Measuring the Driver's Perception Error in the Traffic Accident Risk Evaluation

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Abstract:- As the driver is the information recipient and primary decision maker in the driving process, this research aims to investigate a driver's risk awareness to assess a driver's safety.The Sensation Seeking Scale (SSS) (14 items). The first three scales together cover 14 indicators, and the same 14 indicators are dealt with in the sensation seeking scale. The fourteen indicators area unit named second category indices, like the final perspective towards obeying rules, aggressive violations and awareness of safe driving, etc. In this study, in order to develop a risk awareness model, a survey was conducted in India. Based on the survey, exploratory factor analysis of the scale revealed three risk awareness factors (risk attitude, risk perception and risk behavior), also named first class indices. The respective weights of the 14 second class indices and the 3 first class indices were calculated. Results of statistically analyzing the survey showed that some drivers in our study have high risk awareness. In addition, a diagram was made supported the multivariate analysis of a driver's sensation seeking and risk awareness indices. It appeared that the upper the driver's Selective Service, the lower the driver's risk awareness.

Introduction:

Based on the most recent report of the World Health Organization, in the year 2013 about 1.25 million people were killed on the world roads, that is, about 3 thousand people died every day.The cost of dealing with the consequences of these traffic accidents runs to billions of dollars. The governments of the world declared 2011-2020 as the "Decade of action for road safety"; the goal of the Decade (2011- 2020) being to reduce the increasing trend in road traffic fatalities, saving an estimated 5 million lives over the period [1]. Traffic accidents are generally determined by a combination of more factors related to the components of a system including roads, the environment, vehicles and road users, and the way they interact. For almost all the traffic accidents the main cause is certainly human error. In fact, relative proportion of contributing factors due to the driver behaviour amounts to 93%, while 30% is the relative proportion linked to the interrelation between roadway and driver factors [2]. Considering this evidence, the road safety concept cannot be separated from the analysis of human behaviour, the driver being a contributing factor that can be modified; in other words the driving behaviour can be adapted to the road, environment and vehicle conditions. So, traffic accidents and accident severities can be reduced by implementing specific measures to target the driving behaviour [2]. The report of the World Health The report of the World Health Organization confirms that among all the risk factors related to the driving behaviour, speeding is considered as the major road safety problem in all countries. There are some studies in the literature investigating speeding as the cause of accident. As an example, the study of Cabral et al.[3] aims to contribute to the reduction of accidents caused by speeding, and, through the use of multisensory information, to help the driver maintain a more regular driving and controlled speed.

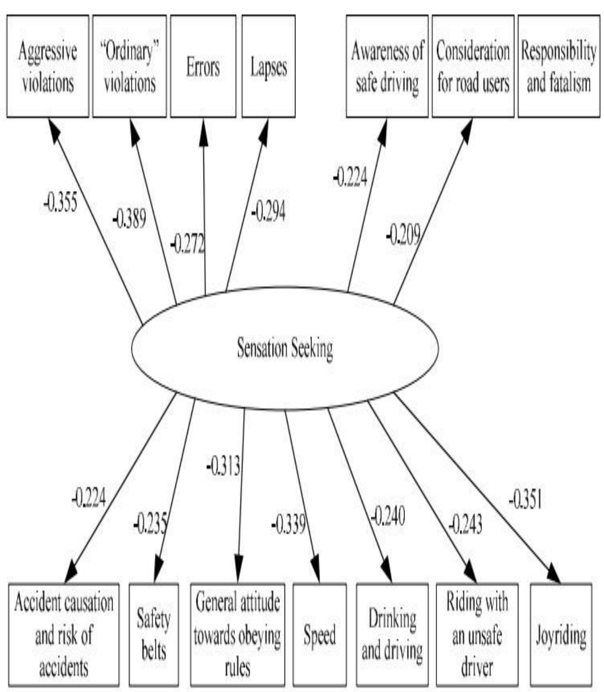
Existing System:

Many research studies focused solely on identifying the fundamental factors that cause road crashes. From these studies, it was noticed that human factors have the most significant impact on accident risk. The basic factors influence on road safety directly associated with the driving force area unit i.e., driving behaviour, driver's perception of traffic risks and driving experience. Drivers involve often in attitudes that cause road issues of safety. Many of these attitudes are dynamic, conscious rule violations, while others are the result of errors due to less driving experience, momentary mistakes, inattention or failure to perform function, the latter often related to age. These behaviours often contribute to traffic collisions. Besides of risky driver behaviour the unhealthy driving practices and poor data at the side of disrespect for road and safety laws area unit the plain issues.

Proposed System:

A recent study investigated the extent to which poor driving behaviour, driving when fatigued and risk taking were risk factors for RTAs. Driver behaviour is usually assessed by questionnaire and the main types of problem that have been identified are speeding, lapses of attention, errors and aggressive driving. Risk taking may be a general sort of behaviour that contains a major impact in safety essential contexts like driving. Much of the analysis on driver fatigue has targeted on the length of your time spent driving. However, fatigue is also because of several factors, a number of which can be gift at the beginning of the drive instead of actual time driving.

System Architecture:



Hardware and Software Requirements:

Hardware:

1. Os - Windows 7,8 or 10(32 or 64 bit)
2. Ram – 4GB

Software:

1. Python IDLE
2. Anaconda – Jupyter Notebook

Modules

- Accident Dataset
- Data Preparation
- Statistical Analysis

Modules

Accident Dataset

Our task was to develop machine learning primarily based intelligent models that would accurately classify the severity of injuries (5 categories). This can successively result in larger understanding of the connection between the factors of driver, vehicle, roadway, and environment and driver injury severity. Accurate results of such information analysis may offer crucial info for the road accident hindrance policy. The records within the dataset square measure input/output pairs with every record have Associate in Nursing associated output. The output variable, the injury severity, is categorical and (as delineated above) has 5 categories. A supervised learning algorithmic rule can attempt to map an input vector to the required output category. There square measure solely single vehicles with ages thirty seven, 41, 46 and 56 years reported in the dataset and therefore these four records were deleted from the dataset (since they were clear outliers). After the pre-processing was completed, the final dataset used for modelling had 10,247 records. There were five,171 (50.46%) records with no injury, 2138 (20.86%) records with possible injury, 1721 (16.80%) records with non-incapacitating injury, 1057 (10.32%) records with incapacitating injury, and 160 (1.56%) records with fatal injury. We have separated every output category and used one- against-all approach.

Data Preparation

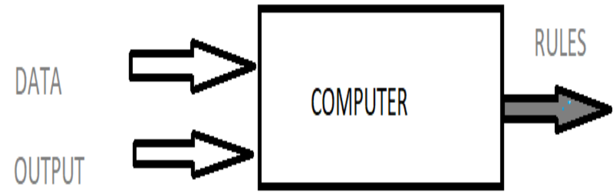
When the input and output variables square measure thought of there are not any conflicts between the attributes since every variable represents its own characteristics. Variables are already categorized and represented by numbers. The manner in which the collision occurred has 7 categories: no collision, rear-end, head-on, rear-to-rear, angle, sideswipe same direction, and sideswipe opposite direction. For these 7 categories the distribution of the fatal injury is as follows: 0.56% for non-collision, 0.08% for rear-end collision, 1.54% for head-on collision, 0.00% for rear-to-rear collision, 0.20% for angle collision, 0.08% for {sideswipe|strike} same direction collision, 0.49% for {sideswipe|strike} {opposite direction|other way|wrong way} collision. Since head-on collision has the highest percentage of fatal injury; therefore, the dataset was narrowed down to head-on collision only. Head-on collision {has a|features a|includes a|contains a|encompasses a|incorporates a} total of {10|ten},386 records, where 160 records show the result as a fatal injury; all of these 160 records have the initial point of impact categorized as front. The initial {point|purpose} of impact has {9|nine} categories: no damage/non-collision, front, right side, left side, back, front right corner, front left corner, back right corner, back left corner. The head-on collision with front impact has {10|ten},251 records; {this is|this is often|this can be} {98|ninety eight}.70% of {the 10|the ten},386 head-on collision records.

Statistical Analysis

Past research focused mainly on distinguishing between no-injury and injury (including fatality) classes. We extended the research to possible injury, no incapacitating injury, incapacitating injury, and fatal injury classes. Our experiments showed that the model for fatal and non-fatal injury performed higher than alternative categories. The ability of predicting fatal and non-fatal injury is extremely necessary since drivers' fatality has the very best value to society economically and socially

Machine Learning vs. Traditional Programming

Traditional programming differs significantly from machine learning. In ancient programming, a computer programmer code all the principles in consultation with AN professional within the business that software package is being developed. Each rule relies on a logical foundation; the machine can execute AN output following the logical statement. When the system grows complicated, additional rules ought to be written. It can quickly become unsustainable to maintai

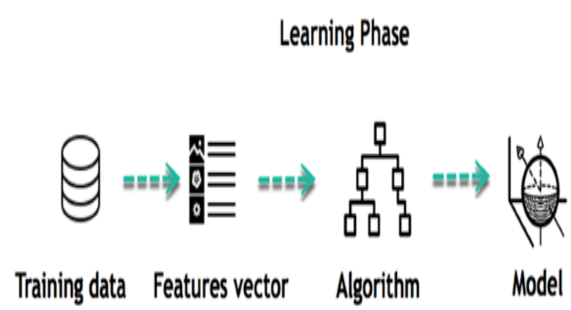


How does Machine learning work?

Machine learning is that the brain wherever all the educational takes place. The manner the machine learns is comparable to the creature. Humans learn from experience. The more we know, the more easily we can predict. By analogy, once we face associate degree unknown scenario, the probability of success is less than the illustrious scenario. Machines are trained the same. To make Associate in Nursing correct prediction, the machine sees an example. When we offer the machine the same example, it will puzzle out the result. However, sort of a human, if its feed a previously unseen example, the machine has difficulties to predict.

The core objective of machine learning is that the learning and reasoning. First of all, the machine learns through the discovery of patterns. This discovery is made thanks to the data. One crucial a part of information|the info|the information} human is to settle on rigorously that data to produce to the machine. The list of attributes accustomed solve a haul is named a feature vector. You can think about a feature vector as a set of information that's wont to tackle a haul.

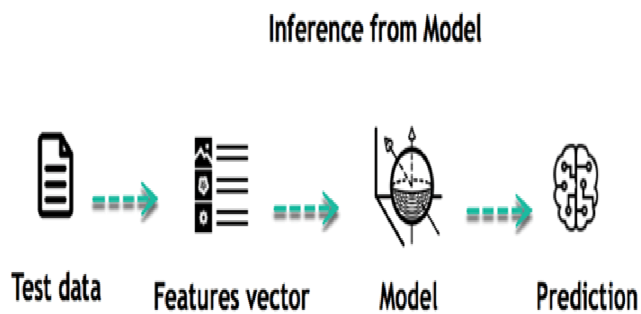
The machine uses some fancy algorithms to change the truth and rework this discovery into a model. Therefore, the educational stage is employed to explain the information and summarize it into a model.



For instance, the machine is making an attempt to grasp the link between the wage of a private and therefore the chance to travel to a elaborate eating house. It seems the machine finds a positive relationship between wage and getting to a high-end restaurant: this is often the model

Inferring

When the model is constructed, it's doable to check however powerful it's on never-seen-before knowledge. The new knowledge ar remodeled into a options vector, bear the model and provides a prediction. This is all the beautiful part of machine learning. There is no need to update the rules or train again the model. You can use the model antecedently trained to form abstract thought on new information.

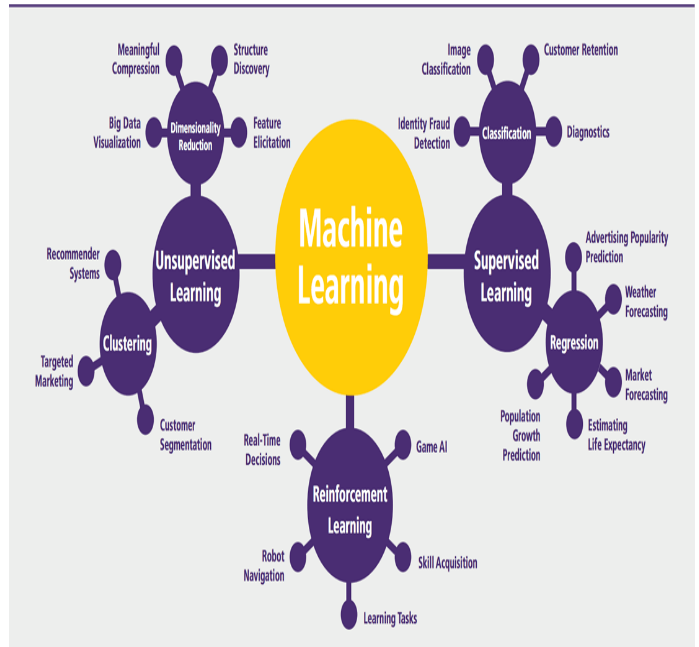


The life of Machine Learning programs is straightforward and can be summarized in the following points:

1. Define a question
2. Collect data
3. Visualize data
4. Train algorithm
5. Test the Algorithm
6. Collect feedback
7. Refine the algorithm
8. Loop 4-7 until the results are satisfying
9. Use the model to make a prediction

Once the algorithm gets good at drawing the right conclusions, it applies that knowledge to new sets of data

Machine learning Algorithms and where they are used?



Machine learning will be classified into 2 broad learning tasks: supervised and unsupervised . There are many other algorithms

Supervised learning

An formula uses coaching knowledge and feedback from humans to find out the connection of given inputs to a given output. For instance, a professional will use selling expense and forecast as input file to predict the sales of cans.

You can use supervised learning once the output knowledge is thought. The algorithm will predict new data.

Imagine you want to predict the gender of a customer for a commercial. You will start gathering data on the height, weight, job, salary, purchasing basket, etc. from your customer database. You know the gender of each of your customer, it can only be male or female. The objective of the classifier will be to assign a probability of being a male or a female (i.e., the label) based on the information (i.e., features you have collected). When the model learned how to recognize male or female, you can use new data to make a prediction. For instance, you just got new information from an unknown customer, and you want to know if it is a male or female. If the classifier predicts male = 70%, it means the algorithm is sure at 70% that this customer is a male, and 30% it is a female.

The label can be of two or more classes. The above example has only two classes, but if a classifier needs to predict object, it has dozens of classes (e.g., glass, table, shoes, etc. each object represents a class)

Regression

When the output is a continuous value, the task is a regression. For instance, a financial analyst may need to forecast the value of a stock based on a range of feature like equity, previous stock performances, macroeconomics index. The system will be trained to estimate the price of the stocks with the lowest possible error.

Conclusion

In this work, we proposed a methodology for measuring the driver's perception error in the evaluation of the risk to be involved in a traffic accident. The methodology is based on the measurement of the risk subjectively evaluated by the driver combined with the risk level objectively evaluated by means of kinematic parameters recorded while driving.Very often, drivers are not aware of the risk taken while driving,and their distorted perception of the risk level is frequently one ofthe main causes of traffic accidents. Raising the awareness ofdrivers to have safer driving is necessary for improving road safety.Therefore, our research can give a contribution for reaching thisgoal. We retain that the proposed methodology has some advantageswith respect to other literature studies because of the conjoint use of subjective and objective risk perception measures.

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