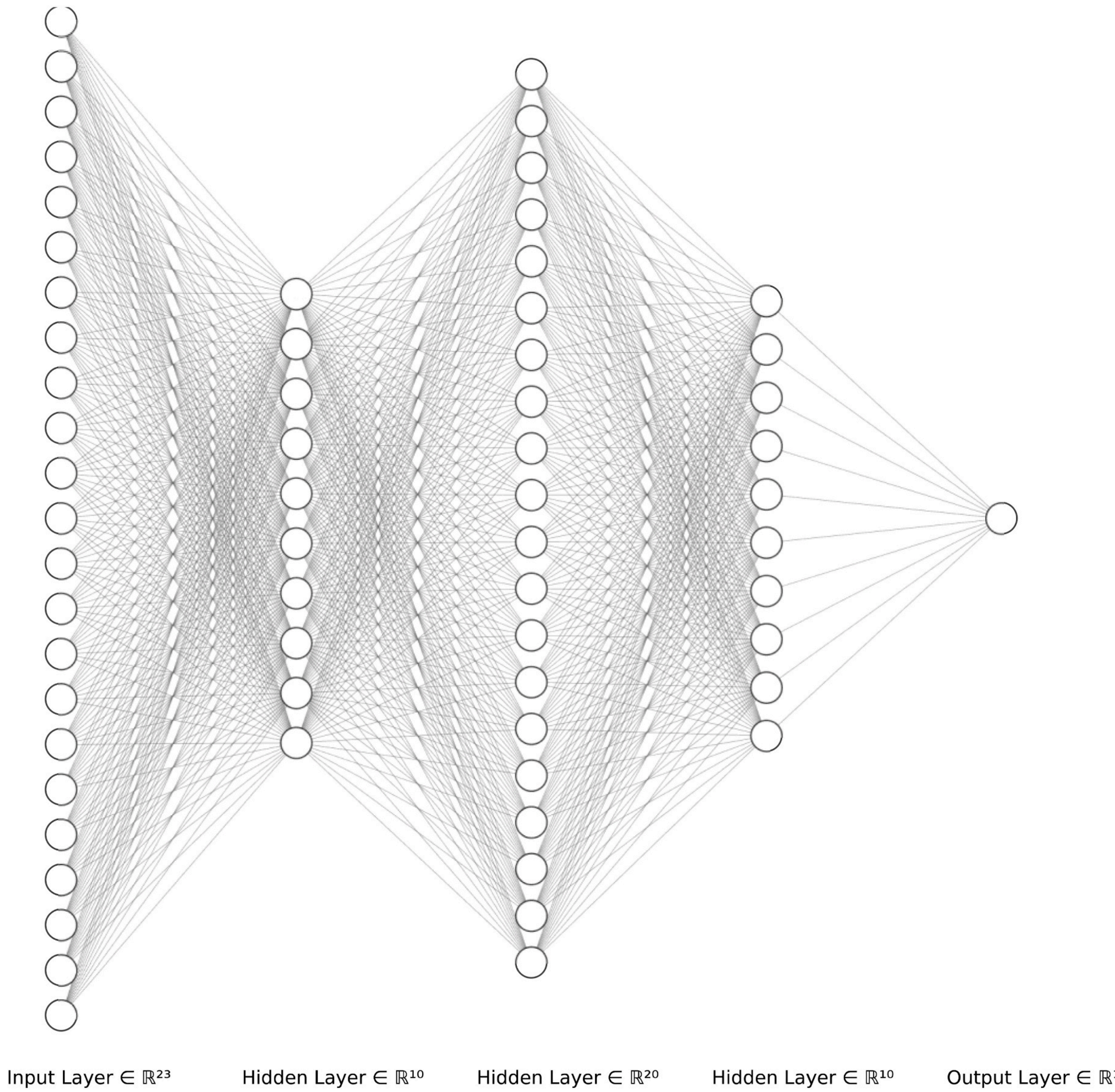

Fig. 1. Architecture of our neural network.

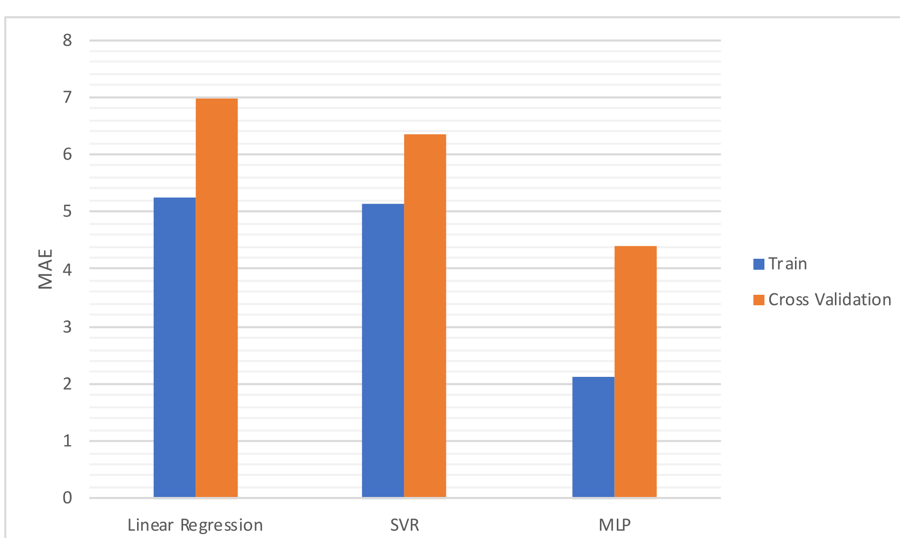

Fig. 2. Mean Absolute Error of different methods.

3. Results

3.1. Evaluation

Figs. 2–4 show MAE, RMSE, and R^2 results for train and test sets, respectively. As expected, MLP outperformed other models in all three metrics, in both train and test sets. We can examine that in the MAE metric; the cross-validation error of MLP is even smaller than the training error of linear regression and ϵ-SVR. The cross-validation MAE of the neural network is 4.66, meaning that on average each predicted incidence rate is only 4.66 off from the gold standard. Furthermore, R^2 of MLP is 0.73, which means that 73% of the variability is captured by the model. All models performed much better on the train sets, which highlights the necessity of having more clean data to infer a function with lower errors.

The weights of features represent how much each feature contributes to the final prediction model. The bigger the absolute value of the weight of the feature is, the more important role that feature plays in the final output of the model. On ϵ-SVR and linear regression, we found features with the largest absolute weights to provide insight for the future. Features with positive coefficients result in higher incidence and vice versa. In ϵ-SVR the top five predictors were "Vehicles in use, Total vehicles/Km of roads", "Injury accidents/100 Million Veh-Km", "Vehicles in use, Vans, Pick-ups, Lorries, Road Tractors", "Inland surface Passengers Transport (Mio Passenger-Km), Rail", and "% paved". The first four features contribute positively to the incidence rate prediction, "% paved" contributes negatively. For linear regression, the top five features were "Vehicles in use, Vans, Pick-ups, Lorries, Road Tractors", "Inland surface Passengers Transport (Mio Passenger-Km), Total "Million Vehicle-Km, annual, Passenger cars", "Road sector energy consumption in the kilotonnes of oil equivalent (ktoe)", and "Injury accidents". Surprisingly, in linear regression "Inland surface Passengers Transport, total" contributes negatively to the incidence rate, which is a reason that exacerbated the linear regression results.

3.2. Outcome

The mean value of incidence in each country was used to generate Fig. 5, showing higher incidence in West Pacific WHO region. The highest incidence was seen in Monaco (172.05 cases per million (cpm) population per year), Korea (154.79 cpm), Indonesia (139.45 cpm), and the United States of America (USA) (138.62 cpm) in 2015, while in 2000, Japan (114.18 cpm), Tajikistan (111.56 cpm), and Bahamas (96.36 cmp) had the highest calculated rate. Regarding the lowest incidence rate, Qatar (4.77 cpm), and Netherlands (5.77 cpm) were the top countries in 2000 and by the year 2015 Botswana (1.09 cpm), Kenya (1.86 cpm), Saudi Arabia (2.22 cpm), and had the lowest incidence rate. During the 15-years period, Tajikistan (97.06%), Saudi Arabia (93.58%), and Botswana (93.21%) were top countries in terms of incidence percent decrease, while Qatar (660.04%), China (576.35%), and Azerbaijan (431.47%) showed an increasing pattern. Detailed predicted incidence of TSCI in different countries based on WHO regions from 2000 to 2015 are presented in Appendix 2.

4. Discussion

In recent years, modeling by machine learning methods has become popular in medicine. A huge part of this popularity is due to the increase in accessibility of data and their complexity, which makes statistical modeling for this data nearly impossible. Using machine learning as a modeling tool enables us to predict complex outcomes using a set of basic data, each with a different level of impact on the predicted outcome. Predicting these outputs is important in terms of political planning and resource allocating. In this project, we have extracted, for the first time, the covariates that may be directly or indirectly related to the occurrence of TRTSCI, from different countries and used them to create a model with the help of machine learning methods to predict the incidence of TRTSCI. Choosing these covariates was done carefully with the consultation of experts. In developing countries, the main etiology of TSCI is road traffic injuries in contrast to the developed countries in which falling is the main etiology.[13] We used 23 covariates that are mostly related to road traffic incidence (Table 1). After modeling and modifications, our model could predict TRTSCI incidence with a MAE of 4.66 based on the selected covariates. ML models using MAE as measure of model performance are promising tools in predicting road accidents.[17] It is known that Machine learning models that utilize MAE as a performance metric show great potential in forecasting road accidents.[17,18]

We found a positive correlation between number of vehicles, number of injuries, number of passengers and negative correlation with % paved with incidence of TRTSCI. We used aggregated IRF data to design our model. Other studies have also used IRF data to predict different outcomes.[19,20] For example Ahmed and colleagues extracted road density and road network information from IRF along with data of 40 Asian countries to design a predictive regression model for road crash fatalities, and found a significant negative correlation between road density and road crash fatalities but no correlation for number of registered

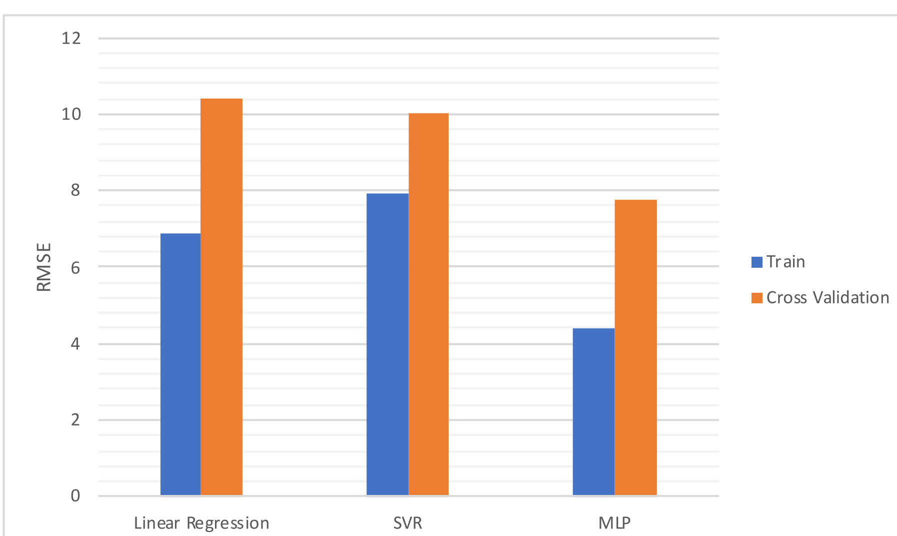

Fig. 3. Root Mean Square Error of different methods.

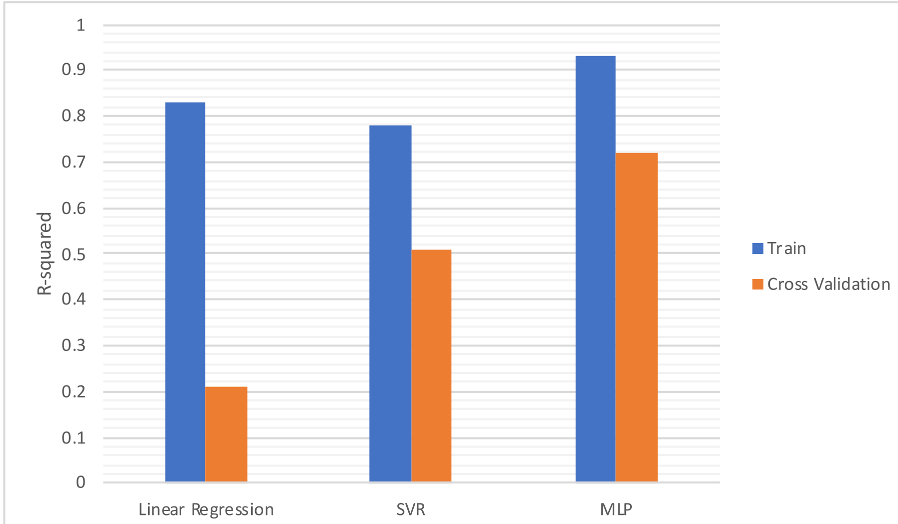

Fig. 4. R-squared of different methods.

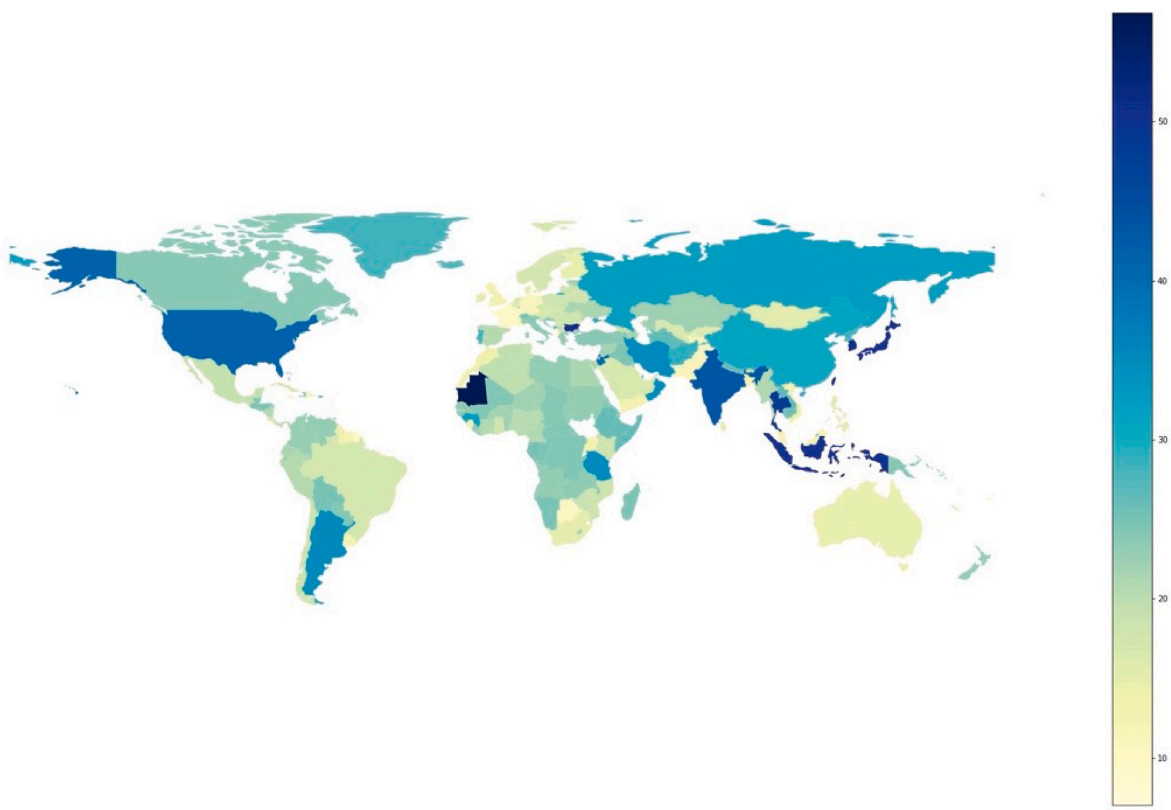

Fig. 5. World map view of average generated TSCI incidence by our model from 2000 to 2015.

vehicles, were found.[20] Similar to our findings a recent study found that the number of vehicles in a country is a predictive feature for both minor and fatal road crashes.[21] In addition, some studies have shown that more severe accidents occur in rural and urban areas where the %pavement is lower compared with motor highways, a finding which is in line with our model.[22,23]

We observed a high incidence of TSCI in some of the developed countries like Japan and the USA. High TSCI incidence in Japan could be partly due to the fact that half of the population are aged over 50 years old and are more prone to SCI in cases of trauma. High TSCI incidence in the USA might be explained by more accurate recording in national registries or higher survival rates in case of severe traffic injuries.[24] Earlier, the Global Burden of Diseases, Injuries, and Risk Factors (GBD) study reported the incidence and prevalence of traumatic brain injury and spinal cord injury from 1990 to 2016 and later updated it to include 2019 data.[24,25] Our estimates are lower compared with rates given by the GBD studies. In the mentioned studies, TSCI incidence is estimated indirectly by collecting data on different etiologies associated with SCI and calculating the proportion of each cause leading to SCI, adding up to form an overall SCI incidence rate in a country or defined region. They used DisMod II tool for their model. Also, they have included pre-hospital deaths while we have only recognized cases from literature

Table 1
List of used covariates to predict incidence.

'Motorways Km'
'Other Roads Km'
'Million Vehicle-Km, Annual, Passenger cars'
'Million Vehicle-Km, Annual, Buses & Motor coaches'
'Million Vehicle-Km, Annual, Total'
'Million Vehicle-Km, Annual, Motorcycles'
'Inland surface freight transport (Mio Tonne-Km), Rail'
'Inland surface freight transport (Mio Tonne-Km), Total'
'Inland surface Passengers Transport (Mio Passenger-Km), TOTAL'
'Inland surface Passengers Transport (Mio Passenger-Km), Rail'
'Vehicles in use, Vans, Pick-ups, Lorries, Road Tractors'
'Vehicles in use, Passengers cars/1′000 pop'
'Injury accidents'
'Vehicles in use, Motorcycles'
'Vehicles in use, Total vehicles/Km of roads'
'Passenger cars, Imports'
'Passenger cars, Exports'
'Total motor vehicles, Imports'
'Expenditures (Mio USD), Regional/Local Gov't'
'Diesel price (US $ cent/liter)'
'Diesel consumption, Kt'
'Road sector energy consumption in ktoe'
'CO2 Emissions from Inland Transport Sector (Mio Tonnes of C02), Rail'

Km: Kilometer, Kt: Kilotonnes, Mio: million, ktoe: kilotonnes of oil equivalent

with a definitive diagnosis of SCI in the hospital. Also, it should be mentioned that we only used road traffic covariates to design our model and therefore our model can be used to evaluate transport-related TSCI not all-cause TSCI. These differences could explain the differences of this study rates with the GBD studies.

Our study has some limitations that should be highlighted. First, there are many other factors that could impact SCI incidence and its related data were either not accessible for us or did not exist for many countries. Our raw data was only limited to the years 2000–2015 and most of the countries had some gaps, this obligated us to impute 40% of the data. Using more covariates and more complete data could make our result far more accurate. Since we only used covariates related to road traffic injury we could not predict SCI in developing countries accurately. By adding covariates related to falling we can have a better prediction of SCI incidence in developed countries in the future. Also, since we have not considered pre-hospital death due to spinal cord injuries and this may contribute to underestimation in our results.

5. Conclusion

We have developed a model based on a machine learning method that can predict the incidence rate of TSCI with the mean absolute error of 4.66. This means that our model can be used with high accuracy to predict the incidence rate of TSCI for countries, especially where the main etiology of TSCI is related to road traffic injuries. Using this model can help the policymakers for resource allocation and evaluation of preventive measures. Future models should use a more comprehensive set of covariates that contain data regarding falls and other etiologies of SCI in developed countries.

Ethical approval

The Ethics Committee of Sina Trauma and Surgery Research Center, Tehran University of Medical Sciences, approved the study, and the reference number is 96-02-38-302.

Data availability

The data regarding our model is available from: https://github.com/Shaya94/Spinal_Cord_Injury.

CRediT authorship contribution statement

Seyed Behnam Jazayeri: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Seyed Farzad Maroufi:** Methodology, Writing – original draft, Writing – review & editing. **Shaya Akbarinejad:** Data curation, Formal analysis, Methodology, Software, Writing – review & editing. **Zahra Ghodsi:** Project administration, Supervision, Writing – review & editing. **Vafa Rahimi-Movaghar:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wnsx.2024.100280.

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Abbreviations

TSCI: Traumatic spinal cord injury
SVR: Support vector regression
MLP: Multi-layer perceptron
IRF: International Road Federation
MAE: Mean Absolute Error
RMSE: Root Mean Square Error