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A MACHINE LEARNING DISTRACTED DRIVING PREDICTION MODEL

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ABSTRACT

Distracted driving is known to be one of the core contributors to crashes in the U.S., accounting for about 40% of all crashes. Drivers' situational awareness, decision-making, and driving performance are impaired due to temporarily diverting their attention from the primary task of driving to other tasks not related to driving. Detecting driver distraction would help in adapting the most effective countermeasures. To find the best strategies to overcome this problem, we developed a Bayesian Network (BN) distracted driving prediction model using a driving simulator. In this study, we use a Bayesian Network classifier as a robust machine learning algorithm on our trained data (80%) and tested (20%) with the data collected from a driving simulator, in which the 92 participants drove six scenarios of handheld calling, hands-free calling, texting, voice command, clothing, and eating/drinking on four different road classes (rural collector, freeway, urban arterial, and local road in a school zone). Various driving performances such as speed, acceleration, throttle, lane changing, brake, collision, and offset from the lane center were investigated. Here we investigated different optimization models to build the best BN in which a Genetic Search Algorithm obtained the best performance. As a result, we achieved a 67.8% prediction accuracy using our model to predict driver distraction. We also conducted a 62.6% true positive rate, which demonstrates the ability of our model to predict distractions correctly.

Keywords: Distracted Driving, Machine Learning, Bayesian Network, Driving Simulator, Data Mining

1. INTRODUCTION

Distracted driving is defined as diverting the attention of the driver from driving to other behaviors, tasks, or situations that lessen the drivers' ability to sustain awareness and be in full control of the vehicle (Masten et al., 2013). Distracted driving may have different causes such as eating, drinking, manipulating dashboard controls, visual deviations like looking at a smartphone screen, or cognitive activities like talking on the phone that take the attention of the driver away from driving. Some activities, such as texting, can include all different types of distractions. For example, texting while driving has physical, visual, and cognitive distractions. Distracted driving is a safety threat as it takes the drivers' eyes off the road, hands off the steering wheel, and thoughts elsewhere. Also, the probability of a crash happening is high among distracted drivers (Fitch et al., 2013; Klauer et al., 2014). Distracted driving has been known as one of the core contributors to crashes in the US; in 2017, distraction resulted in about 3,166 fatalities in the U.S. (NHTSA, 2015). Distracted driving is responsible for almost 40% of all crashes happening on roadways (Distracted Driving 2013).

The advent of in-vehicle technologies and smartphones, which result in distracted driving, prompted concern about driving safety (Ahangari et al., 2019; Mousavi et al., 2020) and inspired researchers to conduct more studies on distraction. Although in-vehicle systems such as adaptive cruise control systems and navigation are designed to advance security and convenience, working with in-vehicle systems occasionally diverts a driver's attention from the main driving tasks (Stanton and Young, 1998; Ahangari et al., 2020). For example, talking on the phone while driving is a distracting behavior, even with hands-free systems (Just et al., 2008; Patten et al., 2004). The subject of the conversation has a broader outcome of distracted driving than does the technique of phone conversation (Patten et al., 2004). Drivers' attention diverts from the driving task to the conversation, which depreciates driving performance. Over time, with improvements in technology, new forms of distraction, including voice command text (Mayhew et al., n.d.) and personalized phone-based digital assistance (Yager, 2013), cause distraction as well.

Several researchers have studied the influence of distracted driving on road safety (Horberry et al., 2006; Joo and Lee, 2014; Neyens and Boyle, 2007, 2008; Wilson and Stimpson, 2010). Different types of distracted driving contain a combination of manual, visual, auditory, and cognitive components, each of which can negatively impact the ability of drivers in keeping lane position, speed, and eyes on the road (Harbluk et al., 2007; Victor et al., 2005). Drivers whose eyes are away from the road because of distraction activity for prolonged periods cannot safely control their vehicles (Hosking et al., 2009; Owens et al., 2011). Driving is mainly a combination of visual, spatial, and manual tasks. Handheld phones diverted visual attention away from the roadway when dialing a number or picking up a call, and one hand was taken off the steering wheel to hold the phone to the ear. Texting not only diverted visual attention away from the roadway but also took both hands off the wheel. Studies show that distracted driving has a tremendous effect on traffic safety. Some studies concluded that distracted driving increases crash risk by increasing the reaction time and response time of drivers (Caird et al., 2008; Harbluk et al., 2007; Horrey et al., 2008). Distracted drivers tend toward unsafe driving behavior that increases the probability of a crash happening on roadways. The likelihood of using the phone while driving among younger and male drivers is higher when compared to older and female drivers based on the survey collected from 834 licensed drivers. The survey also presented that the longer the drive is, the more likely the driver is to use a cell phone. (Pöysti et al., 2005). The young driver may be more vulnerable to a distraction-related crash as they are among the most substantial users of cell phones (Lees and Lee, 2007).

Distracted driving may also reduce the proficiency of the traffic network by increasing the headway between vehicles unreasonably (Victor, Trent, and Emma Johansson). Studies about distracted driving showed that handheld cell phone talking while driving harms the drivers' capability to sustain their speed and location on the road (Narad, Megan, Annie A Garner, Anne A Brassell; Stavrinos et al., 2013); texting while driving increases reaction times to push the brake and increases the variability of lane changing with no change in speed (Hosking et al., 2009; Patten et al., 2004). Reading texts while driving is the most distracting activity for youthful drivers (Atchley et al., 2012).

Studies indicated that the use of cell phones among all drivers increases the risk of a crash by a factor of four (Hosking et al., 2009; McEvoy et al., 2005). Similarly, another study using a simulator involving adolescent drivers showed that texting while driving increases the frequency of deviations in a lane concerning the position from the centerline (Lee et al., 2008).

Talking and driving each requires different levels of an individual's attention, and the more attention-demanding the activity is, the less successful the performance of each task will be (Salmon et al., 2011). As a result of cell phone use, while driving, less visual information is processed by drivers in the driving scene (Strayer et al., 2006), drivers do not stop completely at stop signs (Strayer and Drews, 2007), braking response time increases

(Watson and Strayer, 2010), and more rear-end collisions occur (Strayer and Drews, 2007). Several studies used machine-learning techniques to recognize visual and cognitive distractions for in-vehicle distraction mitigation systems (Lee, J. D. (2009; Strayer, D. L., Drews, F. A., and Johnston, W. A. (2003); Liang et al., 2007; Liang and Lee, 2014; Reyes and Lee, 2008; Victor et al., 2005). Nevertheless, while there is not an absolute correlation between distractive driving and motor vehicle accidents, the probability of a crash happening is high, based on the driving patterns displayed by distracted drivers. Usually, the speed of distracted drivers using cell phones tends to be low (Strayer et al., 2006), their following distance is high (Cooper and Strayer, 2008; Shinar et al., 2005), and the frequency of lanes changing is less, all of which can result in disturbances in traffic flow and increased congestion.

As seen above, different aspects of distracted driving, including various sources of distraction, and their effect on driving performance and road safety have been studied by many researchers. However, to the best knowledge of the authors, there are very few studies related to prediction model development. Driving simulators have been a safe and inexpensive tool for studying distracted driving. Machine learning, which evolved from pattern recognition and computational learning theory in Artificial Intelligence (AI), has recently been applied in many fields. BNs have recently been used in studies that involved uncertainty and complexity.

In this study, we propose a new machine learning model to predict if the driver is distracted. To do this, we use a Bayesian Network (BN) to build our model and a Genetic Algorithm (GA) to optimize its network. We obtained driver performance (behavior) data from 92 participants in a driving simulator driving in various scenarios of distractions and road classifications. Using our model to predict the distraction based on the driver's behavior, we achieve over 70% prediction accuracy, which highlights that driving behavior is different between a distracted driver and a non-distracted driver.

2. METHODOLOGY

2.1 Data Collection

Driving data such as speed, acceleration, throttle, lane changing, brake, collision, and offset from the lane center were collected in a fixed high-fidelity driving simulator. The driving simulator directly logs all the related data. The driving simulator has three 40" screens, and the software (UCWinroad) has the capability of making realistic roads, signals, signs, models, and traffic (Figure 1).

Figure 1. Driving Simulator

A medium road network of Baltimore County, which consists of various road types (rural collector, freeway, urban arterial, and local road in a school zone), was considered as the study area (Figure 2).

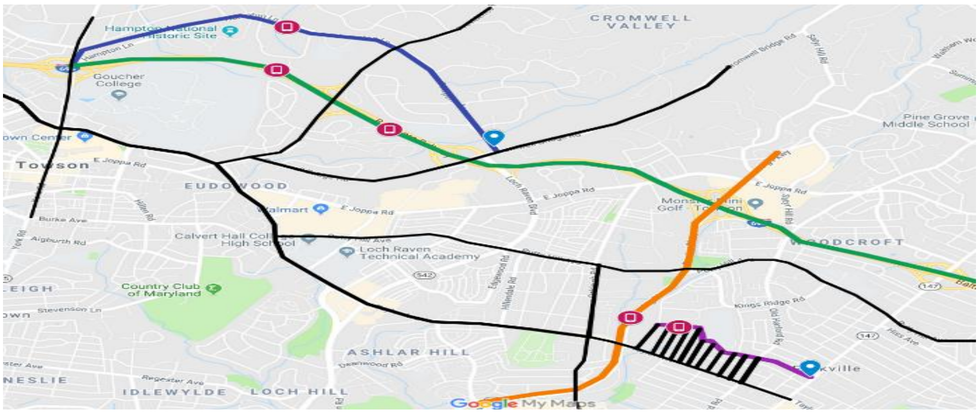

Figure 2. Study Area
(Blue line is a rural collector, green line is a freeway, orange line is an urban arterial and purple line is a local road; the red icons show the location of the distraction)

2.2 Participants and designed scenarios

Using online advertisements, flyers, and email invitations, 92 participants were recruited from Morgan State University and the Baltimore metro area to drive eight different scenarios. Some 56.52% of participants were male, and 43.48% were female. The age group of participants was between 18 to 40 years old; 44.57% of which were in the age group of 21 to 25 years. Participants were required to have a valid U.S. driver's license and were compensated at $15 per hour for their participation in the study.

Participants drove from Hampton Lane (rural road) to I-695 (freeway) to Perring Parkway (urban arterial) to Radar Road (local, school zone) for six different distraction scenarios (hands-free calling, handheld calling, voice command, texting, clothing, and eating/drinking); each of which took about 15 minutes driving.

Each scenario consists of five distractions that each happens in the same location of each road, as shown in Figure 2 with a red icon. The driving experience started with the one-lane two-way rural collector that includes one distraction; then, two distractions happened in the three-lane two-way freeway; after that, one distraction happened in the two-lane two-way urban arterial, and finally, one distraction occurred in a one-lane two-way local road in a school zone.

The driving data consist of average speed, acceleration, throttle, lane changing, brake, collision, and offset from the lane center for each scenario before and during the distraction area; the length of the distraction area is different, based on the road types as the speed limit is different.

In the distraction mentioned above area on each road, the participants were asked a question that they needed to think about and answer in handheld, hands-free texting, and voice command scenarios. They were asked to do a task like eating/drinking or removing or adding clothing in the last two scenarios. For example, in the hands-free calling scenario, an observer called participants 5 times and asked them five different questions. The participants were required to use hands-free and answer the question. The questions—for example, how many of their friends' names start with M? — differed each time, but they had a similar cognitive effect.

Two areas, including before distraction area (no distraction) and during distraction area (hands-free calling, handheld calling, voice command, texting, clothing, and eating/drinking distraction), classified the binary states of distraction (i.e., distracted driving and not distracted driving) for the BN. In the driving experiment, participants drove six different driving with the distraction task, including hands-free calling, handheld calling, voice command, texting, clothing, and eating/drinking. To forecast the distraction based on the driver's behavior during and before the distraction, the area during the distraction task is considered as a distraction area while the area before the distraction task is not. There is a total of 3,877 simulator experiences done with 92 participants, of which half, or 1,952, contain distraction.

2.3 Bayesian Network

A Bayesian Network (BN) is a machine learning method aimed at utilizing Bayesian rules on subsequent simulation using directed graphical presentation of probability-based approach and relations among factors (Dechter and Pearl, 1988). A BN with the visual representation provides a better understanding of the interaction between variables. In its graphical presentation, nodes represent random variables, and links illustrate relationships and conditional dependencies between variables (Koski and Noble, 2011). The BN's learning procedure employs a training dataset, derived from actual events, to identify the possible connections between nodes to be used for future prediction of unseen data (Ben-Gal: Identification of Transcription Factor Binding... - Google Scholar, n.d.).

Building a Bayesian network consists of two steps. The first step is to make a network structure and find the arrangement of the nodes in the network. This process can be defined as an optimization task that can be done using different search or optimization techniques (e.g., Genetic Algorithm, Simulated Annealing, and Hill Climbing). The second step is to learn the probability tables given the network structure (Koski and Noble, 2011).

In this study, we use the BN implemented in a Weka 3.8 software package (Hall et al., 2009) to predict the distraction behavior using a driving simulator.

3. RESULT AND DISCUSSION

A BN is originated based on the fundamental relationship among variables in a visual representation. As explained in Section 2.3, in the BN graph nodes represent the variables and links represent the relationship among them. Building the Bayesian Network and finding the best arrangements among the nodes can be defined as an optimization task.

There are different search algorithms in Weka that can be used for this task, such as Hill Climbing (Mitchell et al., 1994), Simulated Annealing (Aarts and Korst, 1988), Tabu Search (Glover and Laguna, 1998), and Genetic Algorithm (Whitley, 1994). Here we have investigated these algorithms for our task; the best results were obtained using a genetic algorithm. Genetic Algorithm (GA) is considered as a robust optimization algorithm based on the idea of natural selection. It uses mutation, cross over, and selection methods to shuffle the data to find the most optimal solution available (Deb et al., 2002). The structure of the final BN network is displayed in Figure 3.

After the recognition of an exemplary network structure, the conditional probability tables for each of the variables are estimated. A natural way to measure how well a Bayesian network performs on a given data set is to forecast its future performance by guessing expected functions, such as classification accuracy.

To be able to properly conduct our experimentation, avoiding bias, and investigating the generality of our model, we divide our data into training and independent testing sets. We separate 80% of our samples as training (1,563) and 20% as a testing (389). We report 10-fold cross-validation on the training set and the independent test set results to study the generality of our model.

The k-fold cross-validation is considered as an essential prediction estimator (Kohavi, 1995). In this model, the sample set is divided into mutually exclusive subsets. In each step, k - 1 of those subsets are used for training purposes, and the remaining one subset is used for testing. This process is repeated k times and until all the subsets are used for testing. In this way, we utilize our data to use it more efficiently and repeat our experimentation to investigate its generality. Using k = 10 has been shown as an efficient number and widely used in the literature. Note that we use 10-fold cross-validation just for our training set. We also train our model in a different task on the training set and use that for our independent test set. Achieving consistent results for 10-fold cross-validation and on the independent test set is a popular approach to study the generality of a proposed model.

To provide more insight on the performance of our model, we report the prediction accuracy (ACC), sensitivity (true positive rate), precision, Matthews Correlation Coefficient (MCC), and Area Under the ROC curve (AUC).

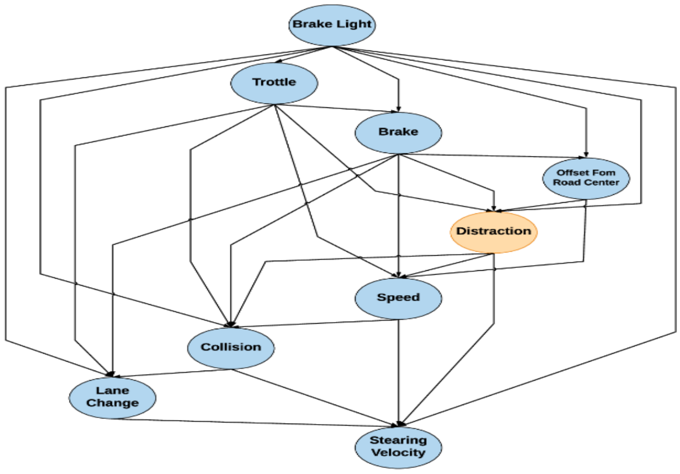

Figure 3. Bayesian Network Structure

As shown in Table 1, we achieve 67.8% prediction accuracy for our independent test set, which demonstrates the ability of the BN as a powerful technique for identifying distracted driving. As shown in this table, we also achieve 62.6% Sensitivity and 75.1% AUC, which highlights the ability of our proposed model to identify distractions correctly.

We also achieve 70.8% accuracy, which is consistent with our results on the independent test set, which demonstrates the generality of our model. Our results demonstrate the ability of the BN optimized using the GA to adequately capture the distraction pattern for our data and identify them for an independent test. Our results also demonstrate the promising performance of a machine-learning algorithm to predict drivers' distraction.

Table 1. Results achieved using Bayesian Network for 10-fold cross-validation and independent test

Results for 10-fold cross-validation					
	Sensitivity	Precision	MCC	AUC	ACC
Before Distraction	61.6%	75.5%	42.3%	77.7%	70.8%
During Distraction	80.0%	67.6%	42.3%	77.7%	70.8%
Results on Independent Test					
	Sensitivity	Precision	MCC	AUC	ACC
Before Distraction	73.0%	66.0%	35.8%	75.1%	67.8%
During Distraction	62.6%	69.9%	35.8%	75.1%	67.8%

4. CONCLUSION

This paper developed a methodology using a BN, a powerful machine learning method, to detect driver distraction from driving performance using a driving simulator. The connections between driving performance and driver distraction are explored in this paper, the results of which can be used to detect distracted driving and find the best strategies to overcome this problem. The results show that the BN model is able to detect driver distraction substantially with 67.8% prediction accuracy. This also demonstrates the promising performance of a machine learning model for the driver distraction prediction problem. More effective policies and technologies could be implemented when driver distraction can be predicted. For our future direction, we aim to investigate other powerful classification methods to tackle this problem.

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