Commute Tracking Mentor Tool for Automobile to Decrease Car Accidents

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***Abstract*— In 2020, nearly 39,000 lives were lost to motor vehicle accidents, and 2.3 million people were injured. In addition, over 5 million not-fatal crashes occurred. New and emerging technology is being introduced and included in automobiles. Vehicles have been equipped with new features and gadgets to assist drivers with commuting. However, regardless of these features, driver error directly causes many accidents. Artificial Intelligence (AI) is used for this research to study and analyze driving patterns. This solution differs from others because the focus is on improving driving behaviors rather than providing the driver with tools that will only assist when the driver is making errors. This proposed solution is implemented and tested on smartphones using the data collected from a mobile app called Phyphox. The goal is to determine and detect irregular driving patterns from the driver to assess and improve their driving skills.**

Keywords—ride, automobiles, acceleration rate, driver-vehicle interaction, machine learning.

I. INTRODUCTION

In 2020, the U.S. The Department of Transportation (DoT) reported 5,215,071 police-reported crashes. Among those crashes, 35,766 were fatal and took the lives of nearly 39,000 loved ones. The report provided by the U.S. DoT does show a decrease in overall car accidents compared to the previous year. However, speed-related crashes increased by 17%, and alcohol-impaired driving crashes up by 14% compared to the previous years' numbers.[6]. There are very few solutions to decreasing these numbers and improving driving scores. Liberty Mutual insurance company has an app, RightTrack, that evaluates its members driving habits. In addition, State Farm also has an app, Drive Safe & Save that is similar to RightTrack. Liberty Mutual's app tracks the user's Acceleration, Braking, Location, Phone Motion, Speed, and more. However, it will evaluate only for 90 days and give a score to determine the pricing of their car insurance. State Farm provides a discount that is adjusted at every new policy renewal. The app limits itself because of the duration its members use it for. Liberty Mutual could provide weekly scores and monthly pricing based on their monthly score. This would encourage drivers to drive safer and adjust their driving skills to be safer and save money. RightTrack uses the user's mobile device to track all data because most smartphones have various sensors to measure the metrics mentioned earlier.

This paper provides a solution to address speeding, distracted drivers, and other factors that result in traffic accidents. The Commute Tracking Mentor (CTM) tool studies drivers' patterns and suggests improving their driving. In addition, the tool is tasked with understanding driving habits and behaviors. The paper aims to demonstrate the use of CTM in analyzing data and determining maneuvers made by the driver. Along with this demonstration, the goal is to improve driving skills and make drivers more aware of recurring errors that could lead to accidents.

The rest of the paper is organized as follows. Section II discusses related work on traffic accidents. Section III discusses the problem that is trying to be addressed and the motivation for the research. Section IV explains the approach and preparation for the data collection. Section V reviews the tool's results and analysis, and Section VI concludes the paper.

II. LITERATURE REVIEW

Reducing traffic accidents will determine how drivers are held accountable. Car companies have added various features that assist the driver. For example, Auto Emergency Braking, or Smart Brake system, is designed to assist the driver in braking by detecting when the car is approaching another vehicle or object at a high acceleration rate. Car features that help the driver by alerting them will not reduce accidents. Priyanka et al. [7] focus on drivers by focusing on unintended acceleration and drowsiness by the driver. Their attention is channeled to solutions that react to users' driving actions, not driving behaviors. The authors in [7] suggest using ultrasonic sensors that use sound waves to determine the distance to an object. This proposition is similar to most intelligent braking systems in newer vehicles. In addition, they propose using a heartbeat sensor that will be attached to the driver's seatbelt. The driver's heartbeat is monitored, and when spiked or presents abnormal rhythms paired with the ultrasonic sensors will cause the car to decelerate and brake. The second solution is to detect if the driver is sleeping or beginning to fall asleep using the input obtained by a webcam using image processing tools [7]. This paper gives an example of technology being researched and created to react to driver behavior rather than improve driver behavior. Although these are excellent additions to a vehicle that will prevent various traffic accidents, they only give drivers the false belief that their hiccups and errors will be stopped due to car features. They do not encourage drivers to drive better, but rather give comfort to making mistakes.

Automobiles of the future could have customizable Driver-Vehicle Interaction (DVI) engines with an interaction system to learn driving propensity and behaviors, as Choi et al. [4] suggested. A successive and repetitive cycle to customize and personalize real-time driving environments will be developed utilizing Machine Learning (ML) [4]. This will allow DVI engines to adjust and adapt to their driver and tailor certain features to them. The learning process is solely to create a better DVI engine for the driver rather than provide feedback to drivers. A great addition is sending the driver an assessment of their performance.

The explainability offered to drivers can inspire the development of training methods and evaluation metrics that guarantee trustworthiness and consistency [2]. In addition, evaluation metrics can be organized and tuned to fit the overall goal of this research. Using the same evaluation metrics for diverse design objectives can be problematic when selecting measurement methods [2]. For CTM, evaluation metrics made preemptively were adjusted and followed an interactive design process. This process and focus ensure that the tool is constantly evolving and improving to ensure feedback given to drivers allows them to identify accurately what driving behaviors can be improved.

Ali et al. [1] use evaluation metrics to evaluate their predictive model's performance. Accuracy is one of their metrics and represents the percentage of correctly classified

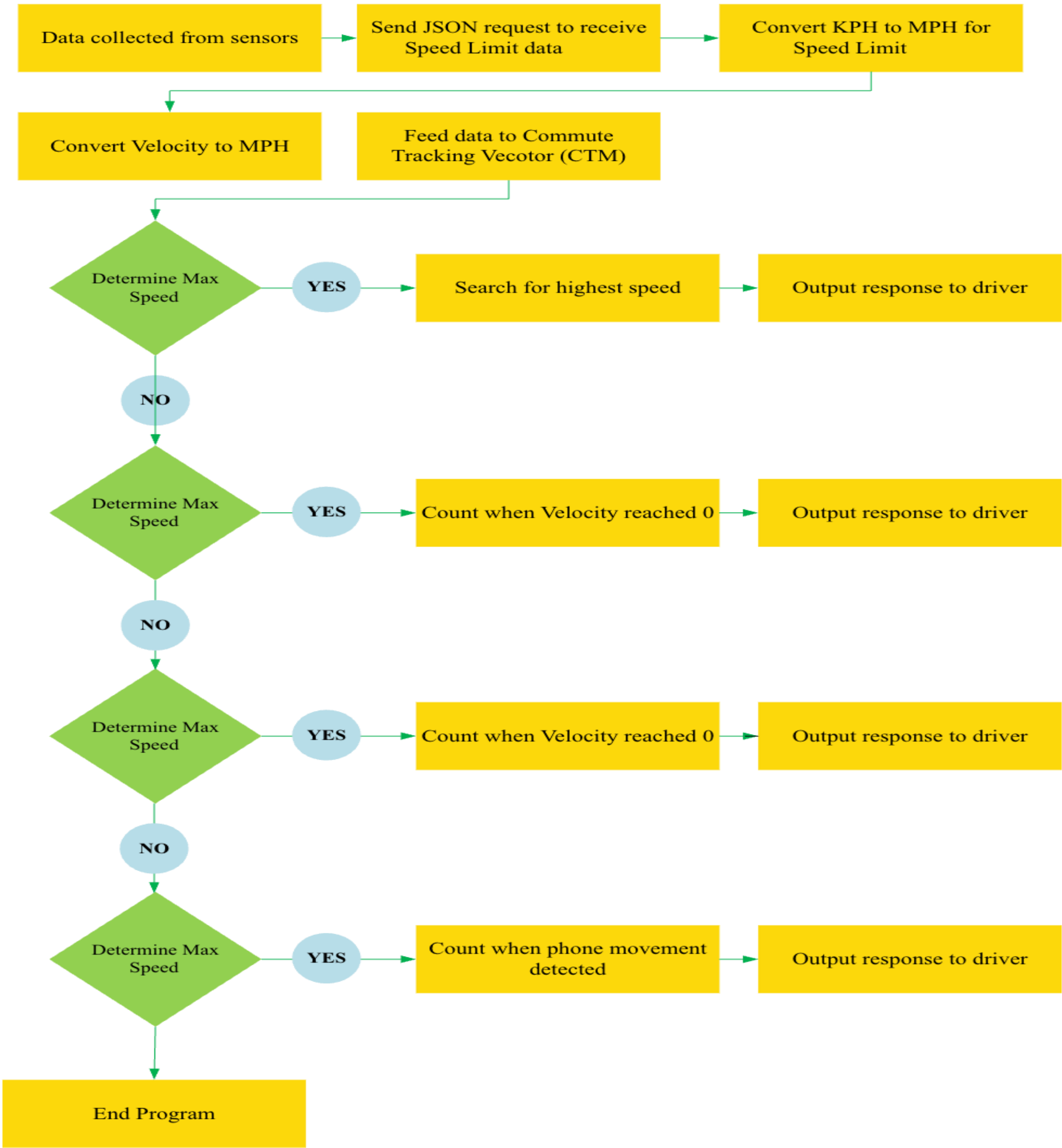

Figure 1. Flow chart demonstrating the data collection and analyzation process of CTM.

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subjects in the test dataset. Another metric is sensitivity, which conveys information about correctly classified patients' percentages. Metrics have been organized for CTM to identify when the driver has stopped their vehicle abruptly or identify their maximum speed. Identifying and analyzing this data throughout their car ride summarizes their actions. In addition, this metric can be tuned to identify poor and good drivers among the datasets.

Unlike previous work, in this paper, the pairing of CTM and mobile phone data is the ambitious factor in addressing drivers' behavior using data collected from their driving patterns. AI will be used as a decision support/augmentation tool rather than as the automation of decision-making [3]. A significant difference in this paper's work is that the environment is not simulated and is recorded in real drivers' performances. Various hardware and software algorithms are being developed; however, they are being tested in simulated environments instead of real driving ones [5]. This is mainly due to the danger of testing and analyzing specific scenarios such as drowsiness and drunk driving. Lastly, CTM focuses on learning drivers' behaviors and providing feedback.

III. PROBLEM STATEMENT AND MOTIVATION

The focus of this paper is to study driving patterns from the driver and detect different drivers' behaviors while they drive. Behaviors can include when the driver is speeding or stops abruptly. The focus of this paper will help address car accidents. If car accidents can be reduced, fewer people will lose their lives each year, and even more will not be injured. This paper proposes a solution that will lead to safer roads for automobiles. Each year, car accidents have a significant effect on countless individuals and their families. Lives are lost, and families are scarred and endure unbearable suffering. The motivation lies in being able to prevent these tragedies. In addition, the motivation is grounded in the belief that through research and practical solutions, car accidents can become less common, lives can be saved, and families can remain intact.

IV. METHODOLOGY/APPROACH

Data collection involves observing automobile trips from Point A to Point B. Data was collected using a mobile app called Phyphox. This app allows users to use tools such as a Gyroscope and Accelerometer in our phone to track the phones movement and its surroundings. Phyphox can gather data without inconveniencing the driver. Data collection was gathered, handled, and utilized with various resources. All experiments used an iPhone 13 Pro Max, the Phyphox app, and an automobile. After experiments, drivers can store the data locally on their phones or export it to another storage type (Google Drive, Dropbox, etc.). The flow diagram in Figure 1 presents a step-by-step process of collecting and processing the data. Data is collected from the sensors and saved locally onto the mobile device.

The Location sensor is then accessed to obtain the Longitude and Latitude. Those coordinates are sent using a JavaScript Object Notation (JSON) request to a Google Application Programming Interface (API). The API it is sent to is the Road API. The API sends back the speed limits of the roads the drivers drove on. This speed limit data is used further when analyzing the driver's commute. The following process is the removal of any unused sensor data from data sheets. Decluttering unnecessary data allows CTM to process and analyze data more efficiently. In the following process, math calculations convert data into Miles Per Hour (MPH). The speed limit data is received in Kilometers Per Hour (KPH); therefore, using Eq. (1), the data is converted into miles per hour:

$$MPH = kph \div 1.60934 \qquad (1)$$

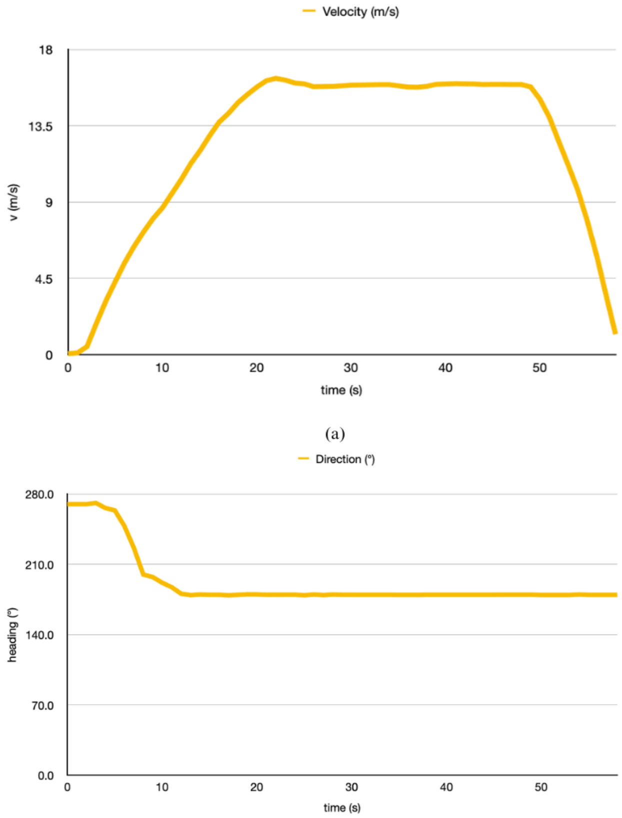
The Velocity data is received from the Location sensor. Velocity is needed to track the drivers' speed throughout their commute. It is measured in meters per second (m/s); therefore, the data needed to be converted to MPH. Eq. (2) was used in the conversion process:

$$MPH = velocity \div 0.44704 \qquad (2)$$

The data is pushed to CTM to begin analysis and provide feedback. CTM can determine the maximum speed reached, total stops, and whether the driver exceeded or remained under the limit. CTM has demands and uses a standard prompt response. However, CTM will add additional comments for the driver.

For this research, the following sensors were selected for the simple experiment: Gyroscope, Longitude, Latitude, Direction, and Velocity. Once set up, the driver must choose their simple experiment in the home screen and push start in the top right corner of the screen. An experiment would begin before leaving Point A and stop when the destination, Point B, was reached.

The Location sensor has seven parameters being collected. Displayed in Figure 2 are two of the four parameters collected from the Location sensor. The four parameters focused on in this paper are Longitude, Latitude, Velocity, and Direction. These parameters enable us to determine the max speed, speed limits, total stops, and directional changes. This is possible because the Location sensor uses the raw data from the phone's Global Positioning System (GPS).



(a)

(b)

Figure 2. Velocity (a) and Direction (b) graphs of a 60-second car ride.

The Velocity graph (a) provides the most accurate vehicle speed data. In the graph, the velocity steadily increases, reaching its maximum velocity at 20 seconds. Toward the end of the journey, the vehicle has a relatively quick decrease in velocity. In Direction graph (b), the vehicle makes a turn early in the ride. This appears only to last a few seconds, eventually leveling into a linear road for the duration of the ride.

The second pair of parameters used from Location is Latitude and Longitude. The coordinates assist the CTM in identifying the minimum speed limit on roads the drivers travel on. The coordinates are sent using JSON. The coordinates arrive at a Google API called Roads API. Roads API accepts Hypertext Transfer Protocol Secure (HTTPS) requests with latitude/longitude coordinates. It uses the points to identify road segments and can return speed limits found. Once this data is received from Roads API, the speed limits are sent to CTM. CTM can see when the driver is below or above the speed limit, allowing the driver to be flagged for going above the speed limit.

These sensors provide the data and knowledge for CTM to accurately analyze their drivers' commutes. Precise points in the driver's commute make it possible to focus on improving their performance and behaviors in particular areas. Data collection, sanitization, and CTM flow are reliable and effective. CTM is given a CSV file where it can begin to analyze and provide the best and most applicable feedback to the driver.

V. RESULTS AND ANALYSIS

CTM's analysis and understanding of drivers' behavior are remarkable. The goal was to determine four data metrics: Exceeded Speed Limit Count, Max Speed, Total Stops, and Total Abrupt Stops. In Table I, five test samples are presented. This data comes from one specific driver who took similar routes when recording their data and driving. The data collected by the sensors is recorded every second the experiment is running. The average seconds for these experiments were a little under 560 seconds, about 9 minutes. In the first column, the driver's speed is investigated. The max speed reached is consistent, remaining between 57 and 64 MPH. The max speed was determined because of the Location sensor mentioned earlier. The Velocity parameter allows to determine the speed.

The following two columns analyzed when the driver was at rest. In the Total Stops, the data is consistent. As mentioned, the driver took an identical route from Point A to Point B; therefore, shouldn't the Total Stops be identical? The answer is no. The driver was unlucky in Test Sample 1, stopping ten times. This could be due to getting a red light or stopping abruptly because of other factors on the road. However, the driver was highly unlucky in Test Sample 5. They stopped a total of 40 times. In reality, this sample is a demonstration of inconsistencies that were found within the CTM analysis. It is important to note and understand that AI is not perfect, but it can be trained to be nearly perfect. This requires more data to train models and provide better and more accurate results.

Total Abrupt Stops were analyzed by analyzing the deceleration of the vehicle the Total Abrupt Stops were able to be determined. If the vehicle's speed decreased by less than 6.7 MPH in one second, it would be considered an abrupt stop. In the following equations, *a* is the vehicle's deceleration in m/s^2. Eq. (3) demonstrates the math needed to decide:

$$athreshold = \frac{6.7\,MPH}{1s} \times 0.44704\,\frac{m}{s^2} \tag{3}$$

Once the threshold as given in the above equation is calculated, the MPH that occurred is compared with the following second. If the threshold exceeds the following MPH, then CTM will flag that as an abrupt stop. Eq. (4) demonstrates a visual of how CTM is pairing the thresholds and MPH. In Eq. (4), the current speed is compared to the previous speed multiplied by the threshold.

$$MPH\,(i + 1) < MPH(\,i\,) \times athreshold \tag{4}$$

Abrupt stops can occur for various reasons. To name a few: distracted driving (driver is on their phone, looking at something, not in front of the vehicle, stop light changes), other drivers abruptly stopping for unknown reasons, or something occurring in the road that forces the driver to stop. Abrupt stops can be avoided by safely following other drivers to react to their stops, keeping eyes on the road at all times, examining the surroundings of the path ahead, and lastly, abiding by the speed limit given for that specific road.

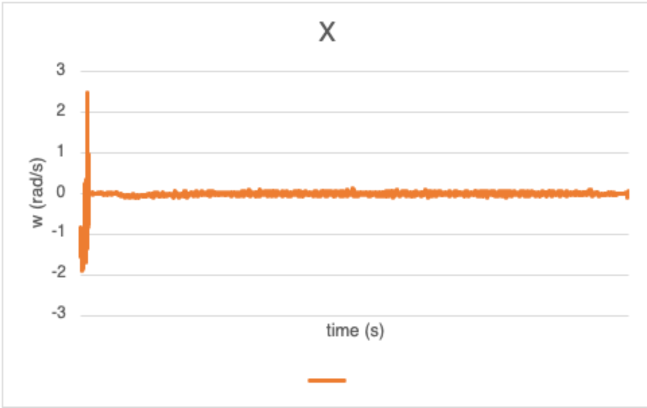
TABLE I. TEST SAMPLE ANALYSIS AND PERFORMANCE

Test Sample	Max Speed	Total Stops	Total Abrupt Stops	Above Speed Limit	Phone Movement
1	64	10	5	271	8
2	57	8	3	301	7
3	60	7	4	246	5
4	57	8	4	279	12
5	58	40	2	232	7

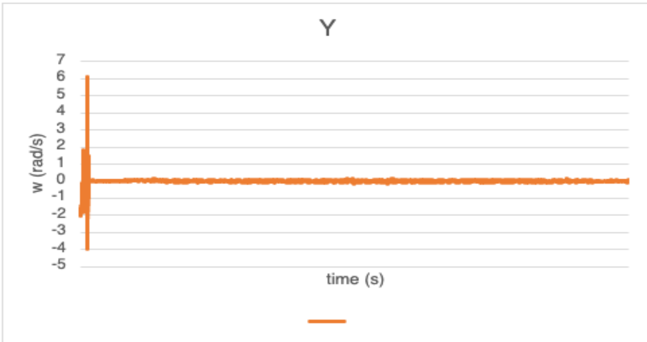
The next column investigates when the driver exceeded the speed limit. The average the driver exceeded the speed limit in seconds was 266 throughout the five samples. They are not very safe drivers. CTM can provide feedback to the driver and notify them where they were speeding. This is an important aspect of CTM because it can interact with the driver and make recommendations. A recommendation could suggest the driver depart to their desired location sooner, so they are not rushing to their destination.

Finally, while the program was running, the drivers could not navigate through their mobile devices without ending the data collection process. CTM was tasked with analyzing drivers operating their mobile devices, but there would be minimal movement between the driver and their device. The final column reports the number of seconds the driver's phone moved. CTM flags when the device is moved. The phone movement mainly occurred when drivers had their devices in their hands, began to run a simple experiment or end one, and then placed their phones down.

Displayed in Figure 3 are three graphs from the gyroscope sensor. In graphs (a) and (b), there are no movements detected in their respective directions; however, in graph (c), there was a movement made in the direction Z. This was an intentional movement made to test CTM on being able to detect this movement. CTM was able to confirm movement for 4 seconds successfully.



(a)



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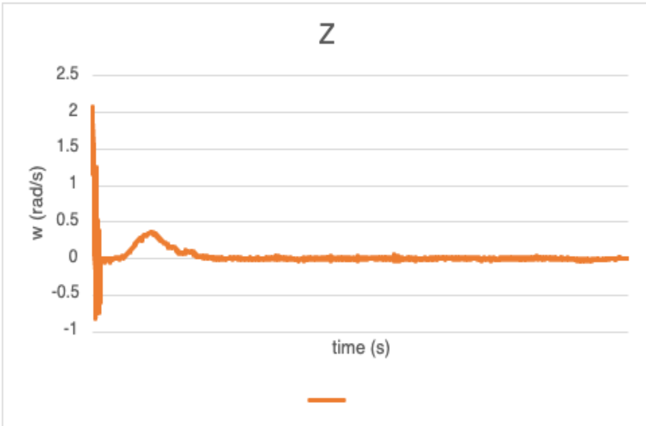

(c)

Figure 3. The X (a), Y (b), and Z(c) Gyroscope graphs of a 60-second car ride.

This overview of mobile device’s sensors and data gathering, and analysis demonstrates the capabilities of providing a detailed response for the user's commute. The significance of these results is the opportunity to improve driving patterns and behaviors in aspiration to decrease automobile accidents. In addition, it focuses on the correction

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of the driver and not the automobile. Mobile devices are in the hands of billions of people and go wherever their user goes; therefore, the accessibility to this tool is obtainable. CTM could be integrated with automobiles; however, this will be another price tag car companies will attach to their vehicles, thus deterring people from this technology and making it accessible. The accessibility, efficiency, and consumable format that this app offers will allow a wide range of applicants to contribute to safer roads.

VI. CONCLUSION AND FUTURE WORK

This research paper has presented a comprehensive solution to address road safety and traffic accidents through AI-driven driving behavior analysis. Automobile accidents primarily occur due to driver errors. This knowledge emphasizes the urgency of finding innovative and practical solutions to improve drivers' skills and behaviors. Car companies cannot continue to focus solely on the equipment and features that will react or assist drivers but focus on improving the drivers' driving capabilities. The solution provided in this paper is utilizing mobile devices to track driving patterns and drivers' maneuvers. Liberty Mutual's RightTrack app and its counterparts have demonstrated that with an incentive involved, driving behaviors can be improved using solely a mobile device. Leaders that can provide incentives are universities, car insurance companies, and government institutions. Solving this problem will require a collective effort and innovative ideas that will lead to better solutions. While some metrics require refinement, the paper's approach significantly promotes responsible driving and expresses its efforts to reduce automobile accidents.

For future work, the goal would be to bundle the device's sensors, data analysis, and a user interface that allows a descriptive and straightforward overview of results into a mobile app. This will allow for a more simplistic data process and a more straightforward data-gathering method. Furthermore, this will allow us to track and analyze when the driver is operating their mobile device. Device movement can be tracked using a Gyroscope, and the operation of the mobile device can be tracked through a mobile app—the possibility to see when they are navigating through their device while the vehicle is moving is obtainable.

Secondly, similarly to how authors in [4] focus on adaptive cockpits and DVI engines, CTM can adapt over time to understand the drivers and how to improve their behaviors. Drivers could have a specific CTM trained solely on their data, allowing the CTM to make concrete suggestions that will be more applicable to their driver.

Lastly, bringing CTM to a larger pool of test subjects will bring exponential growth to the improvement of this tool. Reaching out to large organizations like universities or car companies will open the door to providing better incentives to use the app and perform well. For example, students at university receive scholarship money for good driving behavior, or car companies can offer a specific program to reward their drivers for good behavior. In addition, and most importantly, CTM will be brought to more people, further improving driving behaviors and decreasing traffic accidents. CTM has been proven to study and determine driving behaviors and patterns. It will be an excellent tool and solution to decreasing traffic accidents.

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