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Forecasting monthly road accidents in selected cities of wielkopolska using neural networks

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Abstract: Accurate forecasting of road accidents is essential for urban traffic safety management and preventive planning. This study uniquely integrates meteorological and accident data across five mid-sized Polish cities, providing city-specific forecasting insights. Findings suggest city-specific neural network models can guide targeted interventions, particularly in small vs. large urban areas. This study analyzes monthly road accident data from five cities in the Wielkopolska region of Poland—Piła, Konin, Leszno, Poznań, and Kalisz—covering the period 2018–2024, and evaluates the performance of neural network-based forecasts over 6- and 12-month horizons. The dataset includes meteorological variables (temperature, precipitation, snow cover, humidity, wind, sunshine) and detailed accident counts, distinguishing between minor, serious, and fatal accidents. Descriptive statistics reveal significant differences across cities: Poznań exhibits the highest average monthly accidents and variability, while Piła records the lowest mean with several months of zero accidents. Forecast accuracy metrics (MAE, RMSE, MAPE) indicate that neural network models provide reasonable predictions in absolute terms, particularly for larger cities, while relative errors are high in smaller cities due to low accident baselines. Extending the forecast horizon from 6 to 12 months generally reduces accuracy, although some medium-sized cities show minor improvements, likely reflecting annual seasonal patterns. The results highlight the importance of city-specific forecasting strategies, where absolute errors guide planning in large urban centers and relative errors are critical in smaller cities. The study demonstrates the practical applicability of neural networks in urban accident prediction, while also identifying limitations related to low-frequency events, model interpretability, and available predictors.

1 Introduction

Road traffic accidents constitute a major public safety concern worldwide, resulting in fatalities, injuries, and substantial economic costs. In Poland, despite long-term efforts to improve road safety, accident frequency and severity continue to vary significantly across regions and urban areas. Accurate forecasting of road accidents is essential for urban planning, traffic management, and preventive interventions, enabling authorities to allocate resources efficiently and implement targeted safety measures.

Recent studies have demonstrated the potential of machine learning methods, including artificial neural networks, in predicting traffic accidents. Neural networks are particularly suitable for modeling complex, nonlinear relationships between meteorological, temporal, and traffic-related variables and accident occurrences. Prior research has applied such approaches to various scales, from national-level analyses to city-specific forecasting, highlighting improvements over traditional statistical models in short- and medium-term prediction accuracy.

This study focuses on five cities in the Wielkopolska region of Poland: Piła, Konin, Leszno, Poznań, and Kalisz. The selected cities differ in population size, urban infrastructure, and traffic volume, providing a diverse set of contexts for analyzing accident patterns. The analysis employs monthly data for the period 2018–2024, including weather variables (e.g., temperature, precipitation, snow cover, wind, and sunshine), and detailed records of traffic accidents with distinctions by severity. This comprehensive dataset allows for both descriptive statistical analysis and the development of predictive models using neural networks.

Despite growing interest in machine learning applications for road safety, most studies focus either on national-level analyses or short-term daily/hourly predictions. City-specific monthly forecasting using neural networks, especially in medium-sized European cities and with explicit inclusion of meteorological variables, remains relatively underexplored in the Polish context. This gap is particularly relevant given Poland's persistently high road fatality rates compared to many EU countries and the need for localized, actionable predictions to support municipal traffic safety policies.

The primary objectives of this study are twofold. First, to quantify and compare the descriptive characteristics of monthly road accidents across the five cities, highlighting differences in mean accident frequency, variability, and severity. Second, to evaluate the accuracy of neural network-based forecasts over 6- and 12-month horizons, using standard error metrics (MAE, RMSE, MAPE) to assess both absolute and relative predictive performance. The study also

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examines how forecast accuracy varies with city size and accident baseline, providing insights into the practical applicability of neural network models in urban traffic safety planning.

By integrating regional accident data, meteorological variables, and advanced forecasting techniques, this research contributes to the evidence base for data-driven traffic safety management in medium- and large-sized Polish cities. The findings are relevant for policymakers, urban planners, and researchers seeking to optimize accident prevention strategies and improve the effectiveness of predictive modeling in transport safety contexts. Although prior studies applied neural networks at national scales, city-specific monthly forecasting remains underexplored in Poland.

2 Literature review

Research on road safety (RS) in Poland has traditionally focused on statistical analyses of accident rates, infrastructure, and technical and environmental factors. In recent years, however, there has been a clear expansion of the research field to include a social perspective, covering the opinions of road users, the evaluation of preventive measures, social campaigns, legal solutions, and the functioning of institutions responsible for RS. This direction is consistent with a systemic approach, in which road safety is seen as the result of interactions between people, vehicles, infrastructure, and the institutional environment.

Poland remains one of the European Union countries with relatively high rates of road accidents and fatalities per capita, which has made road safety one of the key areas of public policy for years [1,2]. Analyses show that despite systematic improvements in road infrastructure since EU accession, the development of the transport network also generates new risks, resulting, among other things, from increased traffic intensity, travel speeds, and diversity of road users [1,3]. In this context, public acceptance of risk-reducing measures such as speed controls, changes in traffic organization, and stricter legal regulations is becoming increasingly important.

Social campaigns are one of the basic instruments of preventive action in the area of road safety in Poland. However, their effectiveness remains a subject of debate, mainly due to methodological difficulties in clearly attributing changes in the behavior of road users to specific communication activities [4,6]. Surveys conducted among young adults (aged 18–25) show that respondents are widely exposed to road safety campaigns, primarily through television (approx. 88%), the Internet, and outdoor advertising [2]. At the same time, respondents rate the level of safety on Polish roads as low or moderate, pointing to reckless driving, inappropriate speed, and the condition of infrastructure as the main sources of danger.

The declared impact of the campaigns on the behavior of road users varies demographically. In the study by Goniewicz et al., approximately 67% of women and 42.5% of men declared a change in behavior under the influence of the campaigns, which suggests significant differences in perception and behavior [2]. In turn, analyses of campaigns promoting the use of seat belts and child seats indicate that long-term, consistent education supported by behavior monitoring can lead to a lasting improvement in safety indicators, including a decrease in the number of accident victims [5]. At the same time, the authors emphasize the lack of clear, “hard” measures of campaign effectiveness and discrepancies in assessments of their real impact on the level of road safety on a national scale [4].

An important area of research is the analysis of opinions on legal regulations, especially with regard to vulnerable road users. Studies on pedestrian safety indicate that the existing legal provisions can be considered generally sufficient, but their effectiveness in practice depends on the interpretation of the rules by drivers, pedestrians, and law enforcement authorities [6,7]. The role of pedestrian infrastructure is also emphasized, which in many locations does not meet safety standards, limiting both the actual safety and the subjective sense of protection of road users.

At the institutional level, provincial traffic centers (WORD) play an important role, providing re-education training for drivers who violate traffic regulations and improvement activities for examiners. The scale of these initiatives indicates a growing acceptance of an educational and corrective approach, complementing traditional repressive measures [8]. At the same time, municipal police forces are involved in local preventive activities, including parking control, information campaigns, and educational programs aimed at children and young people [9]. However, studies on the perception of these formations reveal an ambivalent social image, while recognizing their importance for maintaining order and safety in urban areas [10,11].

From the perspective of road users, hazards are increasingly associated not only with infrastructure and driver behavior, but also with distraction caused by the use of mobile devices. Studies indicate the widespread use of mobile phones by both pedestrians and drivers, with an awareness of the risks and a tendency to downplay them [12]. This phenomenon provides an important social background for the acceptance of regulations restricting the use of mobile devices in traffic.

In comparative terms, surveys conducted in India show high public support for tightening regulations, strengthening the penalty system, and raising exam requirements, regardless of the respondent's status as a driver or pedestrian [13]. These results correspond to the need observed in Poland for more decisive action in favor of road safety, although there is still a lack of nationwide studies that would systematically map Poles' opinions on tightening regulations, supervision, and traffic control.

Recent advances in road accident forecasting have shifted from traditional statistical methods (e.g., Poisson and negative binomial regression) toward machine learning techniques, particularly artificial neural networks (ANNs), due to their ability to capture complex, non-linear relationships [14–16]. Several studies have successfully applied multilayer perceptrons (MLP), recurrent neural networks (RNN), and long short-term memory (LSTM) models to predict accident frequency at national, regional, or corridor levels, often incorporating weather, traffic volume, and temporal variables [17–19].

However, most research focuses on daily or hourly predictions, while monthly city-level forecasting remains less common. Studies that do address monthly scales typically analyze larger metropolitan areas or entire countries, with fewer examples from medium-sized cities in Central and Eastern Europe [15,18]. Meteorological factors such as temperature, precipitation, and snow cover have been consistently identified as significant predictors, especially in regions with distinct seasonal weather patterns [18,19].

In the Polish context, existing forecasting efforts have primarily relied on trend models or econometric approaches [15,16]. Neural network-based monthly predictions for individual cities, integrating local meteorological data, have not been widely reported. This study addresses this gap by developing and evaluating city-specific MLP models for five diverse cities in the Wielkopolska region.

3 Materials and methods

The analysis uses monthly data from five cities in the Wielkopolska region of Poland—Piła, Konin, Leszno, Poznań, and Kalisz—covering the period 2018–2024. The dataset comprises meteorological and traffic-related variables extracted from city-level records. For each city, the dataset includes the following monthly variables: mean temperature, minimum temperature, total precipitation, maximum snow cover, mean humidity, mean wind speed, sunshine duration, number of traffic incidents, total number of road accidents, number of accidents with minor injuries, number of accidents with serious injuries, and number of fatal accidents (Table 1-5, Figure 1).

Table 1 Statistic data for Piła [20,21]

Year	Mont	Average temperature	Average minimum temperature	Total precipitation	Maximum snow cover depth	Average humidity	Average wind speed	Sunshine	Number of incidents	Number of accidents	Number of accidents with minor injuries	Number of accidents with serious injuries	Number of accidents with fatalities
2018	I	1.5	-0.6	50.1	13.0	88.7	*2.6*	32.3	69	2	1	1	0
	II	-3.0	-5.9	5.0	2.0	81.2	1.9	107.5	38	0	0	0	0
	III	0.0	-3.8	31.7	5.0	75.7	2.5	137.1	65	1	1	0	0
	IV	12.1	5.9	53.9	0.0	70.4	2.4	265.4	60	1	0	1	0
	V	17.4	10.2	9.5	0.0	57.9	2.4	351.6	65	1	1	0	0
	VI	18.6	12.2	20.3	0.0	60.9	2.3	268.0	54	0	0	0	0
	VII	20.6	14.1	113.1	0.0	66.3	2.1	284.3	73	1	0	1	0
	VIII	20.3	13.9	8.8	0.0	63.9	1.9	285.6	69	1	1	0	0
	IX	15.3	10.0	18.6	0.0	70.5	1.9	207.7	71	6	5	0	1
	X	10.0	5.0	22.2	0.0	77.9	2.2	169.8	70	1	0	1	0
	XI	4.6	2.1	6.7	0.0	87.0	1.9	57.3	62	7	4	4	0
	XII	2.6	0.5	37.5	3.0	90.2	2.3	15.5	91	4	2	1	1
2019	I	-0.2	-2.3	29.1	1.0	89.0	2.5	38.8	63	2	3	0	0
	II	2.9	-0.4	5.9	0.0	81.0	2.3	93.8	54	0	0	0	0
	III	5.9	2.2	23.4	0.0	77.3	2.7	115.3	83	2	0	2	0
	IV	10.3	3.7	2.1	0.0	53.7	2.9	282.3	71	0	0	0	0
	V	12.2	6.9	51.2	0.0	68.6	2.3	181.5	66	1	1	0	0
	VI	22.2	14.5	14.5	0.0	57.0	2.4	349.9	69	0	0	0	0
	VII	19.0	13.4	38.4	0.0	62.7	2.4	233.4	72	0	0	0	0
	VIII	20.0	13.7	24.6	0.0	63.5	1.8	255.7	66	0	0	0	0
	IX	13.5	9.2	99.0	0.0	78.4	2.2	139.2	68	3	3	0	0
	X	10.0	6.1	38.9	0.0	84.6	1.8	119.2	83	1	1	0	0
	XI	5.7	3.5	52.7	0.0	89.8	2.4	43.5	76	1	0	0	1
	XII	3.1	0.8	20.7	0.0	86.8	2.2	44.8	71	3	1	2	0
2020	I	3.1	0.7	38.7	0.0	87.6	2.5	54.4	63	0	0	0	0
	II	4.3	1.5	56.0	0.0	80.0	2.9	61.6	56	2	1	1	0
	III	4.4	0.0	33.8	0.0	68.0	2.5	190.7	54	1	0	0	1
	IV	8.7	0.9	1.6	0.0	53.8	2.3	289.5	29	1	1	0	0
	V	11.4	5.6	48.1	0.0	65.3	2.5	241.7	45	1	1	0	0
	VI	18.2	13.2	102.9	0.0	71.1	2.2	209.7	62	1	1	0	0
	VII	17.9	12.1	51.6	0.0	68.5	2.1	257.9	58	2	1	2	0
	VIII	20.1	14.1	40.8	0.0	69.2	1.9	260.8	70	3	2	0	1
	IX	14.4	8.7	66.7	0.0	81.4	1.8	212.6	60	3	1	2	0
	X	10.4	7.3	67.7	0.0	86.2	2.0	83.3	56	4	2	1	1
	XI	6.1	3.9	8.2	0.0	89.6	2.0	44.6	51	1	0	1	1
	XII	2.1	0.1	37.0	2.0	89.7	2.4	29.7	81	1	1	0	0
2021	I	-0.8	-2.6	62.1	15.0	90.3	2.1	26.5	59	0	0	0	0
	II	-1.3	-4.9	27.3	15.0	84.1	2.1	100.2	50	0	0	0	0
	III	3.5	-0.5	24.4	0.0	76.9	2.1	131.9	47	0	0	0	0

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	IV	5.9	0.7	38.8	4.0	70.4	2.3	163.2	52	3	2	1	0
	V	12.0	6.5	69.8	0.0	70.9	2.3	222.1	79	0	0	0	0
	VI	19.8	12.5	24.8	0.0	61.5	2.1	327.4	74	3	3	0	0
	VII	20.7	15.4	42.8	0.0	71.3	2.1	233.0	59	0	0	0	0
	VIII	17.2	12.3	26.2	0.0	70.0	2.2	183.7	67	1	1	0	0
	IX	14.7	10.0	16.4	0.0	76.0	2.0	168.4	72	0	0	0	0
	X	9.3	4.9	32.9	0.0	81.8	2.0	152.3	69	2	1	3	0
	XI	5.5	3.6	44.7	1.0	92.1	2.2	24.2	71	0	0	0	0
	XII	-0.7	-3.2	36.0	12.0	91.4	2.2	29.6	60	0	0	0	0
2022	I	1.6	-0.7	48.4	4.0	88.7	2.8	54.7	50	1	1	0	0
	II	3.7	1.1	74.2	0.0	82.3	*3.1*	75.7	44	2	1	0	1
	III	3.4	-2.6	0.1	0.0	63.3	2.0	241.9	64	0	0	0	0
	IV	7.3	1.9	30.7	0.0	64.8	2.6	199.6	67	1	0	1	0
	V	13.4	6.9	42.8	0.0	63.5	2.3	259.1	70	2	2	0	0
	VI	18.7	12.1	30.5	0.0	65.0	2.1	305.8	54	1	1	0	0
	VII	19.2	13.0	36.4	0.0	64.6	2.4	288.8	61	0	0	0	0
	VIII	21.6	15.9	60.2	0.0	66.6	1.9	245.5	59	4	4	0	0
	IX	12.6	8.1	36.4	0.0	76.9	1.9	165.3	60	3	3	0	0
	X	10.7	6.6	33.8	0.0	89.0	1.7	116.5	59	1	0	1	0
	XI	4.5	2.4	16.6	5.0	90.7	2.1	49.8	48	3	1	2	0
	XII	0.7	-1.3	32.8	1.0	90.3	2.2	18.1	61	0	0	0	0
2023	I	3.1	1.3	56.3	4.0	88.9	2.4	18.5	48	3	2	1	0
	II	1.8	-1.0	33.0	1.0	81.6	2.5	73.9	43	0	0	0	0
	III	4.0	0.6	58.4	3.0	79.9	2.3	107.7	62	3	3	1	0
	IV	7.9	3.2	31.8	0.0	72.3	2.3	167.8	50	2	2	0	0
	V	13.1	6.3	13.0	0.0	57.9	2.5	318.5	64	1	0	1	0
	VI	18.5	11.7	57.3	0.0	59.3	2.1	295.6	61	0	0	0	0
	VII	18.9	12.5	67.5	0.0	64.2	2.1	258.0	49	2	2	0	0
	VIII	18.8	14.2	114.5	0.0	76.0	1.9	195.7	67	4	3	1	0
	IX	17.5	11.1	6.3	0.0	75.3	1.6	281.0	76	3	2	1	0
	X	10.1	6.6	76.1	0.0	85.6	2.2	72.8	67	3	1	3	0
	XI	3.9	1.0	81.6	6.0	89.4	2.1	48.1	72	0	0	0	0
	XII	2.3	0.0	78.5	7.0	89.5	2.7	25.6	57	2	1	1	0
2024	I	0.2	-2.6	47.9	7.0	85.9	2.7	51.8	63	0	0	0	0
	II	5.5	2.9	75.4	0.0	88.3	2.6	34.1	65	1	0	0	2
	III	6.9	3.0	19.3	0.0	78.5	2.3	130.2	57	0	0	0	0
	IV	10.3	4.7	29.6	0.0	69.9	2.3	179.9	60	1	1	0	0
	V	16.8	10.3	59.2	0.0	61.4	2.5	317.7	63	1	1	0	0
	VI	17.9	11.8	35.7	0.0	69.7	2.1	269.4	53	0	0	0	0
	VII	19.4	13.6	129.8	0.0	71.4	1.9	267.9	60	0	0	0	0
	VIII	19.8	13.7	26.4	0.0	68.2	1.8	304.8	47	1	1	0	0
	IX	16.8	11.7	27.8	0.0	69.7	2.4	232.9	67	1	1	0	0
	X	10.2	6.7	24.3	0.0	82.0	2.1	113.9	74	0	0	0	0
	XI	4.1	2.0	36.4	1.0	90.2	2.2	33.6	54	4	3	1	1
	XII	3.4	1.8	26.0	0.0	92.7	2.4	23.6	59	2	1	1	0

Table 2 Statistic data for Konin [20,21]

Year	Month	Average temperature	Average minimum temperature	Total precipitation	Maximum snow cover depth	Average humidity	Average wind speed	Sunshine	Number of incidents	Number of accidents	Number of accidents with minor injuries	Number of accidents with serious injuries	Number of accidents with fatalities
2018	I	1.9	-0.3	17.8	10.0	84.1	5.5	32.7	99	1	0	2	0
	II	1.5	-1.4	9.4	1.0	81.7	4.1	74.6	101	0	0	0	0
	III	5.5	1.0	28.4	5.0	71.9	4.8	155.2	87	3	1	2	0
	IV	8.7	3.1	26.5	0.0	65.1	4.7	185.9	106	5	3	2	0
	V	13.2	7.6	22.4	0.0	66.1	3.7	229.9	96	1	0	1	0
	VI	17.1	11.2	26.0	0.0	64.2	3.6	231.4	122	4	1	3	0
	VII	20.1	14.0	71.0	0.0	*61.4*	*4.0*	270.4	91	6	2	5	0
	VIII	22.5	15.5	19.1	0.0	53.2	4.4	329.3	92	5	3	4	0
	IX	*15.8*	*10.7*	28.8	0.0	*71.1*	*3.9*	*144.6*	119	3	2	1	0
	X	8.0	3.8	39.4	0.0	79.4	4.5	*82.4*	145	17	11	7	0
	XI	6.1	3.4	47.9	3.0	85.6	3.7	48.9	99	9	8	2	1
	XII	5.6	3.2	14.1	0.0	84.3	3.8	53.7	117	5	3	2	0
2019	I	-2.5	-5.0	16.1	6.0	85.8	3.6	45.6	106	9	5	4	1
	II	3.8	1.2	24.4	12.0	83.3	3.9	64.3	97	8	7	2	1
	III	4.5	1.3	31.5	6.0	81.6	3.2	106.4	101	11	7	3	2
	IV	9.5	4.5	11.3	0.0	66.7	3.1	191.0	122	12	12	3	0
	V	15.8	9.6	28.6	0.0	65.0	3.2	280.2	93	5	5	0	0
	VI	18.8	12.6	51.3	0.0	65.8	2.9	296.2	114	11	13	2	0
	VII	19.8	14.4	72.1	0.0	69.6	*2.7*	218.7	84	7	7	2	0
	VIII	18.9	13.2	23.0	0.0	69.0	2.6	246.5	98	15	12	4	0
	IX	17.2	10.9	7.7	0.0	65.0	2.9	245.1	88	7	7	1	0
	X	8.0	5.6	102.1	0.0	88.6	3.7	51.9	122	11	10	3	0
	XI	3.5	1.0	34.2	0.0	89.3	3.3	52.7	103	11	7	5	0
	XII	1.7	-0.5	37.4	9.0	89.3	3.6	58.3	112	8	7	2	0
2020	I	-3.0	-5.5	8.8	21.0	84.9	3.1	72.0	102	9	6	3	0

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	II	0.1	-2.6	22.6	24.0	82.6	4.1	60.1	93	7	8	3	0
	III	7.0	3.1	22.1	4.0	73.3	3.4	133.3	63	2	2	0	0
	IV	8.3	4.0	37.7	0.0	73.6	3.7	139.3	66	2	1	1	0
	V	14.1	9.0	40.4	0.0	72.6	3.3	261.2	78	6	4	2	0
	VI	18.2	12.7	84.6	0.0	70.4	3.4	241.1	73	5	4	1	0
	VII	18.7	13.6	83.2	0.0	75.0	2.6	231.1	77	6	4	2	0
	VIII	20.0	14.5	46.5	0.0	72.2	2.7	251.2	93	16	10	7	0
	IX	14.3	10.6	104.6	0.0	85.1	3.3	115.7	106	12	9	3	1
	X	10.9	7.6	79.5	0.0	*84.8*	3.7	102.7	96	9	6	2	1
	XI	5.3	3.2	28.2	13.0	88.7	3.3	*26.5*	88	5	4	2	0
	XII	2.4	0.1	31.9	21.0	86.4	4.1	*31.7*	105	7	3	3	1
2021	I	1.2	-1.4	23.1	15.0	84.2	4.3	38.1	74	6	3	3	0
	II	-2.7	-6.0	2.9	2.0	78.0	2.8	97.4	78	4	4	0	2
	III	1.1	-2.8	19.7	2.0	71.3	3.8	141.9	72	5	4	3	0
	IV	13.4	7.3	20.0	0.0	66.6	3.9	251.0	62	2	1	1	0
	V	17.0	11.0	44.5	0.0	65.4	3.2	331.9	102	14	11	6	0
	VI	18.7	12.8	42.1	0.0	67.0	2.9	232.6	86	10	9	2	0
	VII	20.7	15.1	87.7	0.0	70.3	2.6	197.9	98	10	12	1	0
	VIII	21.4	15.3	26.5	0.0	65.5	2.6	293.6	101	6	3	3	0
	IX	16.7	11.1	30.8	0.0	69.0	2.9	232.6	120	11	5	6	0
	X	11.1	6.2	44.0	0.0	76.7	3.5	164.3	110	11	6	6	0
	XI	5.2	2.6	7.6	0.0	86.2	3.6	24.8	87	3	3	3	0
	XII	2.1	0.2	31.9	1.0	88.7	3.7	23.1	95	7	3	4	0
2022	I	-1.0	-3.1	26.1	4.0	86.1	3.9	23.2	101	2	5	0	0
	II	3.5	-0.2	25.2	10.0	78.8	3.7	125.1	55	1	2	0	0
	III	6.9	2.8	35.4	0.0	73.9	4.1	144.5	88	8	8	1	0
	IV	10.2	3.8	14.6	0.0	57.6	4.2	282.9	90	8	6	2	0
	V	12.8	7.9	44.7	0.0	72.6	3.1	191.3	81	8	9	1	0
	VI	22.1	15.1	23.7	0.0	63.5	3.1	334.1	67	4	3	1	0
	VII	19.5	13.8	50.7	0.0	64.4	3.1	221.0	75	4	5	0	0
	VIII	20.8	15.0	44.7	0.0	67.2	2.7	268.8	86	7	9	0	0
	IX	15.0	10.1	58.9	0.0	77.2	3.2	165.6	77	7	10	3	0
	X	11.5	7.2	15.2	2.0	82.6	2.8	141.9	77	5	5	1	0
	XI	6.3	3.3	15.1	0.0	87.8	4.0	55.0	53	3	1	2	0
	XII	3.6	1.2	13.9	7.0	84.4	3.5	38.3	83	2	1	1	0
2023	I	2.9	0.4	20.8	16.0	85.9	3.6	58.7	62	7	8	3	0
	II	4.7	1.7	56.8	15.0	78.1	4.4	52.8	61	3	2	1	0
	III	5.4	0.7	23.1	15.0	65.0	3.9	196.6	96	5	5	0	0
	IV	9.2	2.0	4.2	28.0	52.6	3.3	298.9	87	6	6	3	1
	V	11.7	6.0	68.2	0.0	67.4	3.1	215.5	83	11	9	4	0
	VI	18.5	13.6	122.2	0.0	77.8	2.8	197.7	79	9	10	1	0
	VII	19.1	13.1	28.0	0.0	67.9	2.7	246.6	72	3	3	0	0
	VIII	20.7	14.9	70.7	0.0	66.3	2.9	267.1	86	15	17	2	0
	IX	*16.4*	*11.2*	88.1	0.0	*78.9*	*2.7*	*168.4*	80	8	7	2	0
	X	11.1	8.0	79.4	0.0	86.3	2.8	101.1	84	7	7	2	0
	XI	6.1	3.9	11.0	1.0	88.9	2.9	48.4	93	9	5	4	0
	XII	2.4	0.3	17.9	2.0	87.9	4.2	27.7	80	12	10	4	0
2024	I	0.9	-2.7	24.8	4.0	85.8	4.0	47.5	71	2	1	1	0
	II	1.8	-1.2	22.9	3.0	80.4	3.8	83.9	59	5	5	1	0
	III	5.0	1.1	26.7	0.0	73.3	3.9	154.1	73	4	4	1	0
	IV	11.4	6.5	37.2	0.0	71.7	3.7	186.2	74	7	11	1	0
	V	16.6	10.0	16.1	0.0	62.2	3.0	313.0	84	3	3	0	0
	VI	19.0	13.5	74.6	0.0	*72.2*	2.7	254.3	81	6	9	0	0
	VII	20.9	15.0	124.0	0.0	*69.9*	2.8	305.2	91	5	5	1	0
	VIII	20.6	14.7	45.0	0.0	*68.6*	2.5	280.6	72	7	5	1	1
	IX	17.6	12.0	60.8	0.0	*65.1*	3.6	237.4	94	8	3	5	0
	X	10.9	7.0	32.4	0.0	*79.2*	3.4	158.9	100	13	8	5	1
	XI	4.4	2.3	31.3	0.0	*84.0*	3.8	42.4	85	4	2	2	0
	XII	3.3	1.5	21.3	1.0	*88.3*	3.9	30.1	102	6	6	1	0

Table 3 Statistic data for Leszno [20,21]

Year	Month	Average temperature	Average minimum temperature	Total precipitation	Maximum snow cover depth	Average humidity	Average wind speed	Sunshine	Number of incidents	Number of accidents	Number of accidents with minor injuries	Number of accidents with serious injuries	Number of accidents with fatalities
2018	I	2.5	0.5	44.8	*3.0*	81.5	3.9	37.4	85	7	5	2	1
	II	-2.4	-5.4	2.0	*1.0*	76.6	2.9	135.0	82	5	5	0	0
	III	0.9	-3.1	24.8	*0.0*	73.0	3.6	136.0	89	8	9	0	0
	IV	13.1	6.3	10.2	*0.0*	67.2	3.6	277.1	85	7	6	3	0
	V	16.7	9.4	25.6	*0.0*	64.6	3.2	328.7	109	10	6	4	0
	VI	18.7	12.3	40.0	*0.0*	64.5	3.4	236.2	96	5	5	0	0
	VII	20.3	14.0	86.1	*0.0*	67.2	3.1	293.7	83	12	8	4	0
	VIII	21.3	14.6	13.9	*0.0*	61.3	2.5	285.4	72	7	8	1	0
	IX	15.7	10.4	74.1	*0.0*	71.6	2.8	228.0	98	8	6	3	0
	X	10.7	5.4	35.9	*0.0*	75.8	3.3	173.3	107	15	11	7	0
	XI	5.1	2.2	15.1	*0.0*	85.9	2.9	92.2	84	12	7	5	1

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	XII	3.0	0.9	41.4	*0.0*	88.9	4.0	20.0	98	10	7	3	0
2019	I	-0.1	-2.5	42.8	2.0	87.4	4.3	35.7	90	7	3	4	0
	II	3.2	-0.8	10.7	2.0	78.3	3.7	133.4	66	7	11	1	0
	III	6.4	2.2	36.9	0.0	75.8	4.2	131.3	91	7	5	2	0
	IV	10.4	3.8	8.6	0.0	59.4	3.9	270.2	93	10	7	3	0
	V	11.8	6.1	91.7	0.0	74.3	3.2	224.2	75	14	14	2	0
	VI	22.2	14.7	8.8	0.0	60.6	3.1	373.7	95	17	8	12	1
	VII	19.1	12.8	56.5	0.0	65.1	3.2	233.2	84	15	14	5	0
	VIII	20.6	14.4	43.7	0.0	67.0	2.4	266.2	85	6	5	1	0
	IX	14.4	9.5	83.6	0.0	75.5	3.0	180.2	92	11	7	4	0
	X	10.7	6.3	20.9	0.0	82.5	2.6	151.3	116	11	15	2	0
	XI	6.8	3.9	49.4	0.0	85.1	3.1	93.4	90	8	4	5	0
	XII	3.6	0.6	14.3	0.0	82.9	3.4	53.8	85	13	11	2	1
2020	I	2.9	-0.4	20.5	0.0	84.3	3.7	76.2	95	9	4	6	0
	II	5.1	2.1	63.0	0.0	77.9	5.0	79.1	70	8	7	1	0
	III	5.0	0.2	20.4	1.0	66.8	3.8	208.2	61	1	1	0	0
	IV	9.3	1.1	5.7	0.0	54.4	3.3	310.5	25	1	1	0	0
	V	11.8	5.4	45.9	0.0	67.0	3.5	250.7	60	6	3	3	0
	VI	17.9	12.8	52.6	0.0	76.6	3.2	224.3	76	10	11	3	0
	VII	18.8	12.1	31.9	0.0	65.7	2.8	270.7	55	7	7	0	0
	VIII	20.6	14.7	86.4	0.0	68.6	2.8	250.2	72	5	6	1	0
	IX	15.3	9.2	37.9	0.0	76.8	2.5	217.4	72	9	7	2	0
	X	11.0	8.0	87.4	*0.0*	84.3	2.9	85.0	72	3	3	0	0
	XI	6.0	3.1	15.2	*0.0*	87.4	2.7	68.3	49	1	1	0	0
	XII	2.6	0.1	13.7	*4.0*	85.2	3.1	78.7	81	11	10	3	0
2021	I	-0.2	-2.1	24.6	*8.0*	87.5	3.2	40.8	49	3	3	1	0
	II	-0.4	-4.5	15.7	*9.0*	80.7	3.4	100.8	51	1	1	0	0
	III	4.1	-0.1	15.1	0.0	74.6	3.3	157.3	58	9	9	2	0
	IV	6.4	1.9	32.3	0.0	70.8	3.8	158.0	56	7	7	2	0
	V	12.2	7.2	69.4	*0.0*	71.5	3.5	210.5	74	7	7	2	2
	VI	19.8	12.7	59.5	*0.0*	65.6	2.6	310.6	82	3	4	0	0
	VII	20.4	15.0	72.2	*0.0*	73.1	2.6	220.9	59	4	4	1	0
	VIII	17.4	12.7	126.7	*0.0*	75.6	2.6	185.7	81	7	5	3	0
	IX	15.3	10.7	19.1	*0.0*	77.8	2.6	189.6	89	6	4	2	0
	X	10.0	5.0	20.6	*0.0*	77.3	2.9	167.2	96	8	6	3	0
	XI	5.5	3.1	29.4	*0.0*	88.6	3.4	47.8	63	2	1	1	0
	XII	0.5	-2.0	36.1	*8.0*	89.2	3.4	49.9	75	4	4	0	0
2022	I	2.1	-0.1	29.6	*3.0*	86.1	4.7	63.4	46	3	2	1	0
	II	4.4	1.4	48.7	*1.0*	78.1	5.2	87.1	53	1	0	1	0
	III	4.0	-2.2	0.0	*0.0*	60.4	3.0	254.7	67	7	7	0	0
	IV	7.6	2.4	34.2	*0.0*	67.5	3.8	189.8	59	3	4	0	0
	V	14.6	7.6	51.3	*0.0*	62.9	3.1	281.3	51	2	2	0	0
	VI	19.5	12.2	39.4	*0.0*	64.1	2.8	295.9	66	6	3	2	1
	VII	19.9	13.1	45.7	*0.0*	59.6	3.4	286.8	48	0	0	0	0
	VIII	21.3	15.6	89.1	*0.0*	69.2	2.7	245.6	52	5	2	3	0
	IX	13.3	8.7	50.6	*0.0*	77.0	2.6	189.0	61	8	8	0	0
	X	11.7	7.0	44.9	*0.0*	84.5	2.5	170.8	44	2	1	1	0
	XI	4.8	1.7	10.4	*0.0*	87.8	2.6	70.0	49	2	2	0	0
	XII	1.5	-0.8	28.1	*0.0*	86.5	3.3	32.7	60	11	10	3	0
2023	I	3.4	1.2	37.8	*2.0*	86.1	3.6	35.5	56	3	0	5	0
	II	2.5	-0.5	43.8	*1.0*	80.3	4.1	87.0	44	3	2	1	0
	III	5.0	1.0	36.0	*5.0*	77.4	3.8	101.1	55	1	1	0	0
	IV	7.7	3.1	31.2	*0.0*	75.8	3.2	145.5	62	7	8	0	0
	V	13.2	6.9	23.8	*0.0*	64.1	3.3	295.5	58	9	8	2	0
	VI	18.3	11.0	62.6	*0.0*	64.0	2.7	275.7	44	2	1	1	0
	VII	20.1	12.9	36.4	*0.0*	62.4	2.9	283.8	55	8	7	6	0
	VIII	19.7	15.0	145.9	*0.0*	75.7	2.6	222.9	43	4	3	1	0
	IX	17.9	11.4	11.6	*0.0*	74.4	2.2	284.7	69	6	3	3	0
	X	11.5	7.8	101.3	*0.0*	84.4	2.9	89.3	65	9	10	1	0
	XI	5.2	2.6	70.2	*3.0*	85.0	3.5	76.9	63	4	2	2	0
	XII	2.9	0.6	70.9	*7.0*	86.9	4.1	33.7	74	8	4	4	0
2024	I	0.7	-2.2	29.4	*4.0*	81.6	4.4	74.8	65	4	4	1	0
	II	6.7	4.0	79.6	*0.0*	85.7	4.0	47.0	49	1	0	1	0
	III	8.2	3.9	12.6	*0.0*	75.2	3.1	140.7	65	5	5	1	0
	IV	11.3	5.9	24.6	*0.0*	70.1	3.2	184.9	54	3	2	1	0
	V	17.2	10.9	35.0	*0.0*	63.2	2.8	300.7	61	8	6	2	0
	VI	18.8	13.2	93.7	*0.0*	72.1	2.7	237.0	57	7	8	1	0
	VII	20.3	14.6	86.2	*0.0*	73.2	2.6	283.9	66	7	4	3	1
	VIII	20.7	15.0	150.1	*0.0*	72.4	2.4	286.9	68	5	2	3	0
	IX	16.9	12.3	69.7	*0.0*	74.5	3.5	221.0	62	10	10	4	0
	X	11.2	7.5	16.9	*0.0*	83.5	2.9	142.1	80	7	5	3	0
	XI	4.4	2.1	29.8	*3.0*	91.5	3.3	35.9	57	4	2	3	0
	XII	2.8	0.7	14.9	*0.0*	90.7	3.3	41.8	64	5	6	1	0

Table 4 Statistic data for Poznan [20,21]

Year	Month	Average temperature	Average minimum temperature	Total precipitation	Maximum snow cover depth	Average humidity	Average wind speed	Sunshine	Number of incidents	Number of accidents	Number of accidents with minor injuries	Number of accidents with serious injuries	Number of accidents with fatalities
2018	I	2.2	0.1	48.7	4.0	84.6	4.7	41.7	733	49	45	9	3
	II	-2.6	-5.5	4.4	1.0	78.9	3.3	101.1	652	51	50	10	0
	III	1.0	-2.8	29.4	1.0	72.1	4.3	121.2	781	73	59	26	2
	IV	13.4	7.6	28.1	0.0	64.7	4.3	272.7	813	69	59	18	2
	V	17.9	11.2	16.6	0.0	55.9	3.9	350.4	801	85	75	26	1
	VI	19.4	13.9	22.8	0.0	58.1	4.0	271.8	725	87	67	30	3
	VII	20.9	14.9	81.3	0.0	63.7	3.5	310.2	662	86	67	26	2
	VIII	21.7	15.9	9.8	0.0	57.2	3.3	313.1	662	64	61	15	1
	IX	16.1	11.3	40.7	0.0	67.3	3.4	205.9	799	83	64	27	4
	X	10.9	6.3	23.4	0.0	73.6	4.1	161.1	937	86	74	18	2
	XI	5.2	2.7	7.8	0.0	84.3	3.7	60.1	709	62	57	17	4
	XII	2.8	0.8	59.5	2.0	88.4	4.5	15.5	814	67	68	25	2
2019	I	-0.2	-2.4	58.7	3.0	88.2	4.6	31.8	770	58	48	19	3
	II	3.4	0.0	15.9	2.0	77.2	4.2	107.8	743	57	61	8	0
	III	6.4	3.0	39.8	0.0	73.8	4.8	119.4	797	61	47	27	0
	IV	10.9	4.6	7.2	0.0	52.6	4.6	277.7	801	70	55	24	0
	V	12.4	7.4	83.5	0.0	69.7	3.8	208.6	774	71	58	17	3
	VI	23.3	16.6	3.4	0.0	55.5	3.6	378.8	724	72	57	23	1
	VII	19.7	14.3	22.8	0.0	61.7	3.9	248.4	671	88	84	17	0
	VIII	21.2	15.6	32.4	0.0	63.5	3.1	289.9	705	109	101	21	2
	IX	14.6	10.5	40.1	0.0	75.3	3.8	159.4	752	97	88	23	1
	X	10.9	7.0	19.2	0.0	83.6	3.1	114.4	948	111	105	22	0
	XI	6.6	4.3	46.2	0.0	88.4	4.0	63.2	782	74	48	30	2
	XII	3.7	1.4	23.6	0.0	85.9	3.8	40.7	691	64	53	16	1
2020	I	3.3	1.1	37.4	0.0	87.8	4.1	67.3	705	60	43	23	3
	II	5.0	2.3	76.3	0.0	79.5	5.1	65.4	718	67	70	17	1
	III	5.2	1.0	29.0	0.0	65.7	4.2	*120.3*	491	36	28	8	1
	IV	9.8	2.7	2.6	0.0	50.2	3.9	234.8	361	27	25	6	3
	V	12.0	6.6	47.5	0.0	63.1	4.1	*279.5*	528	44	32	13	2
	VI	18.5	13.8	51.3	0.0	70.8	3.7	225.6	626	60	57	12	0
	VII	19.3	14.0	65.3	0.0	61.6	3.6	286.4	661	61	52	15	1
	VIII	21.0	15.7	60.9	0.0	63.4	3.3	265.1	668	62	43	28	0
	IX	15.6	10.2	37.4	0.0	73.5	2.9	189.3	719	80	66	20	1
	X	11.0	8.3	41.0	0.0	83.4	3.4	81.9	622	57	51	18	0
	XI	6.2	4.0	11.8	0.0	88.6	3.3	46.7	512	35	32	8	1
	XII	2.4	0.3	31.5	2.0	88.1	4.0	34.5	611	30	21	13	2
2021	I	-0.5	-2.2	53.5	12.0	91.1	3.5	30.5	527	32	27	10	0
	II	-0.4	-4.1	35.0	6.0	83.6	3.7	96.2	582	31	27	10	1
	III	4.1	-0.2	22.1	1.0	75.6	3.5	142.7	714	32	21	13	1
	IV	6.6	2.2	33.7	1.0	69.4	4.2	149.0	592	31	25	14	2
	V	12.6	7.9	62.6	0.0	69.9	4.1	188.2	716	44	34	17	0
	VI	20.7	14.4	92.8	0.0	58.9	3.2	264.9	708	47	35	18	2
	VII	21.2	16.4	32.3	0.0	68.6	3.4	198.0	575	33	27	8	1
	VIII	17.9	13.4	81.7	0.0	70.7	3.4	157.8	585	37	34	16	3
	IX	15.5	11.2	13.8	0.0	74.8	3.4	154.4	660	48	34	18	1
	X	10.3	6.1	25.0	0.0	76.7	3.6	153.2	727	49	31	26	1
	XI	5.7	3.8	38.1	0.0	89.8	4.0	34.4	649	49	44	8	1
	XII	0.0	-2.5	36.5	8.0	91.1	4.1	43.4	654	37	33	11	1
2022	I	1.7	-0.5	46.1	4.0	89.0	5.0	50.6	542	30	23	8	1
	II	4.3	1.7	57.2	0.0	78.3	5.5	83.9	579	33	25	10	3
	III	4.3	-1.4	2.1	0.0	57.0	3.4	229.2	642	35	28	12	0
	IV	7.9	2.7	36.3	0.0	63.3	4.3	168.8	588	37	32	10	0
	V	14.9	8.7	22.6	0.0	57.1	3.9	233.1	652	54	41	20	0
	VI	19.9	13.5	63.4	0.0	60.5	3.5	244.6	605	77	63	31	5
	VII	20.2	14.7	22.7	0.0	59.2	4.1	238.9	552	56	36	28	1
	VIII	22.1	16.6	52.8	0.0	64.4	3.3	222.3	561	53	35	21	4
	IX	13.4	9.0	31.6	0.0	73.6	3.3	171.6	551	43	35	14	1
	X	12.0	7.9	28.3	0.0	83.6	3.0	149.9	636	68	60	17	1
	XI	4.8	2.6	16.3	6.0	89.7	3.4	54.1	638	29	24	10	1
	XII	1.3	-0.8	35.2	1.0	89.4	3.8	27.3	609	37	26	16	1
2023	I	3.4	1.5	53.3	6.0	89.1	3.8	27.3	571	35	32	10	1
	II	2.2	-0.8	40.1	0.0	82.1	4.5	82.2	540	39	29	14	1
	III	4.8	1.2	51.4	1.0	79.2	4.0	89.9	602	24	17	7	0
	IV	8.4	4.0	36.8	0.0	72.3	3.7	148.8	582	41	37	7	1
	V	13.8	7.6	29.5	0.0	58.9	3.9	308.2	613	54	40	15	0
	VI	19.4	13.2	38.7	0.0	56.7	3.3	287.0	603	55	44	19	0
	VII	20.5	14.3	61.7	0.0	56.8	3.5	280.2	568	47	34	14	0
	VIII	19.8	15.2	156.1	0.0	70.7	3.1	219.9	576	59	46	23	0
	IX	18.6	12.6	3.3	0.0	68.6	2.8	292.8	640	54	42	14	0
	X	11.1	7.5	78.4	0.0	82.6	3.6	75.1	744	37	31	15	1
	XI	4.7	1.6	84.5	4.0	85.6	3.8	67.6	721	39	28	14	3

	XII	2.7	0.5	76.7	5.0	86.1	4.7	35.9	749	50	39	13	2
2024	I	0.5	-2.1	48.9	6.0	82.3	4.7	64.0	737	36	24	16	0
	II	6.3	3.8	74.4	0.0	85.8	4.4	34.3	787	32	23	10	0
	III	7.7	3.7	20.0	0.0	76.2	3.8	136.9	755	44	38	11	0
	IV	11.3	6.1	49.5	0.0	68.9	3.7	172.2	808	40	31	13	2
	V	17.3	11.1	52.2	0.0	60.0	3.7	303.0	727	53	41	15	0
	VI	18.8	13.8	97.1	0.0	68.6	3.4	241.8	725	60	41	24	0
	VII	20.6	15.2	75.3	0.0	66.9	3.1	272.5	693	77	61	24	5
	VIII	21.3	15.5	38.8	0.0	63.2	3.2	286.2	655	56	36	25	0
	IX	17.5	12.8	56.3	0.0	67.8	4.1	210.6	692	56	45	14	1
	X	10.9	7.2	20.0	0.0	80.4	3.5	138.5	772	62	55	14	2
	XI	4.4	2.5	31.9	0.0	88.1	3.6	26.1	634	41	33	13	0
	XII	3.3	1.6	18.0	0.0	90.0	3.8	27.5	689	45	42	11	1

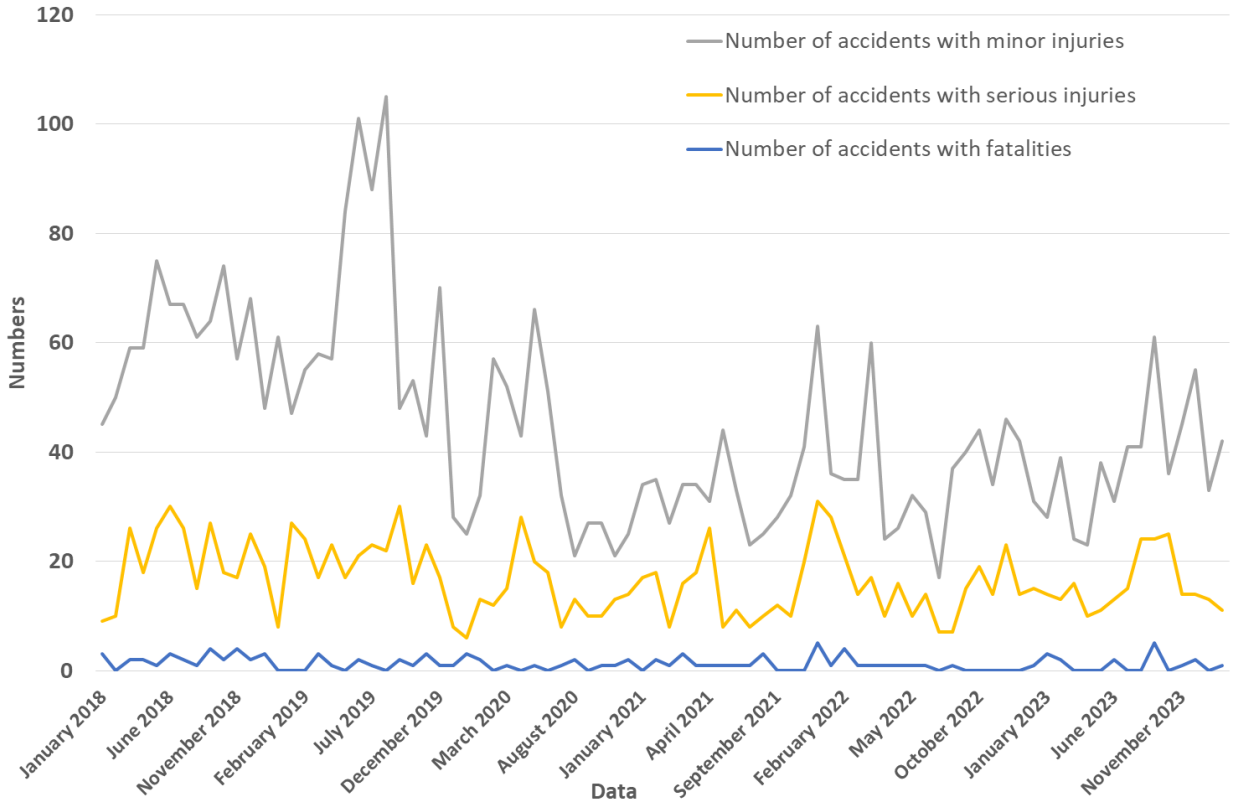


Figure 1 Statistic data for Poznan [20,21]

Table 5 Statistic data for Kalisz [20,21]

Year	Month	Average temperature	Average minimum temperature	Total precipitation	Maximum snow cover depth	Average humidity	Average wind speed	Sunshine	Number of incidents	Number of accidents	Number of accidents with minor injuries	Number of accidents with serious injuries	Number of accidents with fatalities
2018	I	1.8	-0.2	24.7	7.0	87.1	4.6	40.5	161	2	1	1	1
	II	-2.7	-4.9	1.8	1.0	83.6	3.1	116.4	125	5	3	3	0
	III	1.0	-2.4	29.8	4.0	77.3	3.9	125.7	142	3	0	2	1
	IV	13.8	8.3	18.7	1.0	68.6	4.0	258.3	143	6	2	7	2
	V	17.4	11.7	51.2	0.0	67.3	3.3	332.6	145	3	1	2	0
	VI	18.7	13.5	34.0	0.0	69.3	3.2	230.5	153	10	2	8	0
	VII	20.6	14.8	45.1	0.0	70.9	2.8	273.8	147	7	3	3	1
	VIII	21.5	16.0	33.1	0.0	65.5	2.8	270.6	135	7	2	5	1
	IX	16.4	11.4	39.6	0.0	70.8	3.4	209.7	160	15	14	3	0
	X	11.1	6.9	38.5	0.0	78.2	4.0	148.6	185	21	21	3	0
	XI	5.4	3.1	6.4	0.0	87.5	3.3	84.4	138	6	3	5	0
	XII	2.2	0.4	41.1	1.0	93.4	4.3	26.2	138	5	2	2	1
2019	I	-0.8	-2.9	37.8	4.0	90.0	4.4	33.4	154	12	10	4	2
	II	3.1	0.0	26.2	11.0	77.9	4.1	129.2	147	7	7	3	0
	III	6.2	2.7	28.7	0.0	77.8	4.9	120.3	179	14	11	4	1
	IV	10.5	4.7	19.8	0.0	60.4	3.9	240.6	154	22	22	5	0
	V	12.2	7.6	47.7	0.0	76.7	3.4	187.1	143	12	10	4	0

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	VI	22.6	16.3	24.2	0.0	62.2	3.1	345.6	144	11	7	3	1
	VII	19.4	14.0	28.9	0.0	64.9	3.0	205.5	150	18	7	12	1
	VIII	21.0	15.7	37.4	0.0	66.6	3.0	242.6	118	7	8	3	0
	IX	14.7	10.5	50.3	0.0	77.9	3.6	162.6	149	11	13	2	0
	X	11.2	7.3	17.0	0.0	83.3	3.4	150.6	186	20	16	5	0
	XI	6.6	3.8	23.2	0.0	89.6	3.8	58.9	129	12	11	4	0
	XII	3.6	1.5	14.9	0.0	87.4	4.0	52.7	150	3	4	1	0
2020	I	2.5	0.4	24.6	0.0	89.8	4.2	71.9	158	11	7	2	4
	II	4.4	1.9	58.2	0.0	81.9	5.5	66.5	154	8	4	6	0
	III	5.0	1.0	20.7	2.0	68.3	4.3	186.5	113	4	1	2	1
	IV	9.7	3.1	4.5	0.0	53.4	3.6	283.2	75	2	0	2	0
	V	11.7	6.7	73.1	0.0	71.2	3.5	227.1	96	7	4	3	0
	VI	18.1	13.8	79.2	0.0	79.1	3.3	274.3	111	10	4	9	0
	VII	18.9	13.4	41.6	0.0	68.8	2.8	*173.1*	106	3	0	3	0
	VIII	20.5	15.4	92.9	0.0	69.8	2.9	255.2	103	7	3	6	0
	IX	15.7	11.1	70.6	0.0	78.0	2.9	202.9	141	5	2	2	1
	X	10.8	8.4	90.2	0.0	88.4	3.3	85.9	145	7	3	5	0
	XI	5.9	3.8	17.5	0.0	92.5	3.3	54.3	97	3	1	2	0
	XII	2.2	0.5	19.1	1.0	91.6	3.7	51.1	139	3	2	2	0
2021	I	-0.9	-2.7	28.2	13.0	92.8	3.2	35.2	114	3	1	4	2
	II	-0.8	-3.9	19.8	10.0	86.5	2.8	82.8	142	3	1	2	0
	III	4.2	0.9	12.6	0.0	77.8	3.0	137.4	149	4	0	5	0
	IV	6.5	2.5	36.4	0.0	72.5	4.1	148.9	124	1	0	1	0
	V	12.4	7.9	80.7	0.0	73.6	4.1	194.7	159	8	4	5	0
	VI	20.2	14.5	31.4	0.0	64.9	2.7	324.4	142	4	3	2	0
	VII	21.1	16.2	102.4	0.0	73.3	2.8	199.8	128	7	4	3	0
	VIII	17.3	13.4	122.6	0.0	77.9	3.2	157.2	138	3	0	3	0
	IX	15.1	10.9	8.1	0.0	77.2	3.2	*149.4*	123	3	1	2	0
	X	10.3	6.2	12.7	0.0	75.4	4.0	128.4	173	5	2	5	0
	XI	5.3	3.5	32.0	4.0	89.3	4.2	61.5	138	6	0	6	0
	XII	-0.4	-2.6	26.5	7.0	91.1	3.8	32.1	129	3	2	1	0
2022	I	1.3	-0.6	27.3	6.0	88.0	5.3	41.6	96	3	2	1	0
	II	3.7	1.2	34.6	0.0	80.0	5.9	*66.5*	112	2	0	2	0
	III	4.3	-0.5	0.2	0.0	59.0	3.3	241.0	118	3	1	2	0
	IV	7.6	3.2	30.8	0.0	66.3	4.5	160.4	129	1	1	0	0
	V	14.7	9.0	36.9	0.0	60.8	3.4	276.0	116	5	2	1	2
	VI	19.8	14.0	55.1	0.0	65.7	2.9	295.9	123	8	4	5	0
	VII	19.6	14.2	88.4	0.0	66.2	3.1	253.7	117	1	0	1	0
	VIII	21.1	16.1	61.4	0.0	73.5	2.7	248.5	90	5	0	4	1
	IX	12.9	8.7	50.6	0.0	79.5	3.0	173.0	113	3	0	3	0
	X	12.1	8.2	19.0	0.0	84.5	3.1	152.4	117	3	2	2	0
	XI	4.4	2.1	8.8	0.0	90.1	2.9	63.1	127	3	0	3	0
	XII	1.1	-0.9	24.1	8.0	92.7	4.0	20.3	108	4	4	1	0
2023	I	3.3	1.7	26.7	5.0	91.5	4.1	43.7	111	1	2	0	0
	II	1.9	-0.3	27.1	1.0	87.8	4.5	57.3	89	3	2	2	0
	III	4.9	1.5	28.0	2.0	81.6	4.2	85.7	118	4	0	4	0
	IV	8.1	4.3	27.1	0.0	*75.8*	3.5	128.2	117	4	0	4	0
	V	13.5	8.3	31.1	0.0	*60.8*	3.4	277.9	112	2	1	1	0
	VI	18.8	13.0	30.5	0.0	*61.7*	3.0	277.1	123	9	2	6	1
	VII	20.9	14.9	47.9	0.0	59.0	3.2	250.2	116	3	0	3	0
	VIII	20.2	15.9	59.7	0.0	72.8	3.3	212.8	91	4	0	4	0
	IX	19.1	13.6	18.9	0.0	68.8	2.8	261.5	120	6	1	6	0
	X	11.4	8.0	55.3	0.0	85.5	3.8	80.7	151	3	1	2	0
	XI	4.7	2.3	64.0	0.0	87.6	4.1	59.5	123	6	2	4	0
	XII	2.4	0.5	43.0	7.0	88.9	4.9	26.0	137	4	1	2	1
2024	I	0.4	-1.8	27.4	3.0	84.5	5.1	60.4	109	3	0	3	0
	II	6.5	4.1	51.4	4.0	86.4	4.6	48.6	97	2	0	2	0
	III	8.0	4.4	12.4	0.0	77.3	3.7	128.1	141	9	1	9	0
	IV	11.7	7.2	24.3	0.0	69.4	3.9	161.0	134	6	1	5	0
	V	17.1	11.1	31.6	0.0	62.6	2.9	293.8	131	2	0	2	1
	VI	19.1	14.4	88.5	0.0	73.4	2.9	240.8	116	5	0	5	0
	VII	20.9	15.5	93.5	0.0	70.9	2.7	269.5	117	8	2	6	0
	VIII	20.8	15.9	138.0	0.0	71.9	2.6	261.1	130	8	3	5	0
	IX	17.4	12.7	79.7	0.0	72.5	3.8	214.4	139	6	3	3	1
	X	11.0	7.4	22.6	0.0	83.8	3.3	143.4	166	6	0	6	0
	XI	4.0	2.0	27.8	0.0	*89.8*	3.8	41.5	139	5	1	2	2
	XII	3.0	1.4	15.7	0.0	92.4	4.0	43.1	130	2	0	2	0

Descriptive statistics were computed for the monthly number of road accidents in each city, including the mean, standard deviation, minimum, and maximum values. These metrics provide a summary of typical accident frequency, variability, and extreme monthly values, facilitating comparative assessment between cities of different sizes and traffic densities.

Neural network models were applied to forecast monthly road accidents over 6- and 12-month horizons. The input features included historical accident counts, temporal variables (month, year), and meteorological variables. Multilayer perceptron (MLP) networks were selected due to their ability to capture nonlinear relationships between predictor

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variables and accident occurrence. The models were trained on the historical data using a rolling forecast approach, ensuring that each prediction relied only on past information.

Multilayer perceptron (MLP) models were implemented for each city separately. The architecture consisted of an input layer with 10–15 features (lagged accident counts up to 12 months, month index, year, mean temperature, total precipitation, sunshine duration, etc.), one or two hidden layers with 8–32 neurons each (selected via grid search), and a single output neuron predicting the number of accidents in the target month. ReLU activation was used in hidden layers and linear activation in the output layer. A rolling-window approach was applied: the model was trained on all data up to time t and used to forecast t+1 to t+12, then the window was shifted forward.

Data were normalized using min-max scaling. No explicit train/validation/test split was used due to the time-series nature; instead, forecasts were generated in a true out-of-sample manner. Hyperparameters (number of neurons, layers, learning rate) were tuned separately for each city using a grid search over 5-fold time-series cross-validation on the training portion.

Forecast performance was assessed using three standard error metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE and RMSE quantify absolute forecast deviations, while MAPE expresses errors relative to observed values, providing insight into relative accuracy, especially for cities with low accident baselines (1), (2), (3), (4). The analysis compared forecast errors between the 6- and 12-month horizons to evaluate the impact of extending the prediction period on accuracy.

- ME – mean error

$$ME = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_p), \quad (1)$$

- MAE – mean absolute error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - Y_p|, \quad (2)$$

- MPE – mean percentage error

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i - Y_p}{Y_i}, \quad (3)$$

- MAPE - mean absolute percentage error

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - Y_p|}{Y_i}, \quad (4)$$

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

4 Results

Table 5 presents descriptive statistics for the monthly number of road accidents in the five analyzed cities over 2018–2024. Poznań exhibits the highest average monthly accident count (mean ≈ 54.4) and the greatest variability (standard deviation ≈ 19.1), reflecting its larger population and traffic volume. In contrast, Piła shows the lowest mean monthly accidents (≈ 1.4), with several months recording zero accidents, indicating sporadic accident occurrence. Konin, Leszno, and Kalisz have intermediate mean accident counts (≈ 6–7) with moderate variability. Maximum monthly accident counts range from 7 in Piła to 111 in Poznań, demonstrating occasional spikes in larger urban areas.

The descriptive statistics reveal clear differences in accident frequency across cities, consistent with population density and urban traffic conditions. Smaller cities exhibit lower baseline accident levels but proportionally higher variability relative to their mean, suggesting that single events can significantly affect relative accident statistics.

Table 5 Descriptive statistics of monthly road accidents (2018–2024)

City	Mean	Standard deviation	Minimum	Maximum
Piła	1.4	1.5	0	7
Konin	6.8	3.7	0	17
Leszno	6.5	3.6	0	17
Poznań	54.4	19.1	24	111
Kalisz	6.1	4.4	1	22

Table 6 summarizes forecast accuracy metrics for the 6-month-ahead predictions. Poznań's forecasts show the highest absolute errors (MAE ≈ 8.1, RMSE ≈ 9.5) due to the large number of accidents, yet relative errors (MAPE ≈ 17.7%) remain low, indicating robust predictive performance. Conversely, smaller cities such as Piła, Konin, and Kalisz exhibit

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high MAPE values (e.g., Konin ≈ 111.9%), reflecting substantial relative error caused by low accident counts, despite low absolute errors (MAE ≈ 0.9–3.3). Leszno demonstrates intermediate forecast accuracy (MAPE ≈ 43.8%). These results highlight the challenge of predicting rare events: even minor deviations lead to high percentage errors when accident baselines are low.

Table 6 Forecast accuracy measures for the 6-month horizon

City	MAE	RMSE	MAPE
Piła	0.9	1.2	57.7%
Konin	3.3	4.3	111.9%
Leszno	1.5	1.6	43.8%
Poznań	8.1	9.5	17.7%
Kalisz	2.6	3.1	65.5%

Extending the forecast horizon to 12 months generally increases prediction errors (Table 7). MAE and RMSE rise for most cities: for instance, Poznań's MAE increases from 8.1 to 10.1 and Piła's from 0.9 to 1.3. MAPE values also grow for most cities, particularly for Piła (≈ 89.6%), indicating reduced relative forecast accuracy over longer horizons. Notably, Konin and Kalisz display slight reductions in MAPE and RMSE at the 12-month horizon, suggesting that in these medium-sized cities, the 12-month forecast aligned better with actual outcomes than the 6-month forecast, possibly due to annual seasonal patterns captured by the model.

Table . Forecast accuracy measures for the 12-month horizon

City	MAE	RMSE	MAPE
Piła	1.3	1.6	89.6%
Konin	3.3	3.9	81.5%
Leszno	1.7	2.0	38.0%
Poznań	10.1	12.5	19.3%
Kalisz	2.5	2.9	61.7%

Table 8 shows the relative change in forecast accuracy when extending from a 6- to a 12-month horizon. Most cities experience higher MAE and RMSE (e.g., Piła +45.5% MAE, Poznań +32.1% RMSE), confirming the general trend of reduced accuracy for longer-term forecasts. However, Konin and Kalisz show negative Δ values, indicating minor improvements in forecast precision over the 12-month horizon. This anomaly suggests that short-term fluctuations can disproportionately affect 6-month forecasts, whereas the 12-month model benefits from capturing full-year patterns (Figure 2).

Table 8 Relative change in forecast accuracy between 6- and 12-month horizons

City	ΔMAE (%)	ΔRMSE (%)
Piła	+45.5%	+35.1%
Konin	–1.1%	–8.2%
Leszno	+19.8%	+23.0%
Poznań	+25.1%	+32.1%
Kalisz	–1.2%	–6.1%

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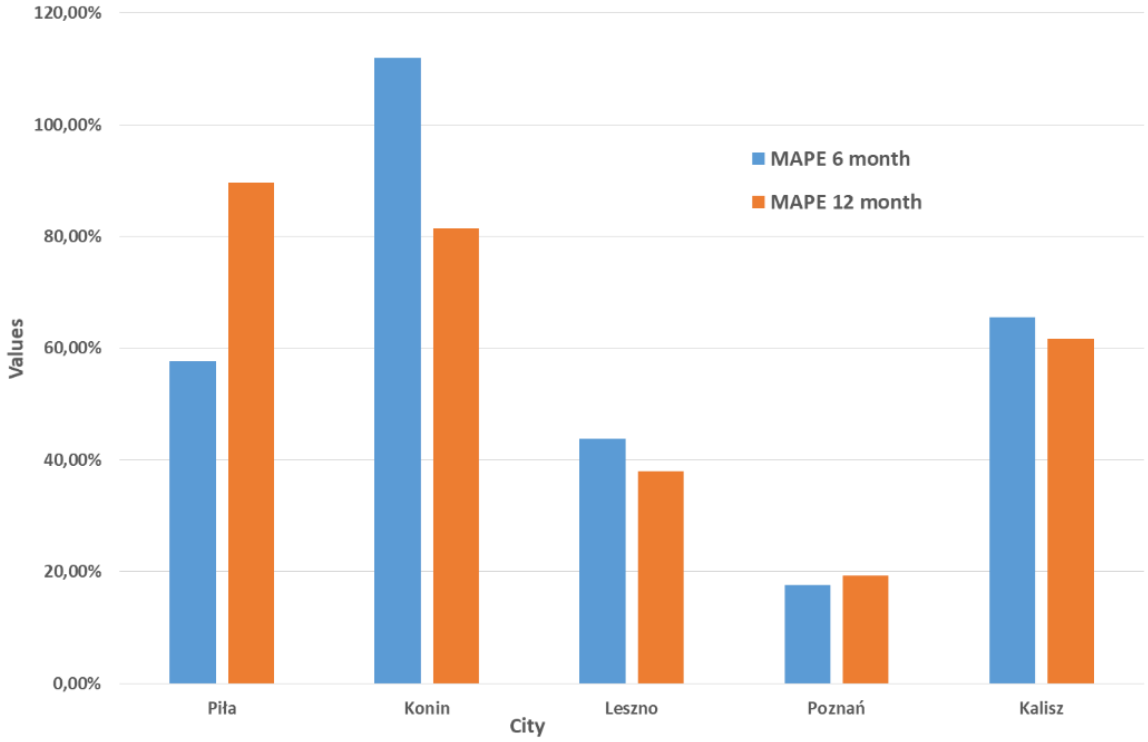


Figure 2 Mean Absolute Percentage Error (MAPE) for 6-month and 12-month forecast horizons across the five cities

Overall, the analysis demonstrates that neural network-based forecasts provide reasonably accurate predictions in absolute terms, particularly for cities with higher accident frequencies. Relative errors are more pronounced in smaller cities with low accident counts, highlighting the importance of considering both absolute and percentage error metrics when evaluating model performance. Extending the forecast horizon generally decreases accuracy, although exceptions in medium-sized cities indicate that model performance can vary depending on the interplay between temporal patterns and accident baselines.

5 Discussion

The analysis confirms substantial variation in road accident patterns across the five cities of Wielkopolska, reflecting differences in urban size, traffic density, and infrastructure. Poznań, as the largest city, consistently exhibits the highest monthly accident counts and greatest variability, in line with prior studies linking urban population and traffic volume to accident frequency. Smaller cities such as Piła show low baseline accident numbers, but high relative variability, indicating that sporadic events can disproportionately affect statistical measures. These findings are consistent with literature emphasizing the challenges of modeling rare events in smaller urban contexts.

Neural network models proved effective in capturing nonlinear relationships between meteorological variables, temporal factors, and accident counts. For the 6-month horizon, predictions for larger cities (e.g., Poznań) were relatively accurate in percentage terms, despite high absolute errors. In contrast, smaller cities with low accident counts exhibited high MAPE values, highlighting a well-known limitation in forecasting low-frequency events: small absolute deviations translate into large relative errors. Extending the forecast horizon to 12 months generally reduced accuracy, as expected due to increased uncertainty over time. The exceptions observed in Konin and Kalisz suggest that annual patterns can sometimes enhance the performance of longer-horizon forecasts, especially when short-term variability is unusually high.

From a practical perspective, the results underscore the need for tailored forecasting strategies. In larger urban centers, absolute error metrics (MAE, RMSE) are most informative for traffic management planning, while relative errors (MAPE) are critical in smaller cities where low accident counts may exaggerate perceived forecasting inaccuracy. Policymakers and traffic safety authorities can use these insights to allocate resources more efficiently, prioritize preventive interventions, and set realistic expectations for forecast performance depending on city size and accident baseline.

Several limitations of the study should be noted. First, the dataset covers only 2018–2024; longer historical series could improve model generalization, particularly for low-frequency events. Second, the models rely primarily on meteorological and temporal predictors, without integrating traffic volume, road infrastructure changes, or driver behavior data, which are known to influence accident occurrence. Third, while neural networks are capable of modeling complex

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patterns, their "black-box" nature limits interpretability; combining neural networks with explainable modeling approaches could enhance understanding of key accident drivers.

Future research could expand the analysis to additional Polish cities, incorporate real-time traffic and infrastructure data, and explore hybrid modeling approaches combining neural networks with statistical or mechanistic models. Such work would improve both short- and long-term forecasting accuracy and support evidence-based traffic safety management across diverse urban contexts.

A key limitation of the MLP approach is its lack of inherent temporal memory. Future work could explore recurrent architectures (e.g., LSTM or GRU) to better capture long-term dependencies in accident time series. Additionally, incorporating real-time traffic volume, road condition indices, or holiday effects could further improve predictive performance.

6 Conclusions

This study analyzed monthly road accident patterns in five cities of the Wielkopolska region—Piła, Konin, Leszno, Poznań, and Kalisz—over the period 2018–2024 and evaluated the performance of neural network-based forecasts for 6- and 12-month horizons. The analysis revealed that city-specific accident patterns vary significantly: Poznań, as the largest city, exhibits the highest accident frequency and variability, whereas Piła shows the lowest mean accident numbers, with several months recording zero events. Medium-sized cities such as Konin, Leszno, and Kalisz display intermediate values, indicating that urban size and traffic volume strongly influence accident occurrence. Neural network models produced reasonably accurate absolute predictions, particularly for larger cities, while relative forecast errors, measured by MAPE, were high in smaller cities due to the low baseline accident counts, illustrating the challenges of predicting rare events. Extending the forecast horizon from six to twelve months generally reduced accuracy, although minor improvements were observed in Konin and Kalisz, likely reflecting annual accident patterns captured by the models. These findings imply that absolute error metrics are most informative for large urban centers, while relative errors are critical in smaller cities, and that forecasts can guide resource allocation, preventive measures, and planning interventions tailored to city-specific accident profiles. The study is limited by the temporal scope of the dataset, the absence of traffic flow or infrastructure variables, and the inherent “black-box” nature of neural networks. Future research should extend the temporal range, incorporate additional explanatory variables, and consider hybrid or interpretable models to improve prediction quality and understanding of accident dynamics. Overall, this research demonstrates that neural networks can effectively model and forecast monthly road accidents across cities of varying sizes, providing actionable insights for urban traffic safety planning while highlighting the difficulties of predicting low-frequency events in smaller urban areas. City administrations can utilize forecasts for targeted interventions, resource allocation, and proactive traffic management.

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