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A Survey on Drowsiness Detection System using Infrared Sensor

Ms.C.Saraswathy[1], Dr.S.Sarumathi[2], Mr.D.Poornakumar[3], Dr.S.Malarkhodi[4]

Associate Professor, Department of Electronics and Communication Engineering, K.S.Rangasamy College of Technology, Tamil Nadu, India[1]

Professor, Department of Artificial Intelligence and Data Science, K.S.Rangasamy College of Technology, Tamil Nadu, India[2]

Assistant Professor, Department of Electronics and Communication Engineering, K.S.Rangasamy College of Technology, Tamil Nadu, India[3]

Professor, Department of Electronics and Communication Engineering, K.S.Rangasamy College of Technology, Tamil Nadu, India[4]

Abstract: Drowsy driving is one of the top causes of road accidents, resulting in catastrophic injuries and deaths every year. Drowsiness is defined as trouble staying awake, which can be detected by systems that analyse physiological indicators, face traits, and driving patterns. The paper also describes and offers the most recently developed strategies for each class. It also compares recently published work in terms of accuracy, dependability, hardware requirements, and penetration capabilities. The advantages and limitations of each category is summarised and analysed. As a result, each technique has both advantages and downsides. A hybrid system that integrates two or more techniques will be efficient, durable, and precise, and will be employed in real time to maximise the benefits of each methodology.

Keywords : Drowsy driving, Physiological cues, Facial features, Driving habits

I. INTRODUCTION

Drowsy driving is the dangerous combination of driving while asleep. This is most commonly caused by a driver not getting enough sleep, but it can also be caused by shift work or untreated sleep problems. Alcohol can exacerbate both impairment and drowsiness, and prescription and over-the-counter medications can also cause sleepiness. Although it is obviously dangerous to fall asleep while driving, being drowsy has an effect on one's ability to do so safely. When someone is sleepy, they are less able to pay attention to the road, respond more slowly when they need to stop or turn unexpectedly, and make wise decisions when things are at stake. Most drivers are aware of the dangers of drinking and driving or texting and driving, but many people underestimate the dangers of sleepy driving. Each year, sleepy driving causes approximately 100,000 collisions, 71,000 injuries, and 1,550 fatalities, according to the National Safety Council (NSC). Furthermore, fatigue was a factor in up to 9.5 percent of all collisions and 10.8 percent of crashes involving airbag deployment, injury, or major property damage, according to AAA Foundation for Traffic Safety research. Drowsy driving is extremely dangerous, and drivers must be aware of the risks.

II. DIFFERENT DROWSINESS DETECTION METHODS

The novel approach proposed in this paper measures driver mental fatigue and drowsiness by monitoring the driver's head posture motions with the XSENS motion capture system. The experiments were carried out on 15 healthy subjects using a MATHWORKS driver-in-loop (DIL) simulator that was linked to Unreal Engine 4 studio. A new modified bidirectional long short-term memory deep neural network for sequence-to-sequence classification was designed, trained, and tested on 3D time-series head angular acceleration data. The proposed classifier outperformed state-of-the-art approaches and traditional machine learning tools, successfully recognizing drivers' active, fatigue, and transition states, with overall training accuracy of 99.2%, sensitivity of 97.54%, precision and F1 scores of 97.38% and 97.46%, respectively. The current work's limitations and future work directions are also discussed[1].

This paper proposes a novel multimodal fusion recurrent neural network (MFRNN), integrating the three features to improve the accuracy of driver fatigue detection. Specifically, a recurrent neural network (RNN) layer is applied in the MFRNN to obtain the temporal information of the features. Since the heart rate feature is a physiological

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signal extracted indirectly, it contains more noise and is fuzzier than the other features. To deal with the fuzziness and noise, we combine fuzzy reasoning with RNN to extract the temporal information of the heart rate. To identify the relationship between the features, we develop a new relationship layer containing a two-level RNN, for which the input is the temporal information of the features. Both the simulation and field experiment results show that the proposed method provides better performance than similar methods[2]

The research offers a DSM (ABI DSM) system based on Adaptive Batch-Image (ABI). The ABI enables the DSM system to use real-time photos while the DSM processes earlier input images. The ABI-DSM system is designed for real-time operation on a lightweight GPU-equipped Single-Board Computer (SBC). First, the system leverages the driver's facial behaviour to lower the dimension of the time-series data in order to recognize the driver's condition. The second is that driver face detection and tracking are not employed for facial behaviour recognition. In addition, for facial behaviour detection, the system uses PydMobileNet, which has fewer parameters and FLOPs than MobileNetV2. Experiments reveal that ABI-DSM systems based on MobileNetV2 and PydMobileNet outperform others in terms of both FPS and Precision[3].

The practicality of employing smartphone acoustic sensors to detect drowsy driving. Some distinctive patterns of Doppler shift generated by three typical drowsy behaviours (i.e., nodding, yawning, and operating steering wheel), among which moving steering wheel is also connected to tiredness levels, were discovered by analysing real driving data to examine aspects of drowsy driving. Then, based on the acoustic sensing capabilities of smartphones, a real-time Drowsy Driving Detection system called D3-Guard is proposed. The research includes various successful feature extraction approaches as well as a carefully designed high-accuracy detector based on LSTM networks for detecting drowsy driving early on. Furthermore, procedures to distinguish sleepiness levels are added into the system by collecting data from the functioning steering wheel. D3-Guard detects drowsy driving activities with an average accuracy of 93.31% and classifies sleepiness levels with an average accuracy of 86% in extensive testing with 5 drivers in real driving conditions [4].

Based on eye state and pupil and iris segmentation, an effective fatigue detection approach is developed. The segmented feature map can direct the detection to concentrate on the pupil and iris. A streamlined network is created, consisting of a segmentation network and a decision network, that considerably increases the accuracy and generalization of eye openness estimate. Specifically, the segmentation network that employs the light U-Net structure classifies eye images at the pixel level, allowing it to reliably extract pupil and iris properties from video images. The derived feature map is then utilised to direct the decision network in estimating eye opening. The experimental results show that the suggested method can accurately detect driver weariness in real time and outperforms state-of-the-art techniques [5].

The paper proposes a fatigue driving detection algorithm that combines driver characteristics using facial multifeature fusion. First, an improved YOLOv3-tiny convolutional neural network is used to capture facial regions under complex driving conditions, removing the inaccuracy and affections caused by artificial feature extraction. Second, based on the Dlib toolkit, the Eye Feature Vector (EFV) and Mouth Feature Vector (MFV) are introduced as evaluation parameters of the driver's eye and mouth states, respectively. Offline training is then used to build the driver identity information library, which includes the driver eye state classifier library, driver mouth state classifier library, and driver biometric library. Finally, the driver identity verification model and the driver fatigue assessment model were built using online assessments. Calculate the driver's closed eyes time, blink frequency, and yawn frequency after passing the identity verification to determine the driver's fatigue state. In simulated driving applications, the algorithm detects fatigue with an accuracy of 95.10% at speeds of more than 20fps [6].

EEG signals are also used in this paper to detect drowsiness, with the proposed method consisting of three main building blocks. The proposed building blocks make use of both raw EEG signals and their corresponding spectrograms. While energy distribution and zero-crossing distribution features are calculated from raw EEG signals in the first building block, spectral entropy and instantaneous frequency features are extracted from EEG spectrogram images. Deep feature extraction is used directly on the EEG spectrogram images in the second building block, using pre-trained AlexNet and VGGNet. The tunable Q-factor wavelet transform (TQWT) is used in the third building block to decompose the EEG signals into related sub-bands. The obtained sub-bands spectrogram images and statistical features, such as mean and standard deviation of instantaneous frequencies, are then calculated. For classification, each feature group from each building block is fed into a long-short term memory (LSTM) network. The LSTM network results are then combined with a majority voting layer. The experimental works made use of the MIT-BIH Polysomnographic database. The proposed method was evaluated using a ten-fold cross validation test, and the average accuracy was represented accordingly. The average accuracy score obtained was 94.31%. The obtained result was also compared to other findings in the literature. The comparison reveals that the proposed method outperforms the compared results in terms of achievement [7].

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A drowsiness detection method based on changes in the respiratory signal is proposed in this paper. The respiratory signal obtained with an inductive plethysmography belt was processed in real time to classify the driver's level of alertness as drowsy or awake. The proposed algorithm detects the fight against falling asleep by analyzing the respiratory rate variability (RRV). In addition, a method for providing a quality level of the respiratory signal is proposed. Both methods have been combined to reduce false alarms caused by changes in measured RRV caused by body movements rather than drowsiness. The validation tests were carried out in a driving simulator cabin, with external observers present. [8].

To accurately detect drowsy driving, this paper collects the characteristic parameters of the driver's operating behavior and the vehicle's running state via simulation experiments. Then, to reduce the dimensionality of the characteristic parameters, factor analysis was used, and the composite factor scores were computed in both normal and drowsy states, forming a time series. Following that, the time series of composite factor scores was split into information granules, and particle swarm optimization (PSO) was used to optimize the dynamic time window for the characteristic parameters. Following that, the mean and standard deviation for each composite factor score in each sub-time window were computed and fused into a single data set. Finally, using the fused data, a drowsy driving model was created with LIBSVM. The experimental results show that the model detected drowsy driving with an accuracy of 86.47%. The findings of the study shed new light on the detection of drowsy driving [9].

This paper proposes a real-time driving drowsiness detection algorithm that takes into account the driver's individual differences. To detect the face region, a deep cascaded convolutional neural network was built, which avoids the problem of poor accuracy caused by artificial feature extraction. The frontal driver facial landmarks in a frame are found using the Dlib toolkit. A new parameter called Eyes Aspect Ratio is introduced based on the eyes landmarks to evaluate the drowsiness of the driver in the current frame. The proposed algorithm is divided into two modules that account for differences in the size of the driver's eyes: offline training and online monitoring. The first module trained a unique fatigue state classifier based on Support Vector Machines with the Eyes Aspect Ratio as input. The trained classifier is then used in the second module as an application to monitor the driver's status online. Because the fatigue driving state develops gradually, a variable based on the number of drowsy frames per unit time is introduced to assess the driver's drowsiness. We show that this algorithm outperforms current driving drowsiness detection approaches in both accuracy and speed in comparative experiments. In simulated driving applications, the proposed algorithm detects driver drowsiness quickly from 640480 resolution images at over 20fps and 94.80% accuracy. The findings of the study can be used to improve intelligent transportation systems, ensure driver safety, and reduce losses caused by drowsy driving [10].

In this article, a Multi-tasking Convolutional Neural Network (ConNN*) model is proposed to detect driver drowsiness/fatigue. Eye and mouth characteristics are utilized for driver's behavior model. Changes to these characteristics are used to monitor driver fatigue. With the proposed Multi-task ConNN model, unlike the studies in the literature, both mouth and eye information are classified into a single model at the same time. Driver fatigue is determined by calculating eyes closure duration/Percentage of eye closure (PERCLOS) and yawning frequency/frequency of mouth (FOM). In this study, the fatigue degree of the driver is divided into 3 classes. The proposed model achieved 98.81% fatigue detection on YawdDD and NthuDDD dataset [11].

In this paper, we propose a system called DriCare, which detects the drivers fatigue status, such as yawning, blinking, and duration of eye closure, using video images, without equipping their bodies with devices. Owing to the shortcomings of previous algorithms, we introduce a new face tracking algorithm to improve the tracking accuracy. Further, we designed a new detection method for facial regions based on 68 key points. Then we use these facial regions to evaluate the drivers state. By combining the features of the eyes and mouth, DriCare can alert the driver using a fatigue warning. The experimental results showed that DriCare achieved around 92% accuracy [12].

The framework proposed consists of four models: spatio-temporal representation learning, scene condition understanding, feature fusion, and drowsiness detection. Spatio-temporal representation learning extracts features from video that can describe motions and appearances at the same time. Scene condition understanding categorizes scene conditions related to various conditions about drivers and driving situations, such as wearing glasses status, driving illumination condition, and motion of facial elements such as head, eye, and mouth. Using two features extracted from the previous models, feature fusion creates a condition adaptive representation. The condition-adaptive representation is used by the drowsiness detection model to recognize driver drowsiness. The condition-adaptive representation learning framework can extract more discriminative features that are specific to each scene condition than the general representation, allowing the drowsiness detection method to provide more accurate results in a variety of driving situations. With the NTHU drowsy driver detection video dataset, the proposed framework is tested. The experimental results show that the framework outperforms existing visual drowsiness detection methods [13].

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III. COMPARISON OF DIFFERENT DROWSINESS DETECTION METHODS

This section explores the various detection techniques and classification methods used for driver drowsiness. In this survey, we considered the author's name, publication year, techniques used, dataset size, classification accuracy, detection type, and parameters of their study work. The techniques for detecting drowsiness are summarized in Table 1.

TABLE I COMPARISON OF DIFFERENT DROWSINESS DETECTION METHODS

S.No	Author	Year	Methodology	Dataset	Parameter	Detection
1.	Fazel Naghdy et.al.,	2021	ReLU - BiLSTM	The sequences obtained from thirteen subjects were used for training of the deep network, whereas the sequence data from two subjects were deployed for validation and testing of the algorithm	The overall training accuracy - 99.2%	Fatigue, Sleep deprivation, Yawning, Nodding, and Shaking
2.	Guanglong Du et.al.,	2021	Multimodal Fusion Recurrent Neural Network	21862 non-fatigue driving feature sets and 38138 fatigue driving feature sets	The accuracy is about 91.67%	Fatigue, Heart rate, and facial features
3.	Whui Kim et.al.,	2020	PydMobileNet and MobileNetV2	A total of 376,000 images in which 865,000 images are sampled for training. the test dataset for ten is about 79,000.	Parameters of the ABI-DSM based on PydMobileNet is about 73%	Facial behaviour such as eye closing and mouth opening
4.	Yadong Xie et.al.,	2020	Acoustic Sensors on the smartphones, DNN and LSTM Network	The dataset consists of two types of training data: real driving data and simulated data	D3-Guard achieves an average total accuracy of 93.31% for drowsy actions detection	Yawning, Vehicle speed, Vehicle maneuvers, Inattentive driving events, and Driver’s action
5.	Qianyang Zhuang et.al.,	2020	SESDM and Dlib Face Key point detection algorithm	The total of 9728 eye data was collected, including 6225 data as training set, 1557 data as validation set	The precision of fatigue detection achieves the accuracy of 96.72%	Fatigue, Eye status with pupil, and Iris

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				and 1946 data as test set		
6.	Kening Li et.al.,	2020	SSD Algorithm, YOLOv3 tiny and Fast RCNN	The public data set WIDER FACE includes 32203 pictures and 393703 marked faces, which is used to train Yolov3-tiny's face network. For testing phase 50 driver's data's are collected.	It detects the fatigue state at a speed of over 20fps with an accuracy of 95.10%	Fatigue, eyes, and mouth
7.	Umit Budak et.al.,	2019	AlexNet, VGGNet16 models and LSTM Network	The MIT/BIH Polysomnograph ic EEG database is collected from 16 subjects whose average age and weight are 43 years and 119 kg, respectively.	Majority accuracy score is 94.31%	Vehicular accidents, EEG Signals, and Drowsiness
8.	Federico Guede-Fernández et.al.,	2019	Thoracic Effort Derived Drowsiness index (TEDD).	Number of test driving sets are taken as sampled datasets	Specificity is 96.6% Sensitivity is 90.3%	Respiratory signal, body movements, and Sleep deprivation
9.	Yan Wang et.al.,	2019	Factor analysis, Information granulation of time series and the SVM.	2000 normal samples and 1600 drowsy samples are used for training set. 1210 normal samples and 830 drowsy samples are used for test set	Accuracy of 86.47% and an AUC of 0.911.	Vehicle's running state, Information granulation and Pseudo code
10.	Feng You et.al.,	2019	DCCN and EAR based on Dlib toolkit.	Training phase of DCCNN, WIDER_FACE data set, and the AFLW data set 1 are used for training data	The accuracy of face detection can reach at 98.8%.	Face, Eye landmarks, and fatigue
11.	Burcu Kir Savaş et.al.,	2019	Multi-tasking Convolutiona l Neural Network	The YAWDD consists of 322 videos with or without glasses and sunglasses. The NTHU-DDD video data	The accuracy of fatigue detection is about 98.81%	Facial landmarks, Fatigue, Eye and mouth opening.

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				set consists of 5 different scenarios		
12.	Wanghua Deng et.al.,	2019	MC-KCF algorithm	10 volunteers to collect the video data captured by the vehicle camera. CelebA and YawDD Dataset.	The accuracy of DriCare is about 92%	Drowsiness, Fatigue, and Facial landmarks
13.	Jongmin Yu et.al.,	2018	The 3D-DCNN is adopted from the ReLU	The training dataset composed of 360 videos(722,223 frames) and the evaluation dataset contains 20 videos (173, 259 frames). The test datasets are not publicly accessible	The Average accuracy rate of the NTHU-DDD is 76.2%.	Drowsiness in facial elemnts: Head, Eye, Mouth and Illuminaton Condition of driving

IV. CONCLUSION

The survey of drowsy driver detection has various methods and classification techniques, as detailed above. According to the survey, this report attempts to implement various algorithms like Image Processing, Machine Learning, Computer Vision, EEG &ECG and IoT. These algorithms are used to assist the vehicle's owner in detecting drowsiness. It is cost-effective, simpler in design and easy to install in real time. This survey is very useful for preventing accidents due to drowsy driving and poor vision.

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