International Journal of Research Publication and Reviews, Vol 4, no 1, pp 1500-1504, January 2023

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Driver Drowsiness Recognition System : A Review

Sunaina Yadav [a]

[a] *Jabalupur Engineering College, Jabalpur, MP, India*

A B S T R A C T

This work is a study of available systems which can detect fatigue of any human and can issue a timely warning. Drivers who do not take regular breaks when driving long distances run a high risk of becoming drowsy a state which they often fail to recognize early enough. This type of system consists of three basic steps which automatically detect human Drowsiness image first, detect face and Eyes second extract the various facial features and last identify Drowsiness based on features. This type of systems can be developed with Machine learning systems with supervised and unsupervised type of ML. Major drawback in unsupervised ML based systems is the time to recognize the drowsiness state. As per the need the detecting must be in real time with supervised ML it can be achieved but this method has less accuracy. It is needed to develop a method which is more accurate and can detect drowsiness state in real time.

Keywords:Machine learning, Least Mean Square Error,Principal Component Analysis, Drowsiness, MATLAB

1. INTRODUCTION

Real Time Drowsiness behaviors which are related to fatigue are in the form of eye closing, head nodding or the brain activity. Hence, we can either measure change in physiological signals, such as brain waves, heart rate and eye blinking to monitor drowsiness or consider physical changes such as sagging posture, leaning of driver's head and open/closed state of eyes.

The former technique, while more accurate, is not realistic since highly sensitive electrodes would have to be attached directly on the driver' body and hence which can be annoying and distracting to the driver. In addition, long time working would result in perspiration on the sensors, diminishing their ability to monitor accurately. The second technique is to measure physical changes (i.e. open/closed eyes to detect fatigue) is well suited for real world conditions since it is non-intrusive by using a video camera to detect changes. In addition, micro sleeps that are short period of sleeps lasting 2 to 3 minutes are good indicators of fatigue. Thus, by continuously monitoring the eyes of the driver one can detect the sleepy state of driver and a timely warning is issued.

Face Detection Scenarios: Face detection scenarios can be classified into two types:

- Face verification (or authentication).
- Face identification (or recognition).

Face verification ('Am I who I say I am?') is a one-to-one match that compares a query Face image against a template Face image whose identity is being claimed. To evaluate verification performance, verification rate (rates at which legitimate users are granted access) vs. false accepts rate (rate at which imposters is granted access) is plotted, called ROC curve. A good verification system should balance these two rates based on operational needs.The Eye detection can be performed by giving an input of an arbitrary image, which could be a digitized video signal or a scanned photograph, determine whether or not there are any human eyes in the image, and if there are, return an encoding of the location and spatial extent of each human Face in the image [5]. There are three major types of standard features extraction methides which can be used for Drowsiness detection techniques:

- PCA
- LDA
- ICA

* *Corresponding author.* Tel.: +91-9479723896.
E-mail address:sunainayadav461@gmail.com

Figure 1 below shows the face identification base on Voila-jones method and figure 2 below shows the eye detection based of haar features used in voila-jones.

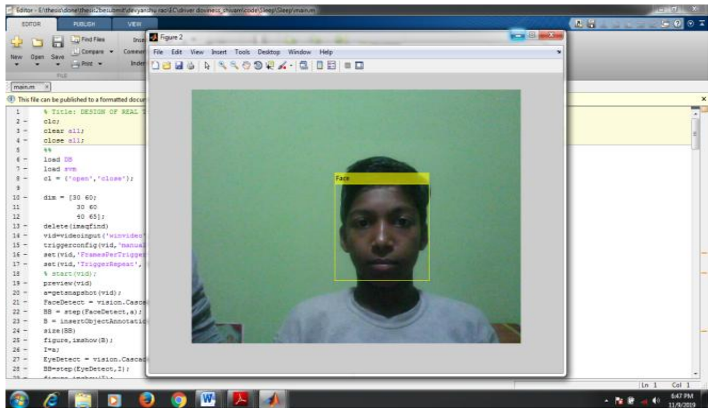

Figure 1: face identification scenario

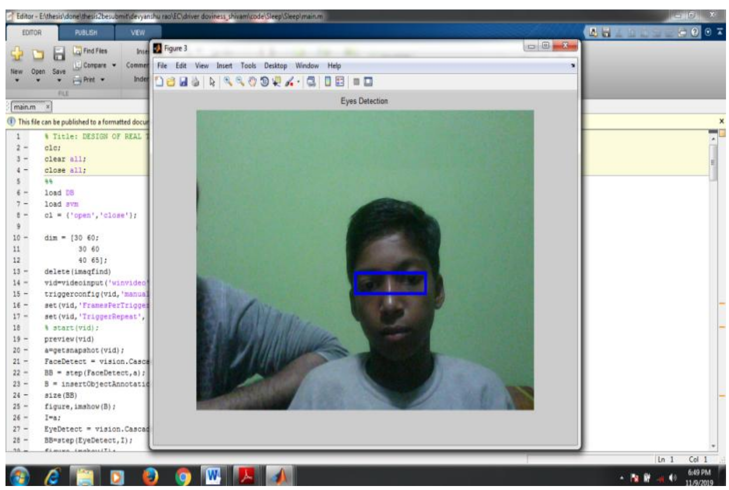

Figure 2: Eye Identification using Proposed Method

2. REVIEW OF LITERATURE

J. R. Paulo et al [1] this paper use EEG signals are used widely for brain-computer interfaces, as well as mental state recognition. However, these systems are still difficult to design due to very low signal-to-noise ratios and cross-subject disparities, requiring individual calibration cycles. To tackle this research domain, here, we explore drowsiness detection based on EEG signals' spatiotemporal image encoding representations in the form of either recurrence plots or gramian angular fields for deep convolutional neural network (CNN) classification. Results comparing both techniques using a public dataset of 27 subjects show a superior balanced accuracy of up to 75.87% for leave-one-out cross-validation, using both techniques, against works in the literature, demonstrating the possibility to pursue cross-subject zero calibration design.

Mika Sunagawa et al [2] This paper presents a drowsiness detection modelthat is capable of sensing the entire range of stages of drowsiness,from weak to strong. The key assumption underlying ourapproach is that the sitting posture-related index can indicateweak drowsiness that drivers themselves do not notice. We firstdetermined the sensitivity of the posture index and conventionalindices for the stages of drowsiness. Then, we designed adrowsinessdetection model combining several indices sensitive toweak drowsiness and to strong drowsiness, to cover all drowsinessstages. Subsequently, the model was trained and evaluated on adataset comprised of data collected from approximately 50drivers in simulated driving experiments. The results indicated

that posture information improved the accuracy of weakdrowsiness detection, and our proposed model using the driver'sblink and posture information covered all stages of drowsiness(F1-score 53.6%, root mean square error 0.620). Futureapplications of this model include not only warning systems fordangerously drowsy drivers but also systems which can takeaction before their drivers become drowsy. Since measuring theinformation requires no restrictive equipment such as on-bodyelectrodes, the model presented here based on blink and postureinformation can be used in several practical applications.

Yaocong Hu et al [3] In this paper, a new deep learningframework based on the hybrid of 3D conditional generativeadversarial network and two-level attention bidirectional longshort-term memory network (3DcGAN-TLABiLSTM) has beenproposed for robust driver drowsiness recognition. Aiming atextracting short-term spatial-temporal features with abundantdrowsiness-related information, we design a 3D encoder-decodergenerator with the condition of auxiliary information to generatehigh-quality fake image sequences and devise a 3D discriminatorto learn drowsiness-related representationfrom spatial-temporaldomain. In addition, for long-term spatial-temporal fusion, weinvestigate the use of two-level attention mechanism to guidethe bidirectional long short-term memory learn the saliency ofshort-term memory information and long-term temporal information.For experiment, we evaluate our 3DcGAN-TLABiLSTMframework on a public NTHU-DDD dataset. Experimental resultsshow that the proposed approach achieves higher precision ofdrowsiness recognition compared to the state-of-the-art.

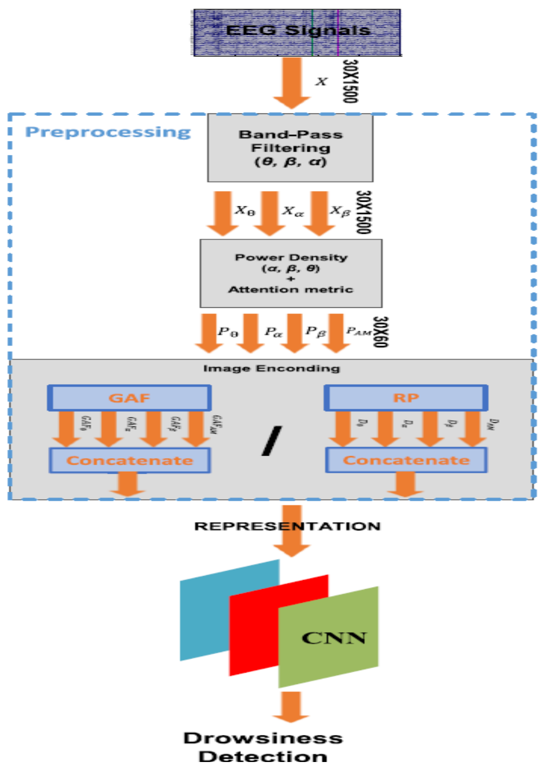

Figure 1 Work flow J. R. Paulo [1]

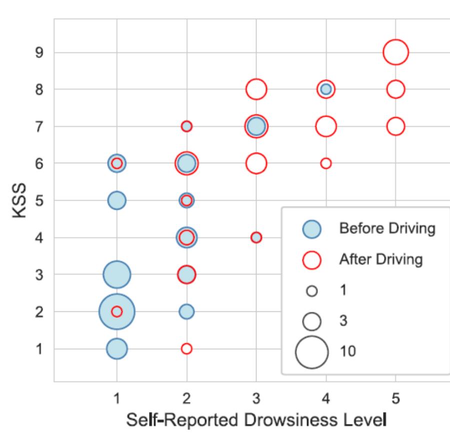

Figure 2 Karolinska Sleepiness Scale(KSS) values observed in Mika Sunagawa et al [2]

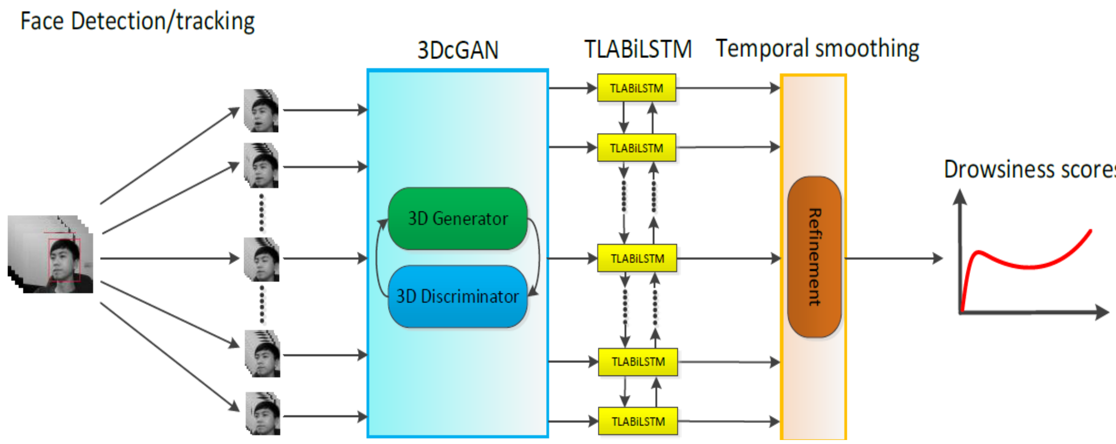

Figure 3 The flowchart of the Yaocong Hu et al [3] drowsiness recognition framework.

Table 1 : Literature Work Summary

Author	Journal	Work	outcome
J. R. Paulo et al [1]	IEEE-Access 2021	Use CNN on ECG signals to detect drowsiness.	75.87 % Accuracy
Mika Sunagawa et al [2]	IEEE- Sensors 2020	posture index detection based on supervised ML and estimate drowsiness based on that.	61.8 % accuracy in best case
Yaocong Hu[3]	IEEE Trnasiction-2020	new deep learning framework based on the hybrid of 3D conditional generativeadversarial network and two-level attention bidirectional long short-term memory network (3DcGAN- LABiLSTM) has been proposed for robust driver drowsiness recognition.	82.8 % Accuracy
Melissa Yauri-Machaca et al [5]	IEEE-2018	Eye detection using SMQT technique and matching of eye for Drowsiness detection using local binary pattern match.	75% accuracy of match with time to detection after monitoring is 12.82s.
LishengJin et al [6]	Hindawi Publishing 2013	sleepiness detection system using support vector machine (SVM) based on eye movements is proposed.	The mean accuracy for the general model is 72.23%
Divya Chandan et al [7]	IJSER-2018	Development of drowsiness detection of machine vision-based concepts	Accuracy obtain is 59% only

3. CONCLUSION

Majority of already designed Drowsiness detection procedures have generally at least one of these two problems: Too high computational (time-, space-) complexity and too low effectiveness.LDA, ICA, and PCA [6] are conventional procedures of Drowsiness detection but major issue with these procedures are that this procedures requires database which improve its cost also detection rate is less, problem with available work [1] & [3] its detection rate is 92.5% & 91% only. [1] uses ML with Deep learning Drowsiness identification which is best so far in Drowsiness identification but it requires lots of computations time and also took lots of time to detect eye only, after identification eye detection done using PDF of 8x8 chunks of Drowsiness [1] means lots of calculation, only problem with procedure [1] that it took lots of time of detection of single eye. [3] Gives a Drowsiness identification procedures based on Viola Jones [2] procedure in that work was real time multiple Drowsiness identification procedure was faster than all old work. Another problem with available method is that this method is been develop for recognizing a single eye Drowsiness at a time and available methods requires to execute twice for two different eyes, The problem is to that the name of person shown on image is not automatic.

REFERENCES

[1] J. R. Paulo, G. Pires and U. J. Nunes, "Cross-Subject Zero Calibration Driver’s Drowsiness Detection: Exploring Spatiotemporal Image Encoding of EEG Signals for Convolutional Neural Network Classification," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 905-915, 2021, doi: 10.1109/TNSRE.2021.3079505.

[2] M. Sunagawa, S. -i. Shikii, W. Nakai, M. Mochizuki, K. Kusukame and H. Kitajima, "Comprehensive Drowsiness Level Detection Model Combining Multimodal Information," in IEEE Sensors Journal, vol. 20, no. 7, pp. 3709-3717, 1 April1, 2020, doi: 10.1109/JSEN.2019.2960158.

[3] Y. Hu, M. Lu, C. Xie and X. Lu, "Driver Drowsiness Recognition via 3D Conditional GAN and Two-Level Attention Bi-LSTM," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 12, pp. 4755-4768, Dec. 2020, doi: 10.1109/TCSVT.2019.2958188.

[4] Melissa Yauri-Machaca, Avid Roman-Gonzalez, Natalia Vargas-Cuentas, *Image Processing Research Laboratory (INTI-Lab), Universidad de Ciencias*, Design of a Vehicle Driver Drowsiness Detection System through Image Processing using MATLAB, 978-1-5386-6122-2/18/2018 IEEE

[5] LishengJin, QingningNiu, Yuying Jiang Huacai Xian, Yanguang Qin, and MeijiaoXu, Driver Sleepiness Detection System Based onEye Movements Variables, Hindawi Publishing Corporation, Advances in Mechanical Engineering, Volume 2013, Article ID 648431, 7 pages, http://dx.doi.org/10.1155/2013/648431

[6] DivyaChandan, Drowsiness Detection System Using MATLAB,International Journal of Scientific & Engineering Research Volume 9, Issue 3, March-2018 435 ISSN 2229-5518 IJSER © 2018 http://www.ijser.org

[7] T. Esteves et al., "AUTOMOTIVE: A Case Study on AUTOmaticmultiMOdal Drowsiness detecTIon for smart VEhicles," in IEEE Access, vol. 9, pp. 153678-153700, 2021, doi: 10.1109/ACCESS.2021.3128016.

[8] Altameem, A. Kumar, R. C. Poonia, S. Kumar and A. K. J. Saudagar, "Early Identification and Detection of Driver Drowsiness by Hybrid Machine Learning," in IEEE Access, vol. 9, pp. 162805-162819, 2021, doi: 10.1109/ACCESS.2021.3131601.

[9] M. H. Baccour, F. Driewer, T. Schäck and E. Kasneci, "Comparative Analysis of Vehicle-Based and Driver-Based Features for Driver Drowsiness Monitoring by Support Vector Machines," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 12, pp. 23164-23178, Dec. 2022, doi: 10.1109/TITS.2022.3207965.

[10] K. Satish, A. Lalitesh, K. Bhargavi, M. S. Prem and T. Anjali., "Driver Drowsiness Detection," 2020 International Conference on Communication and Signal Processing (ICCSP), 2020, pp. 0380-0384, doi: 10.1109/ICCSP48568.2020.9182237.

[11] J. Bai et al., "Two-Stream Spatial–Temporal Graph Convolutional Networks for Driver Drowsiness Detection," in IEEE Transactions on Cybernetics, vol. 52, no. 12, pp. 13821-13833, Dec. 2022, doi: 10.1109/TCYB.2021.3110813.

[12] L. Zhang, H. Saito, L. Yang and J. Wu, "Privacy-Preserving Federated Transfer Learning for Driver Drowsiness Detection," in IEEE Access, vol. 10, pp. 80565-80574, 2022, doi: 10.1109/ACCESS.2022.3192454.

[13] T. Esteves et al., "AUTOMOTIVE: A Case Study on AUTOmaticmultiMOdal Drowsiness detecTIon for smart VEhicles," in IEEE Access, vol. 9, pp. 153678-153700, 2021, doi: 10.1109/ACCESS.2021.3128016.

[14] M. Shahbakhti et al., "Simultaneous Eye Blink Characterization and Elimination From Low-Channel Prefrontal EEG Signals Enhances Driver Drowsiness Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 1001-1012, March 2022, doi: 10.1109/JBHI.2021.3096984.

[15] LishengJin, QingningNiu, Yuying Jiang Huacai Xian, Yanguang Qin, and MeijiaoXu, Driver Sleepiness Detection System Based on Eye Movements Variables, Hindawi Publishing Corporation, Advances in Mechanical Engineering, Volume 2013, Article ID 648431, 7 pages, http://dx.doi.org/10.1155/2013/648431

[16] DivyaChandan, Drowsiness Detection System Using MATLAB, International Journal of Scientific & Engineering Research Volume 9, Issue 3, March-2018 435 ISSN 2229-5518 IJSER © 2018 http://www.ijser.org

[17] GholamrezaAnbarjafari, Anbarjafari, Face recognition using color local binary pattern from mutually independent color channel-surfs Journal on Image and Video Processing 2014,2014:6 http://jivp.eurasipjournals.com/content/2013/1/6, Springer

[18] R. O. Mbouna, S.G.Kong, andM.G.Chun, "Visual analysis of eye state and head pose for driver alertness monitoring," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3,pp. 1462–1469, 2013.

[19] F. Friedrichs and B. Yang, "Camera-based drowsiness reference for driver state classification under real driving conditions," in *Proceedings of the IEEE Intelligent Vehicles Symposium*, pp. 101– 106, June 2010.

[20] T. D'Orazio, M. Leo, C. Guaragnella, and A. Distante, "A visual approach for driver inattention detection," *Pattern Recognition*, vol. 40, no. 8, pp. 2341–2355, 2007.

.