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Driver Behavior Analysis Based on Sensor Data

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Abstract— ***In the realm of transportation, where the dynamics of mobility intersect with considerations of safety, efficiency, and environmental impact, the study of driving behavior holds paramount importance. Within this domain, this project embarks on the exploration of novel methodologies to track driving behavior by integrating diverse smartphone sensors and employing sophisticated machine learning algorithms. The overarching problem addressed in this research pertains to the imperative need for effective solutions in understanding and managing driving behavior. Driving behaviors, ranging from aggressive maneuvers to fuel-efficient driving habits, significantly influence various facets of transportation systems, including road safety, fuel consumption, and emissions. Despite the awareness of these impacts, the challenge lies in developing methodologies that can accurately capture and analyze driving behaviors in a cost-effective manner, thereby paving the way for informed interventions.***

This project focuses on elucidating the optimal combination of smartphone sensors and machine learning techniques to discern driver aggression—a crucial aspect of driving behavior that directly correlates with road safety and overall driving experience. By leveraging a plethora of sensors available in Android smartphones, such as accelerometers, gyroscopes, and GPS, in conjunction with advanced classification algorithms, the research aims to gather comprehensive driving data and extract meaningful insights into driver behavior patterns. Through rigorous experimentation and analysis, the study endeavors to address the fundamental question of which sensor fusion and machine learning approach yield the most effective results in identifying and characterizing driver aggression. By doing so, it seeks to contribute to the development of cost-effective yet high-performance solutions for analyzing driving behavior, thereby laying the groundwork for interventions aimed at enhancing individual driving habits and, consequently, the broader transportation ecosystem.

I. INTRODUCTION

India, one of the most populous countries in the world, is facing increasing problems with increasing traffic accidents in recent years. The main reason for this increase is poor driving behavior, which is also influenced by the diversity and difficulty of roads across the country. As of September 2021, traffic accidents in the country result in more than 150,000 [1] deaths every year, indicating that there is an urgent need for innovative and effective measures to reduce this problem.

To realize that road safety is for people's development, this research paper discusses the main path of development, namely the use of sensors in automobiles and smartphones. Sensors installed in the vehicle as well as in smartphones collect and analyze information about driving behavior.

A. Analysis of Driver Performance:

Our research includes analysis of the driver's performance using in-car sensors [3]. These sensors are designed to monitor various aspects of driving such as acceleration, braking, steering and even physiological data. Through this holistic assessment, we aim to better understand driver behaviors to promote safer driving. By understanding the complexity of individual driving and behavior, interventions can be tailored to address specific issues and create responsible and safe driving.

This research represents a significant step towards using technology to solve the complex road safety problem in India. By using the capabilities of onboard sensors for route determination and monitoring of driver performance, we aim to contribute to the improvement of road safety and management in a country with a large population and diversity. The remainder of this paper examines the methodology, findings, and implications of our study in more depth and highlights the potential for change in this new

II. MATH

Haversine distance [18]: The Haversine (or great circle) distance is the angular distance between two points on the surface of a sphere. The first coordinate of each point is assumed to be the latitude, the second is the longitude, given in radians.

$$D(x,y) = 2\arcsin[\sqrt{\sin^2((x_{lat} - y_{lat})/2) + \cos(x_{lat})\cos(y_{lat})\, sin^2((x_{lon} - y_{lon})/2)}]$$

Box-Cox transformation is a statistical technique that transforms your target variable so that your data closely resembles a normal distribution.

$$w_t = \begin{cases} \log(y_t) & \text{if } \lambda = 0; \\ (y_t^\lambda - 1)/\lambda & \text{otherwise.} \end{cases}$$

Principal component analysis (PCA). Linear dimensionality reduction using Singular Value Decomposition of the data to project it to a lower dimensional space. The input data is centered but not scaled for each feature before applying the SVD.

$$v = \sum_{i=1}^{n} a_i u_i$$

Correlation Matrix c = $C = \left(\frac{X \cdot X^T}{N-1}\right)$

$$C = \left(\frac{X \cdot X^T}{10-1}\right) = \left(\frac{X \cdot X^T}{9}\right)$$

$| C - \lambda I | = 0$

Cumulative Distribution Function formula: $F(x)=P[X \leq x]$.

Weighted sum formula:

$$A_i^{\text{WSM-score}} = \sum_{j=1}^{n} w_j a_{ij}, \text{ for } i = 1, 2, 3, \ldots, m.$$

III. UNITS

International standard of units:
Distance – kilometers (kms)
Time – seconds (s)
Speed – kilometers per second (km/s)
Latitude/ longitude – degrees (^{o})

IV. LITERATURE REVIEW

Using cell phones as sensor platforms to track driving behavior has become a viable way to increase road economy and safety. By developing a system that uses accelerometers and GPS sensors to record driving patterns, Johnson, and Trivedi (2011) [4] pioneered this field and made it possible to classify driving behaviors including aggressive driving, natural driving, and environmentally friendly driving. Their research did, however, point out several difficulties, such as differences in smartphone models that impact data gathering accuracy and privacy issues related to ongoing data monitoring. Expanding on these findings, Castagnoli et al. (2015) [5] presented the SenseFleet system, providing an adaptive and versatile approach to evaluating driving behavior across various devices and automobiles. The SenseFleet system has drawbacks despite its advantages, such as an excessive dependence on GPS data and a lack of standardization, which can impair its dependability in specific circumstances. Alam et al. (2017) [6] addressed the need for equitable and efficient systems for evaluating drivers by putting forth a method that uses machine learning and smartphones to evaluate drivers' performance in an objective manner. Their strategy highlights how crucial it is to guarantee equal access to technology, especially in underdeveloped nations where access discrepancies may occur. However, there are still issues to be resolved before their suggested approach can be used in practical settings, such as scalability and evaluation system constraints. In their investigation of the classification of driving behavior using machine learning and On-board diagnostics (OBD) data, Kumar and Jain (2023) [7] emphasized the possible applications of this method, including driver monitoring, insurance premium computation, and safer driving advice. Despite the potential advantages, there are still issues that must be resolved, like standardizing OBD data across various car models and handling privacy issues related to data collecting and storage. Furthermore, it's possible that the analysis did not fully account for outside variables like traffic patterns and road conditions, pointing to the need for additional study to improve the efficiency and applicability of this strategy. In conclusion, even if the use of cell phones and machine learning to analyze driving behaviors shows promise, more research is required to overcome current obstacles and fully realize the potential benefits for road safety and efficiency.

V. METHODOLOGY

The goal of the suggested system design is to smoothly incorporate in-car sensor data into a framework for assessing driving behaviors. To provide compatibility and interoperability across multiple vehicle designs, it makes use of the AUTOSAR [9] interface to facilitate standardized communication [8] between various electronic control units within the vehicle. The AUTOSAR [10] interface is used by the system to gather sensor data, which is subsequently sent to mobile devices that serve as hubs in between for processing and storing in real time. Making use of the AUTOSAR interface improves adaptability and scalability to various vehicle parts. Once the sensor data reaches the mobile devices, it is fed into a machine learning (ML) model [17] that is tailored to evaluate driving behavior. This machine learning model includes a linear regression model [18] that considers variables including steering, braking, acceleration. Over time, the model continuously learns and adjusts, increasing its accuracy in assessing driving behaviors. This is done by evaluating the driver's performance with respect to the other drivers in the dataset (of 89 drivers and 899611 records) and assigning a metric for the individual driver based on that.

Additionally, mobile devices function as storage devices, safely storing gathered sensor data in a centralized location for quick retrieval and further examination. Additionally, they offer drivers an intuitive user interface with tailored feedback and insights from the ML model assessment. This method has the potential to completely change the way driving habits are assessed, resulting in well-informed interventions, and eventually improving road safety.

Sensor data collected by the AUTOSAR interface is sent t o the mobile device, which acts as a central point for storage. This data is then sent to the cloud where the computing and processing of the data is carried out. An app is used to display the behavior of the driver to act as a source of feedback and can also be used to analyze the drivers' habits over a long period of time.

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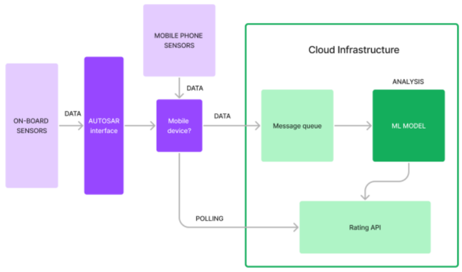


Fig 1.1. System Design

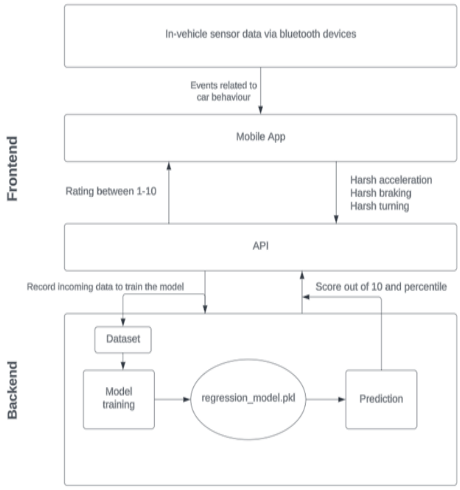


Fig 1.2. Implementation Methodology

VI. RESULTS

Flutter applications work as a user interface, enabling interaction between drivers and traffic data. The application is built using the Dart programming language to ensure cross-platform compatibility and responsive design. It provides instant insights into amplifying emotions, personalized feedback, and historical data analysis. The app easily integrates with mobile devices using Flutter's rich widget library to provide an intuitive and engaging user experience.

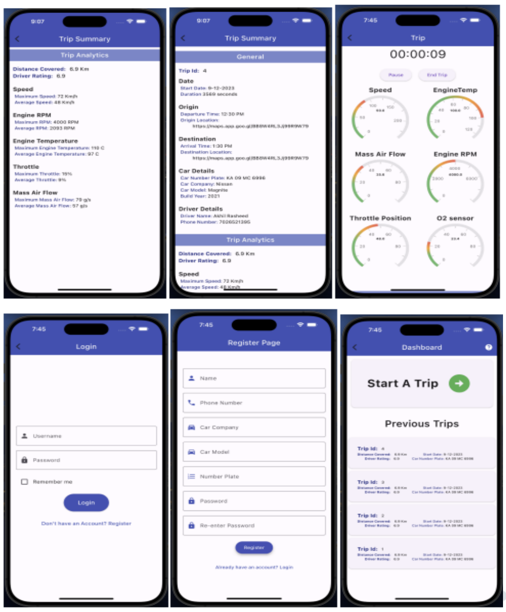
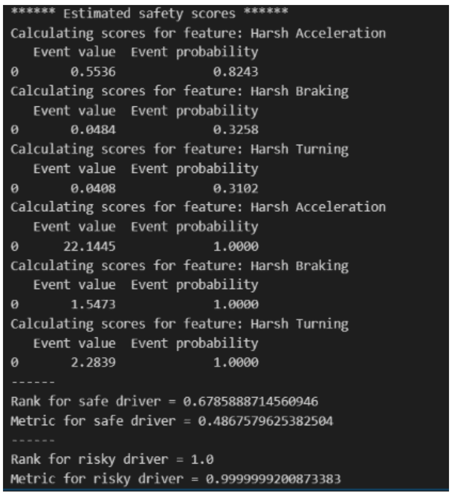


Fig 2.1. Flutter App

Our main idea when analyzing this data is that the worse the situation a driver faces, the more likely he is to be a bad driver. Driving with zero sharp turns, zero sharp acceleration, zero sharp acceleration and zero sharp braking over a given distance is generally classified as a safe driver. Instead, we can assume that a driver who practices too many times over the same distance is a bad driver.

We used several different modelling methods:

- Modeling the problem as a fault-finding problem or using some form of integration to find safe/unsafe driving clusters.
- Find a multivariate indicator that combines our multivariate assumptions and allows us to predict poor driving behavior using multivariate distribution probability.
- Reduce the size to 1 and try to find the rules/levels of the integration index. Use univariate statistical models: Model each event separately using the distribution.



```
****** Estimated safety scores ******
Calculating scores for feature: Harsh Acceleration
   Event value  Event probability
0       0.5536             0.8243
Calculating scores for feature: Harsh Braking
   Event value  Event probability
0       0.0484             0.3258
Calculating scores for feature: Harsh Turning
   Event value  Event probability
0       0.0408             0.3102
Calculating scores for feature: Harsh Acceleration
   Event value  Event probability
0      22.1445             1.0000
Calculating scores for feature: Harsh Braking
   Event value  Event probability
0       1.5473             1.0000
Calculating scores for feature: Harsh Turning
   Event value  Event probability
0       2.2839             1.0000
------
Rank for safe driver = 0.6785888714560946
Metric for safe driver = 0.4867579625382504
------
Rank for risky driver = 1.0
Metric for risky driver = 0.9999999200873383
```

Fig 2.2. Metric and percentile of the driver

VII. VII. CONCLUSION

This project offers a comprehensive strategy for driver behavior analysis and monitoring, utilizing in-vehicle data recording systems that encompass CAN-bus and OBD interfaces, as well as other installed devices, to capture real-time data on vehicle performance and driver actions. In parallel, we harness smartphone-based sensing, using the sensors found in everyday smartphones, to assess driving behavior in real time with dedicated data collection apps. Our efforts go beyond data collection, extending into behavior detection methods. We utilize statistical and machine learning algorithms to continually evaluate and categorize driving behavior, with a strong emphasis on preventing accidents and promoting safe driving practices. This approach can be tailored to monitor specific behaviors based on user or organizational preferences. In brief, this project integrates these approaches to create a comprehensive system for driver behavior analysis and monitoring, with our primary goal being to enhance road safety, reduce accidents, and cultivate responsible driving habits, benefiting all road users.

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