IJMLNCE JOURNAL

International Journal of Machine Learning and Networked Collaborative Engineering

Journal Homepage: http://www.mlnce.net/home/index.html

DOI : https://doi.org/10.30991/IJMLNCE.2019v03i01.003

Artificial Intelligence to Prevent Road Accidents

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Abstract

Due to increasing demand in urban mobility and modern logistics sector, the vehicle population has been growing progressively over the past several decades. A natural consequence of the vehicle population growth is the increase in traffic congestion which in turn will lead to more accidents. Accident prediction is one of the most vital aspects of road safety. An accident can be predicted before it occurs, and precautionary measures can be taken to avoid it. Artificial Intelligence (AI) can help in improved awareness of road conditions, driving behaviour of the people and can avoid accidents with the help of improved active safety and improved traffic condition. Drug impaired driving is becoming a serious cause of accidents as the days go by. Moreover, it is more difficult to detect drivers who are under the influence of drugs than drivers who are the influence of alcohol. So the purpose of this research is to study and review the literature & industry reports and put in the approaches for detecting the unsafe driving pattern and also maintaining the health of the car to avoid accidents.

Keywords

Artificial Intelligence, Accident prediction, Road safety, Drug impaired driving, Connected cars, Detection of driver behaviour, Prognostics, Health Management

1. Introduction

Road Traffic Accidents are the major cause of death and constitutes one-tenth major cause of all deaths worldwide. An estimation is reported [17] that 1.2 million people lose their lives in road accidents, 50 million are injured and about 30-70% people suffer from orthopedic illness. And if this issue continues, then road accident will become third- major contributor to the worldwide burden of disease and injury by 2020.The major bearers of the road accidents are developing countries. Also, Road Traffic Accidents create tremendous hardship due to loss of family's primary source of support for earnings, since 73% of total road accidents affect mainly males and those aging from 15-45 years old [17].

Artificial Intelligence (AI) is a study of Computer Science that focuses on building intelligent machines and developing algorithms and so to make them ready to act like a human. The automotive industry is among the industries of greatest advancement using AI to imitate and support the actions of humans.AI can be used to make life in car more convenient and safer, beyond the shadow of self- driving vehicles. AI can help in improved awareness of road conditions, driving behavior of the people and can avoid accidents with the help of improved active safety and enhanced traffic condition. From manufacturing or management point of view, AI can also help in making processes more efficient and digital [5].

These days companies are using Internet Of Things (IOT) techniques in every field. In context of automotive industry, field of interest are 'Connected Cars'. Connected Cars are vehicles that are provided with internet access and wireless local network and use communication technologies to communicate with the driver about the outside car environment, this helps in improving the road safety. Since, road safety is of prime importance to both the driver and the pedestrians, connected vehicles helps in connecting the driver to different networks i.e. car to infrastructure, car to other cars, car to cloud, car to pedestrian, in short, car to everything [6]. Preventing accidents include major aspects: First is, prognostics and health management, then second is detecting the behavior of the driver and third is intelligent driver assistance. These are defined as under:

1.1. Prognostics and Health Management (PHM)

Prognostic is related to prediction of an asset and is based on prediction about the reliability, availability and health state of an asset. The asset prediction is made in order to reduce the maintenance cost and it also prevents the asset breakdown and further promotes the safety reducing accidents. Prognostics can be used in various applications like aerospace vehicles, civil infrastructures, mining machinery [10]

1.2. Behavior Detection

Behavior detection is a study of paying attention to human signals, both relating to behavior as well as human normal physical functioning. Towards traffic accidents, detection of human behavior is an important area of interest to improve global road safety problem [11].

1.3. Intelligent Driver Assistance

Advanced Driver Assistance System (ADAS) assists the driver of vehicle by providing safety warning messages during critical and life-threatening situations. It not only ensures safety of drivers, but also ensures the safety of cars and outside environment (pedestrians, animals etc.). For instance, the driver drowsiness detection system in which the artificial intelligence tool detects whether the driver is falling asleep during driving and alert the driver so that he can stop driving and take rest. Any of the driving styles can be measured through ADAS in real time and it also provides necessary feedback [7], [10].

2. Background

In any industry, the damage of asset can cause social as well as economic damage due to partial defaults and degradation in the asset. Likewise, in automotive industry, the damage to automotives may lead to car accidents and casualities (social loss). Reason being, in order to avoid accidents, most machines and systems (automotives), depend upon routinal preventive maintainence on regular interval basis. Routinal preventive measures were having their own limitations in preventing failure and incur high cost in case of unnecessary replacement of undamaged parts. So, to prevent this unnecessary cost, PHM came into light gathering real time data about condition of vehicle from wireless sensor network and analysing it**.** PHM offer bundle of servies (a) health monitoring for defaults or degradation (b) diagnosis of abnormal physical condition (c) forecasting of remaining useful life (RUL) (d) accusation when maintainence is necessary.All these services help in predicting the potential failure in the operating device and provide information required for risk mitigation and management [8].

Furthermore, understanding the behavior of Vehicle Driver to predict the accident has become an important topic of research these days. In Vehicle driver environment system driver behavior is an important factor. In increasing driving safety real driving monitoring system has a big role [10],[11].

2.1. Prognostics in automotive industry

Prognostics in automotive industry is a systematic way of observing the reliability of the vehicle on real time basis. In the automotive industry, this technology has been adopted in order to render advance word of advice about safety-related failures, to reduce the unscheduled maintenance of vehicle. Vehicle is a complex combination of mechanical, electronic and computer engineering structure. It comprises of various subsystems such as gearbox, engine, brakes etc., associated with Engine Control Unit (ECU), which ensures the optimum performance of the engine and other parts of the vehicles as their performance is dependent in performance of the engine. ECU is connected with Controller Area Network (CAN), through which different subsystems of vehicle and controller of vehicle communicate with each other. Protocols On Board Diagnostics (OBD) and Unified Diagnostic Services (UDS) are needed communicate with ECU. OBD model provide the vehicle owner or to a repair professional right to obtain the data about current condition of different subsystems of vehicle whereas UDS provide details about the condition. OBD compares real time data received from subsystems like battery, engine, gear with results obtained from exploratory pattern of the conditions of those subsystems. The current situation of system is obtained through diagnostics and prognostics where diagnostics is related to current state of the vehicle subsystem and prognostics is concerned with future state of subsystem [8], [10]. Prognostic maintenance copes with OBD, which collects the data from different sensors when vehicle is on the move. Then, signals generated from data streams are continuously sent to smart devices (smartphones, laptops) connected to the vehicle via wireless communication. Patents related to PHM in automotive have been taken by various research institutes and car manufacturers. Ford car manufacturer owns an automotive patent that presents a vehicle structure consist of prognostic module; On Board Diagnostic. It is used to determine the device characteristics of degradation [14].

There is large cost associated with usage of sensor data as it requires large memory space and high processor space. So various solution for data reduction were given. One of them, was introduced by [9] various techniques using machine learning for engine. [4] introduced an android based application for vehicle health monitoring system in which engine condition, battery condition, emission system were observed, and notification about the same was delivered to the driver of the vehicle via android phone. A real time Vehicle Monitoring and Maintenance system was introduced (VMMS), under this subsystems of vehicle, ignition system, exhaust system, fuel system, and cooling system are examined in detail. Data collected through sensor is used for default prediction using different machine learning; Decision tree, K-NN, Random forest. Through On Board Diagnostics scanner and smart phones, the data is generated, while vehicle is in move. Data is collected in the form of Diagnostic Trouble Codes (DTC) is communicated to smart phone via Bluetooth and then send to back-end using algorithms patterns are learned which can cause failure to system and in abnormal condition user of vehicle is notified through smart phone or email notification [8], [14].

2.2. Driver Behaviour Detection and Intelligent System

Road safety is of prime importance to both the driver and the pedestrians. AI can help in improved awareness of road conditions, driving behaviour of the people and can avoid accidents with the help of improved active safety and enhanced traffic condition. From manufacturing or management point of view, AI can also help in making processes more efficient and digital. One of the major ways that AI has contributed to road safety is radar based communication. This can be employed by using an algorithm that will predict when a person/object is about to come in front of the car and thereby warning the driver to stop. This can be taken one step further when the car is able to use brakes all by itself. Tesla had recently tested this algorithm. It was able to predict an accident seconds before it happened, and the car was able to brake on its own. However, for Indian roads, the algorithms to be developed are slightly more complex as compared to the West. This is because Indian roads have more objects that can block a self-driving car such as cyclists and animals [3]

[1]The **Driver Alcohol Detection System for Safety (DADSS)** helps in detecting alcohol levels by two mechanisms – the first mechanism is a Breathalyzer system which is located on the steering wheel or the driver side door. It is capable of detecting the alcohol in the air particles around it. This will help in determining how many drinks the driver had. The engine will not start if the system detects the presence of alcohol. The second mechanism is a touch sensor either on the ignition button or on the gear shift lever. The sensor employs near-infrared tissue spectroscopy to determine driver's blood alcohol content. Just like the Breathalyzer system, if it detects the alcohol content beyond the legal limit, a running engine would simply stop or will not start at all. [2]Detecting motorists who are Driving Under the Influence of Drug (DUID) is more complicated than detecting drivers who are driving under the influence of alcohol and also difficult to perform tests for medications and prescriptions in DUID case. This is due to presence of large amount of constituents which may lead to impaired driving and increase the risk of accident, the impact of different type of drugs on driving, lack of information about certain drugs, how drugs can affect body and behaviour. As DUID is a scenario which continues to rise, the ability to identify these cases and apply suitable measures correspondingly is still a challenge for researchers to predict and prevent road accidents. [3]Aggressive driving style may be defined as the driving behaviour that can intentionally increase the risk of collisions. This would include irregular, instantaneous and abrupt changes in vehicle speed, inconsistent or excessive acceleration or deceleration. About 56% of deadly crashes occurred between 2003 and 2007 are associated with aggressive driving (according to American Automobile Association Foundation for Traffic Safety).

[4]Inattentive driving style can be observed as an instantaneous deviation from normal driving behaviour with the following of an immediate reaction of the driver to rectify it (i.e. trying to get back into attention). It is instantaneous and sporadic in nature as compared to aggressive driving style in which there is a pattern of misbehaviour over a period of time [11], [13].

3. Approaches

Approach 1 For Health monitoring a new system has been proposed which shows real time monitoring known as Vehicle Monitoring and Maintenance System (VMMS). The schematic diagram has been shown below

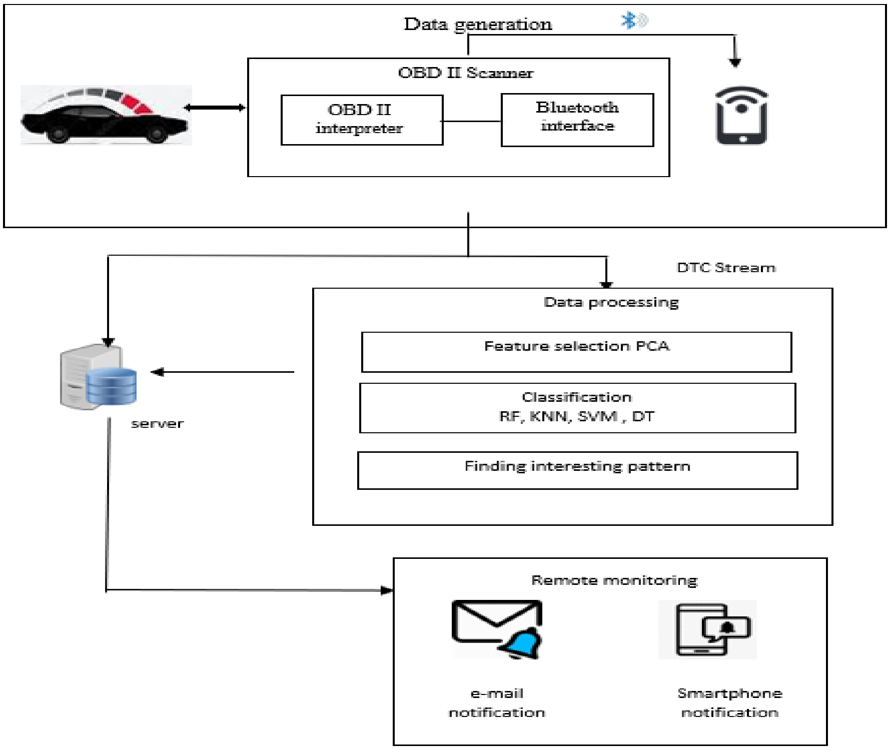

Fig. 1 VMMS Architecture (Source: Ufera Shafi, *et al* Jan 2018 [14])

VMMS Architecture - VMMS Architecture is constituted of three main levels as shown in Figure 1; in first level the data generated. An OBD (On Board Diagnostics) II scanner is wired in the vehicle through OBD II port. There are various car scanner in the market, for say car scanner klavkarr-100 (was developed for only users of Mac or Pc). These scanners are act a link between vehicle and portable device, relevant information from car can be connected to directly laptop screens or smartphones which is supported by Bluetooth or USB cable. Data generated is in form of DTC when vehicle is in move and sent to portable device (laptop or smartphone). Data keeps on generating throughout the vehicle move and transmitted to portable device via Bluetooth. The output of the system is in binary form. The value is set to 1 if DTC is generated (if fault occurs or system breaks down and 0 if system is working perfectly. For this particular case the dataset consisted of 150 examples. Also, the sensor data was used for Corolla Cars owned by Toyota

The algorithms that were selected perform with high accuracy on binary data. The algorithms are as follows:

1) Decision Tree (DT): It is a graphical representation of possible solutions to a decision based on certain conditions. The basic algorithm is applied using Gini Diversity Index (GDI) which shows the measure of node impurity.

   GDI = 1- $\sum p^2(i)$, where

p(i) is the probability of an instance belonging to class Ci where i can be either 0 or 1 depending on the situation.

2) Support Vector Machine (SVM): It is a supervised machine learning algorithm which can be used for classification or regression problems. SVM separates the instances of two classes and by maximizing the margin between both sides of line, it classifies test instance. It uses a function known as Kernel trick (K) to transform the data and finding an optimal boundary between possible outputs based on the transformations.

   K (x, x') = exp ($-\eta$ |x-x'|^2), where

   η is a parameter to handle nonlinear classification

3) K-Nearest Neighbour (K-NN): This method is applied when Euclidean distance (d) is used to measure similarity.

   d (X, Y) = $\sqrt{} \, (\sum_{i=1}^{n} (Xi - Yi)^2)$

4) Random Forest (RF): To improve the accuracy of Decision Trees, RF is employed. For each sample, a decision tree is learned. If data is sampled n number of times with replacement, we get n decision trees. Such multiple number of decision trees constructed is known as Random Forest.

The performance of the above mentioned algorithms are evaluated on the basis of precision, recall, accuracy and F1 scores measures. The equations used for calculating each are as follows.

$$PRECISION = \frac{TP}{TP + FP}$$

$$\mathrm{RECALL} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$$

$$\mathrm{F1\ SCORE} = \frac{2 * \mathrm{P} * \mathrm{R}}{\mathrm{P} + \mathrm{R}}$$

$$ACCURACY = \frac{TP + TN}{TP + TN + FN + FP}$$

Where TP → True Positive (detects a condition when the condition is actually present)

TN→ True Negative (does not detect a condition when the condition is actually absent)

FP → False Positive (detects a condition when the condition is actually absent)

FN → False Negative (does not detect a condition when the condition is actually present)

<u>Approach 2</u> To find out whether drug has a serious impact on increasing amount of accidents, two types of data were collected: Structured and Narrative [13].

Structured data: It refers to information or data that has a defined format. It is organized into what is known as database so that its elements can be used for effective processing and analysis. Examples include numbers, dates or even group of words and numbers termed as strings. In Borba's study, he has used data regarding incidence rates in automobile accidents and percentage of accidents with injury for various conditions such as Time of day, Environment, Nature of Accidents and Driver condition (Fatigued or Alcoholic)

Narrative data: This approach focuses on gathering information for the purpose of research through storytelling. The researchers then interpret stories that are told within the context of research. In the case of Borba's study, data regarding Incidence rates in automobile accidents and percent of accidents with injury due to presence of Medication, Prescription, drug or illegal narcotic have been employed.

Approach 3 iPhones have an app known as Drivesafe which deduces drowsy and aggressive driving behaviours and gives corresponding feedback to the drivers and scores to their driving. From [12], they have taken help of UAH-Driveset which is recorded by Drivesafe app. The data was collected of 6 different drivers and cars and simulated 3 different behaviours (normal, drowsy and aggressive).

In normal driving, the driver was told to drive in the usual way. In aggressive driving, the driver was told to push to his limit (pedal hard on the accelerator, abrupt braking etc). In drowsiness case, the driver was told to act like he was slightly sleepy (slightly unaware of the road ahead). The processed data also contains maneuvers recognition which are acceleration, braking, turning, lane weaving, drifting, overspeeding, car following. Each driver performed on motorways as well as secondary roads.

4. Findings

4.1. Health Monitoring and Prognostic Maintenance (Based on Approach 1)

Table 1: Ignition systems VMMS

Classifiers	Precision	Recall	Accuracy	F1 score
DT	.73	.5	72.5	.68
SVM	.94	.98	96.6	.96
kNN	.82	.78	81.9	.77
RF	.79	.75	79.2	.76

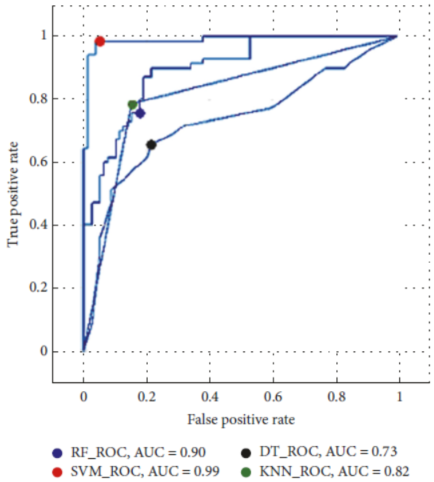

Figure 2: ROC curve for Accuracy **(Courtesy**: Ufera Shafi, *et al* Jan 2018: Vehicle Remote Health Monitoring and Prognostic Maintenance system [14])

For failure prediction of ignition system, selected four classifiers Decision Tree (DT), SVM, K-NN and Random Forest are applied on the dataset as shown in Table 1. ROC curve is basically a graphical representation which is used to compare accuracy of different classifiers as can be seen from Figure 2. The area covered by ROC curve shows the measure of accuracy.

From Table1 and Figure 2, we can see that SVM trumps the other classifiers with 96.6% accuracy.

Similarly, ROC comparison was performed for predicting failure for other parameters like fuel system, exhaust system and cooling system in Table 2. The comparison between accuracies of different classifiers of various parameters are as follows:

Table 2: Classifier's Comparison (**Courtesy**: Ufera Shafi, *et al* Jan 2018: Vehicle Remote Health Monitoring and Prognostic Maintenance system [14])

System VMMS	DT %	SVM %	kNN%	RF%
Ignition system	72.5	96.6	81.9	79.2
Fuel System	76.5	98.5	94.6	90
Exhaust System	78.5	98	89.9	88.6
Cooling System	75.8	96.6	94.6	89.3

It can be clearly observed that SVM shows much better results in every department in comparison to the other classifiers. SVM performs well on smaller observations (150 in this case). Decision Tree considers all dataset and classifies each instances stepwise. The limitation of Decision Tree is that it depends on training data set and therefore, it shows poor performance in test data set.

4.1 Drug Impaired Driving Behaviour (Based on Approach 2)

Table 3: Incidence among automobile accidents and percentage of accidents with injury for various conditions (Structured Data) (**Courtesy**: Predictive Analytics, Text mining and drug impaired driving in automobile accidents by Dr Philip S Borba, 03 Apr 2013 [13])

Condition	Incidence Among Accidents	Percent With Injury	Injury Frequency Compared to "All Accidents"
All accidents	100%	73%	
Time of day/week			
Night	22%	69%	-
Weekend	22%	73%	+
Environment			
Weather	24%	71%	-
Wet roads	16%	67%	-
Nature of accident			
Multiple vehicles	74%	76%	+
Rear-end	18%	70%	-
Head-on	2%	86%	+
Turned into path	16%	81%	+
Driver condition			
Driver fatigued	13%	76%	+
Alcohol (police report)	6%	82%	+

Table 4: Percentage of Accidents with injury due to Medication, Prescription, Drug and Illegal Narcotic (Narrative Data) (Courtesy: Predictive Analytics, Text mining and drug impaired driving in automobile accidents by Dr Philip S Borba, 03 Apr 2013 [13])

Condition	Incidence Among Accidents	Percent With Injury	Injury Frequency Compared to "All Accidents"
All accidents	100.0%	73%	
Medication	15.7%	82%	+
Prescription	6.4%	80%	+
Drug	6.6%	80%	+
Illegal narcotic	2.4%	89%	+

According to Table 3, out of all accidents 73% were injurious. The injury frequency of accidents occurred in different conditions are compared with all accidents. If the value is greater than or equal to 73%, the injury frequency is taken as ‘+’, else ‘-‘ sign is provided.

The Narrative data of Incidence rates in automobile accidents and percent of accidents with injury due to presence of Medication, Prescription, drug or illegal narcotic is as follows

From Table 4, it can be observed that level of injury that occurred during accidents under the influence of drugs, medication etc. are much higher as compared to overall accidents. Using Table 3 and Table 4, i.e. combining the structural as well as narrative data, we can determine whether the influence of drugs really have an impact on accidents which are commonly occurring and if so by how much.

4.2 Analysis of Driver Behaviour (Based on Approach 3)

Drivesafe app performs behaviour analysis, real time maneuver detection, scoring. From the table, the maneuver scores for each driver part provide the scores provided by Drivesafe. The minimum of the attributes are marked in bold. The Behaviour part contains the ratios provided by Drivesafe for normal, aggressive and drowsiness behaviour. All scores provided are in base 10. The scores for acceleration, braking and turning usually depends on driver profile and road conditions. However aggressive driving behaviour will result in abruptness. Therefore, the scores are usually lower as compared to the other driving behaviours, as can be observed from the table. Lane weaving analysis can help us identify whether the driver is changing lanes slowly and carefully or abruptly and with lack of awareness. Drifting analysis is beneficial to understand the capacity of the driver to continue centred on its own lane. Both the scores of Weaving and drifting are observed to be lower in drowsy driving behaviour compared to others. Car following is a very important. The driver has to maintain a safe distance behind the other vehicle in case the vehicle brakes abruptly he/she should have time to react. For aggressive driving behaviour, both over speeding and car following scores are low.

From Table 5, it can be clearly seen that the behaviour detected by Drivesafe was 100% correct on secondary routes, while it was approximate in case of Motorways. E.g. : In case of D2 on Drowsy (Motorway), the score for Normal Behaviour was given 4.2 while for Drowsy Behaviour, score of 4.1 was obtained (which was supposed to be the actual one).

Table 5: Scores of Drivers for Simulated Driving Behaviour in Different Routes **(Courtesy**: Eduardo Romera *et al*: Need Data for Driver Behavior Analysis [12])

State	Driver	Duration		Speed (Km/h)		Maneuver scores							Behavior		
		Time	Km	Avg	Max	Acc	Bra	Tur	Weav	Drift	Overs	Carfoll	Nor	Drow	Agg
Normal (Motorway)	D1	14m.	25	107	131	10	9.7	8.7	9.3	**7.9**	9.4	9.8	**6.8**	1.4	1.8
	D2	15m.	26	98	127	9.9	9.9	**7.2**	10	7.5	9.6	9.3	**6.8**	1.5	1.7
	D3	15m.	26	101	122	10	9.9	9.4	9.4	**8.1**	9.7	9.8	**7.3**	1.3	1.4
	D4	16m.	25	91	120	9.9	9.9	9.7	10	**8.9**	9.9	9.9	**8.2**	0.6	1.2
	D5	15m.	25	99	120	9.0	9.4	**7.8**	10	8.0	9.3	9.1	**6.8**	1.2	2.0
	D6	17m.	25	89	104	9.7	9.7	**3.5**	10	8.7	9.8	9.7	**8.0**	0.8	1.2
Drowsy (Motorway)	D1	15m.	25	97	113	10	3.8	6.9	**2.6**	4.3	9.7	9.7	3.2	**5.6**	1.2
	D2	15m.	25	98	122	9.4	4.8	7.8	5.2	**4.7**	9.7	9.4	**4.2**	4.1	1.6
	D3	16m.	26	91	129	9.8	10	7.9	**1.5**	5.2	9.7	9.9	2.6	**6.0**	1.4
	D4	17m.	25	88	106	9.9	9.8	8.7	**4.1**	4.6	9.0	9.9	3.8	**4.6**	1.6
	D5	18m.	25	83	96	8.6	4.2	8.2	**0.9**	3.1	9.5	9.9	1.8	**6.8**	1.3
	D6	17m.	25	84	99	9.6	9.2	**1.8**	3.9	4.8	7.1	9.9	2.5	**4.7**	2.8
Aggressive (Motorway)	D1	12m.	24	120	148	10	7.0	8.1	10	8.5	**6.1**	9.1	**5.1**	0.9	4.0
	D2	14m.	26	107	147	6.6	5.9	6.6	9.2	5.7	6.7	**2.1**	1.2	2.7	**6.1**
	D3	13m.	26	110	146	9.1	**0.0**	9.4	10	8.0	6.9	6.5	**5.4**	1.2	3.4
	D4	15m.	25	97	130	6.8	**2.7**	8.5	9.0	8.6	8.3	3.3	3.7	1.0	**5.3**
	D5	13m.	25	114	147	7.8	2.4	1.3	10	7.7	6.1	**0.3**	1.3	1.4	**7.3**
	D6	15m.	25	101	127	6.4	5.3	**0.0**	10	8.9	8.4	4.4	**4.8**	0.6	4.6
Normal[1] (Secondary)	D1	10m.	16	96	116	10	10	8.7	10	**6.3**	7.3	9.8	**6.4**	1.5	2.1
	D2	10m.	16	91	103	9.9	10	10	10	**7.4**	7.8	9.9	**6.2**	1.5	2.3
	D3	11m.	16	85	97	9.9	10	10	10	**6.9**	9.6	9.8	**6.9**	1.9	1.2
	D4	11m.	16	82	101	10	10	9.5	10	**8.8**	9.6	10	**9.1**	0.7	0.2
	D5	11m.	16	84	102	9.4	9.9	9.5	10	**7.3**	9.4	8.9	**7.6**	1.6	0.8
	D6	13m.	16	75	90	9.9	9.7	**4.5**	10	9.2	9.9	10	**9.5**	0.4	0.0
Drowsy (Secondary)	D1	8m.	13	94	107	10	4.9	6.6	10	**2.8**	7.7	10	3.3	**4.3**	2.4
	D2	10m.	16	91	110	8.8	3.8	8.1	**0.0**	4.1	8.5	9.6	0.9	**7.2**	1.9
	D3	10m.	17	91	118	10	9.4	9.5	**0.0**	4.0	8.1	9.9	0.7	**7.2**	2.1
	D4	11m.	17	87	102	9.9	9.1	8.1	**2.0**	3.9	9.4	9.9	1.8	**6.0**	2.2
	D5	11m.	16	84	100	10	9.7	4.8	10	**1.4**	9.8	9.2	3.4	**5.1**	1.5
	D6	12m.	16	80	94	8.7	8.8	2.5	**0.0**	4.6	9.9	10	1.4	**7.1**	1.5
Aggressive (Secondary)	D1	8m.	16	112	132	10	2.9	5.7	10	5.9	**0.0**	9.5	0.5	2.4	**7.1**
	D2	10m.	16	96	119	7.2	3.7	10	10	5.8	**0.2**	0.7	0.0	2.5	**8.7**
	D3	11m.	16	87	119	8.4	8.2	8.6	10	6.4	7.3	**1.5**	1.5	2.1	**6.4**
	D4	10m.	16	89	113	6.8	8.0	10	10	6.9	8.0	**2.3**	1.8	1.9	**6.3**
	D5	7m.	12	100	147	9.0	0.1	6.2	10	5.0	**0.0**	4.6	0.0	3.0	**8.0**

5. Conclusion

As vehicles are increasing manifold throughout the year, the risk of road accidents occurring will also be on the rise. Driver behaviour plays a massive role in determining the risk of accidents that can occur. The study of different types of behaviour like normal, aggressive and drowsiness shows the proof. In addition to that Driving Under the Influence of drugs is a huge matter of concern regarding the severity of road accidents. The approaches adopted in this research paper has shown that from the accidents that occurred during different conditions (structured data) and the accidents that occurred due to intake of drugs, medication etc (narrative data), drugs have a huge impact on the rise in amount of accidents and are more fatal. Four classifiers Decision Tree, SVM, K-NN and Random Forest have been used for fault prediction. Even though the objective is to reduce the fault frequency of systems in vehicles, by doing so we can reduce the amount of road accidents that can occur due to malfunction of the components. Researches are still going on in these areas as required algorithms are not easy to implement practically.

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How to Cite

B Jaidev, Garg Sonakshi, Makkar Sandhya, "Artificial Intelligence to Prevent Road Accidents", *International Journal of Machine Learning and Networked Collaborative Engineering,* Vol. 03 No. 1, 2019, pp. 35-45.

doi : https://doi.org/10.30991/IJMLNCE.2019v03i01.003.