

Driver Behavior Analysis using Machine Learning Algorithms – A survey

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ABSTRACT

Driving behaviour has a significant impact on traffic safety, eco-driving, and country development. Despite recent research, driver behaviour continues to have an impact on the automobile industry and government. Hence, this paper attempts to provide a detailed survey of some of the most popular studies on profiling driving behavior using learning and non-learning-based techniques. Profiling was carried out using the different sensors in the low-cost mobile phones. This will help the fleet management as well as automobile industries and RTO to monitor and track the drivers.

Keywords:-*Driving, Traffic, Behaviour, Sensors, Dataset, Smartphones, Machine Learning Algorithms.*

INTRODUCTION

Attitudes and behaviours are learned early on and are critical to safe driving. It's possible that some cultural norms and adult role models encourage risky behaviour, which might result in fatalities or permanent disabilities as a result of accidents.

The number of road deaths per year has increased in recent years to an average of 19 deaths per day [1]. The most common human causes contributing to road accidents are speeding (65 percent of accidents), driver mistake (80 percent of accidents), violation of traffic signals at junctions (50 percent of accidents), and illegal U-turns.

Other causes include vehicles, roads, and the environment (for example, road layout, which contributes to 20% of accidents) [2]. All recent and earlier research found that excessive speeding was the most common cause of death. Driver error has been identified as the primary contributing factor in approximately two-thirds of all

road traffic accidents, which are characterised as reckless driving [3] and excessive speeding.

This paper includes a thorough review of some of the important state of art in the field of driver behaviour profiling, analysis, and prediction. This is being prepared with the intention of identifying various techniques that have been used in several papers to detect driving behaviour. It also shows a comparison of the methodologies, results performed and collected in previous research papers.

An Investigation with Different Smartphone Sensors and Machine Learning

The recent study contribution comes from MIT researchers, who published their findings in 2017. Four MLAs were predominantly used in this MIT study [4]: Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Bayesian Network (BN). Its methodology modelled this task as a multi-label supervised learning

classification problem in which the labels dictate the types of events. Their effort aimed to determine the optimal combination of motion sensor (and its axes), learning algorithm (and its parameters), and sliding window frame rate (nf) for detecting distinct driving event types.

The purpose of this work was to present a quantitative assessment of the exhibitions of four MLAs (BN, MLP, RF, and SVM) with varying designs for the recognition of seven driving event compositions using data gathered from four Android cell phone sensors[10] (accelerometer, linear acceleration, magnetometer, and gyroscope). 69 tests of these occasion compositions were acquired as part of a legitimate investigation of alternative paths for two drivers.

Additionally, the execution was scrutinised while varying the sliding time window sizes. We conducted 15 executions with various irregular seeds of 3865 assessment gathers for the frame EA = 1: sensor, 2: sensor axis(es), 3: MLA, 4: MLA configuration, and 5: number of frames in sliding window. As a result, the top five performing congregations for each driving occasion category were identified.

With regards to the examination, these results demonstrate that I larger window sizes perform better; (ii) the spinner and accelerometer are the best sensors for recognising our driving events; (iii) as general manager, utilising all sensor tomahawks performs superior to anything done with a single one, except for forceful left turns; (iv) RF is by a wide margin the best performing MLA, followed by MLP; and (v) the execution of the first 35 blends is both agreeable and proportional, shifting from 0.980 to 0.999 mean zone under the ROC curve (AUC) values.

Automatic Traffic Accident Detection and Notification with Smartphones

The WreckWatch system, developed by White et al. [5], uses smart phones and sensors to identify accidents as opposed to the original manufacturer's system, which uses readings from the vehicle's electronic control unit to detect traffic accidents and notify users via smart phones (ECU). White et al. disagree because they believe that connecting to the ECU on every road trip is not always possible. Furthermore, because not every vehicle is equipped with ECUs, an accident detection system that is independent of the ECU is beneficial in the end. WreckWatch makes use of the accelerometer, microphone, and GPS in a smart phone in a "soft real-time" (near to real-time) sampling manner. When the sensor values are filtered by a threshold, an accident is discovered. As a result, the data collected during and after the accident is transmitted to the server via GSM. As a result, relevant and critical information about the accident can be sent to the authorities via the database server. False positives (FPs) are more likely in a system that only uses smart phone sensor data. As a result, a simple drop of the phone or an unintentional knock/slap on the phone may be considered an accident.

To avoid FPs, filter context information must be employed. Prior to further analysis, any acceleration values less than 4g are omitted from consideration. To begin with, everyone travelling at a speed more than 25 kilometres per hour is believed to be in a motor vehicle. The user's speed is determined by the GPS on the smart phone. The readings are only assessed while the user is travelling at a speed greater than 25km/h. As a result, energy consumption is reduced, and any incorrect false alerts are avoided if the phone is dropped or slapped unintentionally. The WreckWatch system is further developed and updated.

Mobile Phone Based Drunk Driving Detection

Dai et al. [6] created a system that can detect drunk driving using only the accelerometer of a smartphone. Their motivation for developing such a framework stem from the fact that alcoholic driving frequently goes unnoticed by experts, putting many people's lives in danger. They distilled alcoholic driving practises from a study conducted by the United States National Highway Traffic Safety Administration. There are two types of behavioural signs that indicate a high likelihood of drunk driving.

The primary classification is associated with path positioning issues such as floating and swerving. The second classification is associated with issues with speed control, such as sudden increases in speed or sporadic braking. Both types of signals can be identified by using an accelerometer to delineate prompts into a vehicle's parallel and longitudinal increasing velocities. A monitoring daemon module, a calibration module, a pattern matching module, and an alert module are included in the system's design. The introduction of an advanced mobile phone inside a moving vehicle is determined by the adjustment module. This enables the framework to function regardless of where and how the advanced cell is installed in a vehicle.

Estimating Driving Behaviour by a Smartphone

Eren et al. [7] propose an iPhone application to classify driver behaviour as safe or unsafe in the aftermath of dangerous driving incidents. The application distinguishes between abrupt turns, path flights, braking, and speeding up events. The accelerometer, gyroscope, and magnetometer on a smartphone are used to identify events. The endpoint

location calculation is used by the application to separate the beginning and end times of an event. The event is then contrasted and formatted using methods for the DTW calculation. Finally, a Bayesian classifier classifies a driver's behaviour as safe or unsafe based on the number of occasions over time. The results of the trial show that 14 of the 15 drivers (93.3 percent) were successfully identified. It is important to note that the paper only provides driver classification results. As a result, performance results for event classification are not provided.

Rich Monitoring of Road and Traffic Conditions using Mobile Smartphones

Mohan et al. [8] proposed Nericell, a Windows Mobile smartphone application for monitoring road and traffic conditions. is a smart phone-based system designed to detect a few vehicle and road variables such as bumps, speed breakers, horns, and go/stop traffic. It does so by utilising a smart phone's accelerometer, microphone, global system of mobile (GSM) communications, and GPS.

Nericell aggregated sensed data from the smart phones that were connected and used here on a centralised server. Mohan et al. imagined the system being used to annotate existing traffic maps with necessary data and information, such as turbulent traffic and other updates. Energy-efficient sensor utilisation is a top priority for Nericell. GSM radio, which is necessary for communication, is maintained operational while the accelerometer is continually sampled. Furthermore, to save energy, the microphone and GPS system would only be activated when needed. Before being sent to the server for aggregation, the data is thoroughly filtered and locally processed.

Safe Driving Using Mobile Phones

Fazeen et al. [9] depict the implementation of an advanced driver-assistance system (ADAS) on a high-tech mobile phone. A framework like this alert a driver to potentially hazardous situations that arise because of vehicle movements and natural components. The framework makes use of a smartphone's accelerometer and GPS to enable standard features found in ADAS-equipped vehicles. The framework's purpose is to perceive and organise driving behaviour, as well as to delineate surface conditions.

Any data sent to a server for mapping and machine learning procedures is kept secret. The arrangement of perilous circumstances clearly warns drivers. The vibrations felt by a vehicle when driving on a rough street can be used to identify street inconsistencies. When a vehicle drives over a bump, it rises onto it, causing a sharp rise in the accelerometer's z-axis estimation. A rise in the y-axis value is also monitored, depending on the state of the knock and the longitudinal force applied to the vehicle's wheels. The contrast between progressive accelerometer readings is evaluated on a regular basis. A hindrance is assumed if the distinction exceeds a dynamic limit, which is affected by the vehicle's speed. Using elements conditions, one can calculate the height of a knock.

When a street irregularity is identified, the current GPS aids are spared with a corresponding esteem demonstrating the state of the street. The framework classifies a section of a street as smooth, unpleasant, uneven, or having a knock or pothole. The data could then be used to outline the state of entire stretches of road. The street condition arrangement framework achieved an overall exactness of 85.6 percent during testing. It was discovered through observation that sheltered acceleration and deceleration never exceeds 0.3g, while

sudden movement approaches, but does not exceed 0.5g. In correlation, a progressive path change applies a normal parallel increasing speed of only 0.1g. As a result, it is possible to distinguish between safe and risky driving manoeuvres. It was also discovered that perceiving gear shifts is possible, which would enable the framework to prompt a driver when to change gears to achieve efficient fuel utilisation.

Comparison and Inference

Jair Ferreira Ju'nior conducted a study called "Driver behaviour profiling: An investigation with different smartphone sensors and machine learning"[4] at the Massachusetts Institute of Technology in the United States with the goal of profiling the behavioural aspects of drivers. It was a study that used various smart phone sensors and machine learning to investigate the driving profiles of the drivers.

The sensors used to obtain results for this purpose included an accelerometer, linear acceleration, magnetometer, and gyroscope, with algorithms ranging from Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Bayesian Networks. The primary goal of this paper was to identify the best motion sensor (and its axes) and learning algorithms combination. Their pre-processing technique consisted of combining a number of frames in a sliding window to detect individual driving event types, thereby assisting in determining the drivers' driving behaviour profiles. As a result, Random Forest was deemed the best performing algorithm in their study. MLP, on the other hand, was ranked second best. However, among the top 35 algorithms, Bayesian Network and Support Vector Machine were not deemed the best.

Cit. #	Title of the Paper	Author Name	Place/Date	Machine Learning Algorithms	Sensors	Objective
4	Driver behaviour profiling: An investigation with different smartphone sensors and machine learning	Jair Ferreira Junior, Eduardo Carvalho, Bruno V. Ferreira, Cleidson de Souza, Yoshihiko Suhara, Alex Pentland, Gustavo Pessin	The Massachusetts Institute of Technology USA	Artificial Neural Networks (Ann), Support Vector Machines (Svm), Random Forest (Rf), And Bayesian Network (Bn)	Accelerometer (Acc), linear acceleration (linacc), magnetometer (Mag), and gyroscope (Gyr).	The goal is to identify the best combination of motion sensor (and its axes), learning algorithm and number of frames in the sliding window to detect individual driving event types.
5	Automatic Traffic Accident Detection and Notification with Smartphones	Jules White, Chris Thompson, Hamilton Turner, Brian Dougherty, and Douglas C. Schmidt	United States America (2011)	No algorithm is employed	Accelerometer	The goal is to detect accidents by using mobile phone sensors and provide situational awareness to the authorities
6	Mobile phone based drunk driving detection	Jiangpeng Dai, Jin Teng, Xiaole Bai, Zhaohui Shen and Dong Xuan	The Ohio State University (USA) The southeast university (china)	No algorithm is employed	Accelerometer and orientation	A highly efficient system aimed at early detection and alert of dangerous vehicle maneuvers typically related to drunk driving
7	Estimating driving behaviour by a smartphone	Eren H, Makinist S, Akim E, Yilmaz A.	The Ohio State University, Firat university (Turkey) 2012	Bayesian classification, & DTW algorithm	Accelerometer, gyroscope and the magnetometer	Approach to understand the driver behavior using smartphone sensors.
8	Rich Monitoring of Road and Traffic Conditions using Mobile Smartphones	Prashanth Mohan, Venkata N. Padmanabhan, Ramachandran Ramjee	India, Bangalore	No algorithm is employed	Motion: Accelerometer Audio: Microphone Localization: GPS receiver	Uses Smartphone accelerometer to detect bumps/potholes and braking events.
9	Safe driving using mobile phones	Mohamed Fazeen, Brandon Gozick, Ram Dantu, Moiz Bhukhiya, and Marta C. González	United States America 2012	No algorithm is employed	Accelerometer and orientation	Record and analyze various driver behaviors and external road conditions that could potentially be hazardous to the health of the driver, the neighbouring public, and the automobile.

Table 1: Citations Table

The sensors picked up a drop of the phone and counted it as a bump or pothole, which was one of the major drawbacks investigated in this study. Similarly, a study on automatic traffic accident detection and notification with smart phones was conducted in the United States in 2011 [5] by Jules White, Chris. Many sensors were used in the study, as in previous studies, as well as the two sensors comprised of accelerometer and microphone. The goal of this study was to generate automated detection of traffic accidents and traffic notifications that could be detected using sensors and were updated using a smart phone. GPS was used to determine the user's speed for this purpose. The study's limitation is that it did not include any machine learning algorithms in its methodology. Some events may have increased the likelihood of False Positives (FPs). Dropping a phone on the floor, for example, can be detected as an accident.

Like other studies, Jiangpeng Dai's [6] study on drunk driving detection at The Ohio State University (USA) and The Southeast University (China) used sensors to obtain results. Accelerometer and Orientation are the two main sensors used for this purpose. These two sensors were critical in gathering data related to detecting abnormal curvilinear movement and maintaining speed. This study, like the one conducted in the United States of America (2011) titled "Automatic Traffic Accident Detection and Notification with Smart Phones," used no algorithms. The following results were obtained: For abnormal curvilinear movements (FN: 0% FP: 0.49%); Speed control issues (FN: 0 percent , FP: 2.90 percent) In 2012, Eren H, Makinist S conducted a study titled "Estimating driving behaviour by a smart phone" [7] at The Ohio State University, Firat university (Turkey) to determine individuals' driving behaviours using a

smart phone. This research paper's strong point is that it employs sensors and algorithms as well, making it a reliable study in that regard.

The sensors used to collect data are an accelerometer, a gyroscope, and a magnetometer, and the algorithms used are Bayesian Networks and the DTW algorithm. The experimental results revealed that 14 out of 15 drivers (93.3 percent) were correctly classified, indicating that the study's correctness was a very good and reliable figure. However, one disadvantage of this study is the large amount of data that was gathered. Only 15 drivers participated in the experiment, which is insufficient for conducting research. There is a chance that the study's correctness would have been lower if the sample size had been larger, i.e. the number of drivers was large. In that case, the results could have been different than they are now.

Similarly, one of the studies held in Bangalore, India [8] used low-cost smartphone sensors in their paper. However, their goal was to detect bumps, potholes, and braking events. It made use of an accelerometer, a microphone, and a GPS receiver. There were no machine learning algorithms used for prediction. Some event detection, however, resulted in False Positives (FPs). Another study published in 2012 [9] used low-cost mobile phone sensors to detect driving behaviour. Their primary goal was to analyse and profile behaviour in relation to the external environment. There was no use of a machine learning algorithm. The measurements were as follows:

- Bumps: 81.5%
- Potholes: 72.2%
- Rough roads: 75%
- Smooth roads: 91.5%
- Uneven roads: 89.4

CONCLUSION

A full evaluation of many learning and non-learning-based algorithms for driver behaviour profiling, analysis, and prediction is covered in this article. The article described many main strategies in depth by studying the methodologies and algorithms used to profile and forecast driver behaviour. It is expected that the shortcomings identified in each of the publications may point to further study areas that might be addressed by future scholars in this field. Though many of the publications discussed numerous ways for detecting and profiling driver behaviours, each method has its own set of advantages and disadvantages. Understanding the methodologies would undoubtedly aid in benchmarking our findings against future improvements in this field.

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