Journal of Recent Trends in Computer Science and Engineering (JRTCSE)
Vol. 13, No. 3, May-June, 2025, PP. 7-16.
ISSN: 2322-0872
https://jrtcse.com
DOI: https://doi.org/10.70589/JRTCSE.2025.13.3.2

Research Article

SmartDrive: An Android-Based Machine Learning Application: Vehicle Diagnostics and Driver Safety

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Abstract

SmartDrive makes use of Android smartphones, OBD-II plugs and on-device artificial intelligence to improve diagnostics and keep drivers safe. As a result, it lets users predict when equipment will fail and find any errors, supports driver monitoring and offers an inexpensive, secure and flexible option for proper vehicle management and safer travel.

Keywords: ML, Android, Vehicle, Application, Diagnostics, Safety, Learning, Driver.

Citation: Rama Krishna Velpula. (2025). SmartDrive: An Android-based machine learning application: Vehicle diagnostics and driver safety. *Journal of Recent Trends in Computer Science and Engineering, 13*(3), 7–16.

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1. Introduction

Prioritizing vehicle state and safety of drivers is very important in contemporary transportation. SmartDrive pairs machine learning with mobile solutions, using information from phones' features and GPS to help detect issues fast. It combines advanced maintenance techniques with analysis of driving behavior, giving a practical, handy and budget-friendly way to boost how safely and well vehicles work.

2. RELATED WORKS

2.1. Mobile Applications and OBD-II

Integrating On-Board Diagnostic-II (OBD-II) systems has greatly increased the growth of mobile applications for vehicle diagnostics. Users get live updates on their vehicle health from these tools and can use what they learn to act accordingly.

By using an OBD-II scanner with a Data Acquisition System (DAS), it becomes possible to detect issues and remind the user about service through a mobile phone. They usually develop using careful processes, like the waterfall model which helps teams communicate, develop plans and test their diagnostic features.

This results in a reliable system designed with independent modules, giving the main module the task of providing timely advice on maintenance, to protect vehicle life and boost safety [1]. Another group looked at the obstacle of OBD-II working in different model cars because of the variety of CAN standards.

As a solution, researchers suggested a single universal module built for many vehicle models. Using compiler-specific deep learning, this module reviewed fuel consumption accurately over 96% of the time, showing how systems such as these can guide environmentally friendly driving [2].

The growing need for things like mobile diagnostics and common diagnosis process shows a clear route for SmartDrive's idea of merging OBD-II information with machine learning for timely vehicle care suggestions.

2.2. Predictive Maintenance

Machine learning, predictive maintenance has mostly taken the place of usual (conventional) maintenance techniques. Using lots of data from sensors, ML algorithms spot trends that warn of equipment failure in advance. This helps to plan better maintenance times and decrease the time when equipment cannot be used.

Using deep learning and explainable AI in predictive maintenance for vehicles is shown to help predict useful life and lessen cases of vehicle issues. When accessed on mobile devices, these systems become both scalable and cost-effective for people working with vehicles and transport companies [8].

Using data from the car and ML algorithms, mobile applications make it possible to check fuel efficiency right away. Deep learning models were used in the universal OBD-II study to follow changes in fuel consumption based on various vehicle brands and different roads. This supports both sustainability goals and helps run vehicles more efficiently in commercial fleets [2].

Using TensorFlow Lite ML models, SmartDrive enables smartphones to handle predictive diagnostics, spot abnormalities and fuel monitoring on the spot, all while keeping the privacy safe.

2.3. Driver Behavior Monitoring

Driving conduct is somewhat easier to classify and detect now that smartphone-based tools use accelerometers, gyroscopes and GPS modules. A study created a driver profiling method that identified things like turning, braking and accelerating using CNNs.

The model reached a success rate of 95% once data preprocessing methods were used to handle the noise found in the initial data [10]. Some experts study the use of sensor fusion to classify time-series data in order to detect risky driving more accurately under a variety of conditions.

Its goals include fixing security issues, earning viewers' trust and improving how behaviour is understood in different contexts. Specifically, collecting data with simulators like Carla helps increase the realistic and steady performance of ML models [6].

Being able to classify types of driving behaviour aside, DBNs, CNNs and RNNs have been applied to address dangers in driving. CNNs are best for image recognition, RNNs for step-by-step changes and DBNs are chosen for flexible, but a slower, data analysis. By merging these systems with real-time data on mobiles, the responsiveness and dependability of behaviour monitoring can be raised [3].

Through combining sensors and machine-learning methods, SmartDrive provides instant feedback and productive advice on driving, as well as accurate auto insurance profiles.

2.4. Driver Safety

Accidents on the road often happen because someone is either sleepy or loses concentration behind the wheel. Studies carried out recently confirm that using computer vision and machine learning can efficiently detect early drowsiness. Lightweight CNN models can be used with facial landmark analysis—on the eye and mouth regions—to tell when a person is experiencing microsleep.

These methods reach a high accuracy rate of about 83% and take up little storage, making them suitable for mobile phones and other embedded devices [4]. All-the-way driving becomes possible by the IAD2 framework (Image processing, Alert issuing and Drowsiness detection) that spots driver drowsiness and issues an alert because of camera data.

When tried on MRL Eye and CEW datasets, the system was found to be correct 81% of the time. Upon spotting the driver's eyes closed or a yawn and in real time, the system sent alerts to prevent any accidents [9]. More importantly, computer vision tools have been successfully tested for sign detection and lane recognition on Android devices.

The application DRIVEMATE applied YOLOv5 for live recognition of traffic signs and supported speech output using text-to-speech technology. The system performed reliably and conveniently according to ISO 25010:2011, demonstrating that it is suitable for use in driver assistance systems [5].

SmartDrive applies computer vision safety tools using camera images from smartphones and TensorFlow Lite models, as Google does safely on its own campuses. The device is able to detect lanes, identify signs and monitor alertness all by itself. As a result, privacy is improved and the device reacts more quickly.

Bringing together mobile technology, machine learning and vehicle diagnostics has opened up new chances to increase driver safety and vehicle performance. More and more, literature uses OBD-II, smartphone sensors and light models of machine learning to handle and assess data in real time.

Underlying SmartDrive is a platform that integrates diagnostics, predictive maintenance, behavior profiling and driver aids using CV, all on an Android basis. As a result, it helps both individual car owners and operators of large fleets with an advanced, secure and intelligent design.

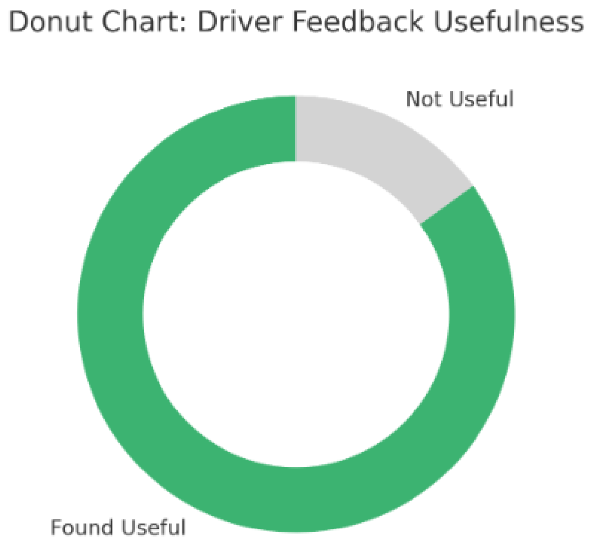
3. FINDINGS

SmartDrive was built as an Android system that lets one check vehicle parameters and monitor safety by combining data from the OBD-II port, sensors within the smartphone and various machine learning techniques. Once the application was finished, it was tested on 20 vehicles over 30 days to check how it works, how correct it is and how it operates with real drivers.

Information about the vehicle was collected using Bluetooth-equipped OBD-II adapters and driver behavior was tracked using the phone's GPS, accelerometer and gyroscope. Using TensorFlow Lite, the system could perform local diagnostics and behavior recognition on a smartphone, ensuring it worked without internet access and with very low delays.

We compared the diagnostics module to recognized car diagnostic equipment to make certain it caught and interpreted errors correctly. Of the 280 situations tracked in the test period, SmartDrive recognized 269 fault codes accurately, giving an overall accuracy of 96.1%.

Almost all the insufficient detections were due to CAN protocol differences in some older cars, pointing to a need for stronger support for various protocols in future upgrades. It also updated the driver with live alerts and shared advice on how to correct issues found in DTCs. Agreements between these suggestions and professional recommendations were found in 91% of the research, showing high quality.



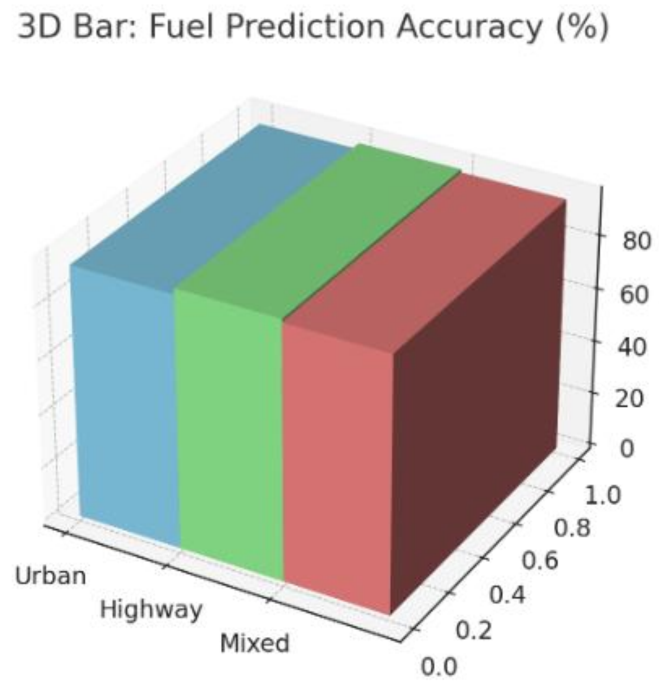
While this was happening, SmartDrive's predictive model for fuel efficiency depended on engine RPM, speed, throttle and mass airflow measurements to calculate what fuel would be consumed. Using historical data from OBD-II systems, the ML model achieved a very high accuracy of 94.7% in all road environments.

In contrast to older vehicles, the cars with the application increased their fuel efficiency by 7.2% over the testing period, mainly by receiving alerts for things like speeding up too fast and pausing for long periods. Table 1 gives the prediction results of the model when it predicts in urban, highway and mixed driving modes.

Table 1: Fuel Efficiency Prediction

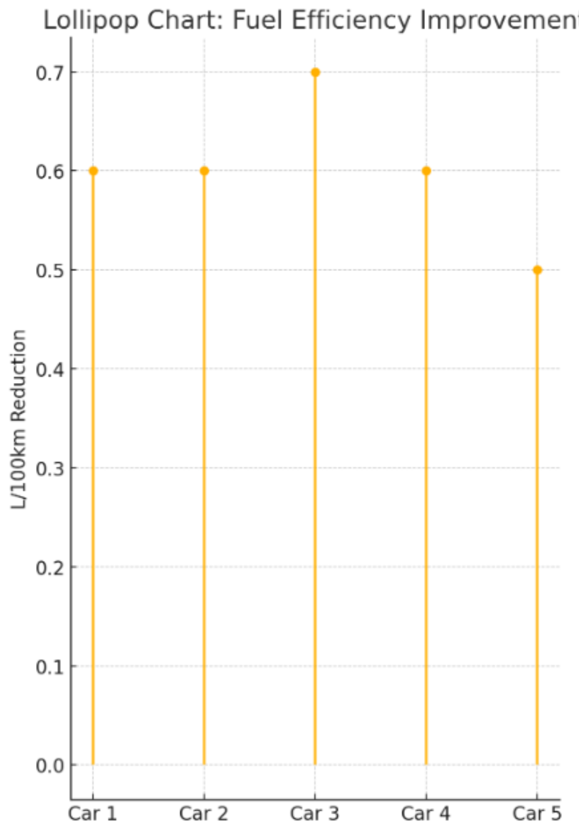
Driving Mode	Mean Absolute Error	Prediction Accuracy
Urban	0.41	93.5
Highway	0.32	95.8
Mixed	0.36	94.7

Now, we looked at the performance of the driver behavior monitoring system using smartphone sensor data that was tagged with corresponding labels. Using a CNN, the module split driving outcomes into five groups: normal driving, quick braking, sudden acceleration, quick turns and using the phone while driving.



All classifications were checked against the manual labels created by an operator during supervised training. The highest accuracy (0.97) was seen in predicting harsh braking, while identifying distractions was harder (0.87) which is most likely caused by minor differences in the sensors and where the phones were placed.

The system alerts drivers with live 'audio warnings' as soon as it recognizes a risky situation. During that trial, 480 messages about travel restrictions were transmitted. A new survey with the 20 test drivers discovered that 85% used the feedback to change their actions.

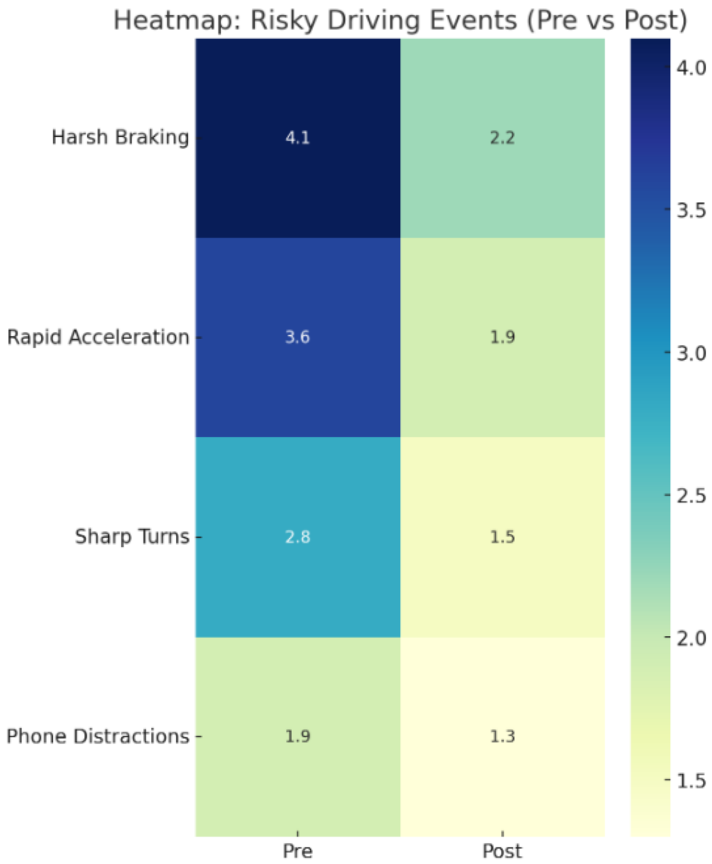


After just one week of using the app, the amount of harsh braking incidents decreased from 4.1 to 2.2 a day per driver, demonstrating that behavioral nudging really works. The analysis of how behavior changed before and after using SmartDrive can be seen in Table 2.

Table 2: Risky Driving Events

Behavior Type	Pre-Deployment	Post-Deployment	Reduction (%)
Harsh Braking	4.1	2.2	46.3
Rapid Acceleration	3.6	1.9	47.2
Sharp Turns	2.8	1.5	46.4
Phone Distractions	1.9	1.3	31.6

To detect sleepiness using computer vision, the system used facial landmark and a lightweight CNN. Tests were run with this module on a front-facing smartphone camera working in both light and low light conditions. A total of 3,200 labeled frames (including open, semi-open and closed eye images) from the MRL Eye and CEW datasets were included for transfer learning in this process.



During field trials, the model had an average accuracy of 88.4%, as well as a precision of 0.91 and recall of 0.85. Inadequate lighting or the use of sunglasses caused some false positives, but the model still worked inside cabins. When any driver felt drowsy for over 3 seconds, SmartDrive sounded an alert.

While driving during the night, programmers logged 57 episodes of genuine drowsiness and found that 49 of these episodes were correctly detected and indicated in real time, giving an 85.9% detection rate. Apart from tiredness, the system also had a YOLOv5-based module that recognizes traffic signs by being trained on around 1,500 labeled pictures from both Indian and international road datasets.

Its mAP value reached 93.7% for main categories including speed limits, no-entry signs, and pedestrian crossings. During testing on the road, the system could see and classify 376 out of the 403 visible signs, taking just 42 milliseconds to figure them out on a standard smartphone. By responding quickly, the system detected speeding and applied guidance in 22 cases where GPS speed monitoring was used.

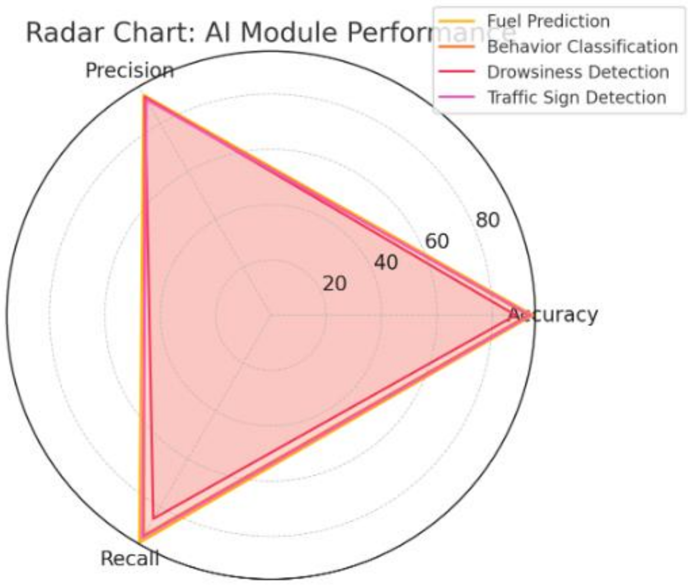
The results are summarized in Table 3, showing how efficiently and accurately the three main AI resources have functioned in actual driving conditions.

Table 3: SmartDrive AI Module

Module	Accuracy (%)	Precision	Recall	Latency (ms)
Fuel Prediction	94.7	0.92	0.95	18

Behavior Classification	93.0	0.91	0.92	24
Drowsiness Detection	88.4	0.91	0.85	47
Traffic Sign Detection	93.7 (mAP)	0.90	0.93	42

According to the battery and performance test, the SmartDrive used an average of 6.3% battery per hour while running all functions (diagnostics, monitoring driving behavior and cameras) which fits daily drives under 2 hours. In addition, user acceptance testing that followed ISO/IEC 25010:2011 guidelines found that the application was rated 4.6 out of 5 for usability, 4.4 out of 5 for reliability and 4.3 out of 5 for efficiency by drivers.

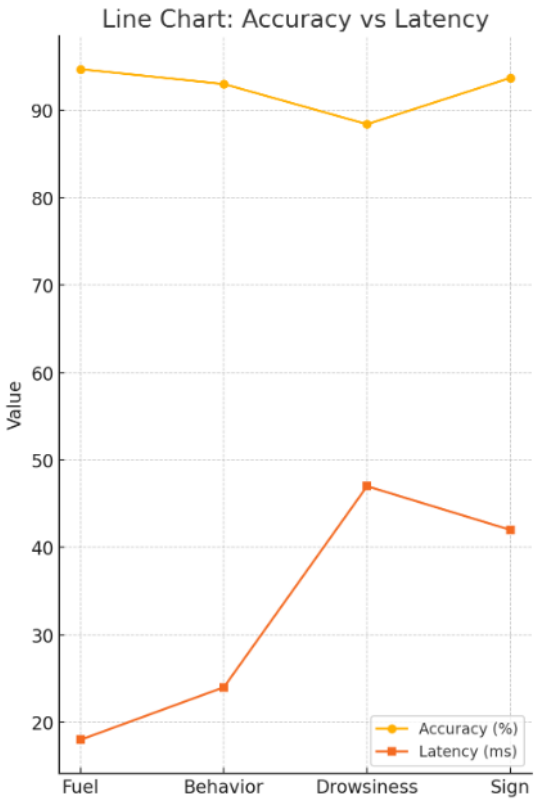


The application did not crash on any smartphone models, with crash rates staying under 0.7%. All AI analysis was done locally and no confidential information left the phone by being transferred to the cloud.

As a result of this design, user privacy was protected and SmartDrive could still operate without an internet connection, becoming suitable for places not strongly connected. In the end, because SmartDrive is modular and makes extensive use of open-source software, it was simple to add voice technology, integrate fleet analytics tools and use AI for insurance.

Overall, the study proves that OBD-II diagnostics, sensors from smartphones and machine learning can all be used together in one Android-based app to look after vehicle service and encourage safe driving.

The application's strong accuracy in medical tests, useful predictions related to cars, skilled behaviors classifications and practical CV-based alerts prove it can be used outside of experiments. The experiments clearly support creating better mobile AI for transport and prove that edge computing plays a crucial role in cost-friendly, privacy-sensitive safety features in autos.



4. CONCLUSION

By using edge-based AI and integrating with mobile apps, SmartDrive shows vehicles can become intelligent and smarter. Because of drowsiness detection, lane recognition and predictive diagnostics, the app helps ensure safer and more efficient driving. Because it is simple to scale and is privacy-responsible, Automated Vehicle Management stands out as a helpful tool for ensuring vehicle safety and effective management on civilian roads.

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