FORECASTING THE NUMBER OF ROAD ACCIDENTS IN POLAND AND BOSNIA AND HERZEGOVINA USING NEURAL NETWORKS

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ABSTRACT
This study aims to forecast the number of traffic accidents in Bosnia and Herzegovina and Poland from 2024 to 2030. To achieve this, annual statistics on traffic accidents in both countries were analyzed, utilizing data from the Polish Police and the UNECE Statistics of Road Traffic Accidents. Several neural network models were employed to predict the number of accidents. The results suggest a potential stabilization in the number of traffic accidents, though this trend may be influenced by factors such as the construction of new motorways and highways, and the increasing number of vehicles on the road. It is important to note that the accuracy of these predictions can be influenced by the size and randomness of the data samples used for training, testing, and validation.

Keywords: traffic accident, pandemic, forecasting, neural networks, Poland, Bosnia and Herzegovina

1. INTRODUCTION
Road accidents are a significant global public health concern, resulting in injuries, fatalities, and substantial economic losses. According to the WHO, 1.3 million people lose their lives annually in road traffic accidents, while these accidents cost the average country 3% of its GDP. Furthermore, traffic accidents are the leading cause of death for individuals aged 5 to 29 [1]. The severity of a traffic collision is a crucial factor in assessing its impact. Accurate estimation of accident severity is essential for competent authorities to develop effective traffic safety legislation aimed at preventing accidents, minimizing injuries, fatalities, and property damage [2, 3]. Identifying the critical factors influencing accident severity is a crucial step before implementing countermeasures to prevent and reduce their severity [4]. Yang et al. propose a multi-node Deep Neural Network (DNN) topology for predicting varying degrees of injury, death, and property loss. This approach enables a comprehensive and precise analysis of road accident severity [5]. Accident data is collected from various sources, primarily by government agencies utilizing data from police reports, insurance databases, and hospital records [6]. This has led to a broader analysis of road accident data within the transportation sector. Intelligent Transportation Systems (ITS) are currently the most significant source of information for analyzing and forecasting traffic events. Data from GPS units in vehicles, roadside microwave vehicle detection systems, and license plate recognition systems provide valuable insights into traffic flow, including vehicle type, speed, and volume [7, 8, 9]. Social media can also be a source of traffic and accident information, although the accuracy of such reports may be limited due to the potential for inaccuracies by untrained observers [10]. Effective accident data analysis often requires utilizing data from multiple sources and integrating heterogeneous data sets [11]. Vilaca et al. [12] conducted a statistical analysis to determine the severity of accidents

and identify relationships between traffic participants and accidents, emphasizing the need for enhanced traffic safety measures and regulations. Bak et al. [13] conducted a statistical analysis of road safety in a selected Polish region, using the number of traffic accidents as a proxy for accident causation research. The choice of accident data source depends on the specific traffic issue being investigated. Combining statistical models with real-world driving data and information from ITS can improve the accuracy of accident prediction and mitigation [14]. The literature offers various techniques for predicting accident probability. Time series approaches are widely used for estimating accident frequency [15, 16], but they often suffer from residual autocorrelation [17] and limitations in evaluating forecast accuracy based on previous forecasts. Procházka et al. [18] utilized a multi-seasonality model for forecasting, while Sunny et al. [19] employed the Holt-Winters exponential smoothing method. A limitation of these models is the difficulty of incorporating exogenous variables [20]. The number of accidents per 10,000 population (NRA) is a crucial indicator. In 2023, Poland, with a population of 37.6 million, recorded 20,936 traffic accidents, resulting in an NRA of 5.57. During the same period, Bosnia and Herzegovina, with a population of 3.21 million, reported 7,665 road accidents, resulting in an NRA of 2.39, which is significantly lower than Poland.

$$NRA = \frac{NR}{NI} * 10000$$

where:
NR - number of road accidents
NI - number of inhabitants

The authors employed neural network models to forecast the number of accidents on Polish and Bosnian highways based on the available data..

2. MATERIAL AND METHODS

Despite a recent decrease in road accidents due to the pandemic, which has influenced the forecasted values, the number of accidents remains significant. This necessitates efforts to reduce this figure and identify road types with higher accident rates (Figure 1).

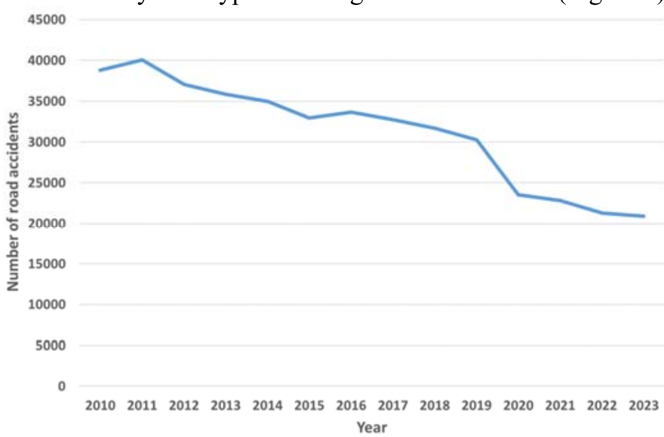

Figure 1. Number of road accidents in Poland between 2010 and 2023 [21]

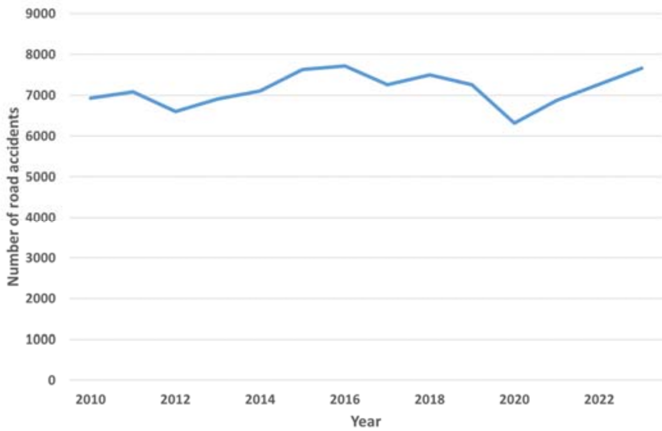

Figure 2. Number of road accidents in Bosnia and Herzegovina between 2010 and 2023 [22]

Neural networks were employed to forecast the number of traffic accidents in Poland and Bosnia and Herzegovina. These models, inspired by the human brain, consist of interconnected nodes with inputs, weights, and outputs. Statistica software was used to optimize the model's weights. Neural networks are mathematical structures that mimic the functioning of the human nervous system. They typically comprise multiple layers, with the input layer receiving data such as images, numbers, text, or sounds. Artificial neurons, the fundamental building blocks of these networks, simulate the behavior of biological neurons by processing multiple inputs and generating a single output.

Neural networks have diverse applications, including [24-27]:

- Recommender systems for streaming platforms.
- Text translation services like Google Translate.
- Personalized product recommendations in online auctions.
- Forecasting, including the frequency of traffic accidents

To predict the number of traffic accidents, a multilayer perceptron (MLP) neural network was utilized. The MLP architecture includes hidden layers of neurons, with the number of neurons in the hidden layer varying from two to eight. The output layer consists of a single neuron representing the time series values of the number of traffic accidents. The predictive performance of the model was evaluated using prediction error metrics derived from equations (2-7)

- ME – mean error

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

- MAE – mean error

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

- MPE – mean percentage error

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

- MAPE - mean absolute percentage error

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

- SSE – mean square error

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

- M^2 - Theila measure

$$M^2 = \frac{\sum_{i=1}^{N}(Y_i - Y_p)^2}{\sum_{i=1}^{N} {Y_i}^2} \tag{7}$$

where:
n – length of the forecast horizon,
Y – observed value of traffic accidents
Y_p – the forecast value of traffic accidents..

Neural network models with the lowest average percentage error and average absolute percentage error were employed to forecast the frequency of traffic accidents in dependence.

3. RESULTS

To forecast the annual number of traffic accidents in Poland, data from the Polish Police from 2010-2023 were used [21], while for Bosnia and Herzegovina, they came from the Unece Statistics of Road Traffic Accidents [22]. In both cases, the research was conducted in Statistica software, assuming two random sample sizes:
1. teaching 70%, testing 15% and validation 15%.
2. 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 (Table 1-4).

Table 1 Summary of neural network learning for the case of random sample size teaching 70%, testing 15% and validation 15% for Poland

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function	Activation (hidden)	Activation (output)	Errors					
									ME	MAE	MPE	MAPE	SSE	Theil
20	MLP 1-7-1	0.97	0.98	0.99	BFGS 12	SOS	Tanh	Logistic	932.03	2374.97	2.85%	6.69%	2747.76	4.56E-03
20	MLP 1-8-1	0.97	0.98	0.99	BFGS 4	SOS	Linear	Logistic	664.14	2092.80	3.19%	6.46%	2667.94	4.30E-03
20	MLP 1-2-1	0.97	0.98	0.99	BFGS 4	SOS	Exponential	Exponential	1168.74	2119.69	3.23%	5.69%	2657.54	4.26E-03
20	MLP 1-4-1	0.96	0.97	0.99	BFGS 4	SOS	Exponential	Linear	1815.06	2891.74	2.84%	7.52%	3551.21	7.61E-03
20	MLP 1-3-1	0.97	0.97	0.99	BFGS 42	SOS	Tanh	Logistic	1113.77	2387.70	3.25%	6.64%	2802.32	4.74E-03
40	**MLP 1-7-1**	**0.97**	**0.98**	**0.99**	**BFGS 8**	**SOS**	**Exponential**	**Exponential**	**837.43**	**2001.24**	**2.77%**	**5.68%**	**2484.15**	**3.72E-03**
40	MLP 1-3-1	0.97	0.98	0.99	BFGS 8	SOS	Exponential	Exponential	909.41	2052.58	2.80%	5.71%	2526.15	3.85E-03
40	MLP 1-2-1	0.97	0.96	0.99	BFGS 7	SOS	Logistic	Logistic	1110.51	2279.94	3.35%	6.40%	2764.05	4.61E-03
40	MLP 1-8-1	0.97	0.96	0.99	BFGS 5	SOS	Logistic	Exponential	1483.15	2363.70	4.57%	6.80%	2927.92	5.17E-03
40	MLP 1-3-1	0.96	0.95	0.99	BFGS 5	SOS	Logistic	Exponential	1035.60	2590.23	3.60%	7.73%	3048.65	5.61E-03
60	MLP 1-4-1	0.97	0.97	0.99	BFGS 7	SOS	Tanh	Logistic	1031.48	2377.94	3.10%	6.68%	2772.29	4.64E-03
60	MLP 1-7-1	0.97	0.97	0.99	BFGS 5	SOS	Tanh	Logistic	777.04	2415.30	2.17%	6.63%	2763.52	4.61E-03
60	MLP 1-2-1	0.97	0.97	0.99	BFGS 9	SOS	Exponential	Logistic	1109.93	2233.82	3.17%	6.12%	2715.75	4.45E-03
60	MLP 1-5-1	0.97	0.97	0.99	BFGS 12	SOS	Tanh	Exponential	1090.27	2283.83	3.28%	6.40%	2721.35	4.47E-03
60	MLP 1-6-1	0.97	0.98	0.99	BFGS 5	SOS	Exponential	Exponential	1071.39	1987.71	3.83%	5.94%	2590.07	4.05E-03
80	MLP 1-5-1	0.97	0.97	0.99	BFGS 7	SOS	Tanh	Logistic	1040.10	2404.10	3.15%	6.78%	2796.23	4.72E-03
80	MLP 1-8-1	0.97	0.98	0.99	BFGS 14	SOS	Exponential	Logistic	1023.90	2217.06	3.03%	6.15%	2661.45	4.27E-03
80	MLP 1-3-1	0.97	0.98	0.99	BFGS 7	SOS	Exponential	Logistic	801.65	2239.47	2.48%	6.27%	2623.54	4.15E-03
80	MLP 1-7-1	0.97	0.96	0.99	BFGS 7	SOS	Logistic	Logistic	978.70	2426.95	2.68%	6.63%	2851.96	4.91E-03
80	MLP 1-7-1	0.97	0.98	0.99	BFGS 13	SOS	Exponential	Logistic	873.08	2237.49	2.54%	6.16%	2638.93	4.20E-03
100	MLP 1-8-1	0.97	0.98	0.99	BFGS 18	SOS	Exponential	Logistic	1021.62	2260.14	2.99%	6.25%	2688.97	4.36E-03
100	MLP 1-5-1	0.97	0.97	0.99	BFGS 6	SOS	Logistic	Logistic	1108.50	2402.26	3.24%	6.69%	2819.42	4.80E-03
100	MLP 1-4-1	0.97	0.98	0.99	BFGS 11	SOS	Logistic	Exponential	909.58	2320.20	2.93%	6.65%	2707.86	4.43E-03
100	MLP 1-2-1	0.96	0.95	0.99	BFGS 7	SOS	Tanh	Logistic	1114.15	2426.31	4.15%	7.43%	3005.79	5.45E-03
100	MLP 1-2-1	0.97	0.97	0.99	BFGS 8	SOS	Tanh	Logistic	894.03	2347.67	2.83%	6.67%	2720.34	4.47E-03
200	MLP 1-6-1	0.96	0.96	0.99	BFGS 8	SOS	Tanh	Logistic	644.88	2480.32	2.22%	7.15%	2814.19	4.78E-03
200	MLP 1-6-1	0.97	0.96	0.99	BFGS 7	SOS	Tanh	Logistic	770.95	2330.09	2.51%	6.64%	2702.56	4.41E-03
200	MLP 1-3-1	0.97	0.97	0.99	BFGS 10	SOS	Logistic	Logistic	970.77	2347.01	2.97%	6.61%	2750.08	4.56E-03
200	MLP 1-2-1	0.95	0.92	0.99	BFGS 7	SOS	Logistic	Exponential	319.55	2657.15	0.32%	7.61%	3035.78	5.56E-03
200	MLP 1-4-1	0.97	0.97	0.99	BFGS 6	SOS	Tanh	Logistic	1200.19	2356.37	3.63%	6.66%	2816.40	4.79E-03
								Minimal	**319.55**	**1987.71**	**0.32%**	**5.68%**	**2484.15**	**3.72E-03**

Table 2 Summary of neural network learning for the case of random sample size teaching 80%, testing 10% and validation 10% for Poland

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function	Activation (hidden)	Activation (output)	Errors					
									ME	MAE	MPE	MAPE	SSE	Theil
20	MLP 1-5-1	0.96	0.99	1.00	BFGS 8	SOS	Logistic	Linear	422.40	1830.32	0.90%	5.12%	2362.11	3.37E-03
20	MLP 1-5-1	0.96	0.99	1.00	BFGS 5	SOS	Linear	Tanh	420.05	2152.64	0.39%	6.51%	2773.07	4.64E-03
20	MLP 1-3-1	0.96	0.99	1.00	BFGS 63	SOS	Tanh	Logistic	702.37	1986.10	2.31%	5.57%	2455.03	3.64E-03
20	MLP 1-8-1	0.96	0.99	1.00	BFGS 6	SOS	Linear	Tanh	326.74	2130.77	0.17%	6.45%	2734.11	4.51E-03
20	**MLP 1-8-1**	**0.96**	**0.99**	**1.00**	**BFGS 6**	**SOS**	**Logistic**	**Tanh**	**265.62**	**1759.88**	**0.80%**	**4.63%**	**2294.49**	**3.18E-03**
40	MLP 1-5-1	0.96	0.99	1.00	BFGS 5	SOS	Tanh	Exponential	1544.71	2539.20	6.27%	8.23%	3300.44	6.57E-03
40	MLP 1-5-1	0.96	0.99	1.00	BFGS 6	SOS	Linear	Tanh	180.47	2355.28	0.72%	7.31%	2994.43	5.41E-03
40	MLP 1-2-1	0.96	0.99	1.00	BFGS 6	SOS	Linear	Tanh	184.52	2325.08	1.67%	7.28%	2934.77	5.20E-03
40	MLP 1-6-1	0.96	0.98	1.00	BFGS 4	SOS	Logistic	Logistic	725.12	2046.17	3.35%	6.03%	2699.40	4.40E-03
40	MLP 1-2-1	0.96	0.99	1.00	BFGS 10	SOS	Logistic	Tanh	397.20	1761.51	1.05%	4.76%	2339.08	3.30E-03
60	MLP 1-2-1	0.95	0.98	1.00	BFGS 5	SOS	Logistic	Exponential	46.12	2638.20	0.89%	7.75%	3021.27	5.51E-03
60	MLP 1-6-1	0.96	0.99	1.00	BFGS 5	SOS	Linear	Tanh	381.15	2625.38	2.79%	8.41%	3359.27	6.81E-03
60	MLP 1-6-1	0.95	0.98	1.00	BFGS 5	SOS	Logistic	Logistic	1436.54	2605.98	2.62%	6.58%	3107.29	5.83E-03
60	MLP 1-3-1	0.95	0.98	1.00	BFGS 7	SOS	Tanh	Tanh	225.51	2181.93	1.10%	6.66%	2827.63	4.83E-03
60	MLP 1-6-1	0.95	0.99	1.00	BFGS 7	SOS	Exponential	Logistic	231.31	2206.35	0.69%	5.98%	2657.70	4.26E-03
80	MLP 1-2-1	0.96	0.99	1.00	BFGS 11	SOS	Logistic	Tanh	63.00	2068.87	0.35%	6.24%	2669.34	4.30E-03
80	MLP 1-3-1	0.96	0.99	1.00	BFGS 4	SOS	Linear	Tanh	261.75	2325.06	0.42%	7.18%	2957.41	5.28E-03
80	MLP 1-2-1	0.96	0.98	1.00	BFGS 7	SOS	Logistic	Linear	553.25	2205.41	2.23%	6.74%	2759.02	4.59E-03
80	MLP 1-2-1	0.95	0.98	1.00	BFGS 6	SOS	Tanh	Logistic	81.51	2328.80	0.41%	6.55%	2719.89	4.46E-03
80	MLP 1-7-1	0.96	0.99	1.00	BFGS 5	SOS	Linear	Tanh	159.97	2374.17	0.82%	7.38%	3018.42	5.50E-03
100	MLP 1-7-1	0.96	0.99	1.00	BFGS 7	SOS	Linear	Tanh	573.15	2175.01	0.84%	6.54%	2792.33	4.71E-03
100	MLP 1-2-1	0.95	0.99	1.00	BFGS 9	SOS	Tanh	Logistic	334.46	2310.29	1.71%	6.79%	2726.36	4.49E-03
100	MLP 1-5-1	0.96	0.99	1.00	BFGS 5	SOS	Linear	Tanh	180.96	2441.21	1.90%	7.72%	3101.83	5.81E-03
100	MLP 1-2-1	0.96	0.99	1.00	BFGS 7	SOS	Linear	Tanh	573.25	2174.78	0.84%	6.54%	2791.98	4.70E-03
100	MLP 1-4-1	0.96	0.99	1.00	BFGS 5	SOS	Linear	Tanh	100.84	2331.11	0.91%	7.25%	2967.66	5.32E-03

200	MLP 1-8-1	0.96	0.99	1.00	BFGS 6	SOS	Tanh	Tanh	380.18	2350.66	2.18%	7.47%	3034.06	5.56E-03
200	MLP 1-2-1	0.96	0.98	1.00	BFGS 7	SOS	Tanh	Linear	265.66	2300.27	1.76%	7.12%	2877.84	5.00E-03
200	MLP 1-8-1	0.96	0.99	1.00	BFGS 2	SOS	Tanh	Tanh	1932.17	2744.39	4.08%	6.86%	3486.86	7.34E-03
200	MLP 1-3-1	0.96	0.98	1.00	BFGS 7	SOS	Logistic	Tanh	38.54	1969.49	0.44%	5.51%	2441.32	3.60E-03
200	MLP 1-4-1	0.95	0.98	1.00	BFGS 5	SOS	Logistic	Logistic	704.60	2296.70	1.35%	6.17%	2731.82	4.50E-03
								Minimal	**38.54**	**1759.88**	**0.17%**	**4.63%**	**2294.49**	**3.18E-03**

Table 3 Summary of neural network learning for the case of random sample size teaching 70%, testing 15% and validation 15% for Bosnia and Herzegovina.

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function	Activation (hidden)	Activation (output)	Errors					
									ME	**MAE**	**MPE**	**MAPE**	**SSE**	**Theil**
20	MLP 1-3-1	0,317852	1,000000	1,000000	BFGS 4	SOS	Exponential	Linear	69,21	211,98	0,75%	2,97%	332,20	3,45E-03
20	MLP 1-7-1	0,273519	1,000000	1,000000	BFGS 5	SOS	Logistics	Linear	76,50	207,68	0,85%	2,91%	332,78	3,89E-03
20	MLP 1-6-1	0,319625	1,000000	1,000000	BFGS 29	SOS	Logistics	Logistics	70,75	268,67	0,72%	3,77%	390,87	1,43E-01
20	MLP 1-3-1	0,298211	1,000000	1,000000	BFGS 4	SOS	Logistics	Exponential	48,21	204,87	0,46%	2,88%	326,47	1,49E-01
20	MLP 1-4-1	0,293075	1,000000	1,000000	BFGS 3	SOS	Logistics	Exponential	79,82	212,18	0,89%	2,97%	335,36	4,39E-03
40	MLP 1-6-1	0,249022	1,000000	1,000000	BFGS 4	SOS	Tanh	Logistics	81,74	212,76	0,91%	2,97%	337,63	3,45E-03
40	MLP 1-4-1	0,284463	1,000000	1,000000	BFGS 3	SOS	Linear	Tanh	51,68	206,92	0,49%	2,91%	330,91	3,89E-03
40	MLP 1-2-1	0,253953	1,000000	1,000000	BFGS 5	SOS	Tanh	Tanh	92,15	266,71	1,03%	3,73%	383,15	1,43E-01
40	MLP 1-8-1	0,278288	1,000000	1,000000	BFGS 2	SOS	Tanh	Tanh	70,83	206,73	0,76%	2,89%	333,49	1,49E-01
40	MLP 1-2-1	0,359220	1,000000	1,000000	BFGS 0	SOS	Exponential	Exponential	70,65	244,36	0,77%	3,41%	346,58	4,39E-03
60	MLP 1-8-1	0,304528	1,000000	1,000000	BFGS 2	SOS	Exponential	Linear	61,13	213,08	0,62%	2,99%	335,49	3,45E-03
60	MLP 1-5-1	0,260790	1,000000	1,000000	BFGS 3	SOS	Logistics	Logistics	64,79	211,59	0,67%	2,97%	334,90	3,89E-03
60	MLP 1-2-1	0,271639	1,000000	1,000000	BFGS 4	SOS	Tanh	Logistics	80,29	263,64	0,86%	3,70%	381,45	1,43E-01
60	MLP 1-3-1	0,297158	1,000000	1,000000	BFGS 4	SOS	Linear	Linear	50,36	203,91	0,48%	2,87%	327,98	1,49E-01
60	MLP 1-4-1	0,305880	1,000000	1,000000	BFGS 2	SOS	Exponential	Linear	70,76	225,43	0,75%	3,15%	342,15	4,39E-03
80	MLP 1-7-1	0,282045	1,000000	1,000000	BFGS 4	SOS	Logistics	Linear	88,83	214,45	1,01%	2,99%	337,65	3,45E-03

80	MLP 1-5-1	0,325481	1,000000	1,000000	BFGS 0	SOS	Linear	Exponential	79,96	225,99	0,90%	3,16%	337,40	3,89E-03
80	MLP 1-3-1	0,259357	1,000000	1,000000	BFGS 3	SOS	Logistics	Logistics	81,07	249,30	0,88%	3,49%	359,58	1,43E-01
80	MLP 1-5-1	0,277988	1,000000	1,000000	BFGS 2	SOS	Tanh	Linear	72,69	213,13	0,78%	2,98%	336,64	1,49E-01
80	MLP 1-8-1	0,281831	1,000000	1,000000	BFGS 15	SOS	Logistics	Tanh	91,94	215,12	1,06%	3,00%	338,82	4,39E-03
100	MLP 1-8-1	0,292978	1,000000	1,000000	BFGS 2	SOS	Exponential	Tanh	65,73	217,43	0,68%	3,05%	337,68	3,45E-03
100	MLP 1-6-1	0,272496	1,000000	1,000000	BFGS 3	SOS	Tanh	Tanh	57,07	199,10	0,57%	2,80%	327,84	3,89E-03
100	MLP 1-3-1	0,307267	1,000000	1,000000	BFGS 6	SOS	Tanh	Exponential	49,79	258,88	0,44%	3,65%	383,97	1,43E-01
100	MLP 1-5-1	0,277397	1,000000	1,000000	BFGS 3	SOS	Tanh	Logistics	53,85	204,13	0,52%	2,87%	329,69	1,49E-01
100	MLP 1-5-1	0,270702	1,000000	1,000000	BFGS 3	SOS	Tanh	Tanh	65,15	199,45	0,69%	2,80%	329,51	4,39E-03
200	MLP 1-6-1	0,306007	1,000000	1,000000	BFGS 2	SOS	Exponential	Linear	61,47	214,97	0,62%	3,01%	336,34	3,45E-03
200	MLP 1-8-1	0,304963	1,000000	1,000000	BFGS 2	SOS	Exponential	Linear	56,29	207,71	0,56%	2,92%	331,07	3,89E-03
200	MLP 1-4-1	0,340518	1,000000	1,000000	BFGS 0	SOS	Logistics	Exponential	67,93	248,55	0,69%	3,49%	366,96	1,43E-01
200	MLP 1-4-1	0,282262	1,000000	1,000000	BFGS 2	SOS	Tanh	Linear	68,14	205,05	0,73%	2,87%	331,77	1,49E-01
200	MLP 1-4-1	0,311897	1,000000	1,000000	BFGS 3	SOS	Exponential	Linear	36,62	204,30	0,29%	2,88%	324,58	4,39E-03
								Minimal	**36,62**	**199,10**	**0,29%**	**2,80%**	**324,58**	**3,45E-03**

Table 4 Summary of neural network learning for the case of random sample size teaching 80%, testing 10% and validation 10% for Bosnia and Herzegovina.

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function	Activation (hidden)	Activation (output)	Errors					
									ME	**MAE**	**MPE**	**MAPE**	**SSE**	**Thail**
20	MLP 1-4-1	0,294584	0,00	0,00	BFGS 5	SOS	Tanh	Logistics	83,95	208,86	0,95%	2,92%	335,34	3,45E-03
20	MLP 1-7-1	0,313873	0,00	0,00	BFGS 7	SOS	Logistics	Logistics	66,70	204,59	0,71%	2,87%	330,54	3,89E-03
20	MLP 1-7-1	0,336784	0,00	0,00	BFGS 6	SOS	Linear	Exponential	69,85	269,72	0,71%	3,79%	392,40	1,43E-01
20	MLP 1-4-1	0,332389	0,00	0,00	BFGS 24	SOS	Tanh	Linear	61,24	210,13	0,64%	2,95%	329,82	1,49E-01
20	MLP 1-3-1	0,329797	0,00	0,00	BFGS 10	SOS	Exponential	Exponential	58,47	208,44	0,60%	2,93%	328,57	4,39E-03
40	MLP 1-5-1	0,338165	0,00	0,00	BFGS 5	SOS	Exponential	Logistics	48,57	214,74	0,46%	3,02%	329,31	3,45E-03
40	MLP 1-4-1	0,328745	0,00	0,00	BFGS 4	SOS	Exponential	Tanh	56,99	211,40	0,58%	2,97%	328,72	3,89E-03
40	MLP 1-8-1	0,329312	0,00	0,00	BFGS 4	SOS	Linear	Linear	64,20	272,61	0,63%	3,84%	397,82	1,43E-01

40	MLP 1-5-1	0,319509	0,00	0,00	BFGS 4	SOS	Tanh	Logistics	49,76	206,07	0,48%	2,90%	326,33	1,49E-01
40	MLP 1-6-1	0,328847	0,00	0,00	BFGS 5	SOS	Tanh	Linear	60,96	206,98	0,63%	2,90%	328,86	4,39E-03
60	MLP 1-5-1	0,317106	0,00	0,00	BFGS 4	SOS	Logistics	Linear	79,00	212,61	0,88%	2,98%	333,69	3,45E-03
60	MLP 1-5-1	0,319065	0,00	0,00	BFGS 4	SOS	Logistics	Logistics	61,58	205,75	0,64%	2,89%	329,65	3,89E-03
60	MLP 1-8-1	0,336788	0,00	0,00	BFGS 4	SOS	Linear	Exponential	73,30	270,87	0,76%	3,80%	392,97	1,43E-01
60	MLP 1-2-1	0,342394	0,00	0,00	BFGS 7	SOS	Exponential	Exponential	58,05	218,91	0,59%	3,07%	331,91	1,49E-01
60	MLP 1-3-1	0,328502	0,00	0,00	BFGS 24	SOS	Tanh	Tanh	62,45	208,22	0,65%	2,92%	329,61	4,39E-03
80	MLP 1-5-1	0,342688	0,00	0,00	BFGS 19	SOS	Exponential	Logistics	58,92	219,36	0,61%	3,07%	332,20	3,45E-03
80	MLP 1-4-1	0,334382	0,00	0,00	BFGS 6	SOS	Exponential	Exponential	53,60	211,72	0,53%	2,97%	329,28	3,89E-03
80	MLP 1-7-1	0,328995	0,00	0,00	BFGS 4	SOS	Logistics	Linear	83,28	274,30	0,90%	3,85%	394,48	1,43E-01
80	MLP 1-3-1	0,309386	0,00	0,00	BFGS 8	SOS	Logistics	Logistics	70,32	208,18	0,76%	2,92%	331,25	1,49E-01
80	MLP 1-5-1	0,326112	0,00	0,00	BFGS 3	SOS	Tanh	Linear	52,57	205,85	0,52%	2,89%	326,80	4,39E-03
100	MLP 1-8-1	0,326079	0,00	0,00	BFGS 10	SOS	Tanh	Logistics	66,98	208,26	0,72%	2,92%	330,57	3,45E-03
100	MLP 1-5-1	0,322826	0,00	0,00	BFGS 11	SOS	Tanh	Tanh	61,55	206,40	0,64%	2,90%	329,64	3,89E-03
100	MLP 1-8-1	0,333002	0,00	0,00	BFGS 9	SOS	Exponential	Tanh	72,59	271,05	0,75%	3,81%	393,10	1,43E-01
100	MLP 1-8-1	0,324301	0,00	0,00	BFGS 4	SOS	Linear	Logistics	62,09	206,77	0,65%	2,90%	329,00	1,49E-01
100	MLP 1-8-1	0,314600	0,00	0,00	BFGS 7	SOS	Logistics	Tanh	62,53	203,37	0,65%	2,86%	328,46	4,39E-03
200	MLP 1-6-1	0,323351	0,00	0,00	BFGS 4	SOS	Logistics	Linear	80,67	211,37	0,90%	2,96%	334,45	3,45E-03
200	MLP 1-7-1	0,322874	0,00	0,00	BFGS 4	SOS	Linear	Logistics	49,11	206,81	0,47%	2,91%	326,36	3,89E-03
200	MLP 1-2-1	0,329312	0,00	0,00	BFGS 6	SOS	Linear	Linear	71,85	274,64	0,74%	3,86%	398,17	1,43E-01
200	MLP 1-5-1	0,329312	0,00	0,00	BFGS 4	SOS	Linear	Linear	47,00	209,48	0,44%	2,95%	326,61	1,49E-01
200	MLP 1-5-1	0,329312	0,00	0,00	BFGS 4	SOS	Linear	Linear	59,40	210,21	0,61%	2,95%	328,78	4,39E-03
								Minimal	**47,00**	**203,37**	**0,44%**	**2,86%**	**326,33**	**3,45E-03**

The analysis suggests that while a slight increase in traffic accidents on Polish roads is possible, the overall accident rate is likely to stabilize in the coming years. The choice of sample sizes significantly influences the model's accuracy. Increasing the proportion of the learning group relative to the test and validation groups can reduce the average percentage error. For instance, with a 70-15-15 split (learning, test, validation), the error was 5.68%. Increasing the learning group to 80% (80-10-10) reduced the error to 4.63%. These results are influenced by factors such as the increasing number of vehicles on Polish roads and the impact of the recent pandemic (Fig. 3).

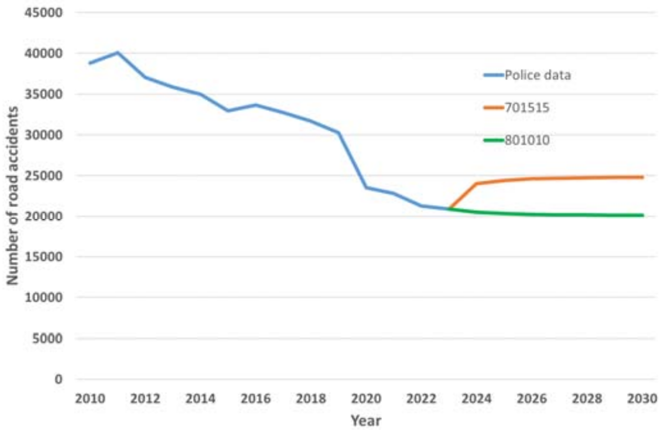

Fig. 3. Projected number of road accidents for 2024-2030 for Poland

The research findings suggest that the number of traffic accidents in Bosnia and Herzegovina may stabilize or even slightly decrease in the coming years. The accuracy of these predictions is influenced by the choice of sample sizes. Increasing the proportion of the training dataset can improve model accuracy. For example, with a 70-15-15 split (training, testing, validation), the error was 5.95%. Increasing the training set to 80% (80-10-10) resulted in an error of 6.03%. These results are likely influenced by factors such as the increasing number of vehicles and the impact of the recent pandemic (Fig. 4)

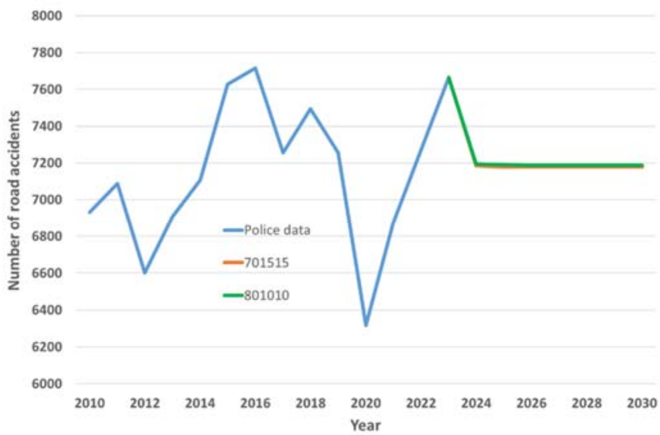

Fig. 4. Projected number of road accidents for 2024-2030 in Bosnia and Herzegovina

4. CONSLUSION

This study utilized neural networks within the Statistica environment to forecast traffic accident frequency in Poland and Bosnia and Herzegovina. The algorithm optimized the model's weights to minimize average absolute error and average absolute percentage error. Based on the analysis, the number of traffic accidents is likely to stabilize in the coming years, influenced by factors such as the ongoing pandemic and the increasing number of vehicles. Forecast errors were calculated to assess model accuracy. These forecasts can inform the development of strategies to further reduce traffic accidents. For example, the implementation of increased fines for traffic violations in Poland, effective from January 1, 2022, represents one such measure. The pandemic significantly disrupted traffic patterns, influencing the accuracy of the research data. Future research will explore alternative statistical techniques for accident prediction, incorporating additional factors such as traffic volume, weather conditions, driver age, and employing exponential smoothing methods.

5. REFERENCES

[1] Abdullah E., Emam A., Traffic accidents analyzer using big data, in: Proc. - 2015 Int. Conf. Comput. Sci. Comput. Intell. CSCI 2015, Institute of Electrical and Electronics Engineers Inc., 2016: pp. 392–397. 10.1109/CSCI.2015.187.

[2] Al-Madani H., Global road fatality trends'estimations based on country-wise microlevel data, Accid. Anal. Prev. 111 (2018) 297–310,https://doi.org/10.1016/j.aap.2017.11.035

[3] Arteaga C., Paz A., Park J. Injury severity on traffic crashes: A text mining with an interpretable machine-learning approach Saf. Sci., 132 (2020), Article 104988

[4] Bąk. I., Cheba K., Szczecińska B. The statistical analysis of road traffic in cities of Poland. Transp. Res. Procedia., 39 (2019), pp. 14-23, 10.1016/j.trpro.2019.06.003

[5] Biswas A.A., Mia J., Majumder A. Forecasting the Number of Road Accidents and Casualties using Random Forest Regression in the Context of Bangladesh July 2019 Economics 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)

[6] Bloomfield P. An exponential model in the spectrum of a scalar time series. Biometrika 60 (1973) 217–226 https://www.jstor.org/stable/2334533.

[7] Central Statistical Office, www.gus.pl (17.04.2022)

[8] Chand A., Jayesh S., Bhasi A.B. Road traffic accidents: An overview of data sources, analysis techniques and contributing factors, Materials Today: Proceedings. Volume 47, Part 15, 2021. Pages 5135-5141. ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2021.05.415.

[9] Chen C. Analysis and forecast of traffic accident big data ITM Web Conf., 12 (2017), p. 04029, 10.1051/itmconf/20171204029

[10] Chudy-Laskowska K. Pisula T. Forecasting the number of road accidents in Subcarpathia. Logistics. N0 4/ 2015

[11] Chudy-Laskowska K., Pisula T. Forecast of the number of road accidents in Poland. Logistics 6/2014.

[12] Dataminingtechnique StatSoft https://www.statsoft.pl/textbook/stathome_stat.html?https%3A%2F%2Fwww.statsoft.pl%2Ftextbook%2Fstdatmin.html

[13] Dudek G. Exponential smoothing models for short-term power system load forecasting. Energy market No. 3 (106) – 2013.

[14] Dudek, G. (2013). Forecasting Time Series with Multiple Seasonal Cycles Using Neural Networks with Local Learning. In: Rutkowski, L., Korytkowski, M., Scherer, R., Tadeusiewicz, R., Zadeh, L.A., Zurada, J.M. (eds) Artificial Intelligence and Soft Computing. ICAISC 2013. Lecture Notes in Computer Science(), vol 7894. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-38658-9_5

[15] Dutta B., Barman M.P., Patowary A.N. Application of Arima model for forecasting road accident deaths in India. Int. J. Agricult. Stat. Sci. Vol. 16, No. 2, pp. 607-615, 2020

[16] Fijorek K., Mróz K., Niedziela K., Fijorek D. Forecasting electricity prices on the day-ahead market using data mining methods Energy Market "- 12/2010

[17] Fiszeder P. GARCH class models in empirical financial research. Scientific Publishers of the Nicolaus Copernicus University. Torun 2009.
[18] Forecasting based on time series (2022) http://pis.rezolwenta.eu.org/Materialy/PiS-W-5.pdf
[19] Gorzelanczyk, P., Pyszewska, D., Kalina, T., Jurkovic, M. Analysis of road traffic safety in the Pila poviat. Scientific Journal of Silesian University of Technology. Series Transport. 2020, 107, 33-52. ISSN: 0209-3324. DOI: https://doi.org/10.20858/sjsutst.2020.107.3.
[20] Helgason A., Fractional integration methods and short Time series: evidence from asimulation study, Polit. Anal. 24 (1) (2016) 59–68http://www.jstor.org/stable/24573204.
[21] Statistic Road Accident https://statystyka.policja.pl/ (24.12.2024)
[22] Unece 2023 Statistics of Road Traffic Accidents https://unece.org/transport/publications/2023-statistics-road-traffic-accidents (24.12.2024)
[23] Lake BM, Ullman TD, Tenenbaum JB, Gershman SJ. Building machines that learn and think like people. Behav Brain Sci 2017; 40: e253.
[24] Becoming Human. How Netflix uses AI, data science, and machine learning – from a product perspective. Available at: www.becominghuman.ai (Accessed: 10.08.2019).
[25] Forbes. The amazing ways eBay is using Artificial Intelligence to boost business success. Available at: www. forbes.com (Accessed: 12.09.2020).
[26] Wu Y, Schuster M, Chen Z, Le QV, Norouzi M, Macherey W, et al. Google's neural machine translation system: bridging the gap between human and machine translation. arXiv:1609.08144. Available at: www.arxiv.org. (Accessed: 12.09.2020).
[27] Oronowicz-Jaśkowiak W. The application of neural networks in the work of forensic experts in child abuse cases. Adv Psychiatry Neurol 2019; 28 (4): 273-282 DOI: https://doi.org/10.5114/ppn.2019.92489