Reasons for using Smart Cars and its effects, ethical issues, on our lives

Based on accidents datasets from UK official reports
and last essays about IoT, AI, Smart Cars, and ethical issues related to them.

School of Computing, Engineering and Digital Technologies

Module: Artificial Intelligence Ethics and Applications

Author Name: Keyhan Azarjoo

Email: keyhanazarjoo@gmail.com

Abstract

The number of people, cars, and drivers has risen over the previous century, and driving has become too crucial in our lives. Software and hardware technology, on the other hand, is advancing, and all businesses are attempting to computerize their processes and products. This computerization has both advantages and disadvantages that have a significant impact on our lives. In this research, we examine data from car accidents in the United Kingdom over the last 16 years, demonstrating how situation was a contributing factor in these accidents. Although the accident rate in the UK is decreasing, this is owing to better road conditions. However, if autonomous vehicles are deployed in the future, this number will plummet even further. We used regression algorithms for analysing the number of accidents. Human error has always been a major factor in traffic accidents, and by incorporating AI into automobiles, we may live a safer life and lower accident number. However, adopting technology like AI and IoT has significant ethical concerns, which are discussed in this research paper.

Contents:

Introduction

While the global number of accidents is increasing, this number in the UK is decreasing annually. According to the government claim, roadways are becoming far safer, and this is the most reason for this reduction. By using smart cars, this figure reduces too more.

Intelligence automobiles can be classified into two categories: self-driving and connected cars and they can be in different autonomous levels (figure 0) [18, 19].

Computerizing cars brings this opportunity for attackers or companies to attack or misuse your information.

In this research paper, we analyzed a dataset related to car accidents and show how smart cars can decrease the number of accidents and what is the ethical issues related to this usage.

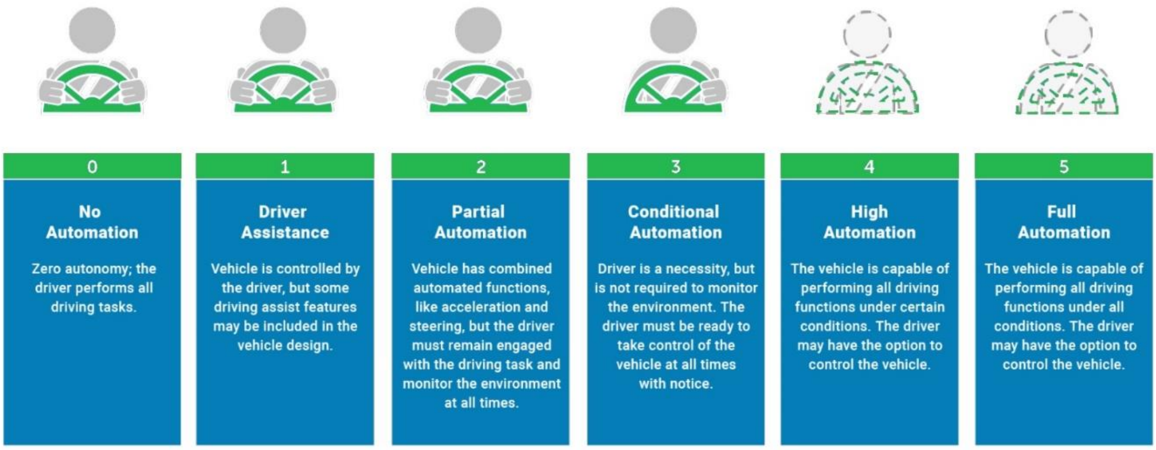

Figure 0. Vehicle automation levels [12]

Literature review

The world's population is aging [3], while in [4] we can see that the number of driving licenses has increased over the last ten years.

According to the World Health Organization (WHO), traffic accident injuries are the leading cause of death worldwide [1], and some factors such as the driver's mental and physical state, as well as environmental conditions, are the primary causes [2].

On the other hand, artificial intelligence, and Machine learning (ML) have surpassed human intelligence in many areas. Examples include AI's stunning victory over humans in Go [5], and chess [6].

Driving a car is the single most risky action that people do regularly and willingly. Because a large portion of the risk connected with driving may be linked to the human aspect, such as drunk driving, poor vision, and so on, it becomes clear why precautions must be taken like using AI. Self-driving automobiles are thought to be safer than those driven by humans. Although many people are hesitant to give up control of their vehicles [9] current research suggests that autonomous vehicles will considerably enhance traffic flow and have the potential to reduce traffic accidents, especially those caused by irresponsible human behaviour [10].

Artificial intelligence and the Internet of Things (IoT) have exploded in popularity in recent years, particularly in the smart car sector [12].

According to [14] there were 5 billion connected objects in 2013 and up to 50 billion by 2020 in the IoT sector.

Contradictorily, as smart cars become more automated, new opportunities for cyber-attacks emerge, including in-vehicle assaults such as hijacking and vehicle-to-vehicle communication attacks such as data theft [15] and as technology advances, ethical considerations increase too.

Research Questions

Why should we employ artificial intelligence in our automobiles?

What are the ethical implications of deploying AI in automobiles?

Methodology

According to the UK government, downloaded dataset, there were 208,643 accidents registered in the UK in 2019 and 2020 and 2,378,534 in the previous 16 years [16]. Speed, weather conditions, driver age, and other factors all have a role in accidents. As a result, data analysis is difficult in this topic [17]. To answer this problem, we first filter out some elements so that we can visualize them properly in two dimensions, and then we analyze the data using different regression models and then we displayed the results. In this research, we used Jupiter lab, Python, for analyzing data.

Sampling

The United Kingdom website is one of the reliable databases that published much information about accidents and their conditions. In this research, we use a dataset related to a car accident in the UK, downloaded from [16].

However, as this topic is new, there are not enough datasets related to smart cars in practical. But academically, researchers published many papers related to this field.

This dataset reveals how many accidents happened and what was the reasons.

Experiment and Methods

In this paper, we used the Quantitative method and we analyzed data about accidents in the UK by python programming language. First, we virtualized data to have a better understanding of data and we separated reasons for accidents, we use different Algorithms like linear and Ridge regression, for analyzing figures. Then, the reasons for accidents have been discussed in different views and we checked how human faults were caused accidents and how these weaknesses can be fixed by using artificial intelligence in smart vehicles. When we were checking these reasons, we find that most of those accidents could be prevented if we used autonomous vehicles. However, the number of accidents in the UK is decreasing by becoming roads safer, But by using smart cars, this number reduces too more. In the second part, the effects of using smart cars in accident reduction have been researched and the ethical issues related to them have been discussed.

Dataset

Based on the UK government [16], this dataset has been provided. The filters related to preparing the dataset areas are below and in figure 1.

Dataset: Accidents

Severities (accidents): Fatal, Serious, Slight

Years: 2005 to 2020

Geography: Great Britain countries regions

Additional fields: Speed limit, Light condition, Weather condition, Carriageway hazards

```
accidents_df
```

	Accident year	Accident severity	Speed limit	Light condition	Weather condition	Carriageway hazards	Accidents	Adjusted serious	Adjusted slight
0	2005	Fatal	1-20 mph	Daylight	Fine no high winds	None	5	NaN	NaN
1	2005	Fatal	1-20 mph	Daylight	Other	None	1	NaN	NaN
2	2005	Fatal	1-20 mph	Darkness - lights lit	Fine no high winds	None	2	NaN	NaN
3	2005	Fatal	21-30 mph	Daylight	Unknown	None	8	NaN	NaN
4	2005	Fatal	21-30 mph	Daylight	Fine no high winds	None	473	NaN	NaN
...	...	...	...	...	...	...	...	...	...
16904	2020	Slight	Motorway	Darkness - lighting unknown	Fine no high winds	Other object on road	1	0.012649	0.987351
16905	2020	Slight	Motorway	Darkness - lighting unknown	Raining no high winds	None	10	0.021170	9.978830
16906	2020	Slight	Motorway	Darkness - lighting unknown	Raining + high winds	None	3	0.003871	2.996129
16907	2020	Slight	Motorway	Darkness - lighting unknown	Fog or mist	None	1	0.012512	0.987488
16908	2020	Slight	Motorway	Darkness - lighting unknown	Other	None	2	0.009878	1.990122

16909 rows × 9 columns

Figure 1

Analysis Data

Data virtualizing

To have a better understanding of the Data, we virtualized these figures separately and gave a summary of these data by their categories To calculate the number of accidents, we should count the number of accidents using the code in figure 3 (for each parameter).

```
[116]: accidents_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16909 entries, 0 to 16908
Data columns (total 9 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Year                 16909 non-null  int64
 1   Severity             16909 non-null  object
 2   Speed_limit          16909 non-null  object
 3   Light_condition      16909 non-null  object
 4   Weather_condition    16909 non-null  object
 5   Carriageway_hazards  16909 non-null  object
 6   Accidents            16909 non-null  int64
 7   Adjusted serious     14615 non-null  float64
 8   Adjusted slight      14615 non-null  float64
dtypes: float64(2), int64(2), object(5)
memory usage: 1.2+ MB
```

Figure 2

SEVERITY: As you can see in figure 3, the most significant number in the severity column is for slight accidents, however, 31,089 people in the UK have died because of these accidents.

```
[251]: Severity_df = accidents_df.Severity.value_counts()
       Index_Array = Severity_df.index.to_numpy()
       Count_array = []
       Type_array = []
       for x in Index_Array:
           count = accidents_df.loc[accidents_df['Severity'] == x].Accidents.sum()
           Count_array.append(count)
           Type_array.append(x)
       my_df = pd.DataFrame({'Type': Type_array, 'Count': Count_array})
       my_df
```

[251]:

	Type	Count
0	Slight	1997365
1	Serious	350080
2	Fatal	31089

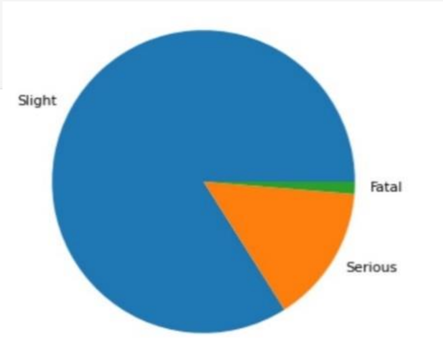

Figure 3

LIGHT: By a glance at the data, it's obvious that almost three-fourths of accidents happened in daylight and one-fort of them were in different circumstances at night.

```
[271]: Light_array = accidents_df.Light_condition.value_counts()
       Index_Array = Light_array.index.to_numpy()
       Count_array = []
       Type_array = []
       for x in Index_Array:
           count = accidents_df.loc[accidents_df['Light_condition'] == x].Accidents.sum()
           Count_array.append(count)
           Type_array.append(x)

       my_df = pd.DataFrame({'Type': Type_array,
                             'Count': Count_array})
       my_df
```

[271]:

	Type	Count
0	Daylight	1732459
1	Darkness - lights lit	472309
2	Darkness - no lighting	129690
3	Darkness - lighting unknown	31656
4	Darkness - lights unlit	12404
5	Unknown	16

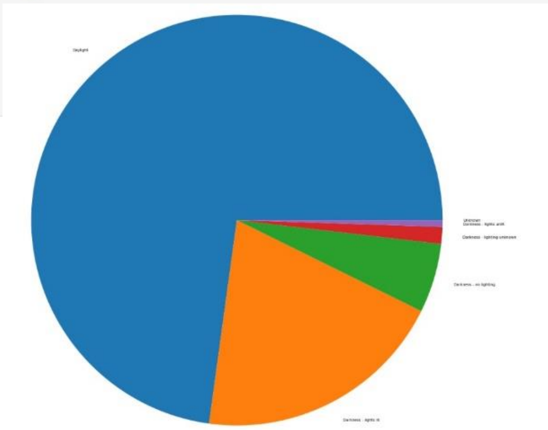

Figure 4

WEATHER: Furthermore, when we compared the weather conditions in reported accidents, we found that approximately four-fifths of accidents were in good weather conditions with no high winds while the other 8 weather conditions were about only one-fifth (Figure 5), and it shows that weather condition was not an important part of accidents.

```python
[273]: Weather_array = accidents_df.Weather_condition.value_counts()
Index_Array = Weather_array.index.to_numpy()
Count_array = []
Type_array = []
for x in Index_Array:
    count = accidents_df.loc[accidents_df['Weather_condition'] == x].Accidents.sum()
    Count_array.append(count)
    Type_array.append(x)

my_df = pd.DataFrame({'Type': Type_array,
                      'Count': Count_array})
my_df
```

[273]:

	Type	Count
0	Fine no high winds	1902298
1	Raining no high winds	278932
2	Other	52354
3	Raining + high winds	32715
4	Unknown	52234
5	Fine + high winds	29581
6	Fog or mist	12420
7	Snowing no high winds	14999
8	Snowing + high winds	3001

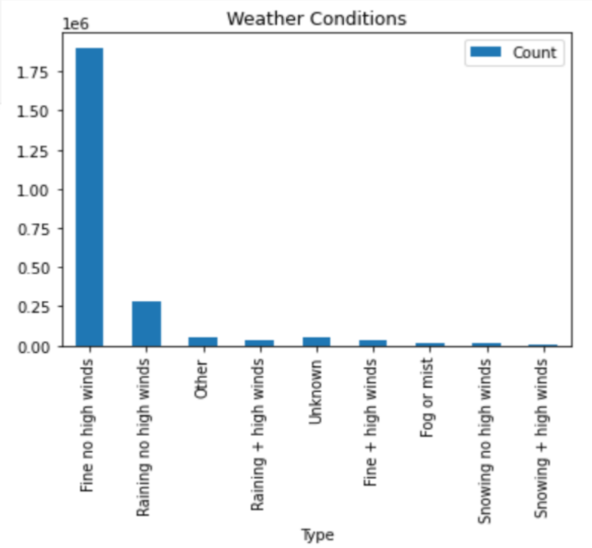

Figure 5

Speed: Less than %65 accidents were happened when the speed limit was between 21 and 30 mph (Figure 6) and almost %90 of these accidents were without any Carriageway hazards (Figure 7).

	Speed	Count
0	21-30 mph	1499773
1	51-60 mph	356976
2	31-40 mph	195150
3	61-70 mph	81255
4	Motorway	94837
5	41-50 mph	78492
6	1-20 mph	72013
7	Unknown	38

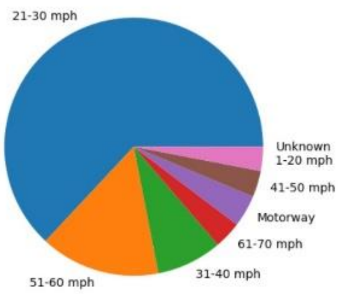

Figure 6

	Carriageway_hazards	Count
0	None	2328661
1	Other object on road	19291
2	Any animal in carriageway (except ridden horse)	11455
3	Previous accident	3674
4	Vehicle load on road	3136
5	Pedestrian in carriageway - not injured	5300
6	Unknown	7017

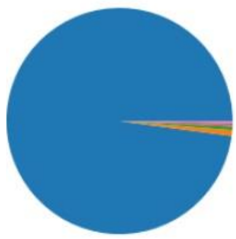

Figure 7

Quantitative approach

For showing the rate of accidents during the given period, we use a linear graph (Figure 8). As you can see the number of accidents has a slight reduction and decreased from just under 200,000 in 2005 to approximately 90,000 in 2020.

	Year	Count
0	2005	198735
1	2006	189161
2	2007	182115
3	2008	170591
4	2009	163554
5	2010	154414
6	2011	151474
7	2012	145571
8	2013	138660
9	2014	146322
10	2015	140056
11	2016	136621
12	2017	129982
13	2018	122635
14	2019	117456
15	2020	91187

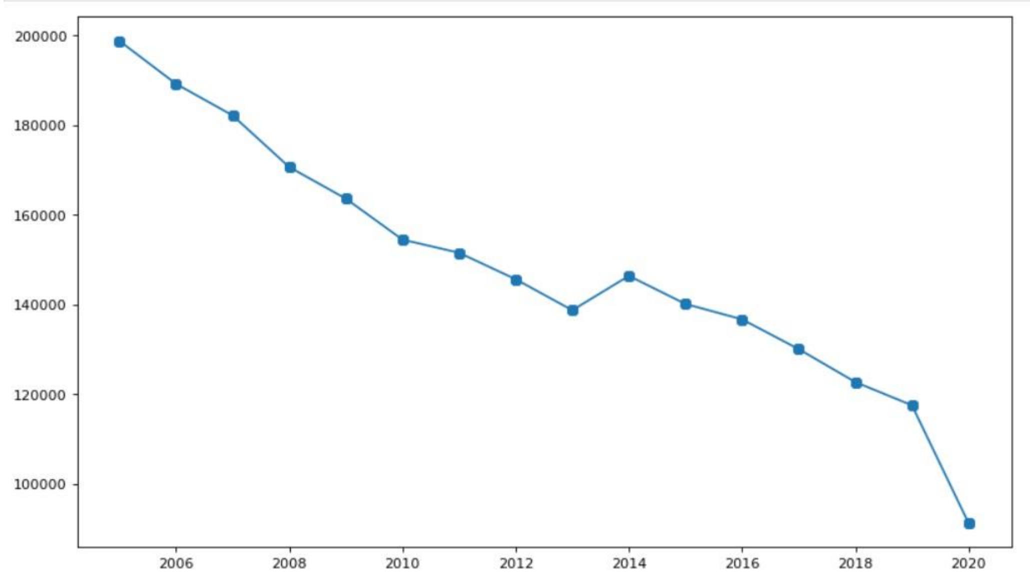

Figure 8

For having a good result, as in the given data, the number of accidents is varied based on the circumstance, we decide to use each accident in a unique row and use only two-parameter, Year and count of accident, in this step.

First, we convert the object types in (figure 2) to integers and convert all values from string to int. Then, we deleted adjusted serious and adjusted slight as they are useless here.

In (figure 9) you can see the Pearson coefficient and correlation for the Year. It shows a negative corr elation between these two parameters.
For better training and predicting data, we normalized them, between 0 and 1, and then we train data by different linear algorithms.

```
pearson_coefficent , _ = pearsonr(my_df.Year, my_df.Count)
pearson_coefficent
```

-0.9667706354453498

```
corr = my_df.corr()
corr
```

	Year	Count
Year	1.000000	-0.966771
Count	-0.966771	1.000000

```
sb.heatmap(corr, xticklabels=my_df.columns, yticklabels = my_df.columns)
plt.show()
```

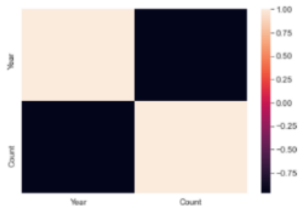

Figure 9

mean	148658.375000	→	mean	0.534379
std	27866.202796		std	0.259105
min	91187.000000		min	0.000000
25%	134961.250000		25%	0.407021
50%	145946.500000		50%	0.509163
75%	165313.250000		75%	0.689239
max	198735.000000		max	1.000000

Figure 10

By using linear regression, a line has been drowning for showing the best line for prediction (Figure 11). After training, some samples have been given to the models and the prediction accuracy can be seen in (figure 12). Based on linear regression and by using the Sklearn metrics library for calculating the mean score error for the prediction, the result for the MSE for real accidents and predicted accidents is 0.0086 (Figure 13), and by using a cross-validation score with cv=3, the result is as shown in figure 14.

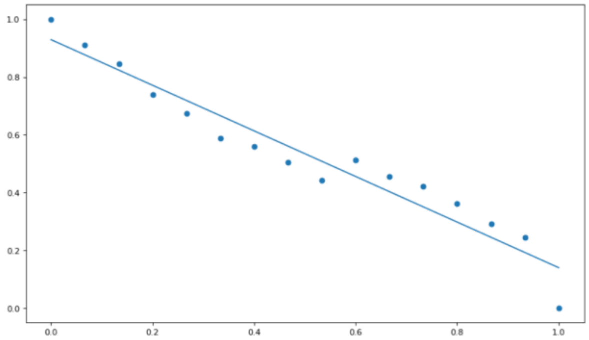

Figure 11

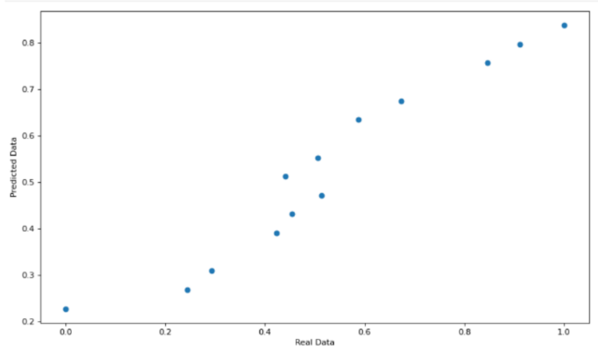

Figure 12

```
mse = metrics.mean_squared_error(y_test, y_pred)
mse
```

```
0.008633251315655953
```

Figure 13

```
cv_scores = cross_val_score(reg, x, y, cv=3)
cv_scores
```

```
array([ 0.81466742, -0.90063936,  0.59692966])
```

```
np.mean(cv_scores)
```

```
0.17031923927536588
```

Figure 14

We use the Ridge model with different alpha between 0.1 and 1 and the result of the mean squared error, or each alpha is shown in (Figure 15). As you can see in Figures, by increasing the alpha, a mean square error will increase. When we put 1 as alpha the mean square error will be 0.018 but by putting 0.1 as alpha, we can see that the MSE is in the best situation. However, we used a cross-validation score with CV = 2 and the mean of scores became 0.0433 while when we put different numbers in CV, the result was different.

```
mse_array = []
_alpha = 0.1
for i in range(10):
    ridge = Ridge(alpha = _alpha, normalize = True)
    ridge.fit(x, y)
    ridge_pred = ridge.predict(x)
    mse = metrics.mean_squared_error(y, ridge_pred)
    mse_array.append(mse)
    _alpha += 0.1
mse_array
```

```
[0.004599536561523161,
 0.005747426217161396,
 0.007246115426454472,
 0.008915491425219382,
 0.010649590275945852,
 0.01238577338009868,
 0.014087324702406008,
 0.015733315966537147,
 0.017312550104690745,
 0.018819863707253276]
```

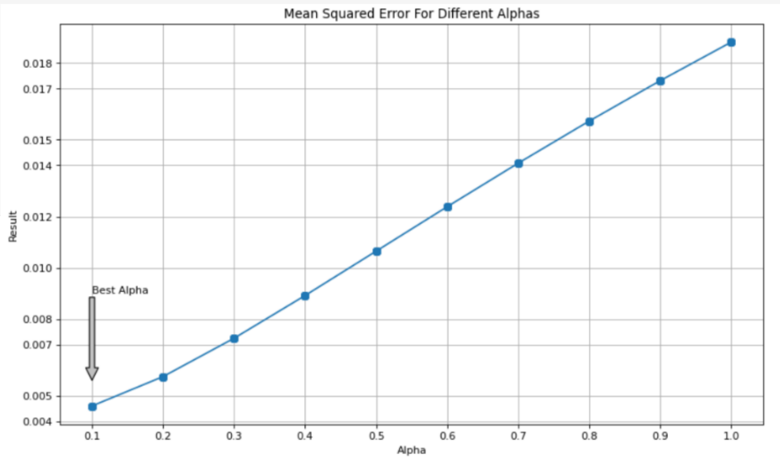

Figure 15

In conclusion, although based on analyses, the number of accidents is decreasing and we do not have any feature related to type of human error, but by using AI in cars, all human errors will be eliminated and only computer errors and environmental situation will be the reason of accidents, the reasons are explained in evaluation part. However, these numbers will reduce by each step of growing in the computer area.

Evaluation and discussion

How do smart cars affect our life and the number of accidents?

According to [20], traffic accidents are caused by four categories of human faults. (1) Practical errors that occur just before an accident, (2) error recovery methods in the case of close errors, (3) Thought processes that lead to an action error, and (4) the underlying causes. As you can see in photos 2 to 7 and in the other papers, human error and environment were always two of the major causes of accidents. Most such incidents would never happen if people could respond as quickly as they can and make decisions in the shortest period possible.

By using smart cars, cameras can see and recognize objects better than human eyes and they can check accidents circumstance on the roads online or using a vehicle to vehicle connections.

Computers can process vast amounts of data far faster and more accurately than humans. Computers can foresee different situations and act based on them, leading to the prevention of accidents and superior performance.

Furthermore, if we employ completely automated cars (Figure 0), a driver's license is not required, anyone can use cars including people with physical or mental problems, inebriated people, or children. Smart vehicles can rotate and determine the optimum route for traveling by using the cloud and various APIs such as google maps or police records.

They can assess your health status and alert you if there is a problem related to your health or call polices or hospitals to keep you safe in a dangerous circumstance.

Other points are reduction in the number of policies, and road signs as well as reducing the number of cars by using the car-sharing schedule.

As we can see, by using these technologies, not only the number of accidents caused by human mistakes well be reduced to 0, but also it will bring more comfortabilities rather than before.

Ethical Issues

System vulnerability and potential attack

By becoming vehicles more computerized, the number of attacks will increase [21] and due to the rising usage of smartphones, cyber-attacks have recently grown in popularity [22]. Furthermore, billions of users rely on biometric sensors for security, and they are gradually but steadily replacing traditional password authentication methods. Biometrics are frequently used to unlock devices [23].

As these technologies are used in cars. They can be hacked because they are digital so companies should be more secure than pass.

The leakage of sensitive personal information by car producers

Consumers' digital footprints are a useful resource for the digital advertising sector. Consumers' digital footprints are tracked by first- and third-party data collectors to predict their wants and expectations based on their online activity and deliver personalized information and targeted advertising to them. Pervasive personal data gathering, on the other hand, leads to privacy infractions [25]. Therefore, people should improve their digital skills for avoiding this kind of misuse and companies should take care of their customers information more.

Bugs in algorithm

Bugs are one of the most common types of programming errors [26]. They can lead to sensitive data leaks or memory corruption, as well as more serious consequences like arbitrary code execution. In practice, bugs crop up frequently in a variety of software projects [27]. This existence of some faults in smart car algorithms may lead to failures, which may result in passenger fatality.

Companies should test their code in different circumstances for preventing these faults.

Conclusion

As the population and number of cars grow, the frequency of accidents rises at an alarming rate. However, this figure is decreasing in the United Kingdom and the reason is improvement in road safety.

Furthermore, technology is advancing and creating several opportunities for businesses to manufacture cutting-edge equipment. Automobile manufacturers are attempting to use modern technology such as AI, and IoT in their cars.

We checked how human errors can cause accidents and found that most of those accidents could be prevented by using AI. As in smart cars, everything is faster, more accurate, more flexible, and more reliable, they can protect human lives even better than ourselves. Decrease in the number of accidents means decrease in the number of death and cost.

If we use these kinds of cars in the future, the errors for accidents will be unrelated to human mistakes.

However, they may be problematic due to several ethical concerns. To avoid these issues, car producers have a significant role.

References

1. World Health Organization. Global status report on road safety 2018. Accessed June 30, 2020.
2. Hiroyasu, T., Tanioka, K., Uraki, D., Hiwa, S. and Furutani, H., 2022. Analyzing the relationship between distracted driving and eye movement using multimodal data collected during car driving. *bioRxiv*, pp.2021-12.
3. .Amin, S., 2020. Backpropagation–Artificial Neural Network (BP-ANN): Understanding gender characteristics of older driver accidents in West Midlands of United Kingdom. *Safety science*, *122*, p.104539.
4. Aljaban, M., 2021. Analysis of Car Accidents Causes in the USA.
5. Koch, C., 2016. How the computer beat the go player. *Scientific American Mind*, *27*(4), pp.20-23.
6. Hsu, F.H., 2002. *Behind Deep Blue: Building the computer that defeated the world chess champion*. Princeton University Press.
7. Sungheetha, A. and Sharma, R., 2020. Transcapsule model for sentiment classification. *Journal of Artificial Intelligence*, *2*(03), pp.163-169.
8. Bajariya, A. and Jaiminee, J.P., 2022, February. A Review on Text Supervised Learning Methods for Classification of IT Ticket and Bugs. In *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)* (pp. 903-907). IEEE.
9. Das, D., Banerjee, S. and Biswas, U., 2021. A secure vehicle theft detection framework using Blockchain and smart contract. *Peer-to-Peer Networking and Applications*, *14*(2), pp.672-686.
10. Oham, C., Michelin, R.A., Jurdak, R., Kanhere, S.S. and Jha, S., 2021. B-FERL: Blockchain based framework for securing smart vehicles. *Information Processing & Management*, *58*(1), p.102426.
11. Donthi, S.R., Sandeep, V., Reddy, M.G., Bhatt, M., Kumar, H.S. and Jayanth, D., 2022. Self-Driving Car Using Image Processing and Deep Learning. *International Journal of Research in Engineering, Science and Management*, *5*(1), pp.270-277.
12. Arena, F., Pau, G. and Severino, A., 2020. An overview on the current status and future perspectives of smart cars. *Infrastructures*, *5*(7), p.53.
13. Singleton, W.T., 1982. Accidents and the progress of technology. *Journal of Occupational Accidents*, *4*(2-4), pp.91-102.

14. Chase, J., 2013. The evolution of the internet of things. *Texas Instruments*, *1*(1388), pp.1-7.
15. Dibaei, M., Zheng, X., Jiang, K., Abbas, R., Liu, S., Zhang, Y., Xiang, Y. and Yu, S., 2020. Attacks and defences on intelligent connected vehicles: A survey. *Digital Communications and Networks*, *6*(4), pp.399-421.
16. https://roadtraffic.dft.gov.uk/custom-downloads/road-accidents/reports/1c009b98-0aa1-4297-bf9b-a4c29f567c65
17. Tyagi, A., Kumar, A., Gandhi, A. and Mueller, K., 2019. Road accidents in the uk (analysis and visualization). *arXiv preprint arXiv:1908.02122*.
18. Arena, F. and Ticali, D., 2018, November. The development of autonomous driving vehicles in tomorrow’s smart cities mobility. In *AIP Conference Proceedings* (Vol. 2040, No. 1, p. 140007). AIP Publishing LLC.
19. Inkoom, S., Sobanjo, J. and Chicken, E., 2020. Competing risks models for the assessment of intelligent transportation systems devices: A case study for connected and autonomous vehicle applications. *Infrastructures*, *5*(3), p.30.
20. Gordon, R., Flin, R. and Mearns, K., 2005. Designing and evaluating a human factors investigation tool (HFIT) for accident analysis. *Safety science*, *43*(3), pp.147-171.
21. Currie, R., 2015. Developments in car hacking. *SANS Institute*.
22. Kang, A., Dong Lee, J., Kang, W.M., Barolli, L. and Park, J.H., 2014. Security considerations for smart phone smishing attacks. In *Advances in Computer Science and its Applications* (pp. 467-473). Springer, Berlin, Heidelberg.
23. Al Momin, M.A., 2022. Analysis of Cell Phone Biometric Sensors and Security Risk of the Sensors. In *Security, Data Analytics, and Energy-Aware Solutions in the IoT* (pp. 50-60). IGI Global.
24. Cooper, D.A., Yalcin, T., Nistor, C., Macrini, M. and Pehlivan, E., 2022. Privacy considerations for online advertising: a stakeholder’s perspective to programmatic advertising. *Journal of Consumer Marketing*.
25. Cinar, N. and Ateş, S., 2022. Data Privacy in Digital Advertising: Towards a Post Third-Party Cookie Era. *Çınar, N., & Ateş, S.(2022)." Data Privacy in Digital Advertising: Towards a Post Third-Party Cookie Era", in Filimowicz, M.(Ed.) Privacy: Algorithms and Society, Routledge*.

26. Liang, W., Wang, L., She, J. and Liu, Y., 2022. Detecting Resource Release Bugs with Analogical Reasoning. *Scientific Programming*, *2022*.
27. Mody, A. and Taylor, M.P., 2003. Common vulnerabilities. *Available at SSRN 385916*.