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RESEARCH ARTICLE

Detection of Driver Cognitive Distraction Using Machine Learning Methods

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the University of Waterloo Office of Research Ethics Committee.

ABSTRACT Driver distraction is one of the primary causes of crashes. As a result, there is a great need to continuously observe driver state and provide appropriate interventions to distracted drivers. Cognitive distraction refers to the "look but not see" situations when the drivers' eyes are focused on the forward roadway, but their mind is not. Typically, cognitive distractions can result from fatigue, conversation with a co-passenger, listening to the radio, or other similarly loading secondary tasks that do not necessarily take a driver's eyes off the roadway. This makes it one of the hardest distractions to detect as there are no visible clues of driver distraction. In this study, we have identified features from different sources including eye-tracking, physiological, and vehicle kinematics data that are relevant towards the classification of distracted and non-distracted drivers via the analysis of data collected from a driving simulator study involving 40 drivers across multiple driving scenarios. The key classification algorithms implemented include Random Forest, Decision Trees and Support Vector Machines. A reduced feature set including pupil area, pupil vertical and horizontal motion was found to be predictive of driver distraction while maintaining an average accuracy of 90% across various road types. Additionally, the impact of road types on driver behaviour was also identified. The findings of the study has practical application towards the design of driver distraction monitoring systems.

INDEX TERMS Driver state, cognitive distraction, physiological measures, eye tracking, road types, classifier.

I. INTRODUCTION

The increase in popularity of in-vehicle technology has emphasized the importance of vehicle safety and driver experience. The driver needs to be alert and situationally aware of his/her distraction status and surroundings while in control of a vehicle, especially in the case of "cognitive distraction" which is difficult to detect through physical changes. This study questions below involve understanding and mitigating cognitive distraction while driving:

1. Training and development of an machine learning model to classify distracted from non-distracted driving.
2. Identification of features among the three modalities: vehicle kinematics, physiological measurements, and eye-tracking that enable detecting distracted driving.
3. Examining the effect of road type on distracted and non-distracted driving.

A. DRIVER DISTRACTION AND ITS TYPES

The risk of crash and near crash among novice and experienced drivers increases significantly while using a cellphone [1]. Distraction is not just limited to cellphone use and expands to conversations with a fellow passenger, adjusting

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the radio, and being lost in thought [2]. Due to distracted driving, fatalities from crashes have increased 28% after the year 2005 and have become a public safety hazard [3].

In Cognitive Ergonomics, ''attention'' is treated as a single resource or multiple resources that are utilized during human information processing. Driver inattention can be classified into two main types [4], including distraction and mental fatigue [5]. Attention can be disrupted in a variety of ways. For example, stress can lead to tunneling of attention, and multitasking can lead to divided attention. Further, driver inattention leads to reduced Situation Awareness [4]. Situation Awareness reflects the degree to which the available knowledge and understanding about the dynamically changing situation meet the need for satisfactory task performance. Situation Awareness is important as it is a measure of driver awareness regarding the task and the environment, leading to a faster assessment of situation and response times. Situation Awareness is affected by fatigue and driver distraction leading to unsafe driving.

Driver distraction can be associated with any secondary task (task not related to driving), especially with tasks involving In-Vehicle Information System (IVIS) and hand-held devices. According to the ''100-Car Naturalistic Driving Study'' conducted by National Highway Traffic Safety Administration (NHTSA), the secondary tasks that contributed to the highest number of crashes or near-crashes were cell phones, internal distraction, and passenger related secondary tasks (primarily conversations).

The majority of the studies have focused on visual [6] or manual distraction [7]. While a few studies have explored cognitive distraction detection [8].

B. WAYS TO DETECT DRIVER DISTRACTION

Driver distraction can be measured through many modalities due to the changes it causes in driver behaviour. The changes such as heart rate, pupil movement, and vehicle acceleration can be recorded through sensors and other sources to deduce distraction. Novel attempts have sought to include lip, eye and brain features to improve the accuracy of detection [9], [10], [11], [12]. The various categories of measurements for driver distraction detection and their descriptions are given below.

1) Driver Physiological Measures: Measurement and inference of physical and physiological signals from the driver's body constitutes driver biological measures. For example, a study showed that bio-signals help with detecting emotions which hinder rational thinking and behaviour [13] with 81% recognition accuracy on eight classes of emotions (No emotion, Anger, Hate, Grief, Platonic love, Romantic love, Joy, Reverence). The relationship between heart rate variability and stressful driving has been studied through simulating a stressful driving environment and observing Electrocardiography (ECG) and Photoplethysmograph (PPG) [14]. ECG signals are the electrical activity of the heart and are generally obtained through placing electrodes on the skin of the individual. PPG uses illumination of skin to measure changes in light absorption to determine heart rate. Most of the methodologies include placing electrodes on the steering wheel, external wearable devices or integration with the car seat for ECG and PPG recording [15], [16], [17], [18], [19].
2) Vehicle kinematics: Significant effects of driver distraction are observed on a driver's vehicle control, such as drivers adapting to drive at a slower speed to increase available response time when distracted [20]. It also has been found that the correlation between steering wheel angle and lane position is affected by driver drowsiness [18]. Vehicle Kinematics are observed by making drivers perform additional secondary tasks such as a cell phone conversation, navigation control, and playing a radio with varying workload to cause driver distraction on a simulator [21], [22], [23]. The numerous features available through this data can aid in driver distraction detection to varying degree.
3) Driver Eye-Tracking Measures: In driver physical behaviour, eye tracking data, head rotation, head nodding, and facial features are a few measures that are used quite extensively. For instance, a study noted that in eye-tracking behaviour, percentage of eyelid closure (PERCLOS) is a very effective drowsiness indicator [24]. In another study, eye movement monitoring was implemented, and through a webcam it collected frames at a specific rate and sent it to a smartphone to fuse it with other data [17]. Whereas other researchers used a bit more intrusive approach for detecting driver cognitive distraction by using an eye-tracking system to capture the gaze vector, which requires the participants to not wear spectacles or eye make-up. It achieved an accuracy of 81.1% [25].

On the whole, having multiple measures has shown to be more accurate in detecting driver behaviour instead of using just a single type, as asserted in [19], [24], and [26]. These measures are further processed, weighted depending on their effect on driver behaviour before being fed into algorithms such as Support Vector Machines (SVM), Dynamic Bayesian Networks, Neural Networks, AdaBoost classifier, Hidden Markov Model and bidirectional long short-term memory network (Bi-LSTM) among others for distraction detection and recognition [17], [18], [22], [26], [27], [28], [29].

C. MACHINE LEARNING METHODOLOGIES

Machine learning is the development of algorithms and statistical models seeking to learn patterns from data which otherwise are intractable to develop using classical rule-based programming. Machine learning eliminates the aspect of developing rules. It directly learns from data to obtain its ability to adapt to new patterns. Supervised learning, a type of machine learning, is fundamentally learning the mapping between inputs and output labels. Therefore, when a new data point is presented to the model, it is able to predict an output label.

The classification step is dominantly carried out using SVM in literature [25], [30], [31], [32], [33]. Additionally, logistic regression, decision trees, random forest, kNN, Adaboost, and Neural Networks are also used [18], [19], [34]. Each of these classifiers provide varying levels of explainability and complexity and therefore should be tested and selected based on the specific data type and the objective of the project.

In this study, a cognitive distraction task was used that better balanced the needs for external validity and experimental control. The task simulates a conversation with a fellow passenger in a well-controlled way. In the literature, many types of secondary tasks have been used to create distraction, such as mental mathematical tasks [35], [36], n-back tasks [37], clock visualization tasks [32], surrogate visual search tasks [38], texting tasks [39], speech comprehension tasks [40], and word generation tasks [41] which provide a range of different cognitive workload and represent actual driving distractions in an abstract way. Additionally, there are some studies that involve a spoken task between the experimenter and the participant [42]. But due to the subjective nature of questions it may result in an inconsistent administration of workload [43]. In the current study, we used a cognitive distraction task where participants responded to pre-recorded speech statements, which simulates conversation with a fellow passenger in a controlled way.

This study tested distraction detection combining three modalities of data sources including eye metrics, physiological data, and vehicle kinematics data, which has not been sufficiently examined in previous studies.

A major contribution of the current study is to examine hybrid measures for detecting driver cognitive distraction, combing eye metrics, physiological data, and vehicle kinematics data [44]. This study is an attempt to identify features among the three sources, which leads to a finer classifier and aids in filtering features that contribute better to the identification of driver distraction. Also, the computational cost is not a concern here, as each model training and prediction could be completed within 5 seconds on a regular PC.

Regarding driver population, we mainly aimed at the age group of 18-23 years in the current study, as they are more susceptible to cognitive distraction [1]. The current work is the first step of a series of studies. While this first one focused on relatively young adult drivers, we have follow-up studies that will focus on middle age and older adult drivers. One previous study used a driver group with mean age 19.5 years, representing young and novice drivers [45]. It demonstrated that distracted driving within the group can be distinguished from focused driving using eye-tracking data. In the current study, we will explore hybrid measures and classification features for this driver group.

Regarding driving scenarios, a variety of six different driving scenarios was used to examine the distraction detection algorithms in a comprehensive way. Previous studies have examined very limited road types such as highway scenarios [32], [46], [47], [48]. Road types used for driving experiments can affect driver behavior and impact the effectiveness of driver state monitoring algorithms. There has not been a comprehensive examination of different road types. In the current study, we explored the aspect of road types and whether different road types favor different driver state monitoring algorithms.

In summary, previous research in this field lacks a comprehensive examination of different driving scenarios with speech conversation distraction. There is also a lack of work combining multiple categories of measures such as eye metrics, physiological data, and vehicle kinematics data. To address this research gap, we applied machine learning techniques in an innovative way in the current study.

II. DESCRIPTION OF THE EXPERIMENTS

A. PARTICIPANTS

This study recruited participants through flyers and emails sent to various departments at the University of Waterloo. Participants within the age range of 18-23 were included in the study if they possessed a valid Canadian full G driver's license, and self-identified as having driving experience under 15000 km. Participants were required to have 20/20 vision or corrected vision with contact lenses/glasses to be included in the study. Individuals known to be prone to vertigo or motion sickness were excluded from the study, due to potential risk of simulator sickness.

Based on the inclusion criteria, 40 participants (14 females, 26 males) with a mean age of 20.5 and standard deviation of 1.65 were recruited for the current study. This study does not intend to test statistical difference between the 6 scenarios. Instead, the data were aggregated for machine learning training and testing with 14076 data points. The average DBQ (Driver Behaviour Questionnaire) [49] score was 0.71, where the scale ranges from 0 (good driver) to 5 (bad driver). The mean age of participants when they received their full G Canadian driving license was 18.87 years, with 27 participants having less than 50km of driving accomplished in the week before engaging in the study. Twenty-four participants had less than 5,000 km of driving experience in the past 12 months, thus suggesting that the participants were novice drivers. Twenty participants were not wearing any corrective eye wear, while 11 participants wore contacts and nine wore glasses during the study.

The study took around 50 minutes on average, and participants were remunerated $20 for their participation in the study. This study was granted ethics clearance (ORE #40678) through the University of Waterloo Office of Research Ethics. All participants provided informed consent.

B. APPARATUS

The following equipment was used for this study.

1) Carnetsoft Driving Simulator: A fixed base driving simulator with a 210-degree Field of View was utilized in the current study. The simulator included three 27'

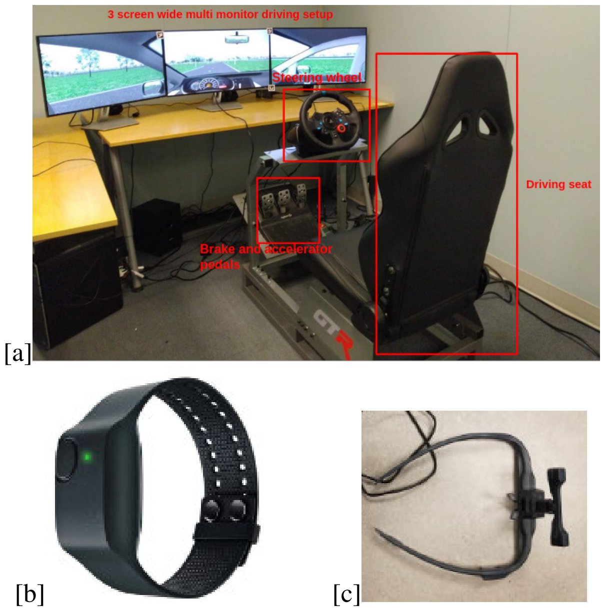


FIGURE 1. **a) Driving simulator with the red bounding boxes indicating the parts b) E4 Empatica wrist band, Source: [54] c) Dikablis Eye tracker.**

LCD display screens with a resolution of 5760 x 1080, as shown in Figure 1. The displays simulated realistic shadows, lighting and animation. The simulator also included a chassis comprising of a seat, pedals and steering console. Animations of people and animals and unexpected situations can be created and controlled to represent road hazards. The density of traffic in scenarios can be controlled. Simulator data such as acceleration and lateral position was collected at 10 Hz. It is a medium fidelity simulator and has been used in several studies [50], [51] [52], [53].

2) Dikablis Glasses 3: The eye-tracker needs 4-point calibration and has an accuracy of 0.1-0.3 degrees. The eye-tracking frequency is 60 Hz (per eye), and the scene camera recording frequency is 30 Hz with a resolution of 768 $\times$ 576 pixel.
3) E4 Empatica wrist band: It is an unobtrusive physiological monitoring band that collects data of PPG (photoplethysmography) and EDA (Electrodermal activity) at 4 Hz, three-axis accelerometer data at 32 Hz, and skin temperature data at 4 Hz. The band can connect to any computing device with a Bluetooth connection and transfer data in real-time.
4) Speakers: They provided sound from the road, wind, tires, engine noise, and the distraction task, which consisted of audio played periodically and controlled based on the driver's location in the scenario.

C. DRIVING TASK AND DRIVING ENVIRONMENT

Scenario design was developed based on the literature of drivers' scanning and mitigating patterns for latent hazards. Latent hazards are potentially dangerous threat that may cause an crash. Latent hazards may not materialize into actual hazards, and in the current study they were designed to not lead to actual hazards. The scenarios covered various road types from sub-urban to highway to explore different driving patterns. Each of these scenarios had a speed limit, which was conveyed through the signage in the simulation as well as mentioned before each drive. Each scenario has a latent hazard presented within a road section, and this zone centered at the latent hazard location is further referred to as the critical zone. Each participant drove all six scenarios, presented to them in a pseudo-random order. Each driver experienced each scenario only one. For each participant, three scenarios were done with distractions, and the other three without distractions. It was determined pseudo-randomly while maintaining that each scenario would be experienced by half of the participants with distraction, the other half participants without distraction. The following are the descriptions of the scenarios.

1) Work zone scenario (speed limit 110 km/h): There is a work zone in the emergency lane of a two-lane highway, with two lanes in each direction. There is light traffic in the opposite lane, which was separated by a divider. The latent hazard is a worker hidden in the work zone behind a bulldozer [55], [56].
2) Curve scenario (speed limit 80 km/h): Two trucks are parked on each side of a curved segment in a sub-urban road type, which makes it harder to perceive oncoming traffic and hazards hidden behind the trucks. There is no other traffic in this scenario, and the latent hazard is a pedestrian hidden behind the truck on the right side [57].
3) Stop-controlled intersection scenario (speed limit 50 km/h): Stop-controlled four-way intersection is to be navigated by the driver in an urban environment where the line of sight of either periphery at the intersection is severely limited by the placement of trucks with the stop signage obscured by vegetation. There are no other traffic participants in the scenario [55], [56].
4) Pedestrian crossing (speed limit 50 km/h): A crosswalk at an intersection of a two-lane city road with one lane in each direction. A truck is parked on the left lane and the latent hazard is a driver hidden behind the truck. There are no other traffic participants in the scenario [58].
5) School zone (speed limit 50 km/h): A sub-urban two-lane road with one in each direction having a crossing in a school zone with early signage cautioning about school children. There is vegetation blocking a pedestrian trying to cross at the crosswalk with the presence of multiple people playing in the park on the other side of the road [58].
6) Parked vehicles (speed limit 50 km/h): A two-lane road with one in each direction, and the driver has to move straight through along a line of parked cars to the right. There are no other traffic participants, and the latent hazard is a car with its turn signal on trying to pull out into the path of the driver [58].

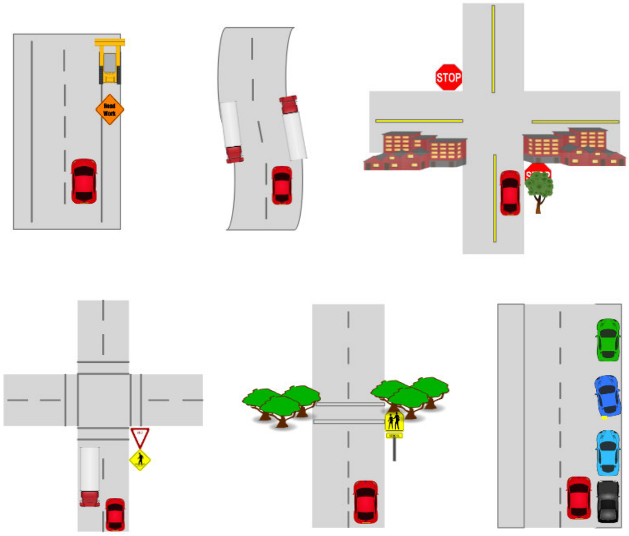


FIGURE 2. (Top left to right): 1. Work zone scenario, 2. Curved scenario with trucks parked, 3. Stop controlled intersection with limited visibility, 4. Pedestrian crossing with a parked truck, 5. School zone scenario, 6. Parking zone scenario.

D. COGNITIVE DISTRACTION GENERATION

The cognitive distraction task was a spoken task, but instead of interacting with the experimenter, a series of statements were played through the speakers after a constant period of five seconds, to which the driver responded. It initiated in the path preceding the critical zone and terminated in the following path after the critical zone. This secondary task acted as an alternative to conversations carried out while driving vehicles.

An auditory beep signified the start of a secondary task, while a similar auditory beep indicated the culmination of the secondary task. The sentences were similar to the grammatical reasoning tasks used in [59], [60], and [61] and are considered to provide a comparative workload as a hands-free cellphone call.

The sentences were about four to five words long, and after hearing the sentence the participant was supposed to answer in the five-second period before the start of the next sentence. For example, a sentence and the answers are given below-
Statement: The rat drove the car.
Expected response: Rat, Car, No
After each sentence, the participant was required to list out aloud the "subject", "object", "yes/no" - depending on whether the sentence was plausible. A positive example would be-
Statement: Ron fixed the door.
Expected response: Ron, Door, Yes.

III. DATA EXTRACTION AND DESCRIPTION

A. VEHICLE KINEMATICS DATA

Each scenario was approximately 2 mins long and was sampled at 10 Hz. The vehicle kinematics variables are described in Table 1 along with engineered features.

TABLE 1. Vehicle kinematics measures from the driving simulator and their descriptions.

ID	Feature	Description
1	Velocity	Velocity in m/s
2	Acceleration	Acceleration in m/s^2
3	Lateral velocity	Lateral velocity in m/s, Left(+ve values) and Right(-ve values)
4	Lateral Position	Left (+ve), Right (-ve) wrt center line of right lane
5	rpm	Engine rotations per minute
6	Steer	Steering wheel angle (in degree)
7	Wheel angle	Front wheel angle (in degree)
8	Heading	Heading wrt road (in degree)
9	TLC	Time to line crossing, Left (+ve) Right (-ve)
10	Gas	Accelerator pedal position (0 to 100)
11	Brake	Brake pedal position (0 to 100)
12	Steering speed	Steering wheel rotation velocity in degree/s
13	Steering error	Deviation b/w actual angle and required angle in degree
14	Longitudnal velocity	Secondary feature (in m/s)
15	Steering standard deviation	Secondary feature (in degree)
16	SDLP	Secondary feature, standard deviation of lateral position (in m)
17	Steering error mean	Secondary feature (in degree)

A windowing step was performed to reduce the frequency of data points and map information from within a window to a single data point to condense the information. A non-overlapping window of 1-second duration was used and a number of secondary features were generated based on literature [19] to get a finer classification. The features generated are given below:

1) Longitudinal velocity: It was derived from the total velocity vector and lateral velocity vector. It represents the vehicle velocity in the direction of advancement.
2) Steering standard deviation: It is the standard deviation of the steering wheel angle.
3) SDLP: It is the standard deviation of lateral position, considered to be a relevant feature as cognitive load has shown to lower SDLP [48].
4) Steering error mean: It is the mean of the steering error, which is the deviation between the expected steering movement and the one performed by the driver.

B. PHYSIOLOGICAL DATA

The participant wore the wrist band while they were training on the simulator (providing the baseline measurements) as well as while they were driving through the experimental scenarios. Data was collected for heart rate, electrodermal activity, temperature and accelerometer.

A windowing step similar to the previous one was performed to bring down the frequency to 1 Hz. This step was necessary for the synchronization of physiological data with driving simulator data.

C. EYE-TRACKING DATA

The Dikablis eye-tracker used in this study had a wide range of data variants available for analysis through the D-lab software. Given below is a brief description of the features used in this study.

1) Gaze point: One gaze point equals to one raw sample captured by the eye tracker; it corresponds to the coordinates where the eyes are looking for a particular point in time.
2) Fixation: Alignment of the eyes such that the image of the fixated area of interest falls on the fovea for a given

time period (duration from 100-300 ms). It corresponds to the gaze point maintained at a consistent position for a certain amount of time. It is an indicator of user attention.
3) Saccades: Brief fast movements of the eyes that change the point of fixation. It refers to eyes moving in jumps.

The eye-tracking data was sampled at 60 Hz, and the timestamps were represented in Coordinated Universal Time (UTC). It consisted of two data streams, eye data and field data, described below.

1) EYE-DATA

Eye-data is based on the image of the eye cameras and measurements on its coordinate system shown in Table 2. The features from the left eye were dropped from further analysis due to their high correlation (measure of how strongly pairs of variables are related) to right eye features.

The saccade and fixation detection is performed by D-lab using a velocity-based algorithm with a threshold of 100 degree/second; movement speed higher than the value is interpreted as saccade, and movement speed lower than this value is interpreted as fixation.

Secondary features were generated according to literature to enhance the classification task along with windowing as given below.

1) Blink: It is predicted by using the pupil values; if 0 then there is no pupil detected (blink), this allows generating a binary feature indicating whether a frame contained a blink or not.
2) Blink ratio: It is the ratio of number of blinks in a window to the length of the window (in datapoints) [62].
3) Fixation ratio: The ratio of number of fixations detected in a window with the length of the window (in datapoints).
4) Saccade ratio: The ratio of the number of saccades detected in the window with the length of the window (in datapoints).

TABLE 2. Features obtained from eye camera and its description.

Feature	Description
Pupil X	X Position in [px] of detected pupil centre in coordinate system of eye-camera
Pupil Y	Y Position in [px] of detected pupil centre in coordinate system of eye-camera
Pupil Area	Size of the detected pupil in [px] of the the eye-camera
Pupil Width	Width of detected pupil in [px] of the eye-camera
Pupil Height	Height of detected pupil in [px] of the eye-camera
Saccades	0 or 1,depends on whether t a saccade was detected
Saccades Duration	Duration of saccade in [s]
Saccades Angle	Angle of saccade in degrees
Fixations	0 or 1,depends on fixation detected in current frame
Fixations Duration	Duration of fixation in [s]

2) FIELD-DATA

Field-data is based on the image of the scene-camera, and the measurements are carried out in its coordinate system. Secondary features were generated to account for the gaze distribution in the horizontal and vertical direction using standard deviation - 'SceneXstd', 'SceneYstd'; described in Table 3. Standard scaling was used with all features to normalize the data to attain columns with zero mean and unit variance based on different dataset splits. It removes the effect of units used in the measurements as well as the range of each column leading to a faster convergence to solutions by a few algorithms. This step was performed selectively based on the algorithm's need such as SVM (Support Vector Machines), kNN (k-Nearest Neighbours), NB (Naive Bayes), and SVM-RBF (Radial Basis Function kernel).

TABLE 3. Features obtained from scene camera and its description.

Feature	Description
Scene Cam Original Gaze X	X Position of the Gaze given in [px]
Scene Cam Original Gaze Y	Y Position of the Gaze given in [px]
SceneXstd	Secondary Feature
SceneYstd	Secondary Feature

IV. FEATURE SELECTION AND CLASSIFIER CONSTRUCTION

Multiple classification algorithms were utilized on different subsets of the data with a focus on obtaining a fine discriminator between distracted and non-distracted driving. Equally important was finding the features which indicate the most difference between distracted and non-distracted driving data. The following algorithms were chose as they are commonly used methods [19], [31], [34], and were trained in Python [63] utilizing the scikit-learn package [64] and trained on the datasets.

- Naive Bayes
- SVM with linear and RBF kernels
- k-Nearest Neighbours
- Decision Tree
- Random Forest

A brief description of the above algorithms is given below: The Naive Bayes classifier is a probabilistic machine learning model based on Bayes theorem given in equation 1,

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)} \tag{1}$$

, showing the probability of A happening given B has already occurred. *P(A)* is called the prior probability, *P(B/A)* is the likelihood and *P(A/B)* is the posterior probability. It is called naïve as it assumes the conditional independence of every pair of features given the class, which almost is never satisfied in real-world datasets.

SVM stands for Support Vector Machine and is a popular binary classifier that provides the most optimum boundary between two classes. Given labeled training examples, the algorithm generates an optimal hyperplane that can categorize unseen examples. In two-dimensional space, a hyperplane is just a line, while in three-dimensional space, its a plane, subsequently the hyperplane dimension keeps incrementing.

Kernel: If there are data points of two classes in a 2-D plane, and they can only be separated through a non-linear boundary, the data points can be projected to a higher dimension via a function Φ. The function N& is written in the form of a kernel function (dot product) K(xi, xj) = $\Phi(xi)^T\ \Phi(xj)$ used in the SVM calculation. There are numerous kernels such as linear, polynomial, gaussian, radial basis function. RBF kernel (or Gaussian kernel) uses a radial basis function (more specifically, a Gaussian function) [65]. The RBF kernel function is widely used and can be applied to a wide range of dimensionality and sample size, and it is often shown to be better than linear, sigmoid and polynomial kernels, especially when the relationship between labels and attributes is nonlinear [66].

k Nearest Neighbours is a lazy learning algorithm; there is no training step. All training examples are stored and at the testing step new examples are classified based on similarity with training examples nearby. The parameter k decides the number of training examples to take into consideration while labeling the new example. The class is assigned based on the majority voting of the k nearest neighbours.

Decision trees are one of the most transparent and explainable classifiers. The decision tree is based on greedy search and hence does not guarantee a globally optimal tree. A decision tree construction involves choosing features for splitting data into subsets having a more homogeneous nature (same labels) [67]. A collection of trees is called a forest. It is based on the ideology that a collective decision outperforms any individual constituent models. There are two key concepts necessary in building a RF (Random Forest):

1) Random sampling of training data points while building trees;
2) Random subsets of features considered when splitting nodes.

Each tree learns from a random sample of data points, which are drawn with replacement (bootstrapping). Accordingly, each tree is trained on different samples and produces an uncorrelated forest of trees whose collective decision is superior compared to an individual decision.

The algorithms were trained on the complete dataset using 10-fold cross-validation to avoid overfitting and to increase generalizability. The algorithms were then evaluated using the accuracy metric (number of correct predictions/total number of predictions) to compare their performance. There are other measures such as sensitivity, precision, and training time that have been considered to compare the algorithms in some studies [25], [27], [28]. However, just accuracy was considered in this study as it was the primary measure in most papers we reviewed [68]. The accuracy metric was chosen because of the balanced nature of the classes coupled with the high numbers for true positives and true negatives in confusion matrices. Furthermore, tree-based algorithms were used to identify features which influence the discrimination the most, particularly the ones which contain the most information about the difference between data in the two categories. To analyse the importance of each source of data and to explore any effect of driving scenario type on driving behaviour, the algorithms were trained for each driving scenario separately as well as all driving scenarios combined together for each of the sources and all the sources combined together.

V. RESULTS

In the first stage, all the scenarios and sources of data were treated together, and classification was carried out using the above-mentioned algorithms. The dataset had 14076 data points and 40 features including the three data modalities of vehicle kinematics (17), eye-tracking (20) and physiological features (3). The dataset was shuffled and split into 80% training data and 20% test data. In the second stage, the dataset was separated based on road types including highway, curved, school zone, parking zone, pedestrian, and stop-controlled intersection to observe the effect of road types on driver distraction classification. The same split described previously for training and test was implemented followed by classification using the algorithms. In Figure 3, the accuracy of different road types and the combined dataset with respect to each algorithm is illustrated. It can be observed that the accuracies improve drastically when the data is split based on road types. It was also found that Random Forest performed the best, so the following comparison for different combinations of data modalities was carried out using Random Forest and is given in Table 4.

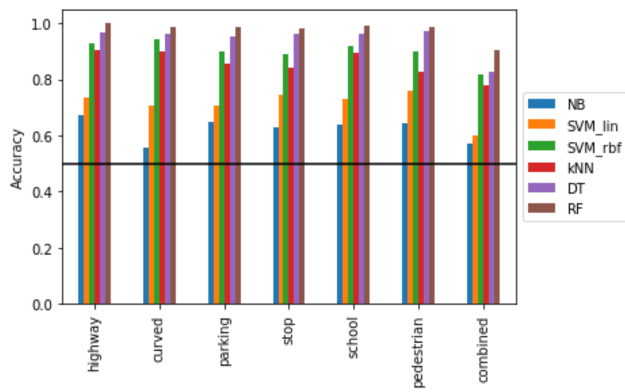


FIGURE 3. The accuracies for the scenarios and the combined set using the chosen parameters for the three modalities. The black line represents the accuracy of a random classifier.

TABLE 4. Cognitive distraction classification accuracy by road scenarios for different combinations of data modalities using Random Forest model, "veh" stands for vehicle kinematics.

Roadtype	All	Eye+Veh	Veh+Physio	Eye+Physio	Eye	Veh	Physio
Combined	91.54%	79.98%	91.59%	90.53%	73.77%	60.83%	96.42%
Highway	98.75%	95.08%	98.13%	99.37%	96.32%	71.57%	99.58%
Curved	99.01%	93.4%	98.19%	97.2%	93.25%	69.71%	100%
Parking	98.75%	93.67%	94.32%	99.37%	93.27%	61.4%	99.59%
Stop	99.59%	88.95%	97.1%	99.18%	89.77%	68.19%	100%
School	99.25%	91.3%	96.12%	98.89%	93.52%	70.44%	99.3%
Pedestrian	98.34%	90.63%	94.72%	99.38%	91.86%	66.66%	98.98%

As shown in Table 4 and Table 5, precision values are very similar to accuracy values for this data set. Therefore, further analysis and results will focus on

TABLE 5. Cognitive distraction classification precision by road scenarios for different combinations of data modalities using Random Forest model, "veh" stands for vehicle kinematics.

Roadtype	All	Eye+Veh	Veh+Physio	Eye+Physio	Eye	Veh	Physio
Combined	91.78%	79.98%	91.49%	90.08%	74.82%	60.46%	96.79%
Highway	98.49%	96.31%	99.23%	99.59%	97.99%	72.11%	99.22%
Curved	99.33%	92.45%	98.29%	97.05%	91.56%	73.35%	100%
Parking	98.45%	91.57%	94.79%	98.76%	92.74%	56.36%	99.18%
Stop	99.6%	87.95%	98.41%	99.21%	91.6%	66.96%	100%
School	100%	93.98%	99.28%	99.25%	92.75%	68.9%	99.31%
Pedestrian	97.93%	89.25%	98.71%	99.15%	91.79%	67.5%	98.78%

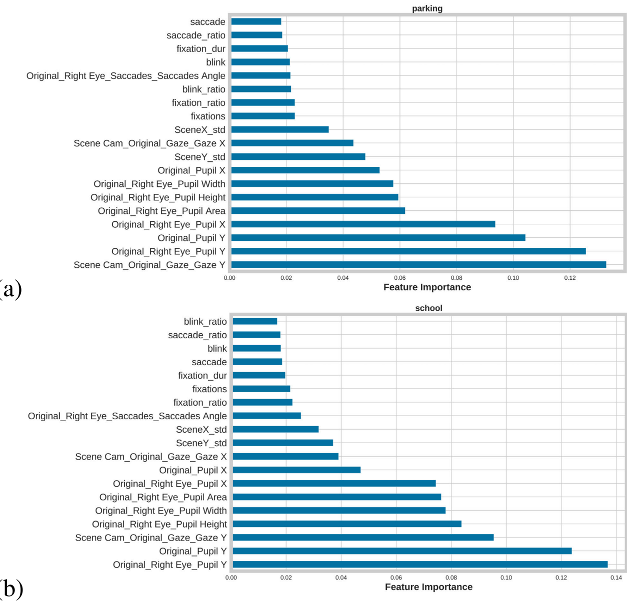
the accuracy measure to simplify the report. After using data from all three modalities, we tested the performance of using only two data modalities. Different combinations of two data modalities were utilized to trim the models to simpler versions. The two-modality combinations were: "Eye+Vehicle", "Vehicle+Physiological", and "Eye+Physiological". A similar procedure as given in the previous sections was carried out for road types combined together and also separated. The results showed that physiological data, when combined with vehicle kinematics or eye-tracking data, resulted in notable increase in accuracy. There was a slight drop in accuracy when vehicle kinematics data were added with eye-tracking data for a few road types compared to using eye-tracking data alone, and the accuracy for the combined scenarios remained lower compared to the cases when data were separated into each road type.

Finally, the performance of using only one data modality was tested. Table 4 shows that the physiological modality performed the best followed by eye-tracking; the vehicle kinematics modality performed the worst.

One of the key factors for feature selection is to eliminate features that are not informative, which involves selecting features that have less correlation to each other and high correlation with class labels. Since physiological data had only three features and vehicle kinematics data did not show much promise, the focus for feature selection was on eye-tracking data. One of the methods for feature selection comes under the category of wrapper methods, where subsets of features are generated and evaluated against a classifier. The classification accuracy is used to evaluate the features, and they are optimized for the classifier utilized.

In this study, there was a keen focus on tree-based algorithms because of their transparency. ExtraTrees classifier from Scikit learn was used to find the feature importance and is visualised in Figure 4. It can be seen that features related to spatial and size features for the eye showed significant contribution while fixations and saccade have minimal relevance.

Furthermore, a Random Forest based wrapper method was utilized to identify essential features while maintaining high accuracy. Random forest classifier, along with permutation feature importance was used to select the reduced feature set. Permutation feature importance is a model inspection technique in which one feature is discarded at a time, and



(a)
(b)

FIGURE 4. a) Feature importance using ExtraTree classifier for parking zone scenario. b) Feature importance using ExtraTree classifier for school zone scenario.

the decrease in classifier accuracy is observed for that action. This technique indicates the dependency of the model on a particular feature. This technique has an issue when features are strongly correlated with each other; as a result, when one feature is discarded, the other correlated feature is able to provide the necessary information to the model. This results in lower importance being given to the correlated features. This problem has been avoided by clustering correlated features and choosing one feature from each cluster for the correlation task as it is able to provide similar information to the other features in its cluster. Hierarchical clustering was performed on the features using Spearman rank-order correlation and a threshold was chosen to pick a single feature from each cluster.

In Figure 5 and Figure 6, the clustering illustrates some expected characteristics, that is, the features corresponding to the fixation x-axis are clustered together, similarly for the fixation y-axis; features corresponding to saccades were clustered together, but fixation duration also showed high correlation with them; height, width and area of the pupil were clustered together; blink and blink ratio formed clusters with sceneXstd and sceneYstd. This pattern was observed through all the scenarios. It was desired to have a simple model learning from a small number of informative features while maintaining the most accuracy.

The above method selected the following features having an accuracy shown in Table 6 for respective scenarios.

- Original Pupil X
- Original Pupil Y
- Original Right Eye Pupil Area
- Scene Cam Original Gaze Y

FIGURE 5. **Hierarchical clustering of features and the corresponding correlation heatmap for parking zone scenario.**

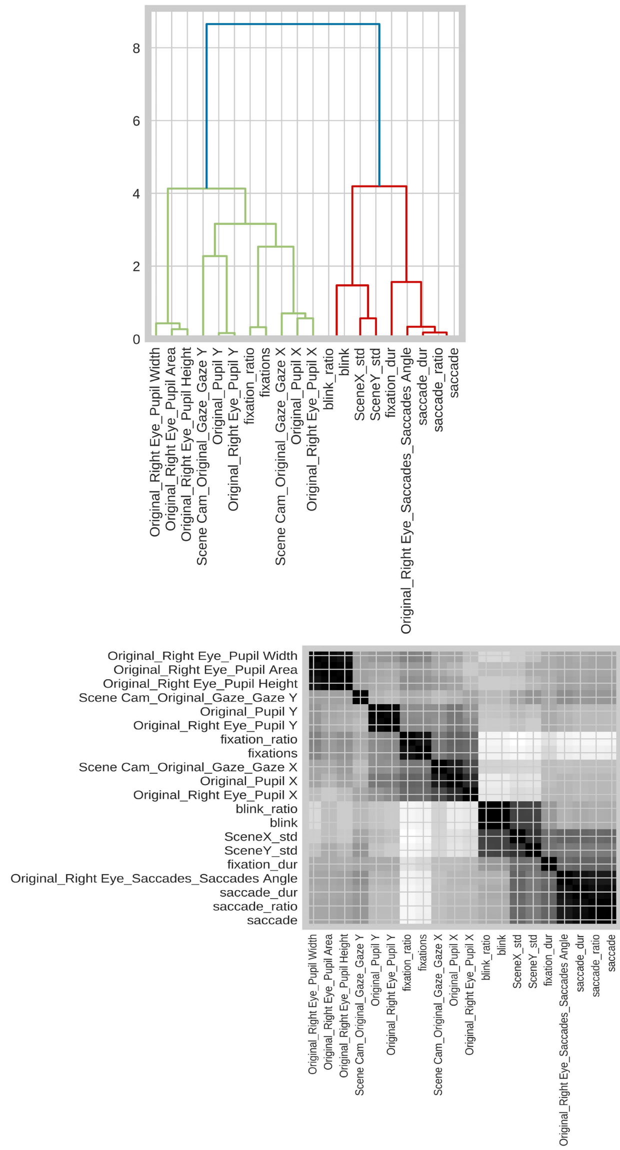


FIGURE 6. **Hierarchical clustering of features and the corresponding correlation heatmap for school zone scenario.**

TABLE 6. **Accuracies of scenarios for features using RF - horizontal eye position, vertical eye position, pupil size and scene camera vertical gaze.**

Scenarios	Accuracy
Highway	93%
Curved	95%
Parking	93%
Stop	91%
School	91%
Pedestrian	86%

T-tests were conducted to examine if there was any significant difference between distraction and no-distraction conditions in terms of average values of Original Pupil X, Original Pupil Y, Original Right Eye Pupil Area, and Scene Cam Original Gaze Y from the participants. The results showed no significant difference, $t(39)$ values $<= 1.692$, p values $>= 0.099$. The violin plots illustrating the features comparing the two groups is shown in Figure 7.

Among the four selected features, the first three are recorded by the eye camera, and only the last one is recorded by the scene camera. Given the additional cost and privacy concerns of using a scene camera on daily wearable devices, designers of smart glasses may want to implement eye tracking functionality without installing a scene camera. As a result, we also analyzed the model accuracy without the scene camera data. The updated accuracies are shown in Table 7. On average, accuracy decreased by 10.2% from 91.5% to 81.3%. Therefore, this trade-off should be considered in design decisions.

TABLE 7. Accuracies of scenarios for reduced set of features using RF consisting of horizontal eye position, vertical eye position and pupil size.

Scenarios	Accuracy
Highway	85%
Curved	83%
Parking	79%
Stop	79%
School	84%
Pedestrian	78%

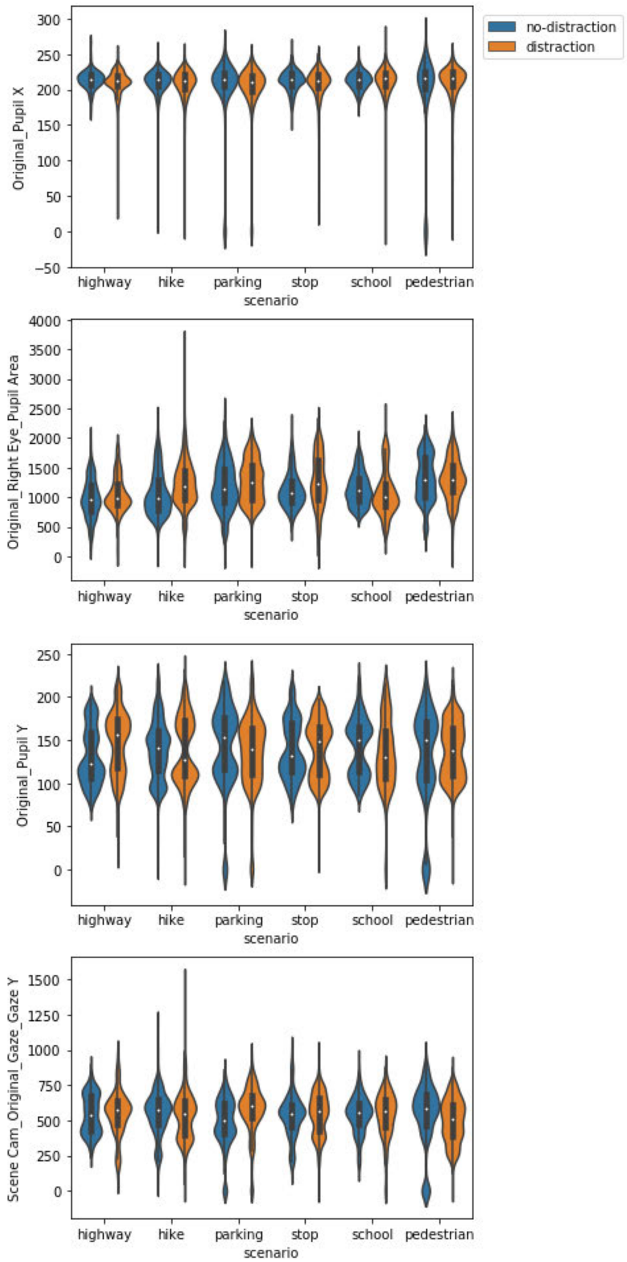


FIGURE 7. Violin plots of selected eye-tracking features comparing two classes. It represents the distribution shape of data with the white dot corresponding to the median and the thick black line representing the Interquartile range (IQR), thin black line extending to 1.5x the IQR range.

VI. DISCUSSION

When all the road scenarios are combined into a single dataset, the classification accuracy is lower than when data are separated into each road type. This finding shows that the addition of driving context as a factor can generate an improved driver distraction monitoring system. The complexity of the driving environment has varied effects on driving; factors like urban driving, highway driving, traffic density, and speed limits have an impact on driver behavior and should be accounted for [69].

Overall comparison between the performance of the six algorithms: NB, SVM linear, SVM-RBF, kNN, DT, RF showed that RF achieved the best accuracies for all datasets. NB performed the worst because of its assumption of samples being independent, which was not the case for the dataset. In this study, there was a significant emphasis on tree classifiers because of their interpretable nature and simplicity to understand, which is in direct contrast to Neural Networks' black box nature, and which were not utilized in this study.

Regarding data modalities, physiological data and eye-tracking data showed better performance than vehicle kinematics data. The inclusion of physiological data showed significant improvement in accuracy for all combinations of sources in Table 4, notably, the combination of eye-tracking data with physiological data. This confirmed the relevance of physiological data such as EDA, HR and temperature as good indicators to differentiate distracted and non-distracted driving behaviour. It could also be attributed to the similarity between training and test datasets due to the short duration of data length for each participant, hence not having much variation between the training and test datasets.

The results from the current study also emphasised the importance of eye-data to support driver distraction identification due to cognitive workload. The dominant features identified illustrated the importance of pupil data and gaze dispersion in both horizontal and vertical directions. It highlighted the need to include pupil size measures. As shown by Wang et al. [70], the effect of cognitive tasks on gaze dispersion is statistically significant. Also, Reimer [71] showed that changes in visual attention can act as an early indicator of driver distraction even before vehicle control is affected, which was observed in this study as well. The study also does a statistical analysis showing a significant change in the mean central location of vertical gaze between driving with 0-back task and pre-task baseline driving, corroborating the significance of vertical pupil measure seen here.

The vehicle kinematics data did not show much promise in the current results. Drivers' driving performance and vehicle control behavior were similar in distracted and non-distracted conditions. It may be due to the limited fidelity of the driving simulator and the distraction task not being distracting enough. It may also be explained by the Cognitive Control Hypothesis, which states that cognitive load leaves automatic performance unaffected. If the driving task is too simple, it might be automatized, leading to no observed effects due to secondary tasks [72].

In summary, we have the following suggestions for the design of driver distraction detection algorithms based on the results from the current study.

- Build the model separately for each road type to increase prediction accuracy.
- Eye-tracking and physiological measures seem to be more useful than vehicle kinematics measures.
- Among eye-tracking measures, data from the eye camera carry most of the weight, and additional data from the scene camera have a marginal gain for prediction accuracy.

VII. CONCLUSION

Various machine learning techniques were utilized and compared for driver cognitive distraction classification. Driving tasks were completed by young drivers in a simulator in various road type conditions, with or without a controlled auditory communication task representing distraction. The results suggest that physiological and eye-tracking data provide good features for distraction classification. Separating models and training for each road type can provide better classification accuracy than combining all the data from all road types in one model. The features identified in the current study can support applications of cognitive distraction monitoring systems for early mitigation and intervention promoting driving safety.

Automobiles are increasingly equipped with instruments that support facial monitoring, eye tracking, emotion tracking and biometric analysis. In commercial truck driving, biometric analysis and eye tracking is already used extensively. We expect this to increase with the onset of fully autonomous vehicles as such instruments provide a way for the autonomous vehicle to effectively track driver state. Agencies can utilize these findings to develop distracted driving policies and guidelines that support safe driving habits. Further, telecommunications companies such as TELUS, Rogers, and BlackBerry are currently developing hardware-agnostic software that can be deployed across different car models and makes. We anticipate that the availability of such software along with inbuilt sensors provided by the automotive manufacturers makes it feasible to measure every driver in the near future.

The short duration of data length for each participant is a limitation of the current study. Further studies are needed to confirm the applicability of the physiological data in tests with longer duration. The models in this study were trained for all participants in general without considering individual differences; in the future, with more data collected from each person, models may be trained for each driver. Moreover, just accuracy was assessed; future research should consider a combination of measures. The other limitation was the sample not being completely randomized as the study was advertised and conducted in a University setting, and just included young drivers. It restricted the participant pool to University students and could only approximate a completely randomized control trial. Finally, a more realistic driving simulator would also contribute positively to data quality.

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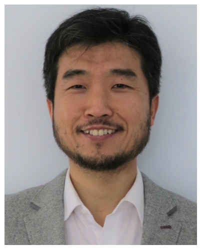

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