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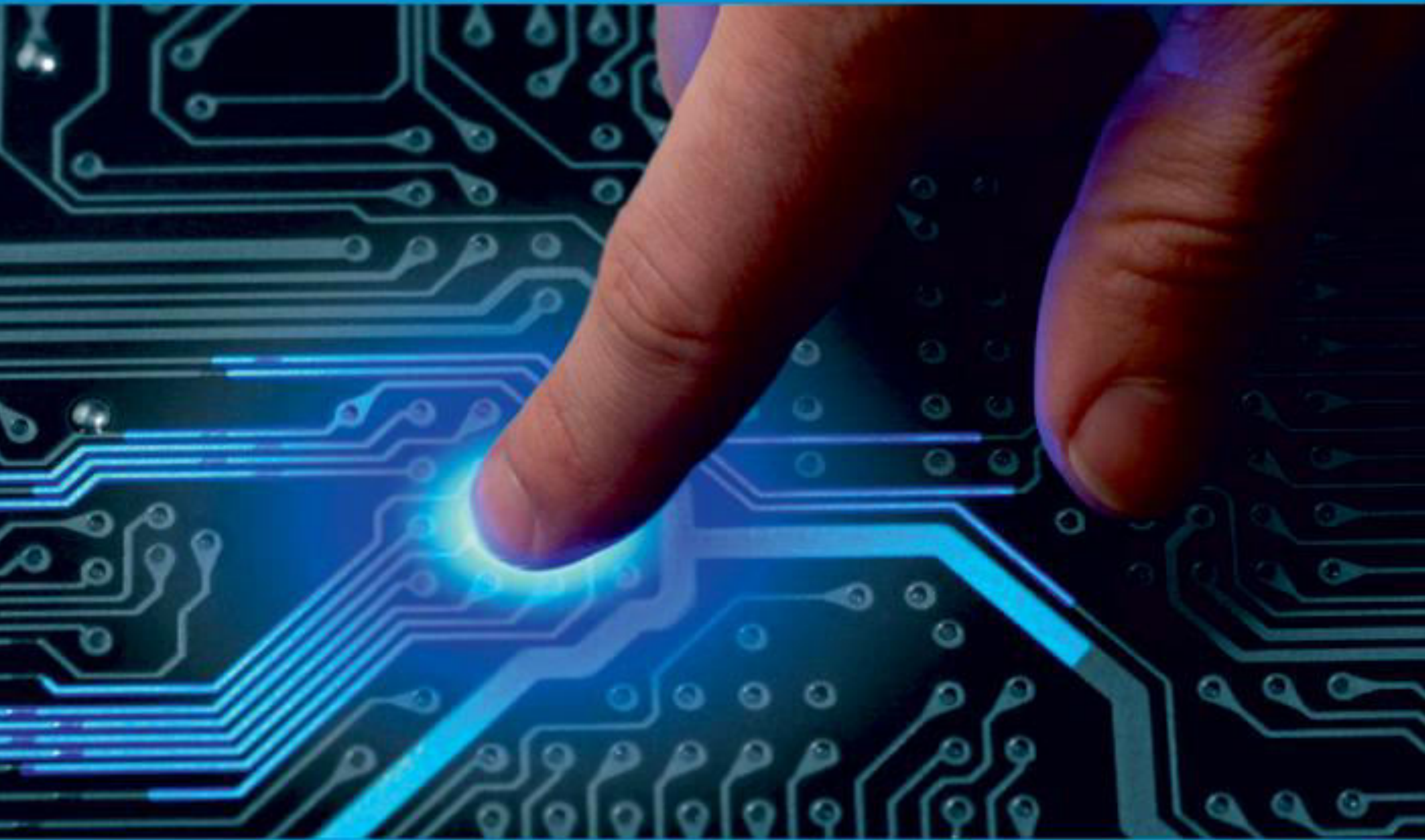

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A Privacy-Preserving Learning Method for Analyzing HEV Drivers Driving Behaviors

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ABSTRACT: Emerging electric-drive vehicles, such as hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs), hold the potential for substantial reduction of fuel consumption and greenhouse gas emissions. User driving behavior, which varies from person to person, can significantly affect (P)HEV operation and the corresponding energy and environmental impacts. Although some studies exist that investigate vehicle performance under different driving behaviors, either directed by vehicle manufacturers or via on-board diagnostic (OBD) devices, they are typically vehicle-specific and require extra device/effort. The main differentiation between all the known tested methods was found to reside in the execution time between the ML and DL algorithms, as was anticipated. A more holistic approach of such tools and technologies could lead to significantly increased safety in highways as well as to optimized performance in environmental and traffic terms. On the other hand, simultaneously with the exploration of new advanced approaches, research on the drawbacks, risks and dangers that come along with the evolution of transportation systems should also be conducted. Thus, researchers should also focus on the computational efficiency of those methods, on trustworthiness of the decision-making AI as well as on cybersecurity aspects and measures.

KEYWORDS: Behavioral sciences, Vehicles, Biological system modeling, Global Positioning System

I.INTRODUCTION

With the vigorous development of the global economy and the continuous expansion of the transportation industry, the number of agricultural vehicles has also continued to increase [1,2], and the resulting or potential driving safety problems have attracted more and more attention. Frequent traffic accidents It has caused huge losses to the people of all countries [3]. According to the report released by the World Health Organization, the number of deaths caused by traffic accidents in countries around the world continues to increase year by year, making road traffic accidents one of the major causes of death in the world [4]. In order to minimize the occurrence of traffic accidents, motor vehicle driving safety issues and motor vehicle safety driving guarantees have become the research hotspots of domestic and foreign experts, which are related to the life and property safety and personal health of drivers and the public [5], [6], [7].

Moreover, the research on traffic safety accident statistics points out that in the process of motor vehicle driving, non-standard and dangerous driving behaviors, including drivers' use of telephone, drinking water and smoking, are the most important factors leading to traffic safety problems. These behaviors will make drivers unable to concentrate on themselves, that is, they cannot pay attention to the road and the surrounding vehicle environment, which leads to more than 75% of traffic safety accidents [8]. Therefore, it is very important to further improve the monitoring ability of vehicle drivers' driving status and driving behavior, and provide timely reminders for drivers according to the monitoring results. It can effectively feedback the driving status to drivers and correct unsafe driving behavior, so as to avoid motor vehicle driving accidents and traffic safety problems [9], [10], [11].

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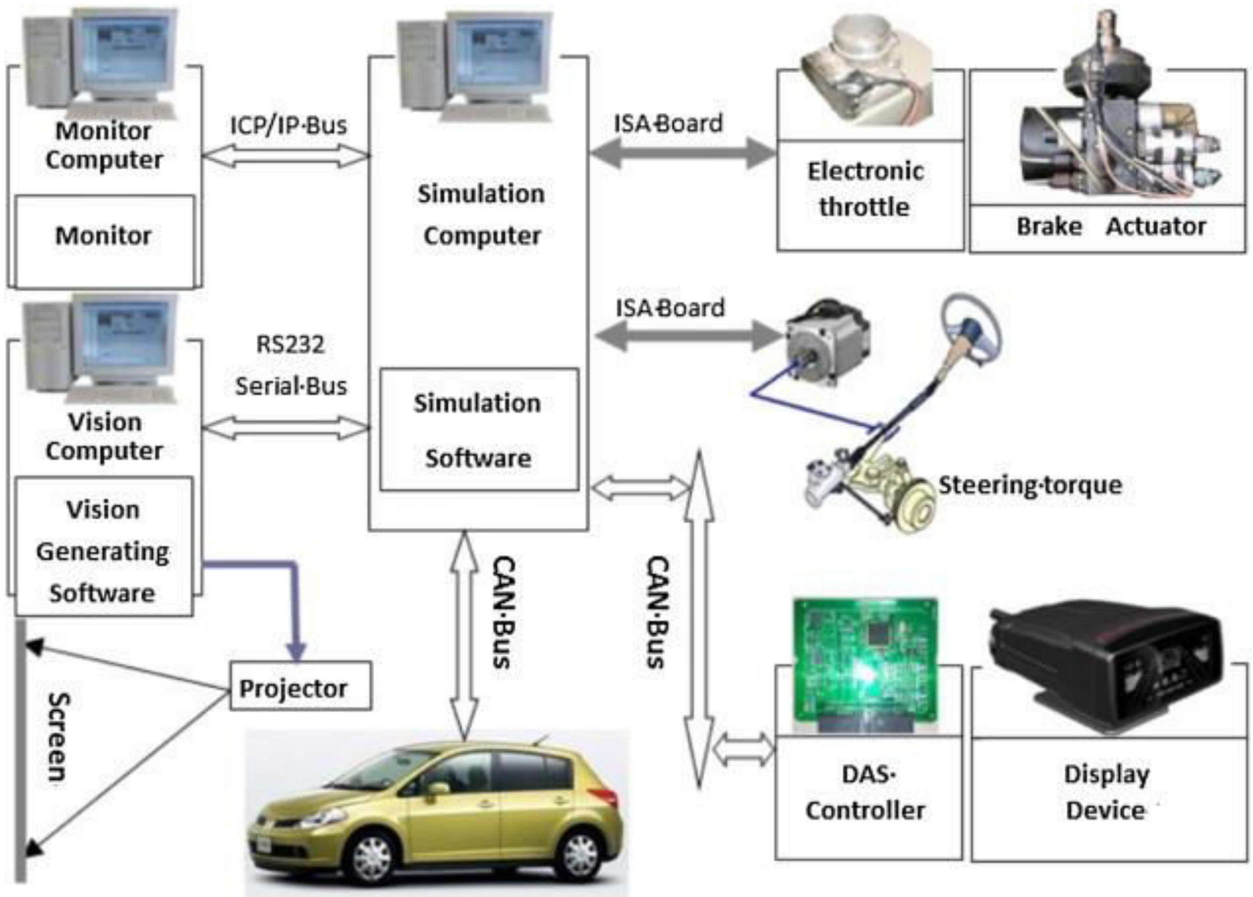

Fig 1: Effect of Human Factors on Driver Behavior

With the rise of computer technology and artificial intelligence technology, several emerging technologies have been applied to industrial practice. Among them, deep learning technology, as one of the most popular research fields, has achieved excellent application results in many fields, including face recognition, automatic driving, natural language processing. Therefore, facing the broad application prospect and practical application advantages of in-depth learning, applying it to the task of monitoring and judging the driving state of motor vehicle drivers will simplify the monitoring difficulty of dangerous driving state to the greatest extent, and then improve the safety factor of motor vehicle driving. However, with the continuous deepening of related works, CNNs model structure becomes increasingly complex, hardware cost increases, and application efficiency decreases, so the research of lightweight deep learning model is an inevitable trend.

II.RELATED WORK

For the driver's dangerous driving state monitoring system based on deep learning, the implementation of the system mainly depends on the recognition and classification of the driver's driving state image. It automatically extracts the feature information in the driver's state image through convolutional neural networks (CNNs), and completes the task of image recognition and classification according to the extracted features. Compared with the traditional image recognition and classification.

Finding data in the most cutting-edge industry takes significant work. Manufacturers are reluctant to provide any details. Yet, the OBD-II interface's data collection process is complicated. The manufacturers have their own protocols to stop rivals and safeguard the vehicles. Using an off-the-shelf IoT reader on the interface is generally impossible. As a result, access to the

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OBD-II data requires a customized IoT device. Studies have also revealed that in order to examine different driving styles, the battery data sampling range should be between 0.1 and 3. To our knowledge, only a few EV datasets shown in an meet the requirements of fine-time granularity, driving data integrity, and being labeled and publicly accessible. The following table compiles the prospective data that are available to the general public, and expands the data set to include the EV CAN data from. The features on the datasets are evaluated to ensure that they include at least the high voltage (HV) battery (e.g., voltage, current, temperature, SOC, and SOH) and driving features (e.g., padding operations, speed, throttle, and temperature). The onboard independent or integrated IMU and GPS sensing data may be included, depending on the vehicles and dataset. The partially annotated datasets included below make it possible to construct and analyze the real-world EV immediately since the driving behavior recognition methods mentioned in the following sections are based on their self-simulated data or remain unpublished.

The RNN may also instantaneously offer relevant responses or suggestions to assist with driving. An LSTM is created by to measure the level of comfort while riding using three inputs: velocity, longitudinal acceleration, and yaw rate. The data are initially divided into the designated zones, with the peak period and traffic flow taken into account as the input for the LSTM neural network. The LSTM network may then offer driving assistance through real-time suggestions. Similarly,] have presented an advanced stacked LSTM model to forecast the energy consumption from the acceleration and deceleration characteristics. They discover that the crucial markers were the frequency and duration of the acceleration and deceleration tendencies. Thus, using LSTM models, safety motion prediction based on trajectories can be accomplished. In the above investigations, the crucial model creation is moved to the preprocessing phases. It is vital to formulate the input based on the objectives.

III.METHODS

Machine learning methods are traditionally applied into projects and datasets that involve the prediction of a target value, attribute or uncovering trends. In these types of applications, data is used to assist machines to be trained with new patterns that they can be later used to perform an accurate prediction on newly added input data, at distinct time instances [**42**,**43**]. The most popular machine learning algorithms include linear regression, decision trees, support vector machines (SVMs), naïve Bayes, discriminant analysis, neural networks and ensemble methods. The current study applies supervised machine learning methods in order to enable a training process using the provided, labelled training dataset. Specifically, the algorithms that are examined in terms of accuracy and loss of the provided model(s) include: logistic regression, SVM and random forest.

Lately, deep learning is gaining high popularity due to its ability to perform well, in terms of accuracy and precision, during training processes with huge amount of data. Deep learning algorithms are used for more complex datasets and architectures such as object, signal and/or image identification. Commonly used deep learning algorithms include recurrent neural networks (RNNs), multiple layer perceptron (MLPs) and reinforcement learning (deep Q networks).

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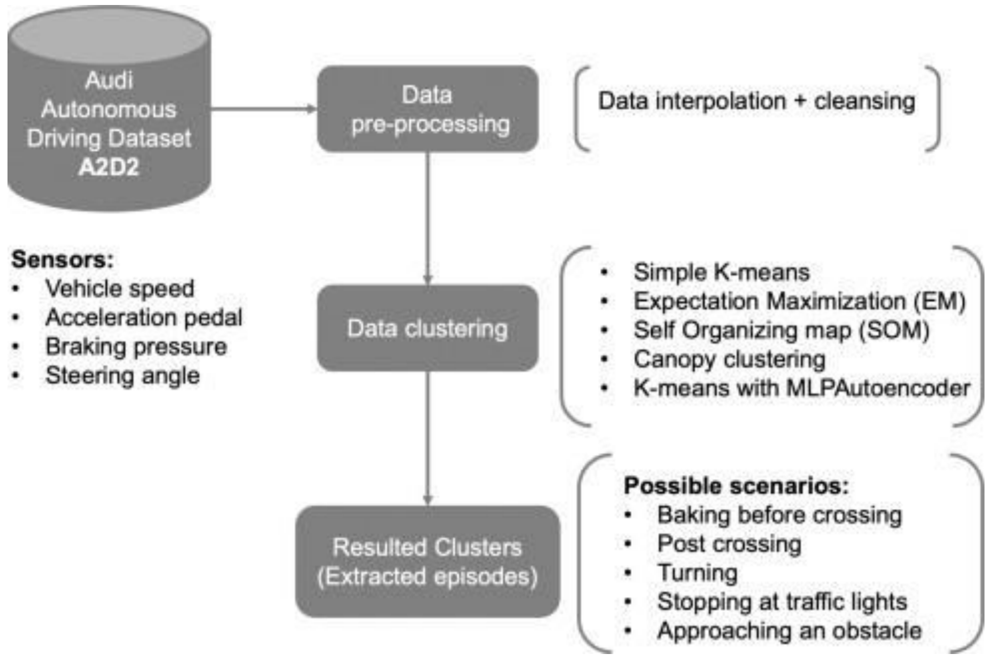

Fig 2: Profiling drivers based on driver dependent vehicle

Machine learning algorithms are faster when it comes to training new ML models and require less computational resources, hence result in quicker results in terms of execution time. In order to improve the model's accuracy, it is important to apply feature preprocessing on the studied dataset in order to reduce its initial complexity and provide more visible patterns through the learning procedure.

In fact, the integration of the data feature extractor is very important and is a desirable module for any large volume data management application. Also, from a mathematical point of view, the above provides maximization of the model's ability to classify patterns by enabling scoring functions and thus improving the overall performance of the model. Feature extraction procedures are of primary importance for the reduction of the complexity of the input dataset, which significantly determines the success or failure of the current ML model in terms of accuracy and loss. As was previously mentioned, the current procedure is important for the implementation of the proposed machine learning algorithms in order to make patterns more visible, so as to enhance the efficiency of the applied algorithms. The feature selection process can be applied in both supervised and unsupervised methods in order to reduce the number of input variables. The main difference between these two methods lies on the selection of the features that are based on the target variable or not. For the purposes of this study, the supervised feature selection techniques to the target variable and more specifically filter-based feature selection which involves statistical-based feature selection methods were applied.

IV.RESULT ANALYSIS

Drive cycles For a given drive cycle or a set of drive cycles, it is possible to deliver optimal results like high fuel economy, low emission and maintain desired state of charge (SOC). Legislative drive cycles (LDC) are commonly used for EMS optimisation. In real world driving, vehicles are not driven in LDC. Hence their performance may not be optimal. Real world drive cycles are more transient in comparison to LDC. They are used for vehicular emission inventory calculation and emission modelling based on time (per day, month and year) and region (urban, rural and national level). Some examples are ARTEMIS, EMPA and TRAMAQ. They are also used for vehicle durability assessment and study.
All three drivers were simulated using real world driving data for driving events like city and highway driving. In section 3.1, the effect of driver style and driving events on total vehicle energy demand, demand on electric motor and internal combustion engine (ICE) are analysed.

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Fig 3: HEV based object detection

During regions A and C, city driving conditions are fairly similar. But the vehicle energy demand for a given driver is not same. In region C after 16 km, vehicle speed is restricted due to traffic and signal. The influence of these external factors are significant but cannot be predicted in exact sense. Also variation due to the driver can be expected even driving exactly the same route again. Reactive driving, role of the driver, uncertainty of traffic and signal makes the prediction of exact vehicle speed to use in EMS for control strategy optimization not possible. By seeing speed profiles at region A and C, the use of average vehicle speed or range does not reflect the complete picture. Use of specific energy range for a given

V.CONCLUSION

Despite the fact that the autonomous vehicles gain more and more ground day by day, driver behaviour analysis is still an active and open research domain. Thus, the outcomes of this study could be expanded in the future by applying training results of the examined ML and DL algorithms for real-time classification of the drivers, according to their driving behaviour. Based on clustering analysis described previously, a future approach could also involve the execution of the actual unsupervised analysis over different pairs of values of the specific dataset (except of the already provided pair of rpm-SpeedOBD), in order to provide additional labels/profiles in the same logic. A meta-profile engine could be a (future) result/proposal of the algorithmic combination of the provided labels from the current dataset, where the evaluation of each driver could be returned in real time through the suggested cloud-based platform, again, based on continuous streams from car sensors, as were described in previous sections. Also, further data and tools, such as semantic technologies and complex event processing (CEP), could be engaged in order to gain more useful insights not only on the driving behaviour but also the ongoing road and traffic conditions.

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