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Paving Low-Temperature Asphalt on the B 169 Highway near Heyda

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Abstract

Research into lowering the temperature during the production and installation of hot asphalt has been going on for a long time. In addition to developing appropriate recipes, it is important to gain experience, particularly in asphalt paving technology, since in addition to the behavior of the different asphalt mixtures during their compaction, external factors such as the location of the project and weather conditions also play an important role. The testing of the low-temperature asphalt on the federal highway B 169 was carried out successfully. Due to the high pre-compaction by the paver screed, the required compaction values were achieved on the binder course with 4 rolling passes and on the surface course with 3 rolling passes. The viscosity-changing additives and the selected rolling technology had a positive influence on the results. However, precise measurement results for compaction could not be achieved using the PQI probe.

Keywords

Low-temperature asphalt; Behavior of asphalt mixtures; Asphalt-related emissions; PQI probe.

Introduction

Temperature reduction during hot mix asphalt production and paving has long been a subject of research, which led to the development of the corresponding information sheet (FGSV, 2021) and recommendations for implementation (DAV, 2021). Tests have been carried out with the main objectives of saving energy and reducing CO_2 emissions.

In addition, the Committee on Hazardous Substances of the Federal Institute for Occupational Safety and Health adopted a significantly lower occupational exposure threshold value for bitumen vapors and aerosols from bitumen in 2019. The 1.5 mg/m³ air threshold value will have to be met by January 1, 2025, which will require changes in the composition of asphalt mixes and other protective measures on paving equipment.

Apart from research into the asphalt formulations themselves, it is important to gain experience, especially in asphalt paving technology, where external factors such as project location and weather conditions, as well as the behavior of different asphalt mixtures during compaction, play an important role.

For these reasons, the German Federal Ministry of Transport and Digital Infrastructure issued Circular 09/2021 (BMDV, 2021) on the implementation of test tracks for construction projects on federal highways using low-temperature roller-compacted asphalt in order to gain as much knowledge as possible.

The aforementioned Circular specifies the principles for the setup of test tracks. These are used to test the material under paving conditions, taking into account external factors.

Chemnitzer Verkehrsbau GmbH was contracted to build a test track on the B 169 highway between Heyda and Stockhausen.

As part of this project, a diploma thesis entitled "Non-Destructive Compaction Control for Quality Assurance in Asphalt Road Construction Using a PQI Probe" was conducted for the asphalt paving process.

1 Definitions

1.1 Low-Temperature Asphalt

In addition to the relevant regulations for the delivery of asphalt mixtures (TL Asphalt – StB 07/13) and the supplementary technical contract conditions and guidelines for the construction of asphalt pavements (ZTV Asphalt – StB 07/13), there are also the "Guidelines for Warm Mix Asphalt" (M TA) (FGSV, 2021).

The aim is to reduce the production and working temperature of asphalt mixtures by up to 30K using viscosity-modified bitumen or viscosity-modified additives. The benefits that can be achieved, such as energy and CO_2 savings and reduced fumes, are offset by the challenges, particularly when it comes to laying the asphalt. As a result, the lower temperature threshold for quality and damage-free compaction of the paved low-temperature asphalt hardly changes, so the effective compaction time is considerably shorter.

1.2 Viscosity-Modified and Polymer-Modified Bitumens for Paving Applications

Paving and polymer-modified bitumens are in accordance with TL Bitumen – StB with viscosity-modifying organic additives.

1.3 Viscosity-Modifying Additives

Organic or mineral substances are added to bitumen to modify properties at production and processing temperatures.

2 Trial Paving of Low-Temperature Asphalt on the B 169 Federal Highway

2.1 Test Field Program

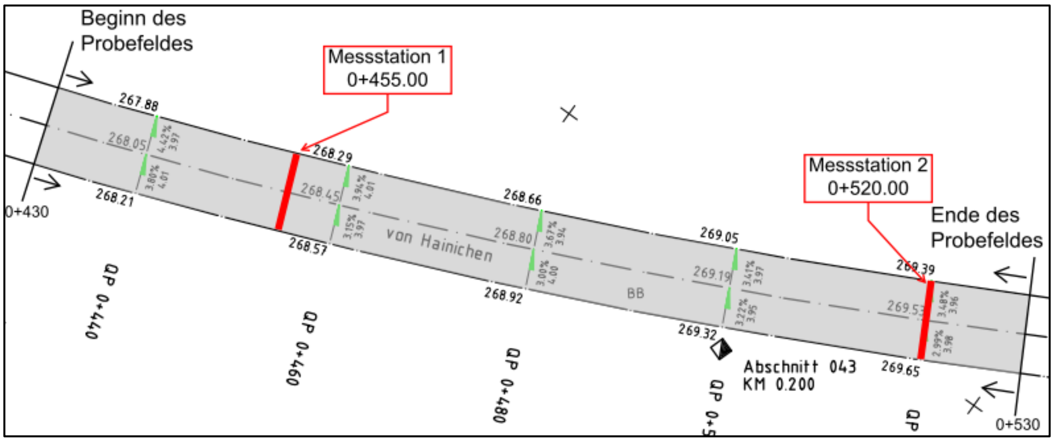
Due to the lack of knowledge about the compaction behavior of temperature-reduced asphalts under construction site conditions, the following priorities were defined for the investigation of both the binder course and the wearing course:

1. investigation of temperature-dependent compaction behavior of low-temperature asphalt by documenting temperature and compaction history,
2. determination of the compaction time during which the asphalt can be compacted in accordance with quality standards,
3. investigation of the influence of weather conditions, air, and subgrade temperatures on the core temperature of paved asphalt,
4. determination of precompaction by the paver,
5. determination of the type and extent of the use of rollers with the number of rollers, the type of compaction, and the number of rollers passes until the completion of work, and

6. investigation of the homogeneity of compaction over the entire road section.

2.2 Measurement Program

Recording of weather conditions, measurement of air and surface temperature in terms of location and number of measuring stations is shown in Figure 1. The stations 0 + 25 m and 0 + 90 m of the test track were defined as measuring stations.



Source: Own

Fig. 1: *Location of the measuring stations in the test field*

Three measuring points were marked at each of stations, as shown in Figure 2:

- Edge area is at 0.50 m from road edge.
- Center of wheel path is at 1.50 m from the road edge.
- Center of lane is at 3.75 m distance from lane edge.

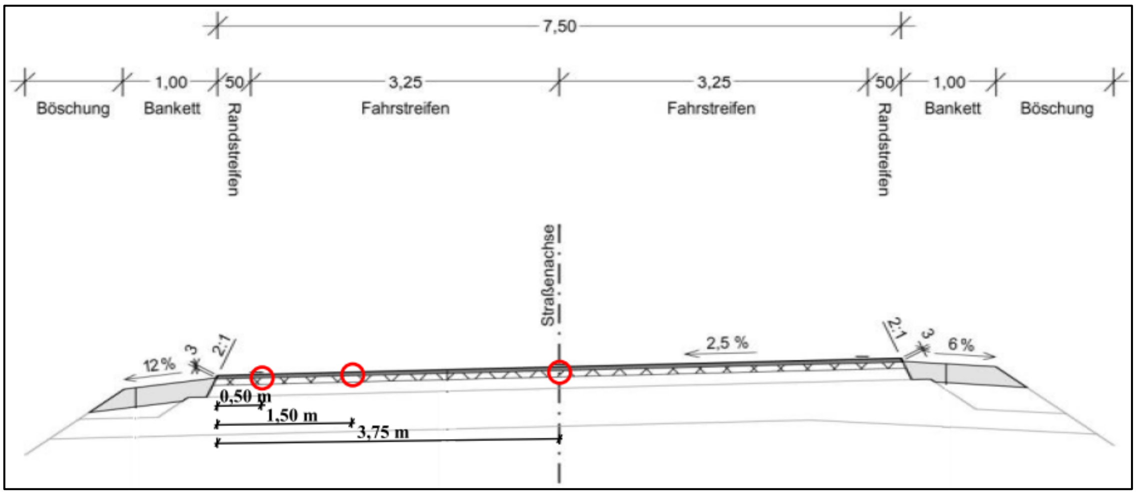


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Fig. 2: *Location of the measuring points at the stations*

2.3 Paving Machinery

The equipment listed in Table 1 was used to carry out the asphalt work.

Tab. 1: *Devices used for building asphalt roads*

Device	Type	Specifications	Use
Feeder	Bomag Feeder BMF 2500 M	Bucket capacity: 15 t Output: 4000 t/h Belt width 1.20 m Mittelanger Gurt 6.50 m	Binder course Wearing course
Paver	Dynapac Tracked Paver SD 2550 CS	Hopper capacity: 15 t Theoretical paving capacity: 1100 t/h Max. paving width: 8.80 m Compaction unit: rammer & vibration Screed heating: gas	Binder course Wearing course
Attachments	Dynapac-V5100TV	Gas-heated Vario screed Compaction unit: rammer & vibration Extension width: 7.50 m	Binder course Wearing course
Rollers	Bomag BW 154 AP-4 AM (with grit spreader)	Tandem vibratory roller Tare weight: 7.30 t Drum width: 1.50 m Static line load: 25.00 kg/cm	Wearing course
	Bomag BW 174 AP-4 AM (with grit spreader)	Tandem vibratory roller Tare weight: 9.50 t Drum width: 1.68 m Static line load: 29.80 kg/cm	Binder course Wearing course
	Bomag BW 174 ACP-5 AM	Combination roller Tare weight: 9.30 t Drum width: 1.68 m Static line load: 29.20 kg/cm	Binder course
	Bomag BW100 AD-5	Tandem vibratory roller Tare weight: 2.50 t Drum width: 1.00 m Static line load: 13.00 kg/cm	Transitions from old to new edges

Source: Own

2.4 Asphalt Mixture for the Test Track

The mixture contained

- temperature-reduced asphalt binder SMA 16 BS, binder PmB 25/45 VL, additive Viatop Premium, and
- temperature-reduced stone mastic asphalt SMA 11 S, binder PmB 25/45 VL, additive Viatop Premium.

The initial tests for both types were confirmed by the contracting authority.

The mixture was delivered from the mixing plant in Breitenau; the transport distance to the construction site was 37.4 km.

2.5 Intended Rolling Technology

The following rolling technology was used:

- first roller pass: tandem rollers with static compaction,
- further roller passes: heavy rollers with dynamic compaction.

The rollers were equipped with the BOMAG measuring system and GPS receiver and are shown in Figure 3.

Source: Own

Fig. 3: *Rollers in operation*

The above-mentioned equipment of rollers allows for the networking of the rollers. The number of passes and the resistance of the asphalt material can be recorded.

2.6 Test Scope

The following points indicate the kinds of tests performed:

- temperature testing of air and substrate at the paving site, recording of weather conditions,
- visual inspection of the condition of the asphalt mixture,
- continuous testing of asphalt temperature on trucks as they arrive at the construction site, in the feeder, in the paver at the auger, during the rolling process on the surface of the paved asphalt, and recording of the core temperature,
- control of paving thickness,
- continuous roller compaction control and documentation,
- compaction measurements with the PQI probe to be tested as a non-destructive and non-nuclear alternative to the Troxler probe,
- drill core tests after asphalt paving is completed to verify the results of the PQI probe measurements.

2.6.1 PQI Probe

The physical principle of the PQI-Probe shown in Figure 4 and its use shown in Figure 5 is based on the different reactions of air and asphalt to the emitted electric field. Calibrating the probe to the initial test of the material provides a target value in the form of the dielectric constant. Deviations are due to the inclusion of air. Once the predetermined dielectric constant is reached, it also means that the required density from the initial test has been achieved.

Source: Labtek, (2021)
Fig. 4: *PQI probe*

Source: Own
Fig. 5: *PQI probe measurements*

2.7 Test Procedure

Measurement of existing ambient conditions has been performed by the paver's mobile weather station: These conditions include air temperature, clouds, precipitation, wind speed, and humidity. Ground temperature was measured with an infrared thermometer. The measured values of those conditions are shown in Table 2.

Tab. 2: *Ambient conditions*

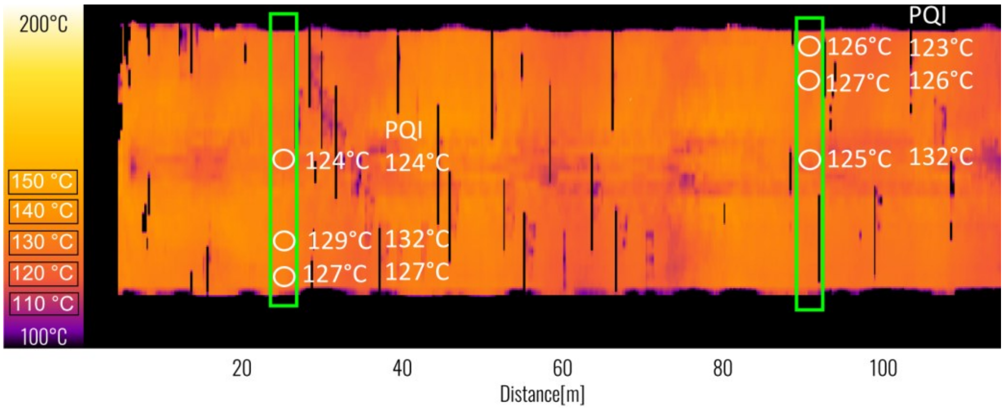
Ambient conditions	Binder course	Wearing course
Substrate temperature	21 °C	22 °C
Air temperature	18 °C	18 °C
Cloud cover	overcast 8/8	slightly overcast 4/8
Precipitation	0 l/m²	0 l/m²
Wind speed	5 km/h	3 km/h
Humidity	94%	91%

Source: Own

The asphalt temperatures were then measured using a penetration thermometer at the "mixing plant", "arrival on-site", and "feeder hopper" stations.

Additional temperature measurements have been taken by infrared thermometers permanently installed on the paver in the hopper and on the spreading auger. The times of all temperature measurements were documented. This enabled a time-dependent curve to be displayed in the subsequent evaluation. The first measurement of compaction and temperature is taken by the PQI sensor as soon as the asphalt is placed on the screed.

It is important that no compaction by the rollers has taken place at this point. The measured compaction value, therefore, corresponds to the precompaction of the screed. This value is measured at the 3 measurement points described in the test program in Figure 2. The comprehensive temperature measurement by an infrared scanner on the freshly paved surface is also free from the influence of the rollers. It can, therefore, be compared with the PQI probe.



Source: Own

Fig. 6: *Surface temperatures of the binder course behind the paver*

Spray paint markings were applied to the surface to ensure that compaction measurements were always taken at the same location. This allowed for better comparability. From that point on, compaction, surface temperature, and core temperature (Figure 6) were recorded for each compaction operation by the rollers, taking into account the type of compaction and time. The core temperature was measured with a penetration thermometer at the edge of the asphalt layer in the center of the layer.

When measuring compaction, it was important to ensure that there were no air pockets due to an uneven surface or materials on the sensor plate. It was important to ensure that the sensor plate was constantly cleaned and in full contact with the surface during the measurement process.

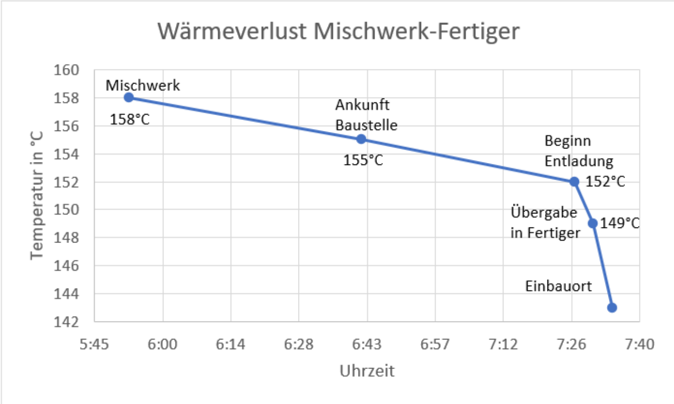
3 Results

3.1 Mixture Heat Loss

Analysis of the temperature data showed that, contrary to expectations, the heat loss during transport was minimal despite the 37 km distance. The temperature drop of the mixture from the time it left the mixing plant to the time it arrived at the paving site was 2-4 K, depending on the truck. This clearly demonstrates the effectiveness of the tarpaulins on the truck and the use of thermal troughs.

When the mixture was exposed to ambient conditions (temperature, weather, wind) during unloading, a sharp drop in temperature was observed. This was significant throughout the conveying process from the feeder to the paver, as shown in the diagram in Figure 7.

For the binder mixture, an average temperature difference of 6.83 K was measured over the entire transport from the mixing plant to the paver. The transport route accounts for 2.83 K, while the remaining 4 K is due to the time spent conveying the material to the paver.



Source: Own

Fig. 7: *Heat loss of the mixture for wearing courses from the mixing plant to the paver*

Proportionally, however, the greatest drop in temperature during the paving operation occurs from the time the mixture leaves the paver. This is due to the rearrangement of the material from a heap to a thin layer with a correspondingly large surface area. This also provides the contact surface for cooler weather conditions. In addition, additional heat is drawn from the rollers and the watering of the drums.

Accordingly, the compaction threshold temperature of 100°C is reached on the surface after 10 minutes for the binder course and after 9 minutes for the wearing course.

This period may be extended depending on the core temperature of the paved layers. The average temperature difference between the surface and the core material is 14.23 K for the binder course and 8.34 K for the wearing course. Because the wearing course is significantly thinner, its temperature drops faster.

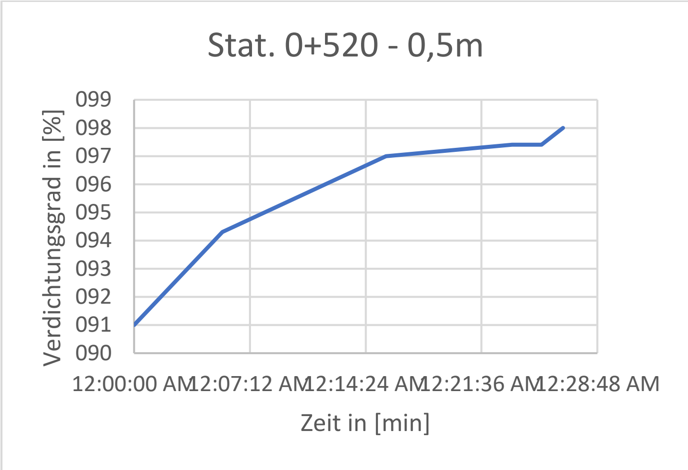
This higher temperature in the center of the layer has a positive effect on the compaction time of 10 minutes for the binder course and 4 minutes for the wearing course.

In this context, it was interesting to observe the temperature evolution over the cross-section. It was assumed that the mixture loses temperature as it travels through the auger and is coolest at the edges of the paved surface. In principle, this assumption was confirmed, but the temperature in the middle of the road was only slightly higher than at the edge.

3.2 Compaction Progression

The compaction process begins with pre-compaction by the paver screed. This ranged from 91% to 94% in the measurements. The lowest value was again measured at the edge. This is due to the thermo-viscous behavior of the material and the structure or vertical stiffening of the screed. This is much lower on both sides, which can cause the screed to deflect due to compaction pressure. Nevertheless, the measured values are consistently in the high range, bearing in mind that a hard bitumen mixture is used, which is difficult to compact. This confirms the positive effect of viscosity-changing additives on the material.

This effect is also evident when looking at the compaction progression of the binder course. Taking all measuring stations into account, it took an average of only 4 roller passes to reach the 98% threshold. The first roller passes show significantly higher compaction efficiency than the subsequent passes, as shown in Figure 8. This is due to the exponential compaction effort and the decrease in thermos-viscous properties during the compaction process. The threshold temperature of 100°C in the core of the layer is not reached until the end of compaction. Therefore, under the described boundary conditions, the mixture could be classified as suitable for practical use.

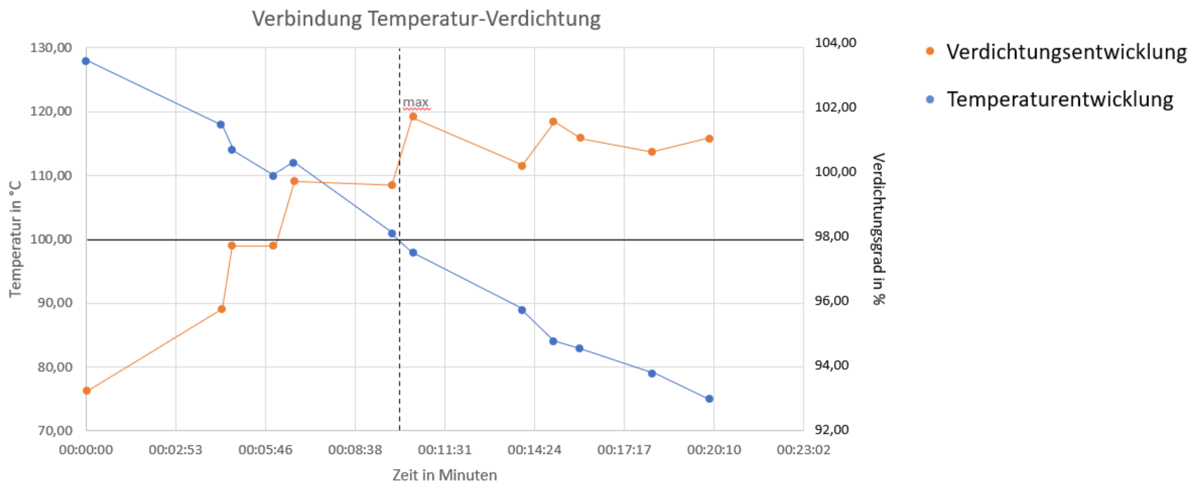


Source: Own

Fig. 8: *Compaction progression of the binder course*

The wearing course shows a similar compaction progression, with an average of only three passes necessary to achieve the required minimum compaction. This can be explained by the thinner layer thickness.

On average, no increase in compaction was observed after the sixth roller pass, and subsequent compaction processes resulted in a slight decrease in compaction. Once a temperature of 100°C is reached, compaction does not increase. Further passes may cause damage to the structure. In addition, the direct correlation between temperature and compaction was demonstrated in the wearing course, as shown in Figure 9.



Source: Own

Fig. 9: *Progression of compaction in the wearing course as a function of temperature*

As a result, the inclusion of the viscosity-changing additives significantly improved the compaction behavior of the stone mastic asphalt and achieved the desired degree of compaction with less compaction effort.

The suitability of the material under the given conditions can be confirmed by the compaction values obtained.

It was important to test the PQI probe's practical suitability. The measured values were collected and compared to the values of the cores taken. The results differed in both the binder course and the wearing course. In the binder course, the 100.4% compaction measured with the PQI probe contrasted with the 98% measured with the core.

Conclusion

Low-temperature asphalt has been successfully tested on the B169 highway. A large amount of measured data allowed detailed conclusions to be drawn.

An important consideration is the temperature development of the mixture from production to paving. It was found that the sub-process of transferring the mixture from the truck to the feeder to the paver must be given great importance, as it is here that the temperature drops significantly. Adverse weather conditions can exacerbate this, further reducing the time frame for successful compaction and compromising the quality of the pavement.

Due to the high precompaction of the mixture by the paver, the required compaction values were achieved with four passes on the binder course and three passes on the wearing course. The selected rollers and the viscosity-changing additives in the mixture had a positive influence on these results.

However, in its current form, the PQI probe can only indicate the compaction achieved. Precise measurements require further improvements.

The increased use of low-temperature asphalt is strongly recommended for environmental and economic reasons. However, in addition to suitable asphalt formulas, suitable mechanical modifications to the paving equipment are essential to meet occupational health and safety requirements for significant aerosol reduction during asphalt paving. This aspect was not part of the testing on the B 169 highway.

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POKLÁDKA NÍZKOTEPLOTNÍHO ASFALTU NA SILNICI B 169 U OBCE HEYDA

Výzkum snižování teploty při výrobě a pokládce horkého asfaltu probíhá již dlouhou dobu. Kromě vývoje vhodných receptur je důležité získávat zkušenosti, zejména v oblasti technologie pokládky asfaltových směsí, protože kromě chování různých asfaltových směsí při jejich hutnění hrají důležitou roli také vnější faktory jako např. umístění projektu a povětrnostní podmínky. Testování nízkoteplotního asfaltu na spolkové dálnici B 169 proběhlo úspěšně. Díky vysokému předhutnění pomocí rozmetadla bylo dosaženo požadovaných hodnot zhutnění na živičné vrstvě při 4 pojezdech a na povrchové vrstvě při 3 pojezdech. Přísady měnící viskozitu a zvolená technologie válcování měly pozitivní vliv na výsledky. Přesných výsledků měření zhutnění však nebylo možné dosáhnout pomocí sondy PQI.

EINBAU VON NIEDRIGTEMPERATUR-ASPHALT AUF DER BUNDESSTRAßE B169 BEI HEYDA

Seit langem wird an der Absenkung der Temperatur bei der Herstellung und dem Einbau von Heißasphalt geforscht. Neben der Entwicklung geeigneter Rezepturen ist es vor allem in der Asphalteinbautechnik wichtig, Erfahrungen zu sammeln, da neben dem Verhalten der verschiedenen Asphaltmischungen bei der Verdichtung auch äußere Faktoren wie die Lage des Bauvorhabens und die Witterungsverhältnisse eine wichtige Rolle spielen. Die Erprobung des Niedrigtemperatur-Asphalts auf der Bundesstraße B 169 wurde erfolgreich durchgeführt. Aufgrund der hohen Vorverdichtung durch die Einbaubohle wurden die geforderten Verdichtungswerte in der Binderschicht mit 4 Walzübergängen und in der Deckschicht mit 3 Walzübergängen erreicht. Die viskositätsverändernden Zusätze und die gewählte Walztechnik hatten einen positiven Einfluss auf die Ergebnisse. Genaue Messergebnisse für die Verdichtung konnten mit der PQI-Sonde jedoch nicht erzielt werden.

UKŁADANIE ASFALTU NISKOTEMPERATUROWEGO NA DRODZE B 169 W POBLIŻU MIEJSCOWOŚCI HEYDA

Badania nad obniżaniem temperatury podczas produkcji i układania gorącego asfaltu trwają już od dłuższego czasu. Oprócz opracowania odpowiednich receptur, ważne jest zdobycie doświadczenia, szczególnie w technologii układania asfaltu, ponieważ oprócz zachowania różnych mieszanek asfaltowych podczas ich zagęszczania, ważną rolę odgrywają również czynniki zewnętrzne, takie jak lokalizacja projektu i warunki pogodowe. Testy asfaltu niskotemperaturowego na autostradzie federalnej B 169 zakończyły się sukcesem. Dzięki wysokiemu zagęszczeniu wstępnemu przez stół układarki, wymagane wartości zagęszczenia zostały osiągnięte na warstwie wiążącej przy 4 przejazdach walca i na warstwie wierzchniej przy 3 przejazdach walca. Dodatki zmieniające lepkość i wybrana technologia walcowania miały pozytywny wpływ na wyniki. Nie udało się jednak uzyskać precyzyjnych wyników pomiaru zagęszczenia przy użyciu sondy PQI.

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Comparison of Waste Production in Regions of the Czech Republic in 2019-2021

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Abstract

The purpose of this article is to illustrate the intuitively understood links between the social and economic characteristics of an area and the waste production at a given location. These relationships have been investigated using statistical data from thirteen regions in the Czech Republic between 2019 and 2021. In order to evaluate the data, freely available tools such as Python 3.8.16 and a number of its libraries, e.g. matplotlib, plotly, sklearn, numpy and others, have been used.

Keywords

Waste production; Spatial distribution; Regions; Social characteristics; Economic characteristics.

Introduction

Waste is produced in different regions of the Czech Republic at different rates. The total waste production consists of hazardous waste (HW) and non-hazardous waste (NHW). A special subgroup of waste is municipal solid waste (MSW), which accounts for about 1/8 of the total production and is generated by the municipality by depositing the waste in a designated place.

The amount of waste produced can be influenced by a number of factors. A major part of the total waste production is the result of economic activities of various kinds, i.e. the business waste. Assessing the total waste production in the regions, four major waste producing sectors and two small quantity waste producing sectors were considered.

Due to the different origins of the waste, the amount of each waste category produced in the regions was also compared with respect to the social and demographic characteristics of the localities.

1 Statistical Data

Data sources for the evaluation of waste production were taken from the website of the Czech Statistical Office (ČSÚ). Specific sources of partial data are given in the relevant chapters.

1.1 Waste Production in the Czech Republic by Sectors

In 2008 the classification of economic activities (CZ-NACE) was introduced in the Czech

Republic. Information on waste production for the so-called CZ-NACE sections is available on the ČSÚ website (ČSÚ, 2021a). On the basis of this source, 4 major waste-producing sections and 2 sections with small waste production have been identified:

- construction (largest waste producers, see Al-Akel (2023),
- public administration and defense; compulsory social security,
- industry and mining,
- trade and transport,
- science, administration (small quantity producers), and
- monetary sector.

1.2 Total Waste Production in the Regions of the Czech Republic

Information on the total waste production in the regions and the part of hazardous waste is also available on the CSU website (CSU, 2021a) (here specifically for 2021, with links to previous years). Both information on total year waste production in tons and data expressing kilograms per capita waste production are available.

1.3 Municipal Solid Waste Production in the Regions of the Czech Republic

Downloadable files with data on the amount of municipal solid waste produced in the districts of the Czech Republic are also available on the CSU website. These figures are also expressed both in tons of production and in kilograms per capita.

1.4 Selected Measures Taking into Account the Characteristics of the Regions

For the impact assessment the following regional characteristics have been selected:

- Population [pcs] (ČSÚ, 2021b).
- Population density [pcs/km^2] (ČSÚ, 2021c).
- Deaths in regions per year [pcs].
- Average wage [CZK].
- Median wages in districts [CZK] (CSTJ, 2021d).
- Number of new dwellings per year [pcs].
- Number of new dwellings per 1000 inhabitants per year [pcs].
- Gross value added of 6 selected industries (CZ-NACE) with differently high waste production in the regions (CSU, 2021e).

2 Data Aggregation and Data Processing

The data on waste production in the regions and selected characteristics of the regions were grouped into a common table by year, thus forming the basic source for the subsequent analysis.

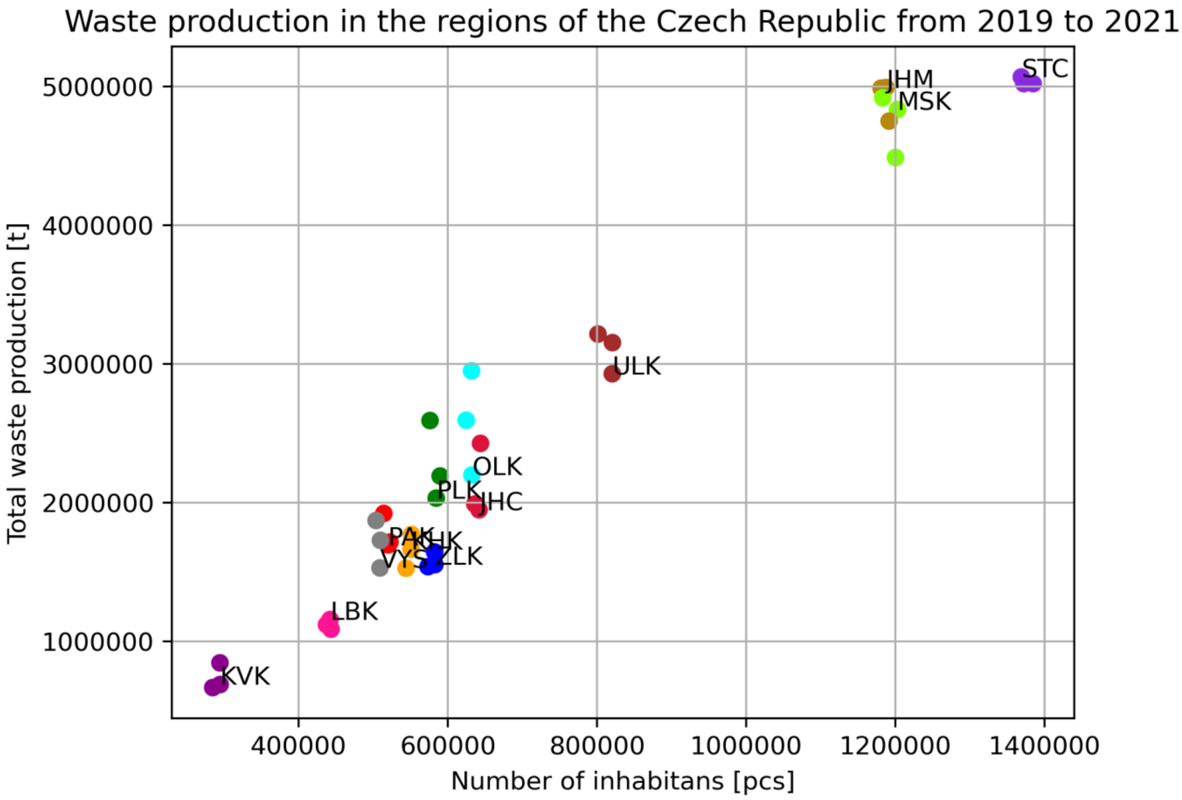
For the purpose of creating interactive graphs and contingency tables (especially in Google Sheets), the characteristics of the regions were reclassified in the form of verbal ratings (quantiles – terciles, quintiles). This partial method of data processing is not presented in this article.

3 Data Evaluation

Waste production is usually quantified either in absolute tonnage or in kilograms produced per capita. The differences in total waste production between regions are more noticeable in the case of absolute waste production in tons. Relating the amount of waste produced to the area of the region leads to the same findings.

3.1 Visualization in Python 3

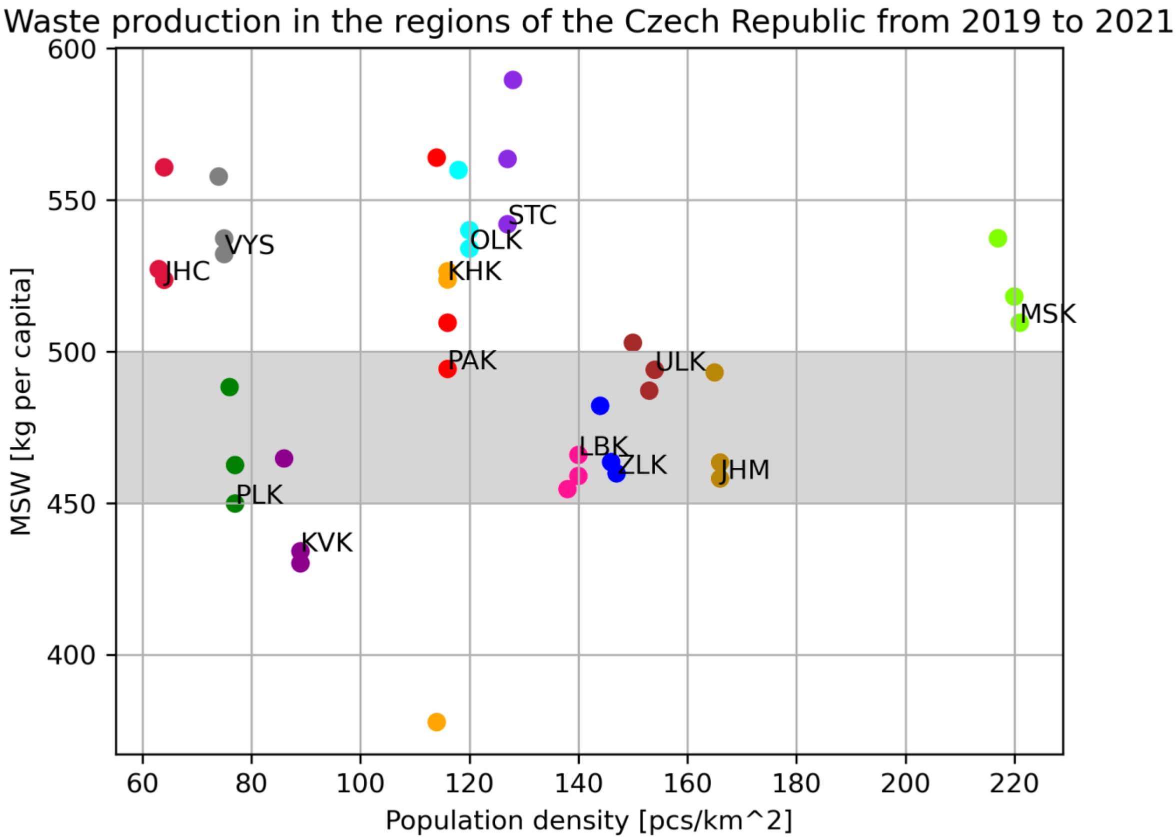
Using Python 3 (Python Software Foundation, 2022) tools data analysis was performed without reclassifying the characteristics into verbal rating categories. First, a linear dependence between a large proportion of the regional characteristics was established through matrix plots. It turned out that all the characteristics expressing general value added (GVA) are linearly dependent on construction and this is further linearly dependent on population. This finding leads to the ability of expressing total waste production from knowing only the population of the region, see Figure 1.



Source: Own

Fig. 1: *Linear dependence of the amount of total waste production on the number of inhabitants, where 'STC' is Central Bohemian Region , 'JHC' is South Bohemian Region, 'PLK' is Plzen Region, 'KVK' is Karlovy Vary Region, 'ULK' is Ústí nad Labem Region, 'LBK' is Liberec Region, 'KHK' is Hradec Králové Region, 'PAK' is Pardubice Region, 'VYS' is Vysočina Region, 'JHM is South Moravian Region, 'OLK' is Olomouc Region, 'ZLK' is Zlín Region, and 'MSK' is Moravian-Silesian Region. Prague is not included.*

It is interesting to observe the relationship between the production of MSW and the differences in the per capita production of MSW in comparison with the population density in the suburbs. With increasing population density, the amount of waste produced per capita varies only in a rather narrow band of values, see Figure 2.



Source: Own

Fig. 2: *Decrease in municipal waste with increasing population density, where 'STC' is Central Bohemian Region , 'JHC' is South Bohemian Region, 'PLK' is Plzen Region, 'KVK' is Karlovy Vary Region, 'ULK' is Ústí nad Labem Region, 'LBK' is Liberec Region, 'KHK' is Hradec Králové Region, 'PAK' is Pardubice Region, 'VYS' is Vysočina Region, 'JHM is South Moravian Region, 'OLK' is Olomouc Region, 'ZLK' is Zlín Region, and 'MSK' is Moravian-Silesian Region. Prague is not included.*

4 Results

For the total waste production in tons, the graphs in Figure 1 and 2 showed its linear dependence on several selected, correlated characteristics of the regions. Demographic characteristics such as the number of retirees, population, and the number of deaths showed the best correlation with waste production followed by economic characteristics, i.e. GVA of trade and transportation and GVA of construction. Pearson correlation coefficients come out close to one.

```
df['Old age retirees [count]'].corr(df['Waste [t]']) => 0.9796
df['Number of residents [count]'].corr(df['Waste [t]']) => 0.9782
df['Deaths [ks]'].corr(df['Waste [t]']) => 0.9564
df['Trade a\nTransport\n[CZK]'].corr(df['Waste [t]']) => 0.9378
df['Construction\n[CZK]'].corr(df['Waste [t]']) => 0.9367
```

For waste production in absolute quantities (tons), population always figured among the three regions' characteristics that are very well correlated with waste (hazardous and municipal) production.

No clear dependence on the characteristics could be found for the amount of waste per capita, but this is unnecessary as the two figures can be transformed to each other.

By analogy to the quantity of waste, much of the remaining demographic and economic characteristics of regions could be approximated from knowledge of population.

Conclusion

The analysis shows that the waste production in the regions of the Czech Republic in the years 2019 to 2021 can be very well expressed by linear functions depending on the number of inhabitants. This means that waste production over a selected time period can be estimated in different locations based on the population of the area. At the same time, it is sufficient to operate with the absolute quantities of waste and not with their values related to the population.

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SROVNÁNÍ PRODUKCE ODPADU V KRAJÍCH ČESKÉ REPUBLIKY V LETECH 2019-2021

Účelem tohoto článku je ilustrace intuitivně chápaných souvislostí mezi společenskými a ekonomickými charakteristikami území a produkcí odpadů na dané lokalitě. Uvedené vztahy byly zkoumány na statistických datech z krajů České republiky v letech 2019 až 2021. Za účelem vyhodnocení dat byly využity volně dostupné nástroje jako Google Sheets, Python 3.8.16 a řada jeho knihoven, např. matplotlib, plotly, sklearn, numpy a další.

VERGLEICH DER ABFALLPRODUKTION IN DEN GEBIETEN DER TERRITORIALEN VERWALTUNG IN DER TSCHECHISCHEN REPUBLIK IN DEN JAHREN 2019-2021

Der Artikel hat sich zum Ziel gesetzt, die intuitiv verstandenen Zusammenhänge zwischen der gesellschaftlichen sowie wirtschaftlichen Ausprägung des Gebietes und der Abfallproduktion an dem entsprechenden Ort darzustellen. Die dargestellten Beziehungen wurden auf der Basis von statistischen Daten aus den Gebieten der territorialen Verwaltung der Tschechischen Republik in den Jahren 2019 bis 2021 untersucht. Für die Auswertung der Daten wurden frei zur Verfügung stehende Tools verwendet, wie zum Beispiel Google Sheets, Python 3.8.16 und eine Reihe Register wie matplotlib, plotly, sklearn, numpy und weitere.

PORÓWNANIE PRODUKCJI ODPADÓW W REGIONACH REPUBLIKI CZESKIEJ W LATACH 2019-2021

Celem niniejszego artykułu jest zilustrowanie intuicyjnie rozumianych zależności między społecznymi i gospodarczymi cechami regionu a produkcją odpadów w danej lokalizacji. Przedstawione zależności zostały zbadane przy użyciu danych statystycznych z regionów Republiki Czeskiej w latach 2019-2021. Do oceny danych wykorzystano ogólnodostępne narzędzia, takie jak Arkusze Google, Python 3.8.16 i szereg jego bibliotek, takich jak matplotlib, plotly, sklearn, numpy i inne.

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Machine Learning Techniques for Fatal Accident Prediction

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Abstract

Ensuring public safety on our roads is a top priority, and the prevalence of road accidents is a major concern. Fortunately, advances in machine learning allow us to use data to predict and prevent such incidents. Our study delves into the development and implementation of machine learning techniques for predicting road accidents, using rich datasets from Catalonia and Toronto Fatal Collision. Our comprehensive research reveals that ensemble learning methods outperform other models in most prediction tasks, while Decision Tree and K-NN exhibit poor performance. Additionally, our findings highlight the complexity involved in predicting various aspects of crashes, as the Stacking Regressor shows variability in its performance across different target variables. Overall, our study provides valuable insights that can significantly contribute to ongoing efforts to reduce accidents and their consequences by enabling more accurate predictions.

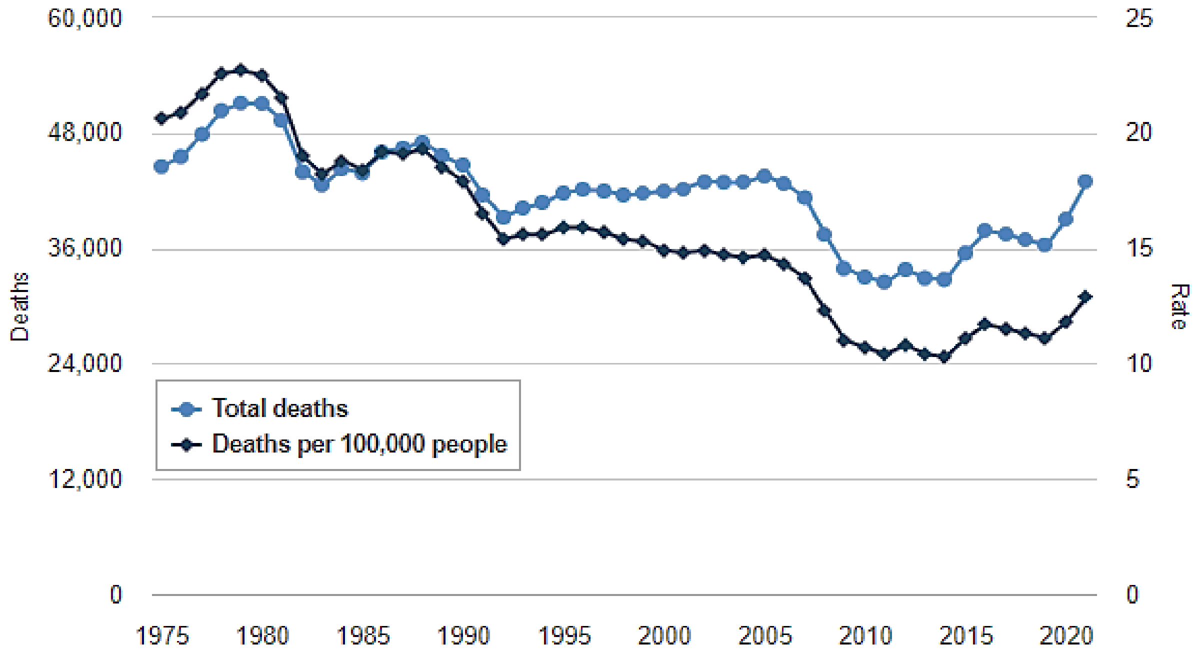
Keywords

Accident prevention; Machine learning; Traffic safety; Road safety; Accident forecasting; Risk assessment.

Introduction

Road traffic accidents continue to be a serious global public health concern, resulting in significant human and economic costs. Several factors contribute to the severity of these accidents, including driver behavior, environmental conditions, vehicle type, and road characteristics (Basagaña & de la Peña-Ramirez, 2023; Behzadi Goodari et al., 2023; WHO, 2018). According to the World Health Organization (WHO), approximately 1.35 million people lose their lives in road traffic accidents annually, with millions more suffering non-fatal injuries (WHO, 2018, 2024). The WHO predicts that by 2030, traffic accidents will be the fifth leading cause of death worldwide (WHO, 2018). Between 20 and 50 million people are injured, and 1.3 million die in motor vehicle accidents yearly. At least 120 people each year are killed, and 2.4 million people are injured due to road traffic accidents in the European Region of the WHO (WHO, 2024; WHO Regional Office for Europe, 2009). However, 90%

of these fatalities occur in low- and middle-income countries. A total of 42,939 people died in motor vehicle crashes in 2021, see Figure 1. These deaths occurred in 39,508 crashes involving 61,332 motor vehicles. This was a 10% increase in deaths compared with 2020 (Insurance Institute for Highway Safety, 2024).



Source: Own processing of data (Insurance Institute for Highway Safety, 2024).

Fig. 1: *Motor vehicle crash deaths and deaths per 100,000 people over the years 1975-2021*

Moreover, road accidents have a significant impact on healthcare systems, societies, and economies (WHO, 2021). Because of the unpredictable nature of road accidents, statistical predictive models have been created to assess their causes and effects (Comi et al., 2022). This research aims to enhance the range of predictive models employed in road crash prediction and severity analysis by utilizing various machine learning models, including Linear Regression, Decision Tree, Random Forest, Ridge Regression, Lasso Regression, ElasticNet Regression, Gradient Boosting, Support Vector Regressor, K-Nearest Neighbors, XGBoost, LightGBM, and a Stacking Regressor. This study aims to identify significant predictors of road crash severity, utilizing data from the Department of the Interior, Servei Català de Trànsit, Government of Catalonia. The exploration of an array of machine learning models to predict road crash severity represents the novelty of this research, moving beyond the predominant focus on Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) in previous studies.

The article provides a comprehensive study covering some key aspects. It starts with an in-depth literature review that categorizes previous studies and highlights the evolution of machine learning methodologies for both classification and regression tasks in this field. The data collection process is then illustrated, addressing the challenges related to data quality and availability. Extensive feature engineering is explored to make the most of various data attributes, which enhances the accuracy and reliability of our predictive models. Finally, the article concludes with important recommendations to prevent road accidents.

1 Related Work

The use of machine learning has improved the prediction of traffic accidents. However, due to the distinct features of road accidents in different areas and the variety of machine learning models that can be used, further investigation is required(Yannis et al., 2017). After a series of Artificial Neural Network models, Delen et al. (2006) speculated on the potential nonlinear relationships between injury severity and crash-related factors (ANNs) (Delen et al., 2006). Crash outcomes were significantly affected by factors such as whether or not the driver was wearing a seatbelt, the driver was under the influence of alcohol or drugs, the driver's age, gender, and the kind of vehicle. The weather and time of the day did not have a significant impact on the severity of the injury risk. Moghaddam et al. used ANNs to assess the severity of crashes and predict their occurrence on urban roads (Moghaddam et al., 2011), which was similar to Delen et al.´s findings (Delen et al., 2006).

The acquired data showed that the most critical factor that significantly increases the severity of crashes on urban highways is road width. Other factors that contributed to the severity of such crashes include head-on collisions, the type of vehicle at fault, disregarding lateral clearance, disregarding the distance, being unable to control the car, exceeding the maximum speed limit, and driver veering to the left. Although algorithms like neural networks are effective in anticipating and classifying data, they lack the interpretive capabilities of people, making them seem like a "black box" that is difficult to understand and get individualized feedback from (Moghaddam et al., 2011). As a result, humans cannot use these algorithms to manage and prevent mishaps. The lack of interpretability in AI-driven decisions can be a concern in fields where transparency is crucial. As a result, researchers and practitioners may choose more interpretable modeling approaches like decision trees or linear models. However, recent advancements in explainable AI have provided methods to understand complex models like ANNs. These techniques allow for the calculation of feature importance, helping researchers identify the most influential input variables in driving the model's predictions. By using these methods, researchers can improve the transparency and interpretability of ANNs and other advanced models, making AI-driven insights more accessible and actionable in critical fields such as healthcare, finance, and autonomous systems. In addition, over six years, Alkheder et al. conducted research over six years using ANN to predict the injury severity of road accidents using 5973 records of traffic incidents that happened in Abu Dhabi (from 2008 to 2013) (Alkheder et al., 2017). Following each incident, 48 individual characteristics were recorded as part of the accident report. The number of features and injury categories during pre-processing was limited to 16. The results of these experiments demonstrate the developed ANN classifiers' ability to forecast the severity of accidents accurately. Prediction accuracy for the whole model was 81.6% on the training data and 74.66% on the test data. Minor, moderate, severe, and fatal were converted from ordinal to numeric (1, 2, 3, 4) forms of the dependent variable, injury severity. An Ordered Probit was performed using R language. Compared to the ANN's 74.6% accuracy, the Ordered Probit model's 59.5% accuracy was much worse. As part of an ANN, Kunt et al. (2012) used a genetic algorithm pattern search and a Multi-Layer Perceptron (MLP) structure modeling strategy. The models were developed using data from the 1,000 incidents on the Tehran-Ghom Freeway in 2007. The R-value for the ANNs forecast was the highest, coming in at around 87%, indicating that it was the most accurate (Kunt et al., 2011).

Kaplan and Prato (2012) conducted a study on school bus safety and found that school buses have lower accident rates and less severe accidents than other buses., ranging from 19.8 to 37.8% (Kaplan & Prato, 2012). The reasons for this could be due to reduced driving speeds and stricter federal school bus regulations. However, there is still room for improvement in school bus safety. To reduce school bus accidents, it is important to educate other drivers, especially teen drivers, in school zones. Chang and Chien (2013) collected truck-involved accident statistics from Taiwan's national roadways for 2005-2006 (Chang & Chien, 2013). The authors used a CART model, a non-parametric combination of a classification tree and a regression tree. The results showed that intoxicated driving, seatbelt use, vehicle type, collision type, and contributory variables resulting in driver/vehicle action, number of vehicles involved, and accident site were the most critical factors in determining injury severity after truck crashes.

An alternative rule-based solution to DTs was proposed in a study by (Hashmienejad & Hasheminejad, 2017). To optimize and find rules based on support, confidence, and comprehensibility metrics, the authors modified a multi-objective genetic algorithm called the nondominated sorting genetic algorithm (NSGA-II). The evaluation results showed that the proposed method outperformed classification techniques like ANN, SVM, and conventional DTs in terms of classification metrics like accuracy (88.2%) and performance metrics of rules like support (0.9) and confidence (0.9). (0.79 and 0.74, respectively).

In another study by Taamneh et al. (2017), rules produced by the decision tree and the rules induction were retrieved to understand the significant factors linked with accident severity. The researchers found that victims' ages, genders, nationalities, crash years, injury counts, and accident types mattered the most among the factors they examined. It was determined if the Support Vector Machine (SVM) model or the Ordered Probit (OP) model was more efficient. The SVM model was found to be superior to the OP model for predicting the severity of injuries sustained in a collision. The SVM model had higher accuracy (48.8%) than the OP model (44.0%) in terms of correct predictions. Despite the SVM model's multi-class classification difficulty, it outperformed the OP model in predicting the frequency of mild injuries.

De Oña et al. conducted a study on the severity of road accidents in Spain using a machine-learning technique. Three different Bayesian Networks (BNs) were built using 18 variables that reflected the relevant parameters to classify incidences as either lightly hurt, dead, or badly injured (de Oña et al., 2014). Accident classification, driver age, illumination, and several injuries were found to be significant inferential variables for predicting fatal and catastrophic injury events (de Oña et al., 2014). In addition, Monedero et al. used time-series techniques based on the concept of fractional integration to analyze the statistical properties of the number of road accidents on Spanish roads. They found that the series examined displayed very low degrees of persistence, with the orders of integration being around 0, showing a short memory pattern (Duarte Monedero et al., 2021).

Statistical analysis has been used along with machine learning techniques to quantify the severity of road accidents and understand the correlation between injury severity outcomes and driver or vehicle characteristics, highway geometric factors, environmental conditions, and accident parameters. Yan et al. (2005) (Yan et al., 2005) applied binary logistic regression models to investigate two-vehicle rear-end collisions at signalized crossings where both vehicles continued straight. There were various intersection-related elements (e.g., division, number of lanes at crash location, and speed limit). The rear-end crash dichotomy-dependent variable (represented by "1") versus other crashes (represented by "0") was used in this modeling. It is important to carefully interpret the results of this modeling as it compares rear-end crashes to other crashes and explores the driver, vehicle, and specific crash conditions in a better way.

Mohamed et al. (2013) analyzed two pedestrian injury severity datasets from New York City, U.S. (2002-2006) and Montreal, Canada (2003-2006) and the Ordered Probit and Multinomial Logit models (Mohamed et al., 2013). They found that fatal pedestrian accidents were more likely to occur in both cities due to various factors, such as the presence of heavy vehicles, lack of lighting, and the prevalence of mixed land use. Researchers Castro and Kim (2016) found that the use of seatbelts, the nature of the accident, and the location of the collision all contributed to a significant increase in the chance of severe injuries in truck accidents (Castro & Kim, 2016). To foretell how severe motorway accidents will be. Zheng et al. (2019) looked at fatigue-related mortality in 21 cities in Guangdong province, the Chinese region with the highest rate of road accidents (Zheng et al., 2019). Compared to evening rush hours, crashes caused by fatigue were 1.79 times more likely to occur during morning rush hours (7 am to 9 am), with odds ratios of 1.79 and 0.55, respectively (5 pm to 8 pm).

It has been found that the probability of being involved in a crash that leads to a severe injury or death is 1.84 times higher during the morning than in the afternoon. These findings support our previous research that indicated that lack of sleep has a negative impact on one's ability to stay in the lane during early-morning drives. These results imply that sleep deprivation is a concern even during short trips in the morning and thus, further investigation is needed to explore this interesting observation. While most machine learning research has concentrated on either the artificial neural network (ANN) model or the Support Vector Machine (SVM), this study examined various models to evaluate which worked best with the data. Based on their analysis, Yokoyama and Yamaguchi (2020) found that the RF model was marginally more precise than the ANN model (Yokoyama & Yamaguchi, 2020). However, RF proved its efficiency in accident prediction accuracy assessment for highway-rail grade crossings (Zhou et al., 2020) as well as other applications, especially in industry (H. Zermane & Drardja, 2022).

Recent years have seen significant improvement in automated vehicle (AV) technology, with many countries actively testing shared automated shuttle buses on public highways, including Australia, France, and Sweden. (Lee et al., 2024; Rezaei & Caulfield, 2020). AVs have been connected to several benefits. They solve a problem with the standard job description for drivers. As AVs become more commonplace, drivers' expectations and concerns will shift towards other Vehicles. Acceptance from drivers is crucial for integrating AVs into existing traffic systems (Kaye et al., 2020). According to Papadoulis et al. (2019) (Papadoulis et al., 2019), automatic cars are safer on the road than human drivers. While Noy et al. (2018) (Noy et al., 2018) show that AV can make prudent judgments on incoming traffic, Beirigo et al. (2018) (Beirigo et al., 2018) highlight AV's capacity to carry freight and operate with unlicensed drivers. Attitudes about AVs, however, may vary by country (Schoettle & Sivak, 2014). To the author's knowledge, there is no research on public opinion of AVs in the Catalan region. Studies of local sentiment toward autonomous vehicles (AVs) in Catalonia are warranted in the future.

Random Forest is essentially a collection of decision trees whose outcomes are aggregated based on voting (A. Zermane et al., 2023). Rezapour et al. (2020) suggested using it instead of a decision tree model. To identify significant determinants of road crash severity, this work adopts a similar strategy to that of Rezapour et al. (2020), using a combination of binary logistic regression and random forest (Rezapour et al., 2020). This study's originality lies in using two different predictive models (statistics and machine learning). Recently several studies oriented to deep learning techniques to predict traffic flow to reduce potential road accidents (Hu et al., 2022; Kashyap et al., 2022).

The literature review presents several models and methods to predict traffic accident severity. The choice of model depends on the available data and the specific context of the study.

2 Problem Statement and Contribution

Efforts to mitigate the occurrence of road accidents and their consequences have traditionally focused on improving infrastructure, enhancing vehicle safety, and enforcing traffic regulations. However, recent advancements in data collection and analysis have opened up new opportunities to predict and prevent accidents.

The focus of this research is to analyze the severity of traffic accidents using two datasets. The goal is to identify the root causes of traffic collisions in Catalonia and Toronto and also to determine the most effective Machine Learning model in this context. Understanding the patterns and trends behind accident severity is crucial in determining the complex variables that contribute to the frequency of collisions of varying severity levels and developing appropriate corrective activities.

In particular, the application of machine learning algorithms to road accident forecasting has gained prominence due to its potential to provide timely and data-driven insights for traffic management and safety measures. This research article delves into the domain of road accident prediction using machine learning techniques. It seeks to harness the power of data-driven models to enhance road safety and reduce accident-related fatalities and injuries. In addition, there is a significant interest in the impact of emerging technologies, such as autonomous vehicles, on traffic safety. Further research in these areas can lead to improvements in traffic safety and the development of more effective intervention strategies.

3 Materials

This research is based on a thorough examination of existing literature. Previous studies on road accident prediction and machine learning applications in traffic safety are categorized and analyzed. This research aims to provide actionable insights for road safety and accident prevention by leveraging the capabilities of machine learning. The findings of this study contribute to the ongoing efforts to reduce the incidence of road accidents and their associated social and economic costs. In the subsequent sections of this article, we delve into the specific details of utilized data on road accidents.

The first dataset is used for road accident classification. It is taken from Toronto Police Service open data for Fatal Collisions published for public reuse available from (Toronto Police Service, 2022). This dataset is a subset of the Killed and Seriously Injured (KSI) data collected from 2006-2022. This part of the research presented here underscores the potential of machine learning algorithms as valuable tools in road accident prediction and prevention.

For the regression task, the second dataset used in this study contains 16,773 records with 54 attributes. The dataset was collected from 2010 to 2018 and reflects traffic incident data in Catalonia (Li et al., 2018). The attributes represent various details regarding the traffic incidents and their circumstances, such as the year, area, world name, severity of injuries, the number of units involved, and other specifics related to the environment and conditions at the time of the incidents. The dataset also includes various qualitative and quantitative features, such as type of day, type of accident, and weather conditions, providing a comprehensive view of each incident's circumstances. The dataset is balanced in urban and road areas, with around 54% of incidents occurring in urban areas and the remaining 46% on the road. Recent reports about fatal accidents are published by (Catalan Traffic Service, 2024). The latest Accident of Mortals 2014-2024 in Catalonia dataset is available from (Augé & Navarro, 2022).

The study methodology, feature engineering approaches, model development, and extensive discussions on the implications of our findings are based on these rich and diverse datasets that allow the application of various machine-learning models to predict the severity of road crashes. They provide a solid basis for examining the many factors that can contribute to the severity of a crash, and the models' performance can be evaluated and compared based on their accuracy in predicting the crash severity.

4 Methods

In order to conduct this study, we began by gathering crucial data related to fatal accidents. As a result, the study relies on a range of data sources including accident reports, meteorological data, traffic information, and road infrastructure data. The process of collecting the data involved addressing various challenges related to data quality and availability. We used rigorous preprocessing techniques to ensure that the data used in model development is reliable and relevant. This research employs a suite of Machine Learning algorithms for the prediction of the class of road accident injuries, including Decision Tree, Random Forest, MLP Classifier, Logistic Regression, Gradient Boosting, Ada Boost, and Gaussian Naive Bayes, to classify road accidents. The predictive models used for the regression task include Linear Regression, Decision Tree, Random Forest, Ridge Regression, Lasso Regression, ElasticNet Regression, Gradient Boosting, Support Vector Regressor, K-Nearest Neighbors, XGBoost, LightGBM.

Different techniques offer unique advantages and are chosen based on the specific characteristics and objectives of the research tasks. The Decision Tree is a tree-like model: each internal node represents a feature or attribute, each branch represents a decision rule, and each leaf node represents an outcome or class label. It is used for both classification and regression tasks, providing interpretability and the ability to handle non-linear relationships in the data. Random Forest is an ensemble learning method that builds multiple decision trees during training and outputs the mode (classification) or mean prediction (regression) of the individual trees. It enhances accuracy and reduces overfitting by averaging the predictions of different trees. Ada Boost (Adaptive Boosting) is another ensemble method that combines multiple weak learners (typically shallow decision trees) to create a strong learner. It adjusts the weights of incorrectly predicted instances to focus on difficult cases, thereby improving overall performance.

The Multilayer Perceptron (MLP) Classifier is a type of feedforward neural network with multiple layers of nodes (neurons) capable of learning non-linear relationships in data. It is effective for classification tasks, especially when dealing with complex patterns. Logistic Regression is a linear model used for binary classification tasks. It models the probability of a binary outcome based on input variables, providing interpretable results and insights into the influence of predictors on the target. Gradient Boosting is an ensemble learning technique that builds models sequentially, with each new model correcting errors made by the previous ones. It is particularly effective in improving predictive accuracy and handling complex interactions between variables. Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming independence between features. Gaussian Naive Bayes is specifically designed for continuous features, making it suitable for tasks where the distribution of features can be assumed to be Gaussian.

Linear Regression models the relationship between dependent and independent variables by fitting a linear equation to the observed data. It provides insights into the relationship between variables and is straightforward to interpret. Ridge Regression is a regularized version of linear regression that adds a penalty term to the loss function, preventing overfitting by penalizing large coefficients. Lasso Regression, similar to Ridge, adds a penalty term but uses the absolute value of coefficients. It can perform feature selection by driving some coefficients to zero. ElasticNet combines the penalties of Ridge and Lasso regression, providing a balance between the two approaches. Support Vector Regressor (SVR) is a variant of Support Vector Machines (SVM) used for regression tasks. It finds a hyperplane that best fits the data, with a margin of tolerance (epsilon) within which no penalties are associated. However, K-Nearest Neighbors (KNN) is a non-parametric method used for both classification and regression. It predicts the output based on the majority class or mean of the k-nearest neighbors in the feature space. XGBoost (Extreme Gradient Boosting) is an optimized implementation of gradient boosting that provides high performance and efficiency, often used for structured and tabular data. LightGBM (Light Gradient Boosting Machine) is another gradient boosting framework optimized for speed and memory efficiency, capable of handling large datasets with high-dimensional features.

In order to assess and confirm the effectiveness of each Machine Learning algorithm, it is important to establish a basic understanding of the evaluation metrics used to assess the predictive models. Thus, this study utilized various metrics such as accuracy, precision, recall, and F1-score. Precision quantifies the accuracy of positive predictions, highlighting the ratio of true positive predictions to the total number of positive predictions. Recall assesses the model's ability to identify all actual positive cases, expressed as the ratio of true positives to the total actual positive cases. F1-score is the harmonic mean of precision and recall, offering a balanced assessment of a model's predictive power, particularly useful when dealing with imbalanced datasets.

However, for the regression task, we utilized the Mean Squared Error (MSE), Mean Squared Logarithmic Error (MSLE), and Explained Variance Score. The goal in any machine learning task is typically to minimize the error (lower MSE and MSLE values are better) and maximize the amount of variance explained by the model (higher Explained Variance Score is better). Accuracy measures the overall correctness of predictions, expressing the ratio of correctly predicted accidents to the total predictions made.

For each target variable, we develop a separate model that undergoes training and evaluation. The script incorporates a pipeline comprising the preprocessing steps and the model itself. The training data is used to train the model, and then we make predictions on the test data. However, some predictions may not make sense in the context of the problem, such as negative predictions for the number of victims, fatalities, etc. Therefore, we replace any negative predictions with 0. The performance of each model is evaluated using the Mean Squared Error (MSE), Mean Squared Logarithmic Error (MSLE), and Explained Variance Score (EVS). If the calculation of the MSLE results in an error (which can happen if the predictions include negative values), the MSLE is set to None for that model.

The second part of regression models aims to construct and evaluate an ensemble model for predicting the severity of road crashes. The script utilizes various regression models, combining them into a Stacking Regressor, which uses the concept of stacking (also known as stacked generalization) to ensemble multiple regression models. The severity of road crashes is measured by four metrics: the number of victims, fatalities, serious injuries, and minor injuries. The Stacking Regressor is a form of ensemble learning where the base models are fitted based on the complete training set; then, the final estimator is fitted on the outputs of the base models to form new predictions.

The script trains and evaluates the Stacking Regressor for each target variable. The Stacking Regressor uses the base models to make predictions, and these predictions are then used as input to the final estimator to make the final prediction. Any negative predictions (which would be nonsensical in this context) are replaced with 0. The performance of the Stacking Regressor is evaluated using the Mean Squared Error (MSE), Mean Squared Logarithmic Error (MSLE), and Explained Variance Score (EVS). If the calculation of the MSLE results in an error (which can happen if the predictions include negative values), the MSLE is set to None. Each algorithm performed in this article is selected based on its suitability for handling the unique characteristics of accident prediction data. The article details the model development process, encompassing feature engineering, hyperparameter tuning, and model selection.

5 Results

Several machine learning models were used to perform a regression task to predict the victims of road crashes. The performance of each of these models was evaluated using different metrics, which provided a unique perspective on the model's performance. In this section, we present the results of our predictive modeling experiments and provide a comprehensive discussion of the findings applied to the two datasets.

5.1 Classification Models (Toronto Dataset)

The Toronto dataset (Toronto Police Service, 2022) has already been introduced in Chapter 3. The data contains two classes, including Fatal, with 2297 cases (13.6%), and Non-fatal, with 14561 cases (86.4%). Several factors are selected for road accident prediction, including object ID, year, date, time, hour, road class, district, Location Coordinate (loccoord), Collision location (accloc), Light condition (traffctl), visibility, light, Classification of accident (acclass), Involvement type (invtype), injury, and vehicle type (vehtype). A descriptive analysis of the Toronto dataset of road accidents is illustrated in Table 1. The less than 0 *P*-value indicates the influence of all factors associated with road accidents, while the *X2* illustrates the dominance of some factors including Involvement Type and Environment Condition.

Tab. 1: *Toronto dataset descriptive analysis*

Factor	Values	Frequency	(%)	Accident class			
				Fatal	Non-fatal	*X2*	*P*-value
Road class	NA	497	2.9	80	417	32.584	0.000*
	Collector	929	5.5	140	789		
	Expressway	52	0.3	5	47		
	Expressway Ramp	4	0	0	4		
	Laneway	10	0.1	6	4		
	Local	761	4.5	96	665		
	Major Arterial	11974	71	1645	10329		
	Major Arterial Ramp	1	0	0	1		
	Minor Arterial	2598	15.4	325	2273		
	Other	25	0.1	0	25		
	Pending	7	0	0	7		
	Total	**16858**	**100**	**2297**	**14561**		
Dıstrıct	NA	141	0.8	2	139	140.837	0.000*
	Etobicoke York	3884	23	529	3355		
	North York	3343	19.8	512	2831		
	Scarborough	3796	22.5	674	3122		
	Toronto and East York	5617	33.3	577	5040		
	Toronto East York	77	0.5	3	74		
	Total	**16858**	**100**	**2297**	**14561**		

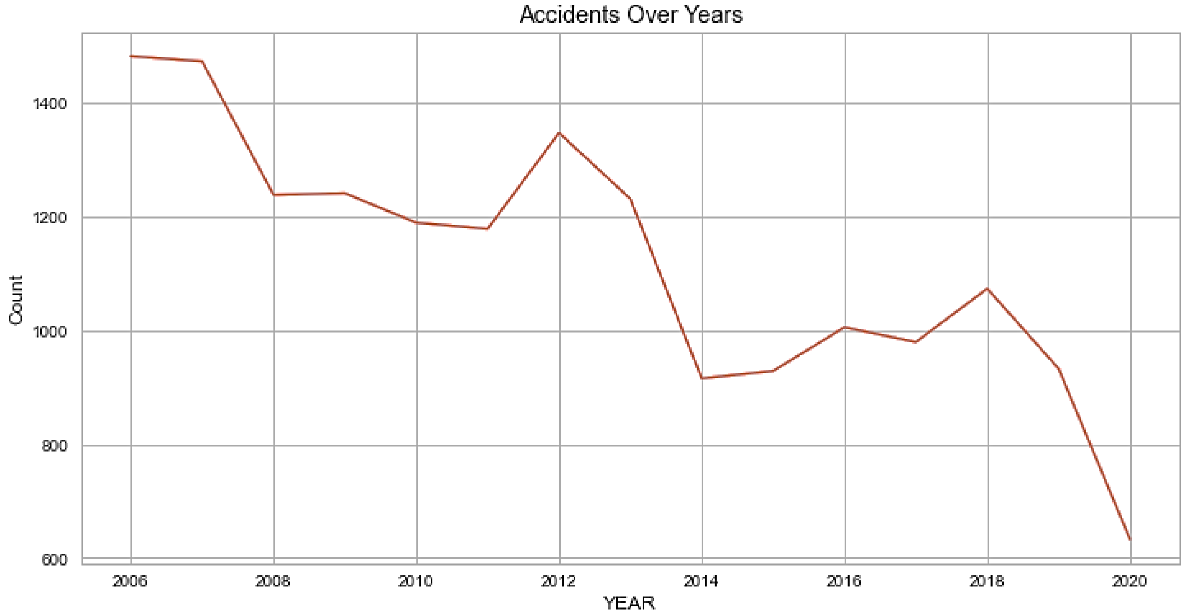
Factor	Values	Frequency	(%)	Accident class			
				Fatal	Non-fatal	*X2*	*P-value*
Location Coordinate	NA	105	0.6	0	105	39.139	0.000*
	Entrance Ramp Westbound	2	0	0	2		
	Exit Ramp Southbound	3	0	0	3		
	Exit Ramp Westbound	5	0	1	4		
	Intersection	11141	66.1	1467	9674		
	Mid-Block	5596	33.2	827	4769		
	Mid-Block (Abnormal)	4	0	0	4		
	Park, Private Property, Public Lane	2	0	2	0		
	Total	**16858**	**100**	**2297**	**14561**		
Collision Location	NA	5450	32.3	795	4655	79.312	0.000*
	At Intersection	8060	47.8	985	7075		
	At/Near Private Drive	318	1.9	11	307		
	Intersection Related	1019	6	153	866		
	Laneway	13	0.1	2	11		
	Non-Intersection	1966	11.7	346	1620		
	Overpass or Bridge	12	0.1	3	9		
	Private Driveway	13	0.1	0	13		
	Trail	1	0	0	1		
	Underpass or Tunnel	6	0	2	4		
	Total	**16858**	**100**	**2297**	**14561**		
Traffic Control Type	NA	29	0.2	0	29	72.694	0.000*
	No Control	8090	48	1245	6845		
	Pedestrian Crossover	195	1.2	28	167		
	Police Control	2	0	0	2		
	School Guard	2	0	0	2		
	Stop Sign	1295	7.7	156	1139		
	Streetcar (Stop for)	16	0.1	0	16		
	Traffic Controller	104	0.6	0	104		
	Traffic Gate	5	0	3	2		
	Traffic Signal	7104	42.1	865	6239		
	Yield Sign	16	0.1	0	16		
	Total	**16858**	**100**	**2297**	**14561**		
Environment Condition	NA	18	0.1	18	0	180.118	0.000*
	Clear	14474	85.9	1976	12498		
	Drifting Snow	19	0.1	0	19		
	Fog, Mist, Smoke, Dust	46	0.3	7	39		
	Freezing Rain	43	0.3	2	41		
	Other	99	0.6	38	61		
	Rain	1819	10.8	224	1595		
	Snow	332	2	32	300		
	Strong wind	8	0	0	8		
	Total	**16858**	**100**	**2297**	**14561**		

Factor	Values	Frequency	(%)	Accident class			
				Fatal	Non-fatal	*X2*	*P-value*
Light Condition	Dark	3582	21.2	603	2979	74.704	0.000*
	Dark, artificial	2852	16.9	398	2454		
	Dawn	104	0.6	17	87		
	Dawn, artificial	93	0.6	20	73		
	Daylight	9683	57.4	1181	8502		
	Daylight, artificial	128	0.8	14	114		
	Dusk	226	1.3	41	185		
	Dusk, artificial	184	1.1	19	165		
	Other	6	0	4	2		
	Total	**16858**	**100**	**2297**	**14561**		
Involvement Type	NA	12	0.1	7	5	187.664	0.000*
	Cyclist	726	4.3	41	685		
	Cyclist Passenger	2	0	0	2		
	Driver	7616	45.2	928	6688		
	Driver - Not Hit	17	0.1	3	14		
	In-Line Skater	5	0	0	5		
	Moped Driver	27	0.2	0	27		
	Motorcycle Driver	607	3.6	76	531		
	Motorcycle Passenger	32	0.2	2	30		
	Other	174	1	40	134		
	Other Property Owner	257	1.5	39	218		
	Passenger	2543	15.1	336	2207		
	Pedestrian	2871	17	512	2359		
	Pedestrian - Not Hit	1	0	0	1		
	Trailer Owner	2	0	0	2		
	Truck Driver	316	1.9	83	233		
	Vehicle Owner	1636	9.7	227	1409		
	Wheelchair	13	0.1	2	11		
	Witness	1	0	1	0		
	Total	**16858**	**100**	**2297**	**14561**		
Severity of Injury	NA	1612	9.6	275	1337	5944.84	0.000*
	Fatal	821	4.9	821	0		
	Major	5667	33.6	98	5569		
	Minimal	1042	6.2	86	956		
	Minor	1311	7.8	218	1093		
	None	6405	38	799	5606		
	Total	**16858**	**100**	**2297**	**14561**		
Classification of Accident	Fatal	2297	13.6				
	Non-Fatal Injury	14561	86.4				
	Total	**16858**	**100**				

Source: Own processing of dataset (Toronto Police Service, 2022)

Over the past decade, Toronto has undergone significant changes in its urban landscape and transportation infrastructure, inevitably influencing the dynamics of road safety resulting in a decreased number of accidents by 2020. The analysis of accidents from 2006 to 2020 unveils crucial insights into the city's evolving traffic patterns and highlights areas of concern.

From improvements in public transportation to changes in commuting behaviors, understanding the trends in accidents is essential. It not only reflects the city's growth but also helps policymakers and authorities implement targeted interventions aimed at promoting a safer and more resilient urban road network. Figure 2 shows a graph illustrating the number of accidents over the years from 2006 to 2020.



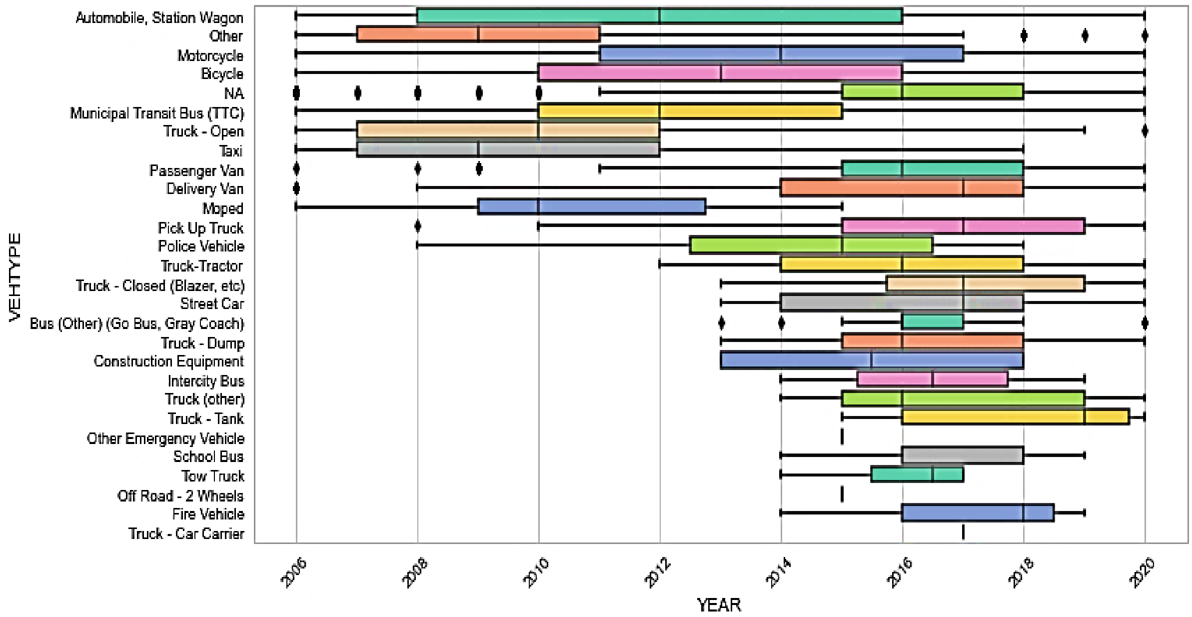
Source: Own processing of dataset (Toronto Police Service, 2022)

Fig. 2: *Accidents over the years 2006-2020*

Based on the vehicle type, accidents over the years demonstrate a huge number of automobiles and station wagons, especially from 2008 to 2016. Motorcycles and bicycles are also associated with road accidents identifying augmented values over the years. Figure 3 illustrates a box plot of accidents based on vehicle types from 2006 to 2020.

In our study, we used specific Machine Learning algorithms chosen for their ability to handle the complexity of road accident prediction. To determine the best combination of hyperparameters for all classifiers, we employed cross-validation along with grid search. This method allows us to optimize model performance by systematically exploring a defined grid of hyperparameter values and assessing each combination using cross-validation.

When comparing different models for a classification task, choosing the right evaluation metric is crucial for accurately assessing the model's performance. While accuracy is commonly used, especially in balanced datasets, it can be misleading in the context of imbalanced datasets. In situations where one class significantly outweighs the others in terms of frequency, a model could achieve high accuracy simply by predicting the majority class for all instances. However, this approach does not reflect the model's ability to correctly identify the minority class, which is often the more critical task in real-world applications.



Source: Own processing of dataset (Toronto Police Service, 2022)

Fig. 3: *Accidents based on vehicle type over the years 2006-2020*

To address this limitation, the F1 score is proposed as a more appropriate metric for evaluating model performance in imbalanced datasets. The F1 score considers both precision and recall, providing a balanced measure of a model's ability to identify positive instances (minority class) while minimizing false positives. Specifically, precision measures the proportion of correctly predicted positive instances out of all predicted positive instances, whereas recall measures the proportion of correctly predicted positive instances out of all actual positive instances.

When evaluating a model, using the F1 score as the main metric allows for a better assessment of the model's effectiveness in capturing true positive instances, especially in imbalanced datasets where identifying the minority class accurately is crucial. This approach ensures a more thorough evaluation of model performance, providing more meaningful insights for practical applications.

We summarized the performance of these algorithms below. Decision Trees are known for their simplicity and interpretability. In our experiments, Decision Trees (max_depth = 5, min_samples_split = 2, min_samples_leaf = 1, criterion = 'entropy') achieved an accuracy of 90.59% with an F1-score of 0.64 (class 0) and 0.95 (class 1), respectively. These results demonstrate the effectiveness of Decision Trees in capturing simple decision boundaries within the data. Random Forest is another technique among ensemble learning techniques.

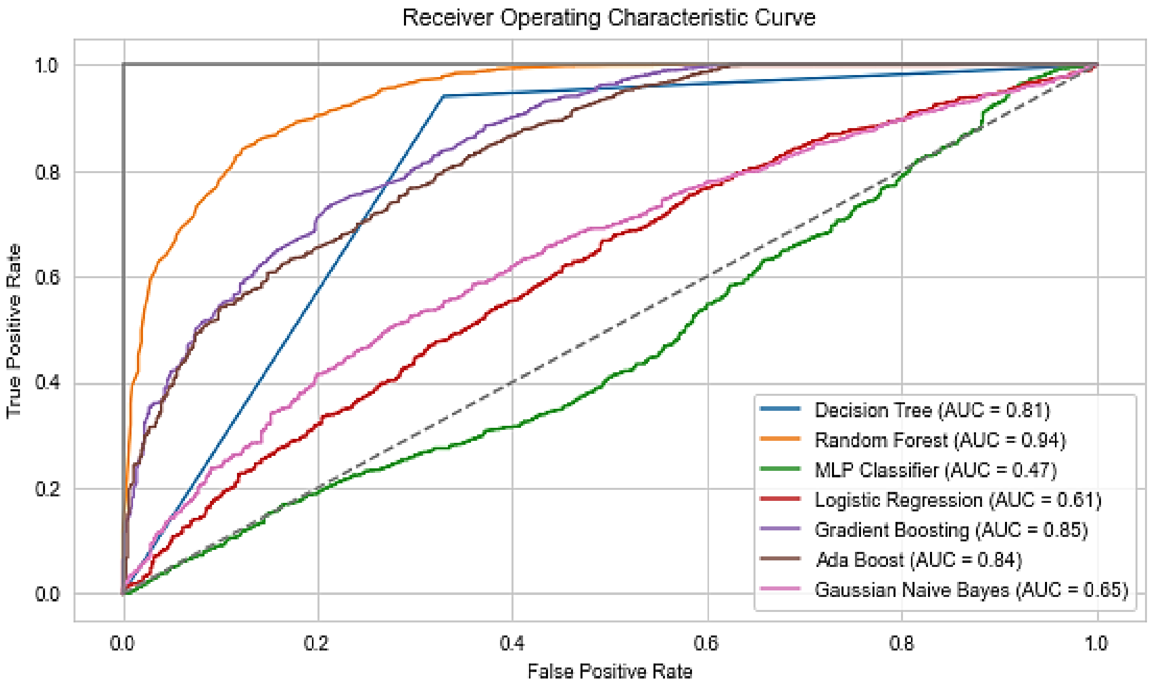
In our experiments, the Random Forest model (n_estimators = 150, max_depth = 20, min_samples_split = 2, min_samples_leaf = 1, max_features = 'sqrt') yielded the highest accuracy with 94.42% and F1-score of 0.72 (class 0) and 0.97 (class 1), respectively. These results suggest that Random Forests are more suitable, contributing to their predictive power. GBoost (Gradient Boosting) algorithm (n_estimators = 100, learning_rate = 0.1, max_depth = 5, subsample = 0.8), is renowned for its high predictive accuracy. In our experiments, GBoost and Ada Boost (n_estimators = 50, learning_rate = 1.0) demonstrated an accuracy of 92% and F1-score of 0.55 (class 0) and 0.96 (class 1) respectively. These results establish GBoost as a robust choice for accident prediction capable of handling complex non-linear relationships in the data. However, MLP (hidden_layer_sizes = (25, 10), activation = 'tanh', alpha = 0.0001, solver = 'adam'), Logistic Regression (max_iter = 100) and Gaussian Naïve Bayes models achieved the lowest accuracies of 87.13%, 87.50% 86.12%, and F1-scores about 0.05 (class 0) and 0.93 (class 1) respectively. Results are collected in Table 2.

Tab. 2: *Classification models' evaluation*

Model	Accuracy	Class	precision	recall	F1-score
Decision Tree	90.59%	0	0.62	0.66	0.64
		1	0.95	0.94	0.95
Random Forest	94.42%	0	0.97	0.57	0.72
		1	0.94	1.00	0.97
MLP Classifier	87.35%	0	0.52	0.02	0.03
		1	0.87	1.00	0.93
Logistic Regression	87.50%	0	0.00	0.00	0.00
		1	0.88	1.00	0.93
Gradient Boosting	92.17%	0	0.99	0.38	0.55
		1	0.92	1.00	0.96
Ada Boost	92.01%	0	0.96	0.38	0.54
		1	0.92	1.00	0.96
Gaussian Naive Bayes	86.12%	0	0.16	0.03	0.05
		1	0.88	0.98	0.93

Source: Own processing of dataset (Toronto Police Service, 2022)

Another evaluation metric is utilized to compare and select the best model, which is the Receiver Operating Characteristic (ROC) curve. It is a graphical representation of a classification model's performance at various thresholds, as illustrated in Figure 4. It shows the trade-off between the true positive rate (sensitivity) and the false positive rate (1 – specificity) as you change the classification threshold.



Source: Own processing of dataset (Toronto Police Service, 2022)

Fig. 4: *Receiver operating characteristic curve of the predictive models*

5.2 Regression Models (Catalonia Dataset)

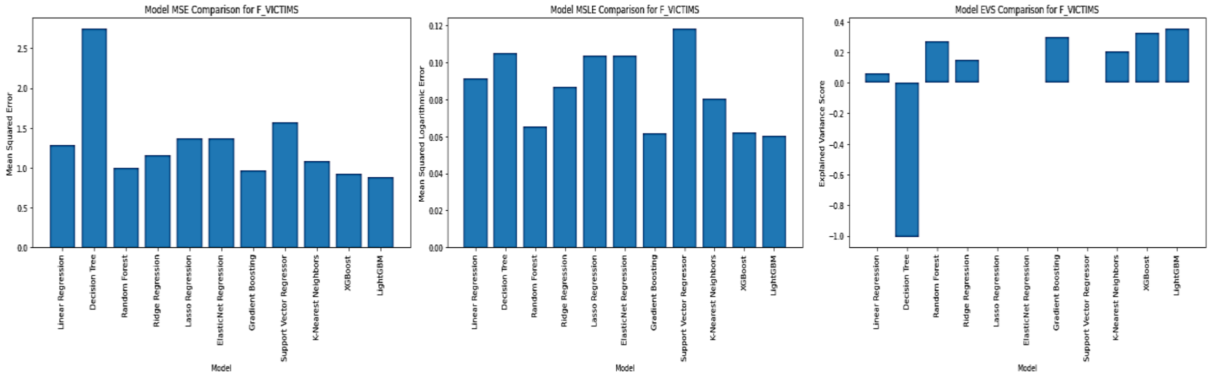
The region of Catalonia has witnessed a high number of road traffic accidents that have resulted in serious consequences for both drivers and pedestrians. Despite numerous countermeasures, such as infrastructure enhancement, increased law enforcement, and public awareness campaigns, road accidents persist as a significant public health concern. Globally, road traffic injuries are a major cause of premature mortality and disability, affecting millions yearly (Rubio-Romero et al., 2013).

In this study, several machine learning models were used to perform a regression task to predict the victims of road crashes. The performance of each of these models was evaluated using three metrics: Mean Squared Error (MSE), Mean Squared Logarithmic Error (MSLE), and Explained Variance Score. The goal in any machine learning task is typically to minimize the error (lower MSE and MSLE values are better) and maximize the amount of variance explained by the model (higher Explained Variance Score is better).

5.2.1 Victims

Linear Regression model recorded MSE of 1.0365, MSLE of 0.0836, and Explained Variance Score of 0.2424. As the first results, they act as a baseline for us to compare the other models. Decision Tree's performance was worse than the Linear Regression model across all metrics, indicating that it was not a suitable model for this particular task. Random Forest performed better than Linear Regression and Decision Tree, with an MSE of 0.9531, MSLE of 0.0668, and an Explained Variance Score of 0.3044. This suggests that an ensemble of decision trees (which is what Random Forest is) is more suited to this task than a single decision tree. The performance of the Ridge Regression model is virtually identical to the Linear Regression model, suggesting that adding L2 regularization (which Ridge Regression does) did not significantly improve performance. Lasso Regression and ElasticNet Regression models apply a form of regularization to the regression model. In these cases, they perform worse than the baseline Linear Regression model, suggesting that the form of regularization they apply (L1 and a combination of L1 and L2) does not benefit this task. The gradient Boosting model performed the best across all the models so far, with an MSE of 0.8740, MSLE of 0.0598, and an Explained Variance Score of 0.3612. This is not surprising as Gradient Boosting is a powerful machine learning model that creates an ensemble of decision trees in a stage-wise fashion, often leading to good performance. Support Vector Regressor performed poorly, with high error metrics and a very low Explained Variance Score. Similarly, the K-Nearest Neighbours model did not perform well on this dataset, with high error metrics and a negative Explained Variance Score, indicating the model was less effective than a simple average. The XGBoost model performed quite well and came in second place after Gradient Boosting. This is expected as both models are based on the same principles of boosting weak learners. The LightGBM model's performance was comparable to that of Gradient Boosting and came in third. Although it is also a gradient-boosting model, it uses a histogram-based algorithm that can be faster and use less memory than other techniques. Considering the ensemble model, the MSE is 1.25, the MSLE is 0.073, and the EVS is 0.087. These results indicate that the model has a relatively high error rate and explains a small portion of the variance in the number of victims. This could be due to various reasons, such as a lack of relevant predictors, noise in the data, or a need for more complex modeling techniques.

Based on these results, the Gradient Boosting model is the best-performing model for the regression task, followed closely by XGBoost and LightGBM. These models seem to capture the underlying structure of the dataset best and make the most accurate predictions of victims. Figure 5 aggregates the model's MSE, MSLE, and EVS Comparison for victims.



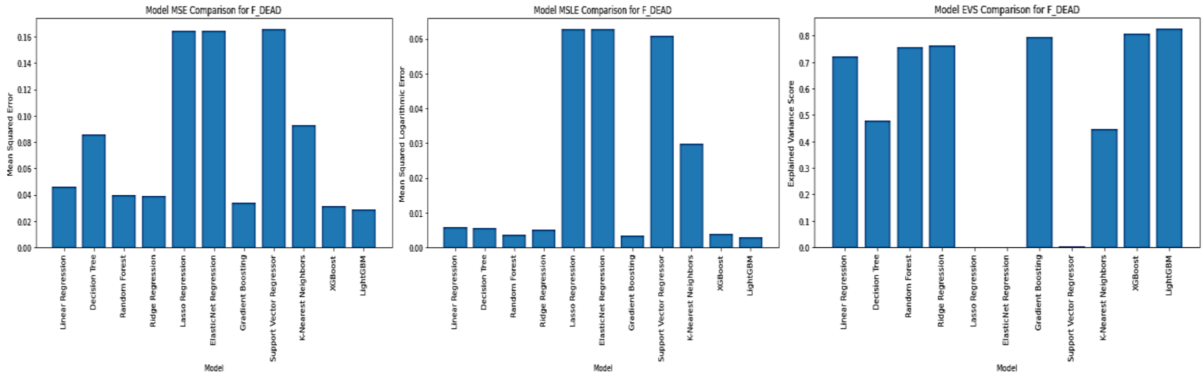
Source: Own processing of dataset (Augé & Navarro, 2022)

Fig. 5: *Models MSE, MSLE, and EVS comparison for victims*

5.2.2 Fatalities

For Linear Regression, MSE of 0.0299, MSLE of 0.0030, and Explained Variance Score of 0.8187. As previously stated, we will utilize these outcomes as a reference point for comparison. The findings indicate that the Decision Tree model has a worse performance than the Linear Regression model in this instance. This suggests that a singular decision tree may be either too uncomplicated or overfitted for this particular task. The Random Forest model is slightly better than the Linear Regression model in terms of MSE and MSLE but slightly worse regarding the Explained Variance Score. This indicates that, as before, an ensemble of decision trees is more suitable for this task than a single decision tree. The performance of Ridge Regression is almost identical to that of the Linear Regression model, which suggests that L2 regularization did not significantly impact the model's performance. Concerning Lasso Regression and ElasticNet Regression models, they have substantially higher MSE and MSLE scores and a drastically lower Explained Variance Score than the baseline. This suggests that L1 regularization (or a combination of L1 and L2 in the case of ElasticNet) is not beneficial for this task. Gradient Boosting has the best performance thus far, with an MSE of 0.0290, MSLE of 0.0029, and Explained Variance Score of 0.8238. This suggests that boosting algorithms, which build an ensemble of weak learners in a stage-wise fashion, are well suited to this task. The Support Vector Regressor performed relatively poorly, with high error scores and a very low Explained Variance Score. The K-Nearest Neighbors model has performed the worst, with the highest error scores and a negative Explained Variance Score. This indicates that it performed worse than a model that predicted the mean of the target variable. The performance of the XGBoost model is good, but not as good as Gradient Boosting. This suggests that, although it is a powerful model, it is not the best choice for this particular task. The LightGBM model has the best performance overall, with an MSE of 0.0285, MSLE of 0.0029, and an Explained Variance Score of 0.8266. This model uses a histogram-based algorithm, which can be faster and use less memory than traditional boosting techniques. In predicting fatalities using ensemble models, the MSE is 0.028, the MSLE is 0.0027, and the EVS is 0.831. These results suggest that the model performs significantly better at predicting fatalities than victims. The EVS is quite high, indicating that the model explains a large portion of the variance in fatalities.

To summarize, the LightGBM model appears to be the best choice for predicting fatalities, followed closely by the Gradient Boosting model and the Random Forest model. The Linear Regression model, which is a simpler model, performs quite well. Figure 6 aggregates the model's MSE, MSLE, and EVS Comparison for fatalities.



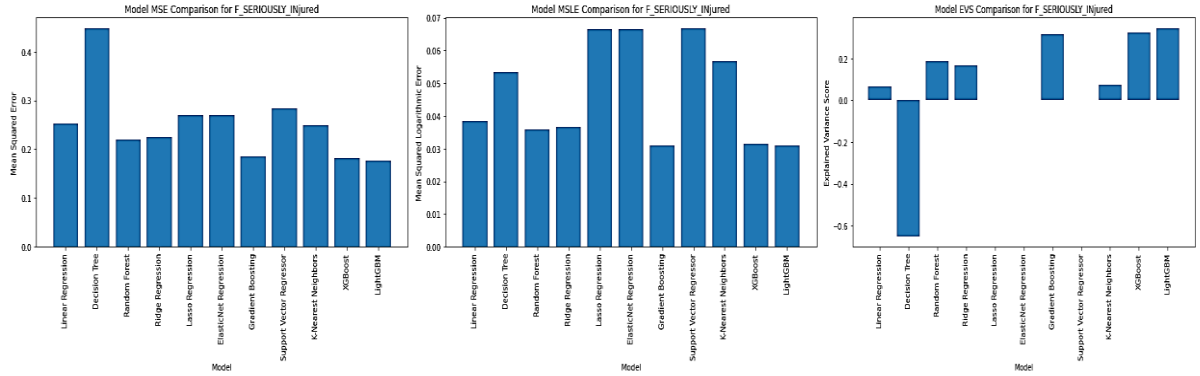
Source: Own processing of dataset (Augé & Navarro, 2022)

Fig. 6: *Models MSE, MSLE, and EVS comparison for fatalities*

5.2.3 Serious Injuries

Linear Regression model MSE, MSLE, and Explained Variance Score for the Linear Regression model are 0.1885, 0.0327, and 0.3025, respectively. As before, we will use these values as the baseline for comparison. The Decision Tree model performed worse than the Linear Regression model, with higher MSE and MSLE and a negative Explained Variance Score. This suggests that, as before, a single decision tree may be overfitting or not complex enough to capture the relationships in the data. The Random Forest model performed better than the Linear Regression model in terms of all three metrics, suggesting that, as with the previous tasks, an ensemble of decision trees is more suitable than a single decision tree. The performance of the Ridge Regression model is nearly identical to that of the Linear Regression model. This indicates that adding L2 regularization did not significantly improve the model's performance. Lasso and ElasticNet Regression models performed significantly worse than the Linear Regression models. This suggests that L1 regularization (or a combination of L1 and L2 for ElasticNet) is not beneficial for this task. Gradient Boosting: The Gradient Boosting model achieved the best performance so far, with an MSE of 0.1722, MSLE of 0.0291, and Explained Variance Score of 0.3628. This indicates that boosting algorithms, which iteratively train models on the residuals of previous models, are well suited to this task. The Support Vector Regressor performed relatively poorly, with high error scores and a very low Explained Variance Score. According to the results, the K-Nearest Neighbors model performed worst, indicating that it is not an appropriate model for this task. It had the highest error scores and a negative Explained Variance Score. On the other hand, the XGBoost model performed better than the baseline Linear Regression model but worse than the Gradient Boosting model. This suggests that it is a reasonable choice for this task, although there may be better models available. The LightGBM model performed well, with MSE of 0.1777, MSLE of 0.0305, and Explained Variance Score of 0.3425. This shows that it is a competitive choice for this task, although it did not outperform the Gradient Boosting model. When predicting serious injuries using ensemble models, the results obtained are: the MSE is 0.184, the MSLE is 0.031, and the EVS is 0.318. These results indicate that the model's performance in predicting seriously injured cases is moderate. The relatively low EVS suggests that there is still room for improvement.

In conclusion, the Gradient Boosting model is the best choice for predicting serious injuries, followed by the LightGBM and Random Forest models. The Linear Regression model also performed decently, suggesting it could be used as a simpler alternative. Figure 7 aggregates the model's MSE, MSLE, and EVS Comparison for serious injuries.



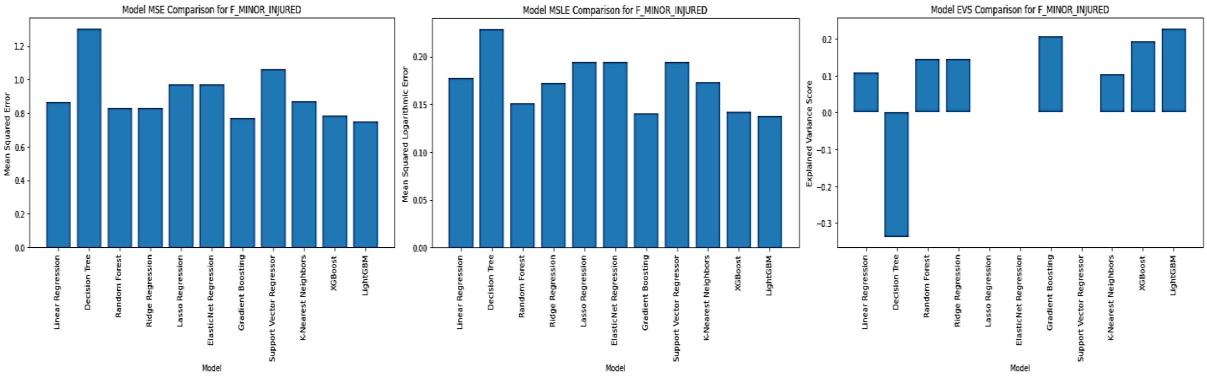
Source: Own processing of dataset (Augé & Navarro, 2022)

Fig. 7: *Models MSE, MSLE, and EVS comparison for serious injuries*

5.2.4 Minor Injuries

Linear Regression MSE, MSLE, and Explained Variance Scores for the Linear Regression model are 0.8035, 0.1671, and 0.1739, respectively. We use these metrics as the baseline for comparison. The Decision Tree model has significantly worse metrics than the Linear Regression model. The Explained Variance Score is even negative, which means the Decision Tree model is a poor choice for this task. According to the metrics, the Random Forest model shows slightly worse performance than the Linear Regression model. It is marginally better than the Decision Tree, suggesting that using multiple trees helps to prevent overfitting. The performance of the Ridge Regression model is nearly identical to the Linear Regression model, implying that L2 regularization does not significantly improve the model's performance for this task. Lasso Regression and ElasticNet Regression models perform worse than the Linear Regression model, suggesting that L1 regularization (or a combination of L1 and L2 for ElasticNet) does not benefit in this scenario. The gradient Boosting model delivers the best performance, with an MSE of 0.7532, MSLE of 0.1389, and Explained Variance Score of 0.2253. This suggests that a boosting model, which iteratively corrects the mistakes of previous models, is well suited for this prediction task. The Support Vector Regressor performs relatively poorly, with high error scores and an almost zero Explained Variance Score. The K-Nearest Neighbors model also performs poorly, with the second highest error scores and a negative Explained Variance Score, indicating that it is unsuitable for this task. The XGBoost model performs worse than the Gradient Boosting model but better than the baseline Linear Regression model. This model may be a reasonable choice, but not the best. The LightGBM model performs slightly worse than the Gradient Boosting model with an MSE of 0.7556, MSLE of 0.1380, and Explained Variance Score of 0.2229. It is still a competitive choice for this task, even though it did not surpass the Gradient Boosting model. The results obtained from predicting minor injuries using ensemble models include the MSE, which is 0.746, MSLE, which is 0.138, and the EVS, which is 0.233. The model's performance in predicting minor injuries is relatively weak, with a higher error rate and lower explained variance compared to other targets.

In conclusion, the Gradient Boosting model is the best choice for predicting minor injuries, followed by the LightGBM and Random Forest models. The Linear Regression model also performed decently, suggesting it could be a simpler alternative. Figure 8 aggregates the model's MSE, MSLE, and EVS Comparison for minor injuries.



Source: Own processing of dataset (Augé & Navarro, 2022)

Fig. 8: *Models MSE, MSLE, and EVS comparison for minor injuries*

These results suggest that the Stacking Regressor model performs differently depending on the target variable. It performs well in predicting fatalities but has more difficulty predicting the number of victims, seriously injured cases, and minor injuries. This could be due to differences in the distributions of these variables or differences in the underlying factors that influence them. It may be beneficial to explore other modeling techniques or feature engineering strategies to improve performance on harder-to-predict targets. Additionally, further model tuning and alternative approaches may be necessary based on these results. Table 3 aggregates Linear Regression, Gradient Boosting, and LightGBM models of MSE, MSLE, and EVS comparison for all categories.

Tab. 3: *Linear Regression, Gradient Boosting, and LightGBM models MSE, MSLE, and EVS comparison for all categories*

	Linear Regression			**Gradient Boosting**			**LightGBM**		
	MSE	**EVS**	**MSLE**	**MSE**	**EVS**	**MSLE**	**MSE**	**EVS**	**MSLE**
Victims	1.0365	0.2424	0.0836	0.8740	0.3612	0.0598	0.900	0.380	0.060
Fatalities	0.0299	0.8187	0.003	0.029	0.8238	0.0029	0.0285	0.8266	0.0029
Serious Injuries	0.1885	0.3025	0.0327	0.1722	0.3628	0.0291	0.1777	0.3425	0.0305
Minor Injuries	0.8035	0.1739	0.1671	0.7532	0.2253	0.1389	0.7556	0.2229	0.1380

Source: Own processing of dataset (Augé & Navarro, 2022)

Considering the significant differences in outcomes among the various target variables, it might be advantageous to create individualized models for each target variable instead of using a universal model. This technique could enable each model to better capture the distinct patterns and trends associated with each target variable.

6 Discussion

After reviewing a body of literature, it is clear that road crashes are still a major public safety issue, despite various efforts to solve them. The studies we reviewed used a variety of methodologies, from statistical to machine learning models, which reflects the complex and multifaceted nature of the problem.

The application of Artificial Neural Networks (ANNs) in predicting crash severity outcomes, as demonstrated in the studies by Delen et al. (2006) and Moghaddam et al. (2011), illustrates the potential of machine learning in this context. These studies highlight the complex, non-linear relationships between various crash-related parameters and the severity of injuries sustained (Delen et al., 2006; Moghaddam et al., 2011). Other studies have utilized different machine learning models, each with strengths and weaknesses. Alkheder et al. (2017) demonstrated that an ANN model could predict accident severity with reasonable accuracy, while Kunt et al. (2012) used a multi-layer perceptron (MLP) structure in a genetic algorithm to predict automobile accidents (Alkheder et al., 2017; Kunt et al., 2011). On the other hand, Hashmienejad and Hasheminejad (2017) proposed a novel rule-based approach that outperformed conventional classification techniques, such as ANN, SVM, and standard decision trees (Hashmienejad & Hasheminejad, 2017). In the recent study of Bridgelall and Tolliver, machine learning and natural language processing are utilized for railroad accident analysis. They found that management decisions, planning, and policies to minimize the risk of human-caused accidents are reasons for accidents (Bridgelall & Tolliver, 2024).

Statistical models, such as binary logistic regression, have also been employed to analyze the association between crash severity and factors like driver attributes, environmental conditions, and highway geometries (Moriano et al., 2024). However, these models may have limitations, particularly when dealing with multi-class outcomes or when the relationships between variables are non-linear. In contrast to the more traditional approaches, this study seeks to leverage various machine learning models. Notably, the authors include the Random Forest (RF) model, which has been employed successfully in multiple domains and has shown promising results (Gatera et al., 2023; Kang & Ryu, 2019; Yokoyama & Yamaguchi, 2020). By doing so, the authors aim to extend the existing body of knowledge and provide a more comprehensive and nuanced understanding of road crash severity predictors.

The study provides valuable insights into the performance of different machine learning algorithms in predicting road accidents based on two datasets. The analysis highlights several noteworthy observations and considerations. Each algorithm exhibits unique strengths and weaknesses. Decision Trees offer interpretability but may struggle with complex relationships, while Random Forests excel in capturing temporal patterns but may require substantial data. GBoost demonstrates high accuracy but demands careful tuning. The choice of the algorithm should align with the specific objectives and constraints of road safety applications.

Understanding feature importance is crucial for road accident prevention efforts. Feature importance analysis reveals which attributes (e.g., weather conditions, road type) have the most significant impact on accident prediction. This knowledge can inform targeted safety interventions and policy decisions. Integrating sentiment analysis applications used recently in deep learning could reduce road accidents.

The ability of these models to generalize to different geographic regions and periods is of paramount importance. The models developed in this research could potentially be integrated into real-time traffic management systems, allowing for timely accident prediction and prevention. However, this requires addressing challenges related to data latency and model deployment. The insights gained from this study have substantial policy implications. Accurate accident prediction can inform proactive safety measures, resource allocation, and emergency response planning, ultimately contributing to reduced accident rates and safer road networks.

Implementing targeted recommendations can significantly diminish the risk of accidents. To achieve this, people must adhere to traffic rules, consistently obeying speed limits, stop signs, traffic lights, and other road signs. Maintain lane discipline, avoiding unauthorized overtaking. Eliminate distractions by refraining from using mobile phones, eating, or engaging in any distracting activities while driving. Never operate a vehicle under the influence of alcohol, drugs, or impairing substances. Ensure a safe following distance, allowing sufficient reaction time in case of sudden stops. Employ seatbelts and child safety seats for all passengers. Exercise vigilance for pedestrians at crosswalks and intersections, yielding the right of way. Watch out for cyclists and motorcyclists, providing ample space on the road. Always use turn signals to communicate intentions. Regularly service and maintain the vehicle to ensure optimal working conditions. Adjust driving behavior during adverse weather conditions, reducing speed and increasing the following distance. Manage fatigue effectively, avoiding excessive tiredness, which impairs reaction time. People must keep calm and eschew aggressive behaviors like road rage. Exercise caution in school zones, especially during pick-up and drop-off times. Plan routes to circumvent heavy traffic or construction zones. Keep an emergency kit in the vehicle stocked with essential items like a first-aid kit, flashlight, and basic tools, and report reckless or unsafe driving to local authorities.

The article highlights the intricacy involved in predicting the severity of road crashes, which calls for a combined effort utilizing various methods and algorithms. Our study emphasizes the potential of machine learning algorithms in predicting road accidents. The results can guide the selection of suitable algorithms and features for improving road safety and preventing accidents.

Conclusion

This research emphasizes the potential of machine learning algorithms as valuable tools for predicting and preventing road accidents. The insights obtained from our experiments contribute to the ongoing efforts to reduce the incidence of road accidents and their associated social, economic, and human costs. As road safety remains a global priority, the intersection of machine learning and traffic safety offers a promising avenue for continued research and innovation. We hope that the findings presented here will inspire further exploration and collaboration in the pursuit of safer roads for everyone.

In this research article, we have explored the application of machine learning algorithms for the predictive modeling of road accidents. Our primary objective was to enhance road safety and reduce accident-related fatalities and injuries. Our study has encompassed a comprehensive analysis of methodologies, data collection, feature engineering, model development, and extensive discussions on the implications of our findings.

Through a meticulous evaluation of several distinct machine learning algorithms for classification tasks, including Decision Trees, Random Forests, GBoost, Logistic Regression, Ada boost, MLP, and Gaussian Naive Bayes, we have discovered that Decision Trees, while easy to understand, may find it difficult to capture complex relationships in accident data. On the other hand, Random Forests, which are good at resolving overfitting problems, have the ability to capture the dynamics of road accidents. Random Forests for classification problems, with their high predictive accuracy, prove to be a reliable option for accident prediction, particularly when dealing with complicated, non-linear data patterns.

This study conducted a thorough evaluation of various regression models to predict the severity of road crashes. The models included several Machine Learning techniques, including single estimator models like Linear Regression and ensemble models like Gradient Boosting and LightGBM. The results indicated the superior performance of ensemble models, particularly Gradient Boosting and LightGBM, in predicting the severity of road crashes.

However, the performance of the models varied across the different outcome variables. Although the ensemble models were successful in predicting fatalities, they were not as effective in predicting the number of victims, seriously injured cases, and minor injuries. This highlights the complexity of the prediction task and suggests that each outcome may have distinct patterns and trends that cannot be entirely captured by a single model.

It is important to note that this study has limitations, particularly when it comes to regression models. This is because the models were evaluated based on a limited set of metrics, and using different evaluation measures may lead to different results. Additionally, it is an ongoing challenge to evaluate the robustness and transferability of models in accident prediction research, which calls for further investigation.

At the end of this article, several recommendations for road accident prevention are suggested. Future research should focus on addressing these limitations. This could involve testing the models considering additional evaluation metrics. Furthermore, developing specialized models for each target variable might better capture the unique patterns associated with each outcome. Lastly, exploring other machine learning techniques or feature engineering strategies might help improve model performance. Despite its limitations, this study offers valuable insights into the utility of machine learning models in predicting road crash severity based on two datasets and provides directions for future research in this area.

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TECHNIKY STROJOVÉHO UČENÍ PRO PŘEDPOVÍDÁNÍ SMRTELNÝCH NEHOD

Zajištění bezpečnosti veřejnosti na našich silnicích je nejvyšší prioritou a výskyt dopravních nehod představuje velký problém. Pokroky v oblasti strojového učení nám naštěstí umožňují využívat data k předvídání a prevenci takových nehod. Naše studie se zabývá vývojem a implementací technik strojového učení pro předpovídání dopravních nehod s využitím bohatých souborů dat z Katalánska a Toronta Fatal Collision. Náš komplexní výzkum ukazuje, že metody ansámblového učení překonávají ostatní modely ve většině predikčních úloh, zatímco Decision Tree (Rozhodovací strom) a K-NN vykazují slabý výkon. Naše zjištění navíc poukazují na složitost spojenou s předpovídáním různých aspektů nehod, protože stohovací regresor vykazuje variabilitu ve své výkonnosti napříč různými cílovými proměnnými. Naše studie poskytuje cenné poznatky, které mohou významně přispět k probíhajícímu úsilí o snížení nehod a jejich následků tím, že umožní přesnější předpovědi.

MASCHINENGEBUNDENE LERNTECHNIKEN FÜR DIE VORHERSAGE TÖDLICHER UNFÄLLE

Die Sicherstellung der Sicherheit der Öffentlichkeit auf unseren Straßen besitzt die höchste Priorität. Das Auftreten von Verkehrsunfällen stellt ein großes Problem dar. Die Fortschritte auf dem Gebiet des maschinengebundenen Lernens ermöglichen uns glücklicherweise die Nutzung von Daten zur Vorhersage und Prävention solcher Unfälle. Unsere Studie befasst sich mit der Entwicklung und der Implementierung der Technik des maschinengebundenen Lernens zur Vorhersage von Verkehrsunfällen unter Verwendung reichhaltiger Dateien aus Katalonien und der „Toronto Fatal Collision“. Unsere komplexe Untersuchung legt dar, dass die Methoden des Ensemble-Lernens die übrigen Modelle der in der Mehrheit Prädikationsaufgaben überholt haben, wohingegen der „Decision Tree“ (der entscheidende Baum) und das K-NN eine schwache Leistung aufweisen. Unsere Feststellungen verweisen darüber hinaus auf die mit der Vorhersage verschiedener Aspekte von Unfällen verbundene Kompliziertheit, da der Stapelregressor in seiner Leistungsfähigkeit quer durch die verschiedenen Zielwandlungen eine Variabilität aufweist. Unsere Studie zeitigt wertvolle Erkenntnisse, welche in bedeutender Weise zur im Verlauf befindlichen Bestrebung um die Senkung von Unfällen und deren Folgen beitragen, indem sie genauere Vorhersagen ermöglichen.

TECHNIKI UCZENIA MASZYNOWEGO DO PRZEWIDYWANIA ŚMIERTELNYCH WYPADKÓW

Zapewnienie bezpieczeństwa publicznego na naszych drogach jest najwyższym priorytetem, a występowanie wypadków drogowych jest poważnym problemem. Na szczęście postępy w uczeniu maszynowym pozwalają nam wykorzystywać dane do przewidywania takich wypadków i zapobiegania im. Nasze badanie skupia się na opracowaniu i wdrożeniu technik uczenia maszynowego do przewidywania wypadków drogowych przy wykorzystaniu bogatych zbiorów danych z Katalonii i Toronto Fatal Collision. Nasze kompleksowe badania pokazują, że metody grupowania jako technika uczenia maszynowego wyprzedzają inne modele w większości zadań predykcyjnych, podczas gdy Decision Tree (drzewo decyzyjne) i K-NN są słabo wydajne. Ponadto, nasze ustalenia wskazują na złożoność związaną z przewidywaniem różnych aspektów wypadków, ponieważ układanie w stosy ma różną wydajność przy różnych zmiennych docelowych. Nasze badania dostarczają cennej wiedzy, która może znacząco przyczynić się do podejmowanych wysiłków na rzecz zmniejszenia liczby wypadków i ich skutków poprzez umożliwienie dokładniejszych prognoz.

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