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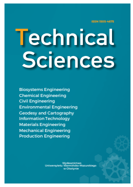

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MANAGEMENT AND FORECASTING OF ROAD ACCIDENTS IN POLAND AND MONTENEGRO USING NEURAL NETWORKS

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A b s t r a c t

Despite a general decline in recent years, road traffic accidents remain a significant public safety concern in both Poland and Montenegro. Although accident rates were affected by the COVID-19 pandemic, the persistent frequency of such incidents underscores the urgent need for further preventive measures to enhance road safety.

The aim of this study is to forecast the number of road traffic accidents in Poland and Montenegro for the period 2024-2030. To achieve this, historical data on annual accident counts were obtained from Monstat (Montenegro) and the Polish Police. These datasets were then analyzed using selected neural network models to generate projections for the specified timeframe.

The results suggest a potential stabilization in the number of traffic accidents in the near future. This forecast is influenced by several factors, including the steady increase in car ownership and ongoing investments in road infrastructure, such as the construction of new motorways and local roads. It should be noted, however, that the inherent uncertainty in data sampling – used for training, testing, and validating the models – places natural limitations on the precision of the forecasts.

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Introduction

Traffic accidents represent a major global concern, both economically and in terms of public health. According to estimates by the World Health Organization (WHO), approximately 1.3 million people die each year as a result of traffic-related injuries, and such incidents cost countries around the world an average of 3% of their gross domestic product (GDP) (*The Global Status…* 2018). Notably, road traffic accidents are the leading cause of death among young people aged 5 to 29 (*The Global Status…* 2018). In response, the United Nations General Assembly has set an ambitious target of reducing the number of road traffic deaths and injuries globally by 2030.

Between 2010 and 2023, Poland experienced a consistent decline in the number of road traffic accidents. In 2010, a total of 38,832 accidents were recorded, decreasing significantly to 20,936 by 2023 (Fig. 1).

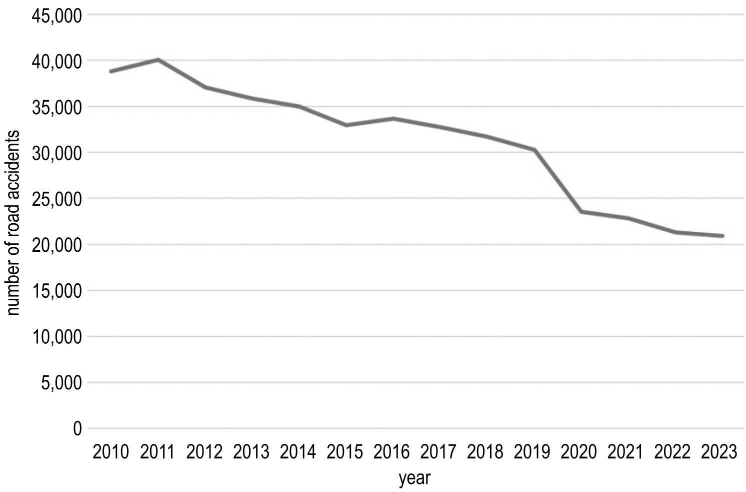

Fig. 1. Number of road accidents in Poland between 2010 and 2023
Source: based on *Wypadki drogowe – raporty roczne* (2024).

In contrast, the number of road accidents in Montenegro showed fluctuations over the same period. In 2010, there were 9,138 recorded accidents, falling to 6,573 by 2023. The lowest number was observed in 2020 (4,595), primarily due to mobility restrictions imposed during the COVID-19 pandemic (Fig. 2).

These statistics highlight the ongoing road safety challenges in both countries, despite Poland's overall improvement.

One of the most important measures of road safety is the number of accidents per 10,000 people (NRA). With a population of 37.6 million, Poland had 20,936 traffic accidents in 2023, yielding an NRA of 5.57. In comparison, Montenegro, which has a population of 0.6 million, had 6,573 traffic accidents, resulting in an NRA of 109.55, which is far higher than Poland's.

$$\mathrm{NRA} = \frac{\mathrm{NR}}{\mathrm{NI}} \cdot 10{,}000 \tag{1}$$

where:

NR – number of road accidents,

NI – number of inhabitants.

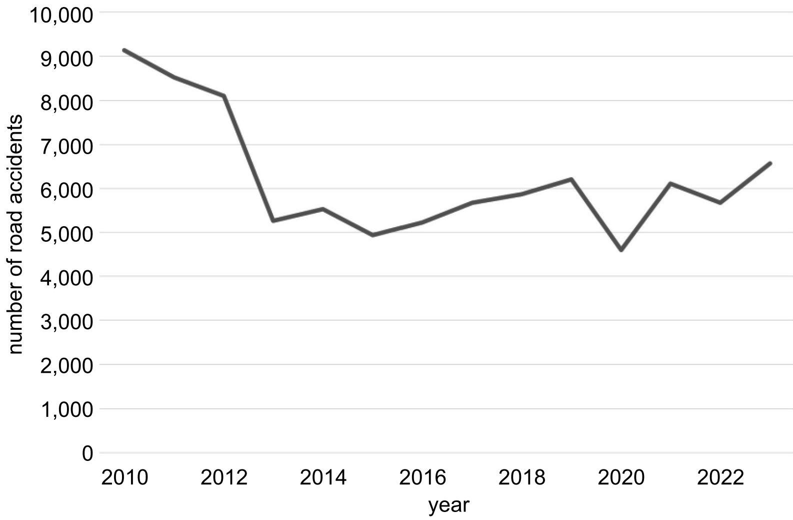

Fig. 2. Number of road accidents in Montenegro between 2010 and 2023
Source: based on *Godišnja statistika saobraćaja, skladištenja i veza – Arhiva* (2024).

Using the previously provided statistics (*Wypadki drogowe*… 2024, *Godišnja statistika saobraćaja*… 2024), the authors estimated the number of accidents on Polish and Montenegrin roadways. Neural networks were used to forecast the amount of incidents in both countries.

The novelty of this study lies in the integration of neural network-based forecasting with a comparative analysis of traffic accident trends in two distinct European countries: Poland and Montenegro. Unlike previous research, which typically focuses on a single national context or uses classical time-series models, this paper offers a cross-national perspective supported by data-driven, non-linear modeling. This approach enables the identification of shared and divergent risk patterns, providing a more generalizable framework for traffic safety analysis.

Literary

Reliable accident analysis and forecasting rely heavily on trustworthy data sources. Government agencies have traditionally collected and analyzed accident-related information from multiple sources, including police reports, insurance databases, and medical records (GORZELAŃCZYK 2022). Modern transportation networks offer abundant data for traffic analysis. Vehicle movement, speed, and traffic flow can be continuously monitored through GPS-equipped vehicles, roadside microwave sensors, and automatic license plate recognition systems (CHUDY-LASKOWSKA, PISULA 2015, KHALIQ et al. 2019, RAJPUT et al. 2015). While social media can provide real-time traffic updates, user-generated content is not always reliable or verifiable (ZHENG 2018). Effective accident analysis often requires the integration of data from multiple sources. Harmonizing heterogeneous datasets and merging them can significantly enhance the accuracy of analytical outcomes (ABDULLAH, EMAM 2015).

VILAÇA et al. (2017) conducted a statistical analysis of the relationship between traffic participants and accident severity, emphasizing the need for stricter road safety policies and regulations. BAK et al. (2019), using accident data as a proxy for studying accident causation, applied multivariate statistical techniques to examine the risk profiles of individuals involved in collisions in a specific region of Poland.

Time series models are frequently used to forecast accident frequency (HELGASON 2016, LAVRENZ et al. 2018). However, such models often fail to assess forecast accuracy based on historical prediction errors and tend to exhibit residual autocorrelation (KOWALSKI 2005). Although methods such as Holt–Winters exponential smoothing (SUNNY et al. 2018) and multi-seasonality models (PROCHÁZKA et al. 2017) have been applied in some studies, they may not sufficiently account for exogenous factors (DUDEK 2013).

The development of effective road safety regulations depends on an accurate assessment of traffic collision severity. Implementing countermeasures aimed at preventing and mitigating the consequences of accidents requires a comprehensive understanding of the factors contributing to their severity (TAMBOURATZIS et al. 2014, ZHU et al. 2019, ARTEAGA et al. 2020). YANG et al. (2022) proposed a Deep Neural Network (DNN) architecture to predict varying levels of injury, mortality, and property damage, enabling a detailed and accurate analysis of accident severity.

The choice of data source for accident analysis depends largely on the specific research question. Combining statistical models with data from intelligent transportation systems and real-world driving behavior can improve the precision of both accident prediction and risk mitigation strategies (CHAND et al. 2021).

Materials and methods

Road accidents continue to pose a serious threat to public safety. Although a temporary decline in accident numbers has been observed in recent years – primarily due to mobility restrictions during the pandemic – the overall incidence remains unacceptably high. To effectively address this issue, it is essential to implement strategies that not only reduce the total number of accidents but also identify road types with the highest accident rates. Such a data-driven approach will facilitate the targeted implementation of road safety initiatives.

Taking into account the above information, the following research hypotheses were made:

H0 – the number of accidents in Poland will increase;

H1 – the number of accidents in Poland will be at this level;

H2 – the number of accidents in Poland will decrease;

H3 – the number of accidents in Montenegro will increase;

H4 – the number of accidents in Montenegro will be at this level;

H5 – the number of accidents in Montenegro will decrease.

To predict the frequency of traffic accidents in Poland and Montenegro, this study employed selected neural network models. Neural networks, inspired by the structure and functioning of the human brain, consist of interconnected nodes that process information through weighted connections.

The accuracy of the forecasts strongly depends on the selection of an appropriate model architecture and the optimization of its parameters. In this study, optimal weight values for the chosen model were determined using Statistica software.

Thanks to their multilayer architecture, neural networks are capable of identifying complex patterns in input data, including text, speech, and images. Achieving accurate predictions requires adjusting the internal parameters of the network during the learning process. The fundamental units of neural networks – artificial neurons – receive multiple inputs and produce a single output, mimicking the behavior of biological neurons.

Neural networks have a wide range of applications, including personalized product recommendations in e-commerce, machine translation (e.g., Google Translate), and content recommendation systems in streaming platforms. In this study, neural networks were applied to forecast the expected frequency of traffic accidents.

Specifically, a Multilayer Perceptron (MLP) neural network was used for the prediction task. The MLP architecture consisted of an input layer, one or more hidden layers (each comprising two to eight neurons), and an output layer. The output layer generated time series forecasts of the number of traffic accidents (Fig. 3). The Multilayer Perceptron model was selected due to its proven effectiveness in capturing stable patterns in time series with limited complexity and relatively small datasets. Unlike recurrent models such as RNNs or LSTMs, which are more suitable for long-range temporal dependencies, MLPs require less training data and computational resources. Given the relatively short forecasting horizon and regularity of the data, MLPs were considered a suitable and efficient choice. The ReLU activation function was used in the hidden layers, and a linear function in the output layer. The model was trained using the Adam optimizer with a learning rate of 0.001 for 200 epochs. Input data were normalized to the [0,1] range prior to training using min-max scaling.

To respect the temporal nature of the data, walk-forward validation was implemented. In this approach, the model was retrained and evaluated iteratively using expanding windows, where each prediction step used only past data available up to that point.

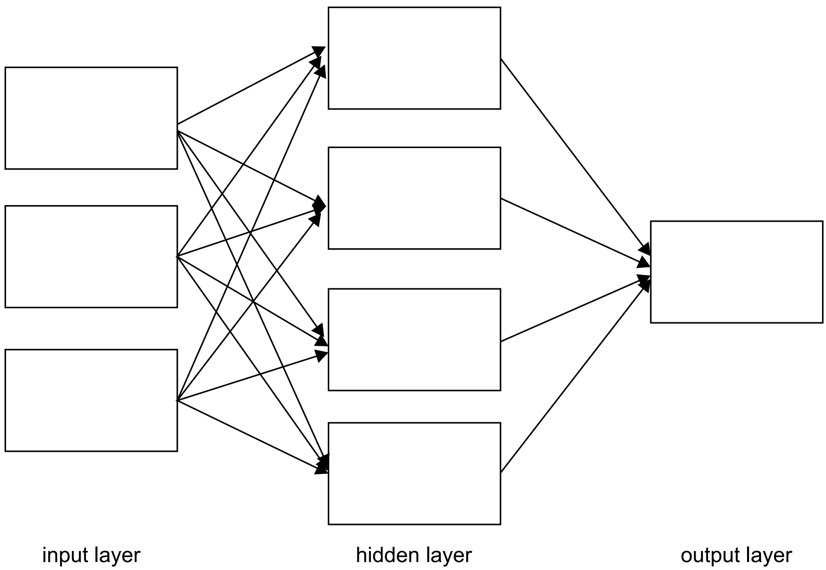

Fig. 3. Neural network models

The performance of the model was evaluated using a set of prediction error metrics, as defined in equations (2-6):

– ME – mean error

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right) \tag{2}$$

– MAE – mean absolute error

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - Y_p\right| \tag{3}$$

– MPE – mean percentage error

$$\mathrm{MPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i - Y_p}{Y_i} \tag{4}$$

– MAPE – mean absolute percentage error

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_i - Y_p\right|}{Y_i} \tag{5}$$

– SSE – mean square error

$$\mathrm{SSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2} \tag{6}$$

where:

n – length of the forecast horizon,

Y – observed value of traffic accidents,

Y_p – the forecast value of traffic accidents.

To predict the probability of traffic accidents in dependency, neural network models with the lowest average percentage error and average absolute percentage error were used.

Results

Data from the Polish Police from 2010-2023 (*Wypadki drogowe…* 2024) and Monstat Statistics (*Godišnja statistika saobraćaja…* 2024) were used to predict the yearly number of road accidents in Poland and Montenegro, respectively. In all instances, two random sample sizes were assumed and the study was carried out using Statistica software:

– teaching 70%, testing 15% and validation 15%;

– teaching 80%, testing 10% and validation 10%,

with the following number of learning networks: 20, 40, 60, 80, 100, 200 for which the MP error value was minimal (Tabs. 1-4).

Summary of neural network learning for the case of random

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function
20	MLP 1-7-1	0.97	0.98	0.99	BFGS 12	SOS
20	MLP 1-8-1	0.97	0.98	0.99	BFGS 4	SOS
20	MLP 1-2-1	0.97	0.98	0.99	BFGS 4	SOS
20	MLP 1-4-1	0.96	0.97	0.99	BFGS 4	SOS
20	MLP 1-3-1	0.97	0.97	0.99	BFGS 42	SOS
40	**MLP 1-7-1**	**0.97**	**0.98**	**0.99**	**BFGS 8**	**SOS**
40	MLP 1-3-1	0.97	0.98	0.99	BFGS 8	SOS
40	MLP 1-2-1	0.97	0.96	0.99	BFGS 7	SOS
40	MLP 1-8-1	0.97	0.96	0.99	BFGS 5	SOS
40	MLP 1-3-1	0.96	0.95	0.99	BFGS 5	SOS
60	MLP 1-4-1	0.97	0.97	0.99	BFGS 7	SOS
60	MLP 1-7-1	0.97	0.97	0.99	BFGS 5	SOS
60	MLP 1-2-1	0.97	0.97	0.99	BFGS 9	SOS
60	MLP 1-5-1	0.97	0.97	0.99	BFGS 12	SOS
60	MLP 1-6-1	0.97	0.98	0.99	BFGS 5	SOS
80	MLP 1-5-1	0.97	0.97	0.99	BFGS 7	SOS
80	MLP 1-8-1	0.97	0.98	0.99	BFGS 14	SOS
80	MLP 1-3-1	0.97	0.98	0.99	BFGS 7	SOS
80	MLP 1-7-1	0.97	0.96	0.99	BFGS 7	SOS
80	MLP 1-7-1	0.97	0.98	0.99	BFGS 13	SOS
100	MLP 1-8-1	0.97	0.98	0.99	BFGS 18	SOS
100	MLP 1-5-1	0.97	0.97	0.99	BFGS 6	SOS
100	MLP 1-4-1	0.97	0.98	0.99	BFGS 11	SOS
100	MLP 1-2-1	0.96	0.95	0.99	BFGS 7	SOS
100	MLP 1-2-1	0.97	0.97	0.99	BFGS 8	SOS
200	MLP 1-6-1	0.96	0.96	0.99	BFGS 8	SOS
200	MLP 1-6-1	0.97	0.96	0.99	BFGS 7	SOS
200	MLP 1-3-1	0.97	0.97	0.99	BFGS 10	SOS
200	MLP 1-2-1	0.95	0.92	0.99	BFGS 7	SOS
200	MLP 1-4-1	0.97	0.97	0.99	BFGS 6	SOS
Minimal						

Table 1

sample size teaching 70%, testing 15% and validation 15% for Poland

Activation (hidden)	Activation (output)	Errors				
		ME	MAE	MPE [%]	MAPE [%]	SSE
tanh	logistic	932.03	2,374.97	2.85	6.69	2,747.76
linear	logistic	664.14	2,092.80	3.19	6.46	2,667.94
exponential	exponential	1,168.74	2,119.69	3.23	5.69	2,657.54
exponential	linear	1,815.06	2,891.74	2.84	7.52	3,551.21
tanh	logistic	1,113.77	2,387.70	3.25	6.64	2,802.32
exponential	**exponential**	**837.43**	**2,001.24**	**2.77**	**5.68**	**2,484.15**
exponential	exponential	909.41	2,052.58	2.80	5.71	2,526.15
logistic	logistic	1,110.51	2,279.94	3.35	6.40	2,764.05
logistic	exponential	1,483.15	2,363.70	4.57	6.80	2,927.92
logistic	exponential	1,035.60	2,590.23	3.60	7.73	3,048.65
tanh	logistic	1,031.48	2,377.94	3.10	6.68	2,772.29
tanh	logistic	777.04	2,415.30	2.17	6.63	2,763.52
exponential	logistic	1,109.93	2,233.82	3.17	6.12	2,715.75
tanh	exponential	1,090.27	2,283.83	3.28	6.40	2,721.35
exponential	exponential	1,071.39	1,987.71	3.83	5.94	2,590.07
tanh	logistic	1,040.10	2,404.10	3.15	6.78	2,796.23
exponential	logistic	1,023.90	2,217.06	3.03	6.15	2,661.45
exponential	logistic	801.65	2,239.47	2.48	6.27	2,623.54
logistic	logistic	978.70	2,426.95	2.68	6.63	2,851.96
exponential	logistic	873.08	2,237.49	2.54	6.16	2,638.93
exponential	logistic	1,021.62	2,260.14	2.99	6.25	2,688.97
logistic	logistic	1,108.50	2,402.26	3.24	6.69	2,819.42
logistic	exponential	909.58	2,320.20	2.93	6.65	2,707.86
tanh	logistic	1,114.15	2,426.31	4.15	7.43	3,005.79
tanh	logistic	894.03	2,347.67	2.83	6.67	2,720.34
tanh	logistic	644.88	2,480.32	2.22	7.15	2,814.19
tanh	logistic	770.95	2,330.09	2.51	6.64	2,702.56
logistic	logistic	970.77	2,347.01	2.97	6.61	2,750.08
logistic	exponential	319.55	2,657.15	0.32	7.61	3,035.78
tanh	logistic	1,200.19	2,356.37	3.63	6.66	2,816.40
		319.55	**1,987.71**	**0.32**	**5.68**	**2,484.15**

Summary of neural network learning for the case of random sample

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function
20	MLP 1-5-1	0.96	0.99	1.00	BFGS 8	SOS
20	MLP 1-5-1	0.96	0.99	1.00	BFGS 5	SOS
20	MLP 1-3-1	0.96	0.99	1.00	BFGS 63	SOS
20	MLP 1-8-1	0.96	0.99	1.00	BFGS 6	SOS
20	**MLP 1-8-1**	**0.96**	**0.99**	**1.00**	**BFGS 6**	**SOS**
40	MLP 1-5-1	0.96	0.99	1.00	BFGS 5	SOS
40	MLP 1-5-1	0.96	0.99	1.00	BFGS 6	SOS
40	MLP 1-2-1	0.96	0.99	1.00	BFGS 6	SOS
40	MLP 1-6-1	0.96	0.98	1.00	BFGS 4	SOS
40	MLP 1-2-1	0.96	0.99	1.00	BFGS 10	SOS
60	MLP 1-2-1	0.95	0.98	1.00	BFGS 5	SOS
60	MLP 1-6-1	0.96	0.99	1.00	BFGS 5	SOS
60	MLP 1-6-1	0.95	0.98	1.00	BFGS 5	SOS
60	MLP 1-3-1	0.95	0.98	1.00	BFGS 7	SOS
60	MLP 1-6-1	0.95	0.99	1.00	BFGS 7	SOS
80	MLP 1-2-1	0.96	0.99	1.00	BFGS 11	SOS
80	MLP 1-3-1	0.96	0.99	1.00	BFGS 4	SOS
80	MLP 1-2-1	0.96	0.98	1.00	BFGS 7	SOS
80	MLP 1-2-1	0.95	0.98	1.00	BFGS 6	SOS
80	MLP 1-7-1	0.96	0.99	1.00	BFGS 5	SOS
100	MLP 1-7-1	0.96	0.99	1.00	BFGS 7	SOS
100	MLP 1-2-1	0.95	0.99	1.00	BFGS 9	SOS
100	MLP 1-5-1	0.96	0.99	1.00	BFGS 5	SOS
100	MLP 1-2-1	0.96	0.99	1.00	BFGS 7	SOS
100	MLP 1-4-1	0.96	0.99	1.00	BFGS 5	SOS
200	MLP 1-8-1	0.96	0.99	1.00	BFGS 6	SOS
200	MLP 1-2-1	0.96	0.98	1.00	BFGS 7	SOS
200	MLP 1-8-1	0.96	0.99	1.00	BFGS 2	SOS
200	MLP 1-3-1	0.96	0.98	1.00	BFGS 7	SOS
200	MLP 1-4-1	0.95	0.98	1.00	BFGS 5	SOS
Minimal						

Table 2

size teaching 80%, testing 10% and validation 10% for Poland

Activation (hidden)	Activation (output)	Errors				
		ME	MAE	MPE [%]	MAPE [%]	SSE
logistic	linear	422.40	1,830.32	0.90	5.12	2,362.11
linear	tanh	420.05	2,152.64	0.39	6.51	2,773.07
tanh	logistic	702.37	1,986.10	2.31	5.57	2,455.03
linear	tanh	326.74	2,130.77	0.17	6.45	2,734.11
logistic	**tanh**	**265.62**	**1,759.88**	**0.80**	**4.63**	**2,294.49**
tanh	exponential	1,544.71	2,539.20	6.27	8.23	3,300.44
linear	tanh	180.47	2,355.28	0.72	7.31	2,994.43
linear	tanh	184.52	2,325.08	1.67	7.28	2,934.77
logistic	logistic	725.12	2,046.17	3.35	6.03	2,699.40
logistic	tanh	397.20	1,761.51	1.05	4.76	2,339.08
logistic	exponential	46.12	2,638.20	0.89	7.75	3,021.27
linear	tanh	381.15	2,625.38	2.79	8.41	3,359.27
logistic	logistic	1,436.54	2,605.98	2.62	6.58	3,107.29
tanh	tanh	225.51	2,181.93	1.10	6.66	2,827.63
exponential	logistic	231.31	2,206.35	0.69	5.98	2,657.70
logistic	tanh	63.00	2,068.87	0.35	6.24	2,669.34
linear	tanh	261.75	2,325.06	0.42	7.18	2,957.41
logistic	linear	553.25	2,205.41	2.23	6.74	2,759.02
tanh	logistic	81.51	2,328.80	0.41	6.55	2,719.89
linear	tanh	159.97	2,374.17	0.82	7.38	3,018.42
linear	tanh	573.15	2,175.01	0.84	6.54	2,792.33
tanh	logistic	334.46	2,310.29	1.71	6.79	2,726.36
linear	tanh	180.96	2,441.21	1.90	7.72	3,101.83
linear	tanh	573.25	2,174.78	0.84	6.54	2,791.98
linear	tanh	100.84	2,331.11	0.91	7.25	2,967.66
tanh	tanh	380.18	2,350.66	2.18	7.47	3,034.06
tanh	linear	265.66	2,300.27	1.76	7.12	2,877.84
tanh	tanh	1,932.17	2,744.39	4.08	6.86	3,486.86
logistic	tanh	38.54	1,969.49	0.44	5.51	2,441.32
logistic	logistic	704.60	2,296.70	1.35	6.17	2,731.82
		38.54	**1,759.88**	**0.17**	**4.63**	**2,294.49**

Summary of neural network learning for the case of random sample

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function
20	MLP 1-4-1	0.73	1.00	1.00	BFGS 5	SOS
20	MLP 1-2-1	0.80	1.00	1.00	BFGS 1	SOS
20	MLP 1-7-1	0.81	1.00	1.00	BFGS 1	SOS
20	MLP 1-5-1	0.84	1.00	1.00	BFGS 3	SOS
20	MLP 1-3-1	0.81	1.00	1.00	BFGS 3	SOS
40	MLP 1-6-1	0.80	1.00	1.00	BFGS 2	SOS
40	MLP 1-4-1	0.77	1.00	1.00	BFGS 2	SOS
40	MLP 1-5-1	0.79	1.00	1.00	BFGS 1	SOS
40	MLP 1-4-1	0.74	1.00	1.00	BFGS 3	SOS
40	MLP 1-8-1	0.81	1.00	1.00	BFGS 2	SOS
60	MLP 1-7-1	0.84	1.00	1.00	BFGS 1	SOS
60	MLP 1-6-1	0.81	1.00	1.00	BFGS 1	SOS
60	MLP 1-7-1	0.81	1.00	1.00	BFGS 1	SOS
60	MLP 1-2-1	0.81	1.00	1.00	BFGS 1	SOS
60	**MLP 1-3-1**	**0.87**	**1.00**	**1.00**	**BFGS 4**	**SOS**
80	MLP 1-3-1	0.81	1.00	1.00	BFGS 1	SOS
80	MLP 1-5-1	0.80	1.00	1.00	BFGS 2	SOS
80	MLP 1-2-1	0.71	1.00	1.00	BFGS 4	SOS
80	MLP 1-5-1	0.63	1.00	1.00	BFGS 3	SOS
80	MLP 1-6-1	0.77	1.00	1.00	BFGS 2	SOS
100	MLP 1-7-1	0.81	1.00	1.00	BFGS 1	SOS
100	MLP 1-4-1	0.86	1.00	1.00	BFGS 1	SOS
100	MLP 1-7-1	0.78	1.00	1.00	BFGS 1	SOS
100	MLP 1-8-1	0.81	1.00	1.00	BFGS 3	SOS
100	MLP 1-2-1	0.80	1.00	1.00	BFGS 1	SOS
200	MLP 1-8-1	0.81	1.00	1.00	BFGS 1	SOS
200	MLP 1-3-1	0.84	1.00	1.00	BFGS 1	SOS
200	MLP 1-3-1	0.81	1.00	1.00	BFGS 1	SOS
200	MLP 1-6-1	0.87	1.00	1.00	BFGS 1	SOS
200	MLP 1-7-1	0.81	1.00	1.00	BFGS 1	SOS
Minimal						

Table 3

size teaching 70%, testing 15% and validation 15% for Montenegro

Activation (hidden)	Activation (output)	Errors				
		ME	MAE	MPE [%]	MAPE [%]	SSE
logistics	tanh	159.90	389.99	4.22	7.41	642.91
exponential	tanh	329.11	413.80	6.65	7.96	616.80
logistics	tanh	319.01	402.40	6.46	7.74	610.05
tanh	exponential	432.99	511.23	8.60	9.84	758.52
linear	linear	425.22	517.65	8.47	9.94	763.44
tanh	linear	258.19	420.81	5.48	8.06	656.73
tanh	tanh	410.08	499.20	8.18	9.59	735.03
exponential	exponential	316.17	399.73	6.41	7.69	607.68
logistics	tanh	452.02	550.36	8.96	10.54	807.86
linear	linear	316.65	449.92	6.52	8.63	680.99
exponential	exponential	329.57	412.78	6.66	7.94	618.55
logistics	exponential	327.57	411.96	6.63	7.93	617.05
linear	logistics	319.98	402.87	6.48	7.75	610.78
tanh	linear	334.40	414.91	6.75	7.99	622.24
tanh	**exponential**	**188.57**	**375.59**	**4.20**	**7.15**	**579.97**
exponential	logistics	339.05	417.95	6.83	8.05	625.56
logistics	linear	405.49	495.52	8.10	9.52	731.78
tanh	linear	522.11	533.38	10.07	10.24	803.83
exponential	logistics	276.40	433.61	5.79	8.30	661.23
linear	tanh	236.65	415.77	5.10	7.95	658.47
logistics	logistics	331.86	413.66	6.71	7.96	620.23
exponential	exponential	329.04	412.62	6.66	7.94	618.21
exponential	exponential	317.71	400.34	6.44	7.71	608.81
exponential	exponential	378.26	477.76	7.61	9.18	710.43
exponential	logistics	314.85	407.34	6.40	7.83	608.20
logistics	logistics	329.36	412.73	6.66	7.94	618.43
exponential	exponential	330.60	413.06	6.68	7.95	619.17
tanh	tanh	324.56	405.57	6.56	7.80	614.34
exponential	exponential	326.95	411.80	6.62	7.92	616.67
linear	exponential	330.83	413.29	6.69	7.96	619.51
		159.90	**375.59**	**4.20**	**7.15**	**579.97**

Summary of neural network learning for the case of random

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function
20	MLP 1-7-1	0.87	0.00	0.00	BFGS 0	SOS
20	MLP 1-4-1	0.79	0.00	0.00	BFGS 1	SOS
20	MLP 1-3-1	0.87	0.00	0.00	BFGS 0	SOS
20	MLP 1-3-1	0.79	0.00	0.00	BFGS 1	SOS
20	MLP 1-6-1	0.80	0.00	0.00	BFGS 1	SOS
40	MLP 1-4-1	0.79	0.00	0.00	BFGS 1	SOS
40	MLP 1-7-1	0.79	0.00	0.00	BFGS 1	SOS
40	MLP 1-5-1	0.83	0.00	0.00	BFGS 1	SOS
40	MLP 1-3-1	0.77	0.00	0.00	BFGS 1	SOS
40	MLP 1-3-1	0.76	0.00	0.00	BFGS 0	SOS
60	MLP 1-2-1	0.79	0.00	0.00	BFGS 1	SOS
60	MLP 1-5-1	0.79	0.00	0.00	BFGS 1	SOS
60	MLP 1-5-1	0.76	0.00	0.00	BFGS 0	SOS
60	MLP 1-6-1	0.87	0.00	0.00	BFGS 0	SOS
60	MLP 1-8-1	0.86	0.00	0.00	BFGS 0	SOS
80	MLP 1-5-1	0.77	0.00	0.00	BFGS 1	SOS
80	MLP 1-3-1	0.79	0.00	0.00	BFGS 1	SOS
80	MLP 1-8-1	0.60	0.00	0.00	BFGS 1	SOS
80	MLP 1-8-1	0.86	0.00	0.00	BFGS 0	SOS
80	MLP 1-2-1	0.76	0.00	0.00	BFGS 0	SOS
100	MLP 1-5-1	0.79	0.00	0.00	BFGS 1	SOS
100	MLP 1-6-1	0.79	0.00	0.00	BFGS 1	SOS
100	MLP 1-4-1	0.79	0.00	0.00	BFGS 1	SOS
100	MLP 1-3-1	0.79	0.00	0.00	BFGS 1	SOS
100	**MLP 1-2-1**	**0.87**	**0.00**	**0.00**	**BFGS 0**	**SOS**
200	MLP 1-5-1	0.78	0.00	0.00	BFGS 1	SOS
200	MLP 1-5-1	0.86	0.00	0.00	BFGS 0	SOS
200	MLP 1-7-1	0.79	0.00	0.00	BFGS 1	SOS
200	MLP 1-7-1	0.79	0.00	0.00	BFGS 1	SOS
200	MLP 1-3-1	0.80	0.00	0.00	BFGS 1	SOS
Minimal						

Table 4

sample size teaching 80%,testing 10% and validation 10% for Montenegro

Activation (hidden)	Activation (output)	Errors				
		ME	MAE	MPE [%]	MAPE [%]	SSE
exponential	tanh	16.23	330.19	0.46	5.99	485.34
tanh	tanh	329.22	413.04	6.66	7.95	618.72
tanh	tanh	10.05	343.23	0.58	6.21	489.80
tanh	logistics	326.77	412.07	6.62	7.93	616.91
exponential	linear	329.12	413.21	6.66	7.95	618.89
linear	logistics	339.79	418.60	6.85	8.06	625.98
linear	logistics	332.71	414.38	6.72	7.98	621.26
exponential	logistics	327.75	406.82	6.62	7.83	616.54
exponential	logistics	328.07	412.40	6.64	7.94	617.67
linear	tanh	60.91	372.59	1.96	6.97	619.70
tanh	logistics	330.60	413.37	6.68	7.96	619.51
exponential	linear	329.84	413.84	6.67	7.97	619.79
linear	tanh	50.63	400.79	1.64	7.46	548.18
tanh	tanh	7.45	332.13	0.61	6.03	479.95
exponential	linear	21.44	322.97	0.38	5.88	491.54
logistics	tanh	332.40	414.00	6.72	7.97	620.76
exponential	linear	330.09	413.70	6.68	7.96	619.72
exponential	logistics	318.71	402.15	6.45	7.74	609.82
exponential	linear	17.60	321.42	0.44	5.86	492.49
linear	tanh	60.91	372.59	1.96	6.97	619.70
logistics	logistics	329.13	412.78	6.66	7.94	618.41
linear	logistics	325.18	411.48	6.59	7.92	615.78
logistics	exponential	320.05	402.23	6.48	7.74	610.69
linear	exponential	333.07	414.47	6.73	7.98	620.97
exponential	**tanh**	**21.65**	**331.41**	**0.36**	**6.01**	**480.43**
exponential	exponential	329.67	413.23	6.67	7.95	619.05
tanh	linear	10.39	326.63	0.57	5.95	487.09
linear	logistics	313.02	399.52	6.35	7.69	605.59
logistics	logistics	330.27	413.21	6.68	7.95	619.23
exponential	logistics	335.56	415.70	6.77	8.00	623.04
		7.45	**321.42**	**0.36**	**5.86**	**479.95**

In summary, Tables 1-4 show a consistent pattern of forecast accuracy improvement when using neural networks over linear models. The highest accuracy was observed for Poland in the 2018-2022 period, while Montenegro exhibited greater variance. Notably, the MAPE values remain within acceptable ranges for both countries, underscoring the robustness of the applied models.

In addition to MAPE, Root Mean Squared Error (RMSE) was used to evaluate model performance, providing a more robust measure of error magnitude. Forecasts were also supplemented with 95% confidence intervals based on the residual standard deviation from the validation set.

According to the forecasts, the number of traffic accidents in Poland is expected to stabilize in the coming years, with a potential slight increase. The accuracy of these projections is influenced by several factors, including the sample sizes used for model training, validation, and testing. In general, increasing the proportion of data allocated to the training set can enhance prediction accuracy. For example, when the training set size was increased to 80% (with a 80-10-10 split for training, testing, and validation), the average percentage error decreased from 5.68% (in the 70-15-15 split) to 4.63%.

Furthermore, the growing number of vehicles on Polish roads and the impact of the COVID-19 pandemic also influence the model's predictions (Fig. 4). Based on the aforementioned indicators, hypotheses H0 and H2 can be rejected.

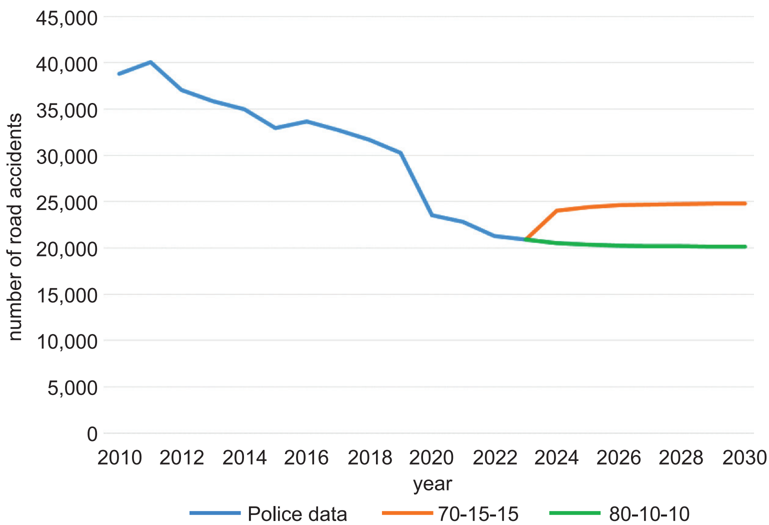

Fig. 4. Projected number of road accidents for 2024-2030 for Poland

The results of the study indicate that the number of traffic accidents in Montenegro may stabilize in the coming years and may even show a slight decline. As in the case of Poland, the accuracy of these forecasts is influenced by factors such as the sample sizes used for model training, validation, and testing. Generally, increasing the proportion of data allocated to the training set can improve prediction accuracy; however, in this case, the average percentage error increased slightly – from 4.27% (with a 70-15-15 split) to 4.31% (with an 80-10-10 split).

In addition, the model's projections are affected by the combined impact of the recent COVID-19 pandemic and the continued increase in car ownership in Montenegro (Fig. 5). Based on the above considerations, hypotheses H3 and H5 can be rejected.

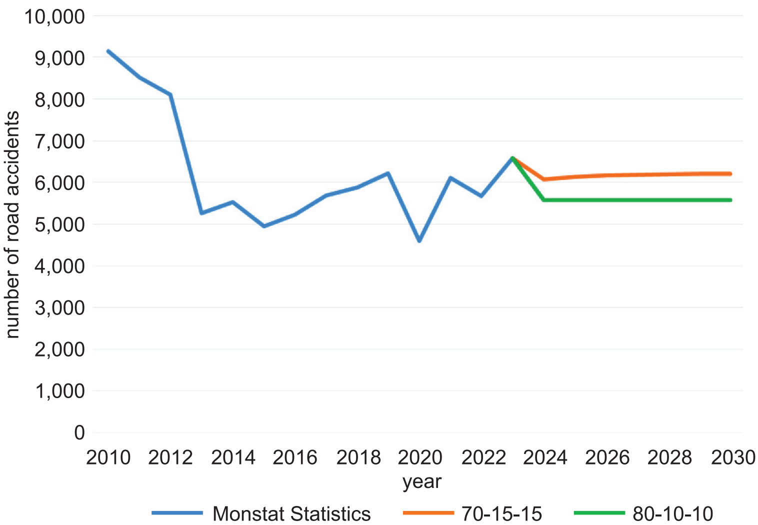

Fig. 5. Projected number of road accidents for 2024-2030 in Montenegro

Conclusion

Based on the analysis of road accident forecasts in Poland and Montenegro using neural network models, it can be concluded that the number of accidents in both countries is expected to stabilize in the coming years. The results indicate that the applied methodology enables the generation of accurate predictions, which may be valuable for planning preventive measures and shaping transport policy.

Neural networks, as advanced analytical tools, allowed for the inclusion of non-linear relationships between various factors influencing accident frequency, such as weather conditions, traffic volume, changes in road infrastructure, and prevention campaigns. The observed stabilization in accident numbers may reflect the effectiveness of existing interventions, but it also highlights the need to implement new strategies aimed at further reducing traffic incidents.

Practical applications of the research results include:

– supporting decision-makers in transportation policy planning – providing forecasts to enable more efficient allocation of resources for prevention activities;

– optimization of prevention activities – targeting public campaigns and infrastructure investments to the highest risk areas;

– planning traffic management systems – forecasts can help design intelligent transportation systems (ITS) that enhance safety;

– long-term analysis – predicting future traffic accident trends in the context of demographic and economic changes.

The research makes a significant contribution to the scientific literature through:

– application of neural networks in accident number prediction – demonstrating the effectiveness of AI algorithms in analyzing highly variable data;

– identifying significant factors affecting the number of accidents – determining which variables have the greatest impact on the number of traffic incidents;

– modeling non-linear relationships – showing how advanced models can outperform traditional statistical methods in terms of forecast accuracy.

Despite the high effectiveness of the forecasts, the study has some limitations:

– quality of input data – the accuracy of forecasts is strongly dependent on the quality and completeness of historical data;

– unpredictable variables – sudden changes in traffic regulations, pandemics or other unpredictable events can significantly affect actual accident numbers;

– model transferability – models trained on data from one country may need to be adjusted when applied in another country;

– interpretive complexity – neural networks are more difficult to interpret compared to classical statistical models, which can make it difficult to fully understand the impact of individual variables.

Forecasting the number of traffic accidents using neural networks provides valuable insights that can support efforts to enhance road safety. Future research should focus on improving data quality, incorporating additional variables, and integrating AI models with other analytical methods to develop a more comprehensive approach to understanding and preventing road accidents.

Compared to traditional models such as ARIMA, neural networks demonstrate improved capacity to capture non-linear dependencies in accident data. However, hybrid approaches that combine statistical and machine learning methods (e.g., ARIMA–ANN models) have shown promising results in similar contexts. Future research might explore whether such hybridization could enhance forecasting accuracy, especially for countries with volatile accident patterns or limited datasets.

The forecasting results presented in this paper can inform evidence-based transport policies. For instance, the identification of periods with higher predicted accident rates may guide temporal allocation of police patrols or awareness campaigns. Moreover, the differences between Poland and Montenegro suggest that traffic safety interventions should be adapted to national contexts rather than adopting a one-size-fits-all strategy.

While the current model is based solely on historical accident counts, future studies should incorporate exogenous variables such as vehicle ownership, road infrastructure development, and weather conditions. These factors can significantly influence accident trends and improve model relevance and forecasting accuracy.

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