© September 2024 | IJIRT | Volume 11 Issue 4 | ISSN: 2349-6002

Survey On Detection of Driver Distraction and Classification Using Machine Learning

Mr. Varad Bagal, Dr. Sangram T. Patil, Dr. Jaydeep B. Patil,

[1] *Student, Dept. of Artificial Intelligence & Machine Learning Engineering, DY Patil Agriculture and Technical University, Talsande -416112 India*

[2] *Associate Professor, Dept. of Artificial Intelligence & Machine Learning Engineering, DY Patil Agriculture and Technical University, Talsande -416112 India*

[3] *Associate Professor, Dept. of Artificial Intelligence & Machine Learning Engineering, DY Patil Agriculture and Technical University, Talsande -416112 India*

***Abstract*—Distracted driving is one of the main reasons for collisions. Therefore, it is crucial to constantly monitor the driving condition of drivers and offer suitable solutions to those who are distracted. When a driver's eyes are fixed on the road ahead but their mind is elsewhere, it's referred to as cognitive distraction. Cognitive distractions typically come from being tired, talking to a fellow passenger, listening to the radio, or engaging in other mentally taxing side activities that don't need a driver to take their eyes off the road. Because there are no outward signs of driver distraction, it is one of the most difficult diversions to identify. Authors have identified features from various sources, including eye tracking, physiological, and vehicle kinematics data, that are relevant towards the classification of distracted and non-distracted drivers in this study. The three main classification techniques that were used are Support Vector Machines, Decision Trees, and Random Forest. It was discovered that a condensed feature set consisting of pupil area, pupil vertical motion, and pupil horizontal motion could predict driver distraction with an average accuracy on a variety of road conditions. Additionally, the impact that various road types had on drivers' behaviour was discovered. The study's conclusions can be applied practically to the development of technologies that monitor driver distraction.**

***Index Terms*—cognitive distraction, eye tracking, vehicle kinematics data etc**

I. INTRODUCTION

The importance of vehicle safety and the driving experience has been highlighted by the rise in popularity of in-car technologies. When operating a vehicle, a driver must be vigilant and situationally aware of both the environment and their level of distraction, particularly in the case of "cognitive distraction," which is hard to identify through physical changes.

When using a telephone while driving, both inexperienced and seasoned drivers greatly increase their risk of collision and near collision. Distractions include talking to other passengers, fiddling with the radio, and getting lost in one's own thoughts. They are not just restricted to using a cell phone while driving. Since 2005, the number of crash fatalities caused by distracted driving has climbed by 28%, posing a threat to public safety.

"Attention" is viewed in Cognitive Ergonomics as either a single resource or a collection of resources used by humans when processing information. Distraction and mental exhaustion are the two primary categories of driver inattention. Disruptions to attention can occur in several ways. For instance, multitasking can result in fragmented attention and stress can cause attention tunnelling. Moreover, a distracted motorist has less situation awareness. The degree to which the requirements for satisfactory task performance are met by the knowledge and understanding now accessible about the situation, which is changing dynamically, is reflected in situation awareness. Situation awareness is crucial since it gauges a driver's awareness of the task and the surrounding conditions, enabling a quicker assessment of the situation and quicker reaction times. Fatigue and driver distraction can impair situation awareness and result in risky driving.

Methods for identifying distracted drivers

Due to the behavioral changes, it generates, driver distraction can be measured using a variety of techniques. It is possible to determine distraction by recording changes in heart rate, pupil movement, and vehicle acceleration using sensors and other sources. Innovative approaches have attempted to incorporate features from the brain, eyes, and lips in order to increase detection accuracy [1], [2], [3], and [4]. The list below includes descriptions of the many measurement categories used to identify driver distraction.

1. Driver Physiological Measures: Driver biological measures include the measurement and interpretation of physical and physiological cues from the driver's body. For instance, a study found that bio-signals have an 81% detection accuracy on eight classifications of emotions (none, anger, hate, grief, Platonic love, romantic love, joy, reverence) and can assist in recognizing emotions that impair rational thought and behavior [5]. Electrocardiography (ECG) and photo plethysmo graph (PPG) observations have been made while a stressful driving environment is simulated in order to examine the connection between heart rate variability and stressful driving [6]. Electrodes are typically applied to the skin of the patient to gather ECG signals, which are the electrical activity of the heart. PPG measures variations in light absorption through skin lighting to calculate heart rate. For ECG and PPG recording, the majority of approaches involve attaching electrodes to the steering wheel, integrating wearable technology outside, or integrating the automobile seat.
2. Vehicle kinematics: Driver distraction has been shown to have a significant impact on a driver's ability to control their vehicle. For example, drivers who are distracted have been observed to adjust their speed to increase their available response time [7]. Additionally, it has been discovered that driver tiredness influences the relationship between steering wheel angle and lane position [8]. In order to analyze vehicle kinematics, drivers are forced to undertake extra secondary tasks on a simulator, such as using a cell phone, controlling navigation, and listening to a radio station with various workloads. To differing degrees, the many aspects made possible by this data can help with driver distraction detection.
3. Driver Eye-Tracking metrics: A few metrics that are frequently utilized in driver physical behavior are eye tracking data, head rotation, head nodding, and facial features. For example, a study found that percentage of eyelid closure (PERCLOS) is a highly useful sleepiness predictor in eye-tracking behavior [9]. In a different study, eye movement monitoring was used. A camera was used to capture frames at a predetermined rate, which were then uploaded to a smartphone to be combined with other data [10]. Conversely, other researchers employed a little more invasive method to identify driver cognitive distraction by capturing the gaze vector using an eye-tracking device, which necessitates that subjects forego eyeglasses or makeup. With 81.1% accuracy, it performed well.

II. RELATED WORK

Y. Liang, M. L. Reyes, and J. D. Lee, 2007 [11], A major and developing safety risk is driver distraction as the usage of in-vehicle information systems (IVISs) like satellite radios, cell phones, and navigation systems has expanded. The detection of driver attention and the adaptation of in-car equipment to reduce it is a promising solution to this issue. In order to implement this strategy, this article used data mining techniques such as support vector machines (SVMs) to create a real-time system for identifying cognitive distraction based on driving performance data and eye movements of drivers. In a simulator experiment, data were gathered as ten individuals drove and interacted with an IVIS. Three distinct model aspects were examined: how distraction was defined, which data were input into the model, and how the input data were summarized. The data were utilized to train and test both SVM and logistic regression models. The findings demonstrate that the SVM models outperformed more conventional logistic regression models in their ability to identify driver distraction, with an average accuracy of 81.1%.

When driving and eye movement measures were used to characterize distraction under experimental settings (i.e., IVIS drive or baseline drive), and when the data were summarized over a 40-s window with a 95% overlap of windows, the best performing model (96.1% accuracy) was produced. These findings show that driver distraction may be identified in real time using eye movements and basic driving performance metrics. This paper may find use in the development of adaptive in-car technologies and the assessment of driver distraction.

M. H. Kutila, M. Jokela, T. Mäkinen, J. Viitanen, G. Markkula, and T. W. Victor, 2007 [12], Driving attention is being diverted more and more by electronics and driving assistance systems (such as cell phones and navigators). As a result, the auto industry is working to create a driving environment where input-output devices are carefully timed to provide drivers enough time to concentrate on the traffic around them. A smart human–machine interface (HMI) requires measuring the driver's transient condition. This study gives some preliminary evaluation results and describes a facility for tracking driver distraction. By combining stereo vision and lane tracking data, the module can determine the driver's visual and cognitive workload by applying both rule-based and support-vector machine (SVM) classification techniques. Test data for the module was obtained from a truck and a passenger automobile. The results demonstrate an acceptable 68–86% success rate in detecting cognitive distraction and over 80% success rate in detecting visual distraction.

Y. Liao, S. E. Li, W. Wang, Y. Wang, G. Li, and B. Cheng, 2016[13], One of the main causes of risky driving has been found to be driver distraction. Research on cognitive distraction detection has primarily addressed high-speed driving scenarios; low-speed traffic in urban driving has received less attention. This study compares the feature subsets and classification accuracy of a technique for detecting driver cognitive distraction at stop-controlled intersections with those of a speed-limited highway. A total of twenty-seven participants were enrolled in the simulator trial. The clock task causes cognitive distraction in drivers by using up visuospatial working memory. Using the recursive feature elimination procedure of the support vector machine (SVM), an ideal feature subset is extracted from the features derived from driving performance and eye movement. The SVM classifier is trained and cross-validated within subjects following feature extraction. Out of four types of SVM models based on different candidate features, the classifier based on the fusion of driving performance and eye movement yields the best correct rate and F-measure (correct rate = 95.8±4.4% for stop-controlled intersections and correct rate = 93.7±5.0% for a speed-limited highway) on average. We offer a comparison of the SVM performance and extracted optimal feature subsets between two common driving scenarios.

Y. Ma, G. Gu, B. Yin, S. Qi, K. Chen, and C. Chan, 2022[14], One significant contributing element to driver distraction is the in-vehicle information system, or IVIS. Variance analysis was used to confirm that driving performance indicators were a reliable means of identifying driving distraction while studying the driver distraction detection technique when using IVIS. A total of forty individuals were chosen to carry out the driver distraction experiment while using IVIS. Data on driving performance indicators, including speed and eye movement, were also collected. Based on the driving performance data from IVIS, a support vector machine was used to build a real-time distraction detection system. Three model kernel functions underwent validation and comparative analysis. The outcomes demonstrate that SVM algorithms are capable of assessing drivers' levels of distraction with accuracy. In addition, the accuracy of detecting driver preoccupation when the Radial Basis Function is employed as a kernel function is 89.9%, greater than when the SAVE-IT model and sigmoid polynomial kernel function are employed. The findings could be used to inform the development of vehicle-mounted information systems and the administration of driver distraction prevention strategies, as well as to create adaptive in-car systems and assess driving distraction.

L. Li, K. Werber, C. F. Calvillo, K. D. Dinh, A. Guarde, and A. Konig, 2014 [8], Active safety technology for automobiles is always being improved by sophisticated algorithms, cutting-edge sensing systems, and growing computing power. One of the main elements of an advanced driver assistance system that can increase vehicle and road safety without sacrificing the driving experience is driver status monitoring. In order to detect drowsiness, this study provides a novel method of driver status monitoring based on depth camera, pulse rate sensor, and steering angle sensor. Owing to its NIR active illumination, depth cameras can offer trustworthy three-dimensional head movement data in addition to non-intrusive eye gaze estimate and blink recognition. A warning can be provided to avert traffic accidents based on the assessment of driver drowsiness degree, which is made easier by multisensor data fusion on feature level and multilayer neural network. An integrated soft-computing system for driving simulation (DeCaDrive) equipped with multi-sensing interfaces is used to accomplish the suggested methodology. On the basis of data sets containing five test subjects with a driving sequence of 588 minutes, a classification accuracy of 98:9% for up to three sleepiness levels was obtained.

A. D. McDonald, T. K. Ferris, and T. A. Wiener, 2020 [15], In order to identify the most effective algorithms for identifying driver distraction and identifying its cause, this study aimed to examine a set of physiological and driving performance data using advanced machine learning techniques, such as feature generation. Context. Numerous car crashes that result in injuries and fatalities frequently have distracted driving as a contributing component. The capacity to identify and reduce driver distraction is becoming more and more crucial as mobile devices and in-car information systems proliferate. Approach. Twenty-one algorithms were trained in this study to detect instances in which drivers were preoccupied with texting and secondary cognitive tasks. The algorithms handled behavioural and physiological data using a full feature generating program, Time Series Feature Extraction, which was based on Scalable Hypothesis testing. Based only on driving behaviour metrics and omitting physiological data from the driver, the Random Forest algorithm was shown to be the most effective algorithm for properly diagnosing driver distraction, according to the results. The most significant feature types were non-linear transformations, quantiles, and standard deviation, whereas the most significant input measures were steering, lane offset, and speed. In conclusion. According to this research, taking into account ensemble machine-learning algorithms that are trained using non-standard characteristics and driving behaviour measurements may help to improve distracted detection algorithms. The study also offers a number of novel distraction indicators that are based on steering and speed measurements. Utilization. Distraction mitigation systems should be developed with an emphasis on driver behaviour-based algorithms that employ sophisticated feature generation techniques in the future.

A. Sathyanarayana, S. Nageswaren, H. Ghasemzadeh, R. Jafari, and J. H. L. Hansen, 2008[16], Almost everyone uses a car to get from one point to another in their daily lives. There are many different ways for drivers to become distracted while operating a vehicle in this kind of fast-paced transportation. Distractions can take many different forms, such as getting delayed in traffic or multitasking while driving by drinking, reading, or talking on the phone. An early identification of distracted driving can lower the number of collisions. This study reports on the preliminary examination of a motion sensor (accelerometer and gyroscope) and Controller Area Network (CAN) data-driven system for driver distracted detection. The primary focus of the paper is on distractions that can be identified by the driver's head and leg movements. Over 90% of the driver's expressive portions provide data with a high accuracy of distraction detection. With such high accuracy, dependable systems with early warning or corrective mechanisms might be developed to prevent or lessen the severity of accidents brought on by distracted drivers.

J. He, A. Chaparro, B. Nguyen, R. J. Burge, J. Crandall, B. Chaparro, R. Ni, and S. Cao, 2014 [17], Studies reveal that talking or texting on a cell phone while operating a car reduces one's ability to drive safely. The distracting effects of texting while using a hands-free (speech-based) versus a handheld mobile phone, however, have not been thoroughly compared in published studies. This is a significant issue for legislation, car interface design, and driving safety education. In order to compare the effects of speech-based and handheld text entry on simulated driving performance, this study had participants complete a secondary text-entry task that controlled the duration while also doing a car-following task. The findings demonstrated that, in comparison to the drive-only condition, speech-based and handheld text entry hampered driving performance by increasing variance in speed and lane position. Additionally, there was an increase in headway distance fluctuation and brake response time with handheld text entry. Handheld text entry was found to be less damaging to driving performance than text entry using a speech-based cell phone. Even yet, compared to the drive-only condition, the speech-based text entry task still markedly reduced driving ability. These findings imply that while speech-based text entry interferes with driving, it does so at a lower degree than text entry using a handheld device. Furthermore, the variation in task time is not the only factor contributing to the variance in the distraction impact between speech-based and portable text entry.

In summary, this field of study has never before conducted a comprehensive review of a variety of driving scenarios involving spoken conversation distraction. Furthermore, not enough work has been done to incorporate measures from other sources, like ocular metrics, physiological data, and vehicle kinematics data. In the current study, we used novel applications of machine learning techniques to fill this research gap. Based on the findings of the current study, we have the following proposals for the design of driver distraction detection algorithms.

- To increase prediction accuracy, develop the model for each type of road separately.
- Eye-tracking and physiological measures seem to be more useful than vehicle kinematics measures.
- The majority of eye-tracking measures' data come from the eye camera, with additional data from the scene camera adding only a little amount to prediction accuracy.

III. CONCLUSION

Various machine learning techniques were utilized and compared for detection of driver distraction classification. Young drivers did drive exercises in a simulator on a variety of road types, either with or without the addition of a controlled auditory communication task to simulate distraction. The findings imply that eye-tracking and physiological data offer useful characteristics for classifying distractions. More classification accuracy can be achieved by building separate models and training for each type of road than by incorporating all the data from all the road types into a single model. Applications of cognitive distraction monitoring systems for early mitigation and intervention improving driving safety can be supported by the characteristics found in the current study.

REFERENCES

[1] E. T. M. Beltrán, M. Q. Pérez, S. L. Bernal, G. M. Pérez, and A. H. Celdrán, ‘‘SAFECAR: A brain–computer interface and intelligent framework to detect drivers’ distractions,’’ Exp. Syst. Appl., vol. 203, Oct. 2022, Art. no. 117402.

[2] G. Li,W. Yan, S. Li, X. Qu,W. Chu, and D. Cao, ‘‘A temporal-spatial deep learning approach for driver distraction detection based on EEG signals,’’ IEEE Trans. Autom. Sci. Eng., vol. 19, no. 4, pp. 2665–2677, Oct. 2022.

[3] C. Fan, Y. Peng, S. Peng, H. Zhang, Y. Wu, and S. Kwong, ‘‘Detection of train driver fatigue and distraction based on forehead EEG: A time-series ensemble learning method,’’ IEEE Trans. Intell. Transp. Syst., vol. 23, no. 8, pp. 13559–13569, Aug. 2022.

[4] A. Azman, M. Abdullah, F. Azli, S. Yogarayan, S. Razak, H. Azman, K. Muthu, and H. Suhaila, ‘‘Measuring driver cognitive distraction through lips and eyebrows,’’ Int. J. Electr. Comput. Eng., vol. 12, no. 1, pp. 2088–8708, 2022.

[5] R. W. Picard, E. Vyzas, and J. Healey, ‘‘Toward machine emotional intelligence: Analysis of affective physiological state,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 23, no. 10, pp. 1175–1191, Oct. 2001.

[6] H. B. Lee, J. S. Kim, Y. S. Kim, H. J. Baek, M. S. Ryu, and K. S. Park, ‘‘The relationship between HRV parameters and stressful driving situation in the real road,’’ in Proc. 6th Int. Special Topic Conf. Inf. Technol. Appl. Biomed., Nov. 2007, pp. 198–200.

[7] P. Papantoniou, E. Papadimitriou, and G. Yannis, ‘‘Review of driving performance parameters critical for distracted driving research,’’ Transp. Res. Proc., vol. 25, pp. 1796–1805, Jan. 2017.

[8] L. Li, K. Werber, C. F. Calvillo, K. D. Dinh, A. Guarde, and A. Konig, ‘‘Multi-sensor soft-computing system for driver drowsiness detection,’’ in Soft Computing in Industrial Applications (Advances in Intelligent Systems

and Computing), vol. 223. Cham, Switzerland: Springer, pp. 129–140, 2014.

[9] I. G. Daza, L. M. Bergasa, S. Bronte, J. J. Yebes, J. Almazán, and R. Arroyo, ‘‘Fusion of optimized indicators from advanced driver assistance systems (ADAS) for driver drowsiness detection,’’ Sensors, vol. 14, no. 1, pp. 1106–1131, 2014.

[10] B.-G. Lee and W.-Y. Chung, ‘‘Driver alertness monitoring using fusion of facial features and bio-signals,’’ IEEE Sensors J., vol. 12, no. 7, pp. 2416–2422, Jul. 2012.

[11] Y. Liang, M. L. Reyes, and J. D. Lee, ‘‘Real-time detection of driver cognitive distraction using support vector machines,’’ IEEE Trans. Intell. Transp. Syst., vol. 8, no. 2, pp. 340–350, Jun. 2007.

[12] M. H. Kutila, M. Jokela, T. Mäkinen, J. Viitanen, G. Markkula, and T. W. Victor, ‘‘Driver cognitive distraction detection: Feature estimation and implementation,’’ Proc. Inst. Mech. Eng., D, J. Automobile Eng., vol. 221, no. 9, pp. 1027–1040, Sep. 2007.

[13] Y. Liao, S. E. Li, W. Wang, Y. Wang, G. Li, and B. Cheng, ‘‘Detection of driver cognitive distraction: A comparison study of stop-controlled intersection and speed-limited highway,’’ IEEE Trans. Intell. Transp. Syst., vol. 17, no. 6, pp. 1628–1637, Jun. 2016.

[14] Y. Ma, G. Gu, B. Yin, S. Qi, K. Chen, and C. Chan, ‘‘Support vector machines for the identification of real-time driving distraction using in-vehicle information systems,’’ J. Transp. Saf. Secur., vol. 14, no. 2, pp. 232–255, Feb. 2022.

[15] A. D. McDonald, T. K. Ferris, and T. A. Wiener, ‘‘Classification of driver distraction: A comprehensive analysis of feature generation, machine learning, and input measures,’’ Hum. Factors, vol. 62, no. 6, pp. 1019–1035, Sep. 2020.

[16] A. Sathyanarayana, S. Nageswaren, H. Ghasemzadeh, R. Jafari, and J. H. L. Hansen, ‘‘Body sensor networks for driver distraction identification,’’ in Proc. IEEE Int. Conf. Veh. Electron. Saf., Sep. 2008, pp. 120–125.

[17] J. He, A. Chaparro, B. Nguyen, R. J. Burge, J. Crandall, B. Chaparro, R. Ni, and S. Cao, ‘‘Texting while driving: Is speech-based text entry less risky than handheld text entry?’’ Accident Anal. Prevention, vol. 72, pp. 287–295, Nov. 2014.