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Analysis of Traffic Safety Factors and Their Impact Using Machine Learning Algorithms

Liridon Sejdiu [1], Tomaz Tollazzi [2], Ferat Shala [1], Halil Demolli [3*]

[1] *Traffic and Transport Engineering, University of Prishtina "Hasan Prishtina", Prishtina, Kosovo.*

[2] *Department of Civil Engineering, University of Maribor, Maribor, Slovenia.*

[3] *Engineering Design and Vehicles, University of Prishtina "Hasan Prishtina", Prishtina, Kosovo.*

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Abstract

The safety of road traffic is facing increasing challenges from a range of factors, and this study aims to address this issue. The paper describes the development of a model that assesses both the quantitative and qualitative aspects of the current traffic situation and can also predict future trends based on monthly data on traffic accidents over a period of years. The dataset is composed of the number of accidents that occurred in the Pristina region over a 10-year period, and these are categorized based on the type of accident and safety factors, including human, vehicle, and road factors. By using machine learning algorithms, a model has been developed that determines the factor with the greatest impact on traffic safety. To create the model, the algorithms Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Random Trees (RT) were used. The model evaluates the contribution of human, road, and vehicle factors to traffic accidents, using machine learning algorithms and 36 types of traffic accidents to analyze the relevant statistics. The results indicate a very good fit of the model according to the MLR algorithm, and this model also identifies the road factor as the main influencer of the traffic safety level.

Keywords: Traffic Safety Factors; Traffic Accident; Machine Learning; Multiple Linear Regression.

1. Introduction

Traffic, particularly road traffic, plays a crucial role in a country's economy, modern human life, and the globalization process by connecting different countries. However, as the number of vehicles increases, managing the growing number of accidents has become more challenging. Traffic accidents cause significant injuries and fatalities worldwide, with an economic impact that can cost up to 3% of a country's GDP. Traffic safety has recently faced serious challenges due to the high number of fatal accidents globally. According to the World Health Organization, approximately 1.35 million people die in traffic accidents each year, with over half of the victims being pedestrians and cyclists. Additionally, 93% of fatal accidents occur in developing countries. These alarming statistics highlight the urgent need for research to find solutions for preventing fatal accidents, especially in developing nations [1].

The global increase in the number of accidents can be attributed to several factors: the rising level of motorization, the large number of vehicles in poor technical condition, and the lack of adequate traffic knowledge and culture among both drivers and pedestrians. This issue is especially prevalent in developing countries, where, according to the World Health Organization, the number of accidents is significantly higher.

* Corresponding author: halil.demolli@uni-pr.edu

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To mitigate traffic accidents, especially fatal ones, a thorough study must be conducted on the key factors that affect traffic safety and contribute to the development of traffic. These factors include human behavior, vehicles, and road infrastructure, all of which interact through environmental conditions. The environmental factor also plays a significant role in traffic safety and the occurrence of accidents.

Humans in traffic assume multiple roles—driver, passenger, or pedestrian—each with varying levels of responsibility and influence on traffic safety. Human behavior is a critical factor, significantly impacting overall traffic safety, and it can vary widely from person to person. This behavior is shaped by a range of factors, including temperament, education level, physical and mental health, moral values, emotional state, and intelligence. Each of these influences how individuals respond to traffic situations, make decisions, and contribute to either the safety or risk in the traffic environment [2-5].

Vehicles also play a crucial role in traffic safety, with their impact largely depending on regular maintenance and technical conditions. The construction and operational characteristics of a vehicle, such as braking systems, tire quality, lighting, and overall mechanical health, directly affect its safety performance on the road. Vehicle safety is continuously improving with the introduction of new technologies, many of which utilize artificial intelligence to prevent accidents. Modern vehicles are now equipped with advanced safety systems, such as automatic emergency braking, adaptive cruise control, lane-keeping assistance, and even semi-autonomous driving capabilities. These AI-driven innovations enhance driver assistance and can anticipate and respond to potential hazards more effectively than ever before, significantly reducing the risk of accidents and improving overall traffic safety. However, this progress is not universal. In developing cities, including Pristina, approximately 80% of registered vehicles are more than 20 years old, according to statistics. The outdated condition of these vehicles negatively impacts traffic safety [6-8].

Roads must be designed to meet the requirements of vehicle dynamics effectively. Technical defects in road infrastructure are often a cause of traffic accidents, and these defects can arise during construction, design, or even maintenance. Currently, challenges remain in the construction and development of road networks. However, it is essential to always consider cost-effectiveness during road construction without compromising basic technical standards.

Today, this principle must also include the goal of minimizing traffic accidents, which means reducing vehicle and property damage as well as minimizing traffic casualties to the lowest possible level. The geometric elements of roads and structures—such as intersections, roundabouts, curves, and gradients—play a crucial role in ensuring traffic safety. These design features determine how smoothly traffic flows and how safely vehicles navigate the roads. When these geometric elements are not professionally designed or implemented, they can create hazardous conditions that increase the likelihood of accidents. For example, poorly designed intersections or roundabouts may confuse drivers, leading to wrong turns, abrupt stops, or dangerous merging. Similarly, sharp curves or steep gradients that are not adequately marked or engineered can result in loss of vehicle control. These situations increase the risk of both single-vehicle accidents, where a driver loses control, and multi-vehicle collisions. In the most severe cases, such accidents can result in fatalities, making the proper design and implementation of road geometry a critical aspect of traffic safety. Key elements that contribute to traffic safety from a road infrastructure perspective include the road layout, technical elements, road condition, intersections, side obstacles, road maintenance, etc. [9-12].

2. Literature Review

The study highlights that economic factors play a significant role in influencing the frequency and severity of traffic accidents, particularly focusing on investments in healthcare and transportation infrastructure. Adequate funding in the healthcare sector ensures that accident victims receive timely and effective medical treatment, which can reduce injury severity and improve recovery outcomes [13].

Recent research shows that traditional methods are yielding diminishing returns, while a newer strategy known as the Safe Systems approach is showing promising results in reducing accidents. This approach also incorporates the use of artificial intelligence [14].

The study employs empirical models to enhance the road network and identify critical nodes within it, using RSUs (Roadside Units) and algorithms based on traffic dynamics to achieve real-time optimization of the model [15].

Another study, which considered three factors—economy, roads, and population—revealed that increased investment in traffic infrastructure, along with overall economic growth, leads to a reduction in accidents. However, an increase in population and new vehicles correlates with a rise in accidents [16]. Additionally, a study on automated traffic systems found that the use of automated and decision-making systems significantly reduces traffic accidents [17].

Another study focused on the human factor by comparing five personality traits with driving behaviors for various purposes. The results indicated that dangerous and aggressive driving is positively associated with neuroticism, while positive driving behaviors are linked with conscientiousness, agreeableness, and openness [18].

The environment, specifically atmospheric conditions, also affects traffic safety, particularly in the occurrence of traffic accidents. The study analyzed the impact of adverse weather conditions (rain, snow, fog) on vehicle speed and road capacity, revealing a reduction in both speed and capacity under such conditions [19].

Recent research has identified a gap in data mining approaches, particularly in data collection. After examining over 30 accident databases, it was found that current methods are insufficient, suggesting a need for optimization in data mining to more accurately identify the causes of accidents [20].

Another study on the human factor analyzed drivers' first aid skills, which can help reduce fatalities when administered promptly. Two groups of 15 participants were gathered, and simulated situations were divided into three phases: knowledge, skill, and performance. Results showed a significant difference between experience-based training and standard first aid courses, concluding that psychological preparedness, along with the skills and knowledge of drivers, can reduce accidents, especially fatal ones [21]. Another study focused on traffic capacity, road conditions, and atmospheric factors, leading to the creation of an accident prevention model using MLR (Multiple Linear Regression) and ANN (Artificial Neural Networks) algorithms. The results showed that the ANN algorithm provided the best fit, with the majority of accidents occurring during good weather conditions. Distinctive accidents were found to be linked to overloaded vehicles, and it was also noted that female drivers were less likely to cause accidents [22].

A subsequent study developed a model for predicting accidents using rare event logit models, analyzing the correlation between traffic volume, average speed, and the percentage of heavy vehicles. The model demonstrated a strong correlation with statistical data, showing a negative relationship between accident occurrence and the natural logarithm of speed at the accident location [23]. Considering Europe's aging population, a study was conducted on the impact of elderly drivers on accident rates, using accident data from Slovenia. Thirteen factors leading to accidents were analyzed, and statistical distribution was assessed through the Kolmogorov-Smirnov and Anderson-Darling tests. The relationship between accidents and these factors was established using an ordinal logistic regression model [24].

Given the ineffectiveness of conventional accident prevention methods, a new approach known as the Safe System Approach (SSA) has emerged. This approach integrates human, vehicle, road, and post-accident care factors. A review of 82 studies demonstrated the effectiveness of SSA in reducing accidents [25].

The reviewed literature addresses various factors influencing traffic safety, yielding promising results and demonstrating the importance of each factor. In this paper, approximately 36 types of accidents are categorized based on human, vehicle, and road factors. All accidents in the city of Pristina have been thoroughly analyzed through in-depth data mining to provide the most reliable results from a traffic safety perspective. A unique aspect of this study is the development of an indicator using accident statistics and machine learning algorithms. This model not only describes the current situation both quantitatively and qualitatively but can also serve as a predictive tool for future accidents.

3. Research Methodology

In collaboration with the Kosovo police, data on traffic accidents that occurred in the city of Prishtina from 2014 to 2021 were collected. This dataset includes monthly observations, resulting in a total of 96 data points. The data are categorized based on three factors: human involvement in accidents, the road on which the accident occurred, and the number of vehicles involved. The dataset was divided into 80% for training and 20% for testing purposes.

The objective of this study is to assess the impact of various factors on traffic safety, with a particular focus on identifying which factors have the greatest influence. These factors—human, vehicle, and road—are examined through specific parameters that represent each category. Each factor was analyzed separately, using parameters that align with accident classifications based on human, vehicle, and road factors. These parameters, which also correspond to different types of traffic accidents, are presented in Figure 1.

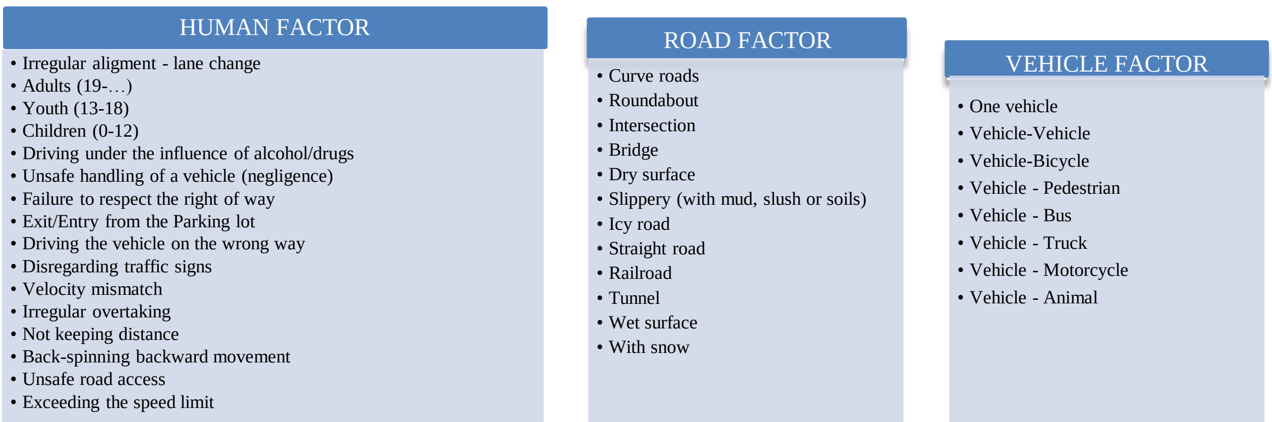

Figure 1. The parameters of traffic safety factors

In Figure 1, the parameters sorted based on the occurrence of accidents in the territory of Prishtina during the monthly periods of 2014-2021 are presented. The parameters are then divided according to which safety factor they belong to.

By examining Figure 1, it is evident that the number of parameters is not equal within the factors. To standardize the analysis, four parameters with the highest weights are extracted from each factor using machine learning algorithms within the constructed model. This was done initially by analyzing each factor individually, creating a separate model with only the parameters of the human factor, then the road factor, and finally the vehicle factor. This pertains to the first scenario, where within this scenario, the most suitable model was chosen from each factor, While the criterion for comparison between different algorithm models is considered the factor of correlation. The algorithms used were Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Random Trees (RT).

The second scenario involved the joint analysis of the safety factors. In other words, the parameters with the greatest impact selected in stage 1 were analyzed in stage 2, using the same algorithms for model creation as in stage 1 (MLR, ANN, and RT). Furthermore, the structure of the analysis in this study is explained through Figure 2.

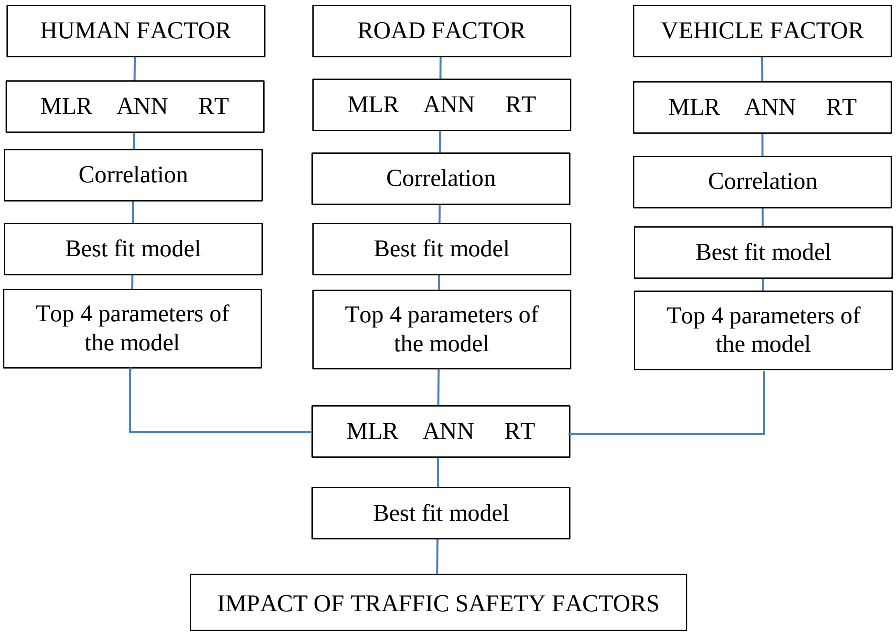

Figure 2. The structure of the analysis in this study

In all stages, what remains unchanged is the dependent variable, traffic safety scale, which is a component of the total number of accidents, the number of residents, i.e., 100 k residents, the number of vehicles registered in Pristina, as well as the total length of the road network in Pristina, while the equation is presented as follows:

$$y = \frac{y_1 \times 100}{y_2 + y_3 + y_4} \tag{1}$$

where; y – traffic safety scale, y_1 – total number of accidents, y_2 – 100 k inhabitants, y_3 – number of registered vehicles in Prishtina, and y_4 – total length of road network in Prishtina.

In Equation 1, the total number of accidents is multiplied by 100 due to the very small value compared to the values in the denominator.

3.1. Study Area

The research will focus on the city of Prishtina, the capital and largest city of the Republic of Kosovo. Kosovo is located in southeastern Europe, at the heart of the Balkan Peninsula. It remains one of the poorest countries in Europe in terms of economy and GDP, and is still classified as a developing country.

Prishtina is situated in the northeastern part of Kosovo, covering an area of 7,768.8 hectares. The city lies at a latitude of 42º40'00" and a longitude of 21º20'15", occupying a central position in the Balkan Peninsula. The terrain of Prishtina varies in elevation, ranging from 535 to 730 meters above sea level. The city is surrounded by slopes on three sides, creating a natural amphitheater-like topography. To the north and east, the Gërmia forest rises to an altitude of 1,100 meters (Figure 3).

Several road categories pass through Prishtina's urban territory, including:

- Highways, which serve a transit function through the urban area, facilitating connections with other cities in Kosovo and neighboring countries,
- Local roads, which link the urban area with surrounding settlements, and
- Roads that pass through residential areas within the city.

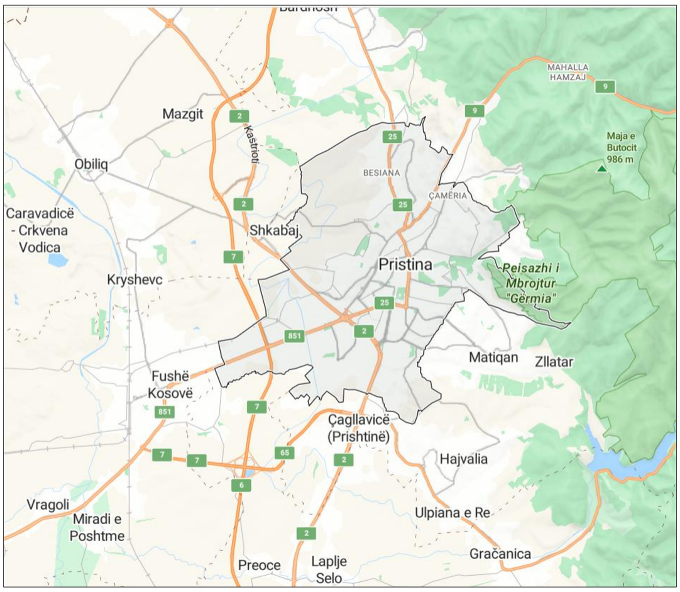

Figure 3. Map with the borders of the urban area of the city of Prishtina.

In the city of Prishtina, the five main roads of Kosovo converge, while the average annual daily traffic (AADT) on these roads has the following values:

- Prishtinë-Podujevë, 13500 veh/day,
- Prishtinë-Mutivodë (border with Serbia) 1 368 veh/day,
- Prishtinë-Gjilan, 8 000 veh/day,
- Prishtinë-Ferizaj, 12 695 veh/day,
- Prishtinë-Prizren, 12 526 veh/day,
- Prishtinë-Pejë, 19 741 veh/day and
- Prishtinë-Mitrovicë, 11 802 veh/day.

4. Results and Discussion

In the following, the Results and Discussion chapter is divided into two parts: the first stage, which is the analysis for each factor, and the second stage, the joint analysis of safety factors.

4.1. Stage 1

Figure 4 illustrates the actual values of the Traffic Safety Scale (TSS) and the predicted values generated by models created using MLR, ANN, and RT algorithms, along with the corresponding correlation values. Considering Figure 4, it can be observed that the MLR algorithm-based model is more reliable, as indicated by both the graph and the correlation value. While the other two models demonstrate a similar level of correlation, the graph in Figure 4 reveals deviations from the actual values at certain points. Additionally, it is important to note that the values presented in Figure 4 are obtained from the testing phase of each respective model. It should also be clarified that in the Figure 4, the testing portion of the model is represented, specifically 20% of the dataset or 24 values, which correspond to the testing segment of the model.

In Figure 4, the results section shows that, in terms of correlation value, the model based on the MLR algorithm aligns perfectly with the actual values. Therefore, it is considered the most suitable model for analyzing the human factor. According to this model, the four parameters with the highest weights—indicating the greatest impact—were identified using IBM Modeler software as follows:

- Speed mismatch,
- Irregular overtaking,
- Driving under the influence of alcohol/drugs,
- Unsafe road access.

These parameters represent the key human factor errors that contribute to traffic accidents, as derived from analyzing only human-related accident data. The findings indicate that speed mismatch is the most dominant human factor, often caused by insufficient driving knowledge, particularly on roads with curves.

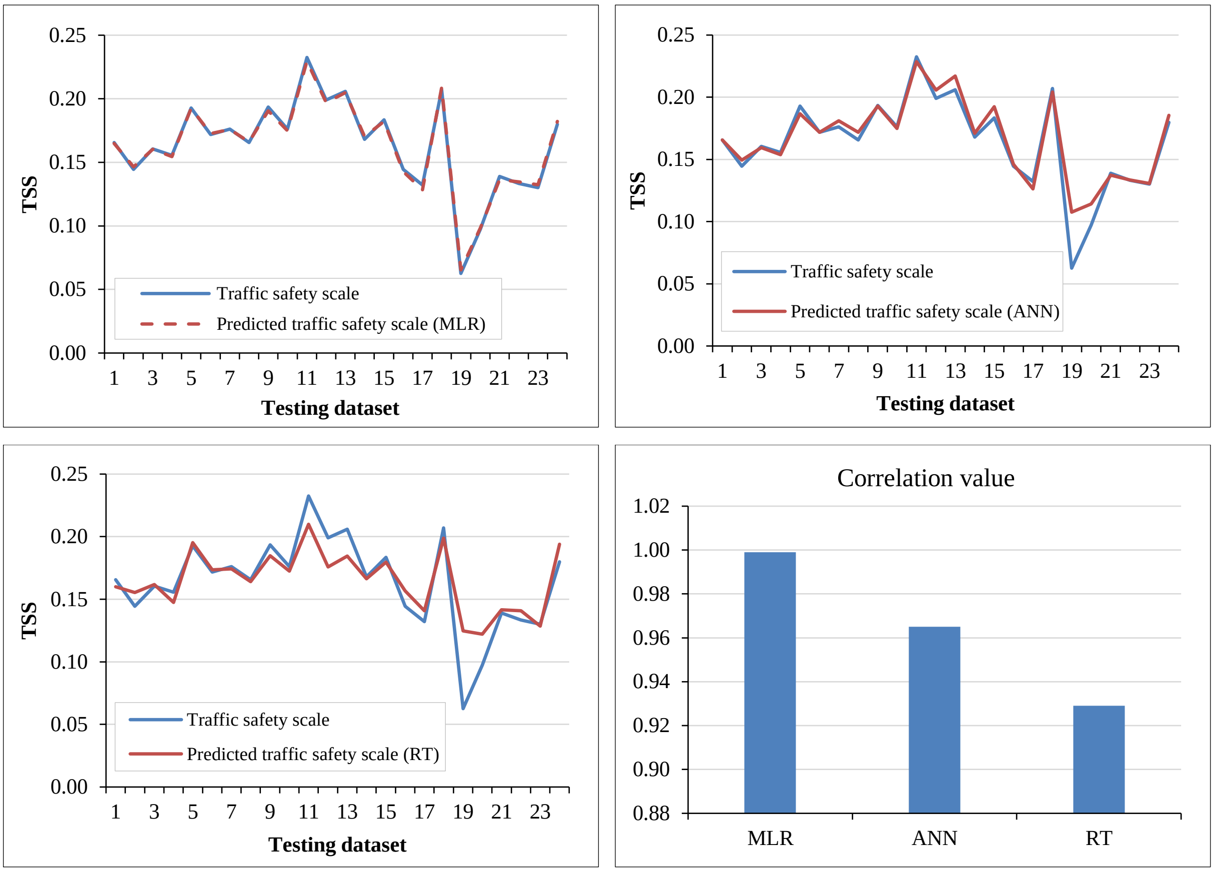

Figure 4. Comparison between TSS and predicted TSS and algorithms used

Regarding the road factor, the results from models created using the MLR, ANN, and RT algorithms are illustrated in Figure 5. Based on the figure, the MLR model provides the best fit, supported by a correlation value of 1, which indicates a perfect match. However, for the road factor, the models developed using ANN and RT algorithms appear to be more suitable when considering the respective correlation values.

Based on the most suitable model, which is according to the MLR algorithm, the most important predictors according to this model are:

- Wet surface,
- Icy road,
- Intersection, and
- Roundabout.

So, these parameters have the greatest impact on the occurrence of accidents in the city of Pristina, as well as on overall traffic safety, which is influenced by the road factor. For the first two parameters, this may also be due to the terrain configuration, as in some cases the roads in Prishtina have a longitudinal gradient of over 8%, which particularly affects icy roads during the winter season. As for intersections and roundabouts, this could also be attributed to the geometric aspect, which remains to be analyzed in further studies. Generally, within the city of Pristina, there are roundabouts with three lanes on the ring road, and there are also three lanes on the entrance approaches. This could negatively impact traffic safety. Additionally, there are intersections with traffic lights that have a cycle of 120 seconds, which might affect drivers psychologically. Furthermore, due to the terrain configuration within the urban area, there are roads with longitudinal slopes exceeding 12% in the vicinity of the intersections. This is also related to previous work concerning road geometry and the overall road factor.

Similarly, as with the two previous factors, even for the vehicle factor, the results presented in Figure 6 indicate that the most suitable model is according to the MLR algorithm, with a correlation value of 0.999. This value indicates that the fit is almost perfect in the same direction. In this section, the types of accidents are categorized according to type of vehicle, including cars, trucks, buses, and bicycles.

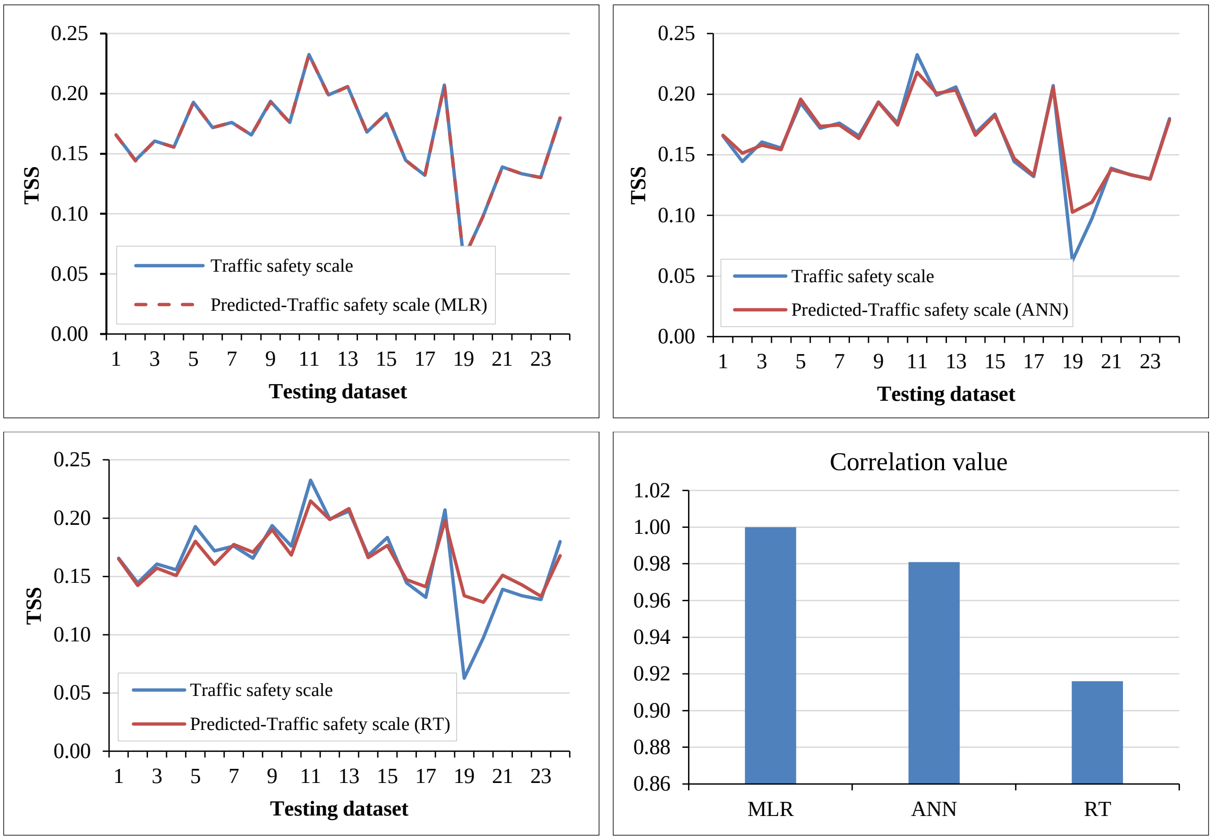

Figure 5. Comparison between TSS and predicted TSS and algorithms used according to stage 1 (road factor)

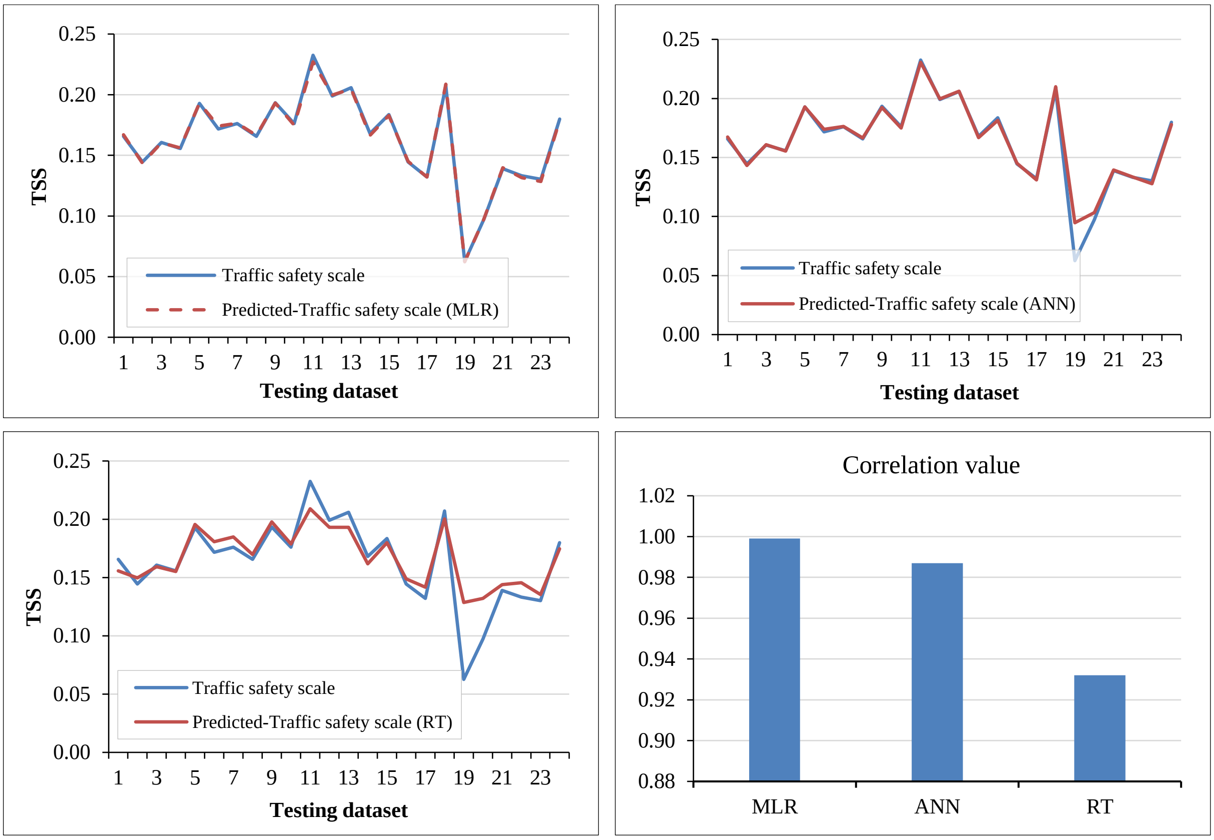

Figure 6. Comparison between TSS and predicted TSS and algorithms used according to stage 1 (vehicle factor)

Based on the model of the vehicle factor, the most important predictors are:

- Vehicle - motorcycle,
- Vehicle - truck,
- Vehicle - vehicle,
- Vehicle – bicycle.

So, these parameters classify accidents that occur in Pristina according to the vehicle factor. Therefore, the MLR model assigns importance to vehicle-motorcycle and vehicle-truck accidents, which may be more fatal due to significant differences between them, especially in terms of mass. From this, it can be said that while the frequency of car-motorcycle accidents is rare, they often result in fatalities. Therefore, they carry greater weight in the model and in the traffic safety factor.

Considering the nature of the MLR algorithm and the historical accident data in the city of Pristina, it demonstrates a better correlation compared to other algorithms, as indicated in section 19 of the dataset. During this period, which coincides with the pandemic, the number of accidents was lower compared to other periods, and the MLR algorithm has been effectively adapted to this context.

4.2. Stage 2

In the second stage, the model is created using the most important predictors identified from all three factors in the first stage, resulting in a total of 12 predictors. These, along with the three factors, are combined into a single model. Figure 7 presents a graphical comparison of the results for each model, utilizing the MLR, ANN, and RT algorithms. It is clear from the graph that the MLR model outperforms the ANN and RT models. The performance of each model was assessed using the correlation coefficient, a statistical measure that shows the strength and direction of the relationship between variables. The MLR model demonstrated a significantly higher correlation value of 0.981, indicating a strong positive relationship between the predictors and the target variable.

In contrast, the ANN and RT models exhibited lower correlation values. While these models also showed some level of correlation, they were inferior compared to the MLR model. This suggests that the MLR model more accurately captures the underlying patterns and relationships in the data, leading to improved predictive performance. The high correlation value of the MLR model indicates that the selected predictors have a strong influence on the target variable. By utilizing linear regression techniques, the MLR algorithm effectively identifies and integrates the key predictors, resulting in a more suitable and reliable model.

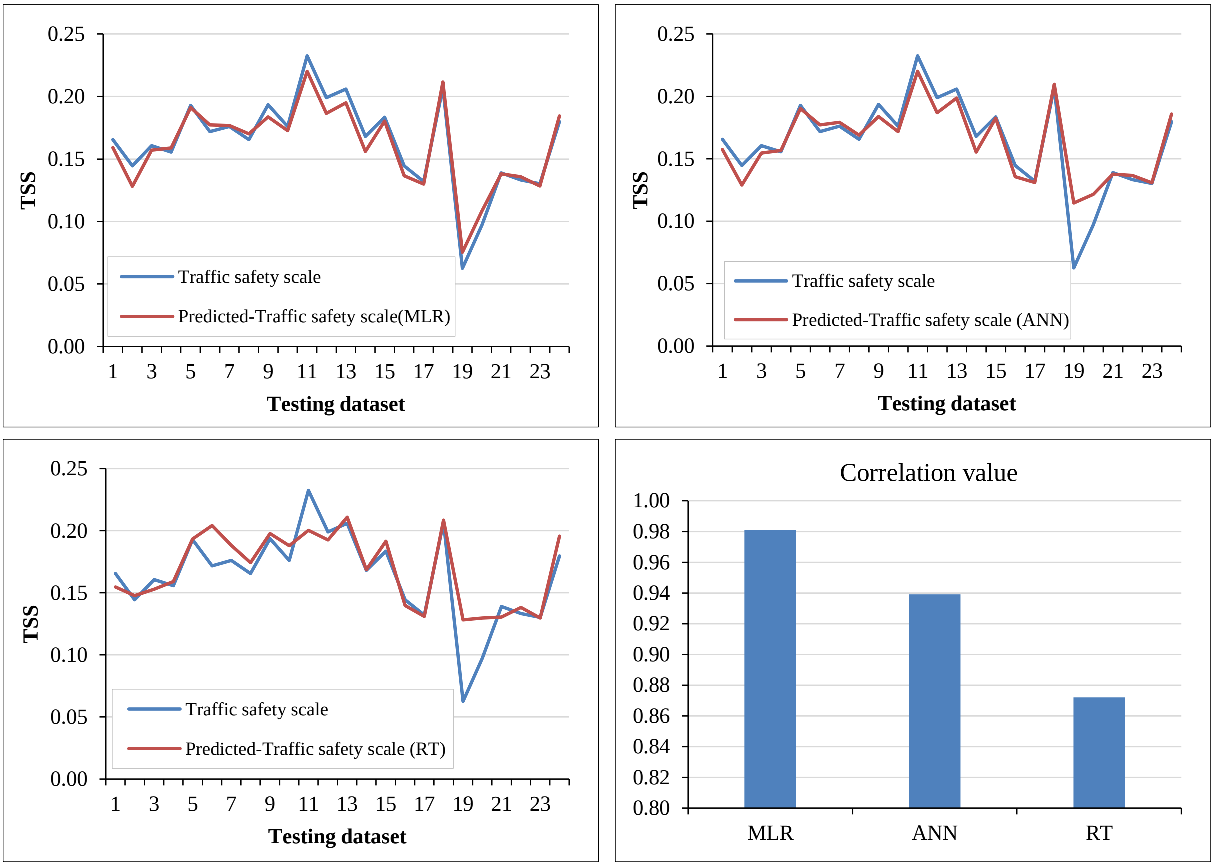

Figure 7. Comparison between TSS and predicted TSS and algorithms used according to stage 2

After selecting the most suitable model, which in this specific case is based on the MLR algorithm, Table 1 presents the data regarding the weights of each predictor in the created model, as well as which factor of traffic safety they belong to. Therefore, the parameters with the greatest weight in Stage 1 are presented, where each factor has been analyzed individually. In this phase, the parameters with the highest weight from all three factors have been collected.

Table 1. The importance of the predictors and their traffic safety factor belonging

Predictor	Predictor importance	Traffic Safety Factor
Vehicle-truck	0.1	Vehicle
Icy road	0.1	Road
Vehicle-motorcycle	0.09	Vehicle
Vehicle - bicycle	0.08	Vehicle
Irregular overtaking	0.08	Human
Wet surface	0.08	Road
Driving under the influence of alcohol/drugs	0.08	Human
Roundabout	0.08	Road
Intersection	0.08	Road
Unsafe road access	0.08	Human
Velocity mismatch	0.08	Human
Vehicle - vehicle	0.05	Vehicle

As mentioned earlier, the weight of each parameter was determined by the IBM Modeler software based on the traffic accident dataset created. According to Table 1, accidents involving cars and trucks, as well as those occurring on icy roads, have the highest weight and impact on traffic safety. Specifically, in Pristina during winter, the terrain configuration contributes to vehicle accidents and incidents caused by snowfall, which also affect the city's main roads. This has been confirmed by the model developed in this study.

The data in Table 1 indicate that the importance values of the predictors are almost the same, except for the top two: vehicle-truck and icy road. The last predictor, vehicle-vehicle, has a lower importance value of 0.05. To determine which safety factor is most significant among the predictors, the data presented in Table 2 continue from Table 1 and show the aggregated importance of each predictor according to their respective safety factor.

Table 2. The aggregation of predictor importance values according to the relevance of the traffic safety factor

Traffic safety factors	Aggregate value of predictor importance	Traffic safety factors
Road Factor	0.34	Road Factor
Vehicle Factor	0.32	Vehicle Factor
Human Factor	0.29	Human Factor

From the data in Table 2, it can be observed that the values are close for all three factors; however, the road factor takes the lead, followed by the vehicle factor, and finally the human factor. This indicates that road infrastructure plays a significant role in traffic safety, and inadequate maintenance and improper design according to standards can lead to negative outcomes and an increased likelihood of accidents.

While much of the literature often identifies the human factor as the primary cause of traffic accidents, the situation in a city like Pristina—the capital of Kosovo and a developing country—presents a different perspective. In this context, road infrastructure is crucial and has a profound impact on traffic safety. The less-than-ideal economic conditions in Pristina contribute to the road infrastructure not meeting the desired standards. Inadequate road design, poor maintenance, and limited resources for infrastructure development exacerbate safety issues. Consequently, while human factors remain important, the quality and condition of road infrastructure are significant determinants of traffic safety in Pristina. This underscores the need for targeted improvements in road planning and maintenance to enhance overall traffic safety.

5. Conclusion

Based on the analysis in this paper, which begins with the statistics of accidents and extends to the creation of a model for evaluating the current state of traffic safety and predicting future outcomes, the conclusion is that the best model for reflecting the current state of traffic safety is through the MLR algorithm. As mentioned earlier, this may also be a result of the monthly accident statistics in the city of Prishtina.

The results obtained, which are the primary focus of this study, clearly indicate that the road factor is the main influence on traffic safety and has a stronger correlation with the occurrence of accidents. In developing countries, including Pristina, there is often insufficient emphasis on road maintenance and proper construction. Consequently, the vehicle factor emerges as the second most significant contributor. In these developing countries, a high number of vehicles are often not in proper technical condition, which poses additional challenges to traffic safety. Conversely, regarding the human factor—typically viewed as the primary cause of accidents in many literature sources—this study finds that it plays a lesser role, although its values are close to those of the vehicle factor. Further in-depth study is necessary to understand driver behavior and the human factor more generally as participants in traffic.

Additionally, conducting a comprehensive study focused on the qualitative assessment of road infrastructure and its direct correlation with traffic safety is crucial. This study should examine various aspects such as road design, road conditions, signage, intersections, and overall infrastructure quality. By thoroughly investigating these factors, we can gain deeper insights into how they contribute to traffic safety outcomes.

By conducting an in-depth study from this perspective, focusing on the qualitative assessment of road infrastructure and its direct relationship with traffic safety, we can gather essential data and knowledge. The findings will help formulate evidence-based policies and interventions aimed at improving the overall level of traffic safety and reducing the occurrence of accidents on our roads. The same applies to the vehicle factor as well.

6. Declarations

6.1. Author Contributions

Conceptualization, L.S. and T.T.; methodology, L.S., T.T., and F.Sh.; software, H.D.; validation, L.S. and H.D.; formal analysis, L.S. and H.D.; investigation, L.S. and H.D.; resources, L.S.; data curation, H.D.; writing—original draft preparation, L.S.; writing—review and editing, T.T. and F.Sh.; visualization, L.S. and H.D. supervision, T.T.; project administration, F.Sh. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Conflicts of Interest

The authors declare no conflict of interest.

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