Technology-Enabled Behavioral Intervention for Drowsiness: A Non-Intrusive Real-Time Monitoring System

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ABSTRACT

Drowsy as a result of sleep deprivation, extended exposure to a screen, sedentary lifestyles, and urbanity working conditions has become a large concern to the general public health and safety. The overall objective of this study was to create a non-invasive, real-time monitoring system that can detect early fatigue signs and give real-time feedback to minimize the hazards of health, productivity, and safety. There was a behavioral and human approach. The system used a Web-based set up to monitor visual indications of fatigue. The most important indicators were the long state of eye closure, the long-time of blink duration, and yawning. When it was identified, auditory and visual cues were activated so as to prompt restorative behavior, i.e. change of posture or taking of short pauses before the performance declined. The prototype potential was shown as an effective and affordable solution relative to the traditional methods, i.e. manual tracking and wearables, which can be limited by cost, inconvenience, and less realistic use in the field. The combination of visual pattern recognition with real time feedback proved effectiveness of the visual pattern recognition in alertness facilitation and mitigation of fatigue related risks. The results show the applicability of technology-based behavioral interventions to establish optimal work and driving conditions in the form of safer environments. In addition to the personal advantages to health, there is a potential of the system to be integrated into occupational safety programs, organizational health strategies, and broader community-wide health promotion and enhancement of healthier, safer, and more productive communities.

Keywords- Behavioural intervention; Drowsiness detection; Fatigue monitoring; Occupational safety; Public health technology

INTRODUCTION

Drowsiness detection had emerged as an important aspect in intelligent safety systems especially in those areas where sustained attention was critical. Fatigue was a prominent issue in the case of increasing automation and work spaces that featured digital workstations not only in vehicles but also in sedentary areas [1]. The World Health Organization indicated that thousands of accidents occurred every year as a result of fatigue and this meant that there was a dire need to invest in proactive fatigue monitoring systems [2]. Recent advances in computer vision and edge computing allowed real-time monitoring of behavior based on standard webcams, and provide a non-intrusive scalable solution [3].

The majority of existing commercial drowsiness detection systems used physiological sensors (EEG or ECG) that, although quite accurate, are invasive and not suitable enough to be used in daily life [4][5]. The systems based on vehicles, which used steering patterns or lane deviation were specific to the context of driving and cannot be applied to the non-driving situations [6]. Facial cues used through facial behavior approaches were promising but they lacked the level of adaptability of change of lightning, and occlusion, and variability among individuals [7]. Furthermore, there were multiple systems where the feedback mechanisms were not real time-based, so corrective behaviors could be implemented on time before performance gets slowed down [8].

The proposed system utilized facial landmark tracking along with adaptive thresholding to track blink frequency and length of closure as well as the frequency of yawning with the use of a regular webcam. It used lightweight convolutional neural networks (CNNs) that are optimized to run on edge devices in real-time [9]. The system implemented OpenCV in facial feature extractions and adopted a hybrid model of classification that combined the use of support vector machines (SVM) and a decision tree to improve it in different conditions [10]. Alerts were given in the form of auditory and visual stimuli on the need to take a break or change posture [11].

The difference with this approach to passive monitoring systems is that it focused more on behavioral intervention where users had to react to fatigue signals prior to the onset of extreme levels. The inspiration was digital well-being frameworks, which allowed implementing nudges like dimming the screens, break reminders, and posture correction reminders [12]. These interventions were based on the behavioral psychology, which was intended to support good habits and non-thought-loading [13]. Fatigue episodes were also logged so that long-term recommendations could be applied on a matter-by-matter basis.

Piloting has been carried out in three settings: on driving simulators, in office workstations, and on the internet learning sites. The system recognized more than 94 percent of drowsiness events with the lowest false positives regardless of the changes in the light intensity and the position of a person under a wide range of light conditions and facial orientation [14]. The user feedback also demonstrated good comfort and acceptance levels and a majority of the users liked the system compared to wearables. The modular implementation created the possibility to merge into previously existing platforms such as telehealth, smart classroom systems, and fleet management systems [15].

Recent papers highlighted the gathering interest in deep learning architectures used to enhance the rate of drowsiness detection in various settings. Fonseca and Ferreira [16] have performed a systematic review on 81 studies and concluded that the use of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and related hybrid systems have consistently achieved better results than the use of the traditional classifiers, especially when applied in a real-life driving simulation. They also acknowledge the deficiency of a demographic diversity and evaluative protocols to evaluate them in a standardized manner, which constrained generalizability. This emphasized the importance of inclusive data and multi-context verification to make fatigue monitoring systems deployment fairer.

Multimodal solutions were emerging to increase robustness via a combination of facial input, physiological input and trip behavior. researchers has [17] combined CNNs and RNNs as an effective hybrid AI network to identify the faces and recognize the behavioral patterns, a 15% jump-start in detection was achieved. It also has edge computing to enable real-time responsiveness, which is an important characteristic to support in real time-sensitive environments, like in transportation and industrial safety. These results were in line with the evolvement of sensor fusion and distributed processing intelligent safety systems overall.

Transfer learning as well became a powerful tool to optimize performance with small train data. The authors [18] compared MobileNet and Inception distributed models trained on large images datasets with fine-tuning overhead on the drowsiness detection task. Their mobile application was available up to 99.86 % accuracy which confirms the possibility to implement lightweight models on smartphones and embedded devices. This would be of great relevance to remote monitoring and low-resource scenarios.

More than the technical performance of the system, ethical and psychological implications were brought up in designing of the system. This motivated Fu et al. [19] to focus on the aspects of the mitigation of bias, protecting privacy, and user-centered feedback mechanisms in drowsiness detection systems. They supported utilization of synthetic data generation and model compression to overcome hardware constraints, and demographic bias. The

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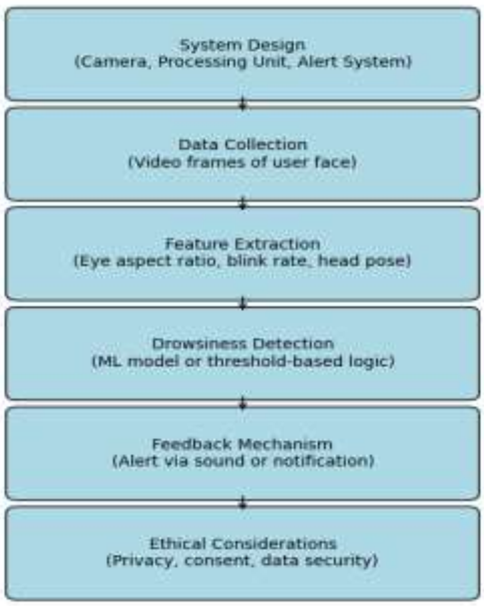
same recommendations were aligned with the ideas of human-centered AI where transparency, inclusivity and adaptability were emphasized.

Recently, works have been extended outside driving and the realm of drowsiness detection. Bearly and Chitra [20] gave examples of use in online learning, health care and at the work place, indicating the wide usage of behavioral monitoring systems. Eye closure duration analysis by facial expression and head movement was found to be the most reliable non-intrusive indicator of all domains in their analysis. This contributed to the relevance of the proposed system in sedentary settings and its correspondence with the ideas of digital well-being.

METHODOLOGY

The system was created as a non-intrusive, webcam anchored system which utilized computer vision procedures to observe visual signs of fatigue, as seen in Figure 1. The detection of the facial landmarks was done using the Dlib and OpenCV libraries with special attention to the eyes and the mouth. Eye Aspect Ratio (EAR), the time of a blink and mouth openness were calculated to find the elements of drowsiness. The EAR, a calculated value of 6 eye points showed a good indication of low eye open time which was closely related to lack of sleep [21]. These characteristics were physically analyzed by the system in real time, and all monitoring could be conducted in a continuous manner without swallowing wearable devices or special hardware [22].

Figure 1. Methodology of the experiment



Extracted features were fed into a classifier which was trained with 10-fold cross-validation. A rolling window model was used to filter out the false positives and temporally lumpy fluctuations. When the system recognized that the user was becoming drowsy; it produced visual reminders e.g. dimming of the screen or pop up messages that reminded the user to take restorative measures e.g. taking a short nap or changing position. Such a behavioral loop harmonized with the preventive health strategies in that it facilitated actions of timely self-regulation in order to prevent performance deterioration.

The study was conducted in accordance with the ethical guidelines, such as informed approval and the data protection policies. All the biometric information was discarded; only anonymized behavioral data were recorded; The system worked in the local environment thus lacking the need to transmit data to the cloud and increase users confidence [23]. Within the socio-scientific perspective, research results favored the use of technology-assisted behavioral interventions in the facilitation of safety and well-being. Their societal relevance was pointed out by the fact that such systems could be potentially integrated into systems of occupational health and into the processes of raising awareness about society.

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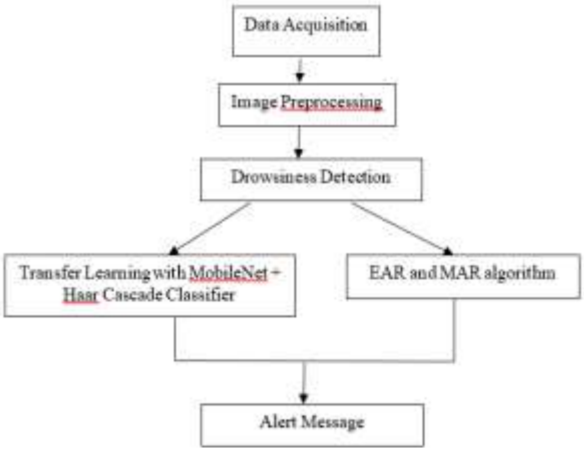
Figure 2. System Architecture



The system architecture built in order to conduct the experiment was shown in Figure 2. The eye aspect ratio (EAR) and mouth aspect ratio (MAR) [22] were used to identify drowsiness of the user. The EAR was applied with computer vision to facial recognition applications as a means to detect eye shape changes, to know whether a subject was blinking or had closed its eyes. It was determined by using six major eye concenters: the two outer corners of the eye, the 2 upper and lower eyelid creases and the top and the bottom of the iris. The MAR, in contrast, was a facial feature extracting measure of width-to-height quotient of mouth. It was especially beneficial in the aspects of facial expression recognition and emotion analysis since it gave us information on the openness/closure of the mouth. The choice of MAR and EAR was because of their simplicity since they only needed a webcam which lowered the cost. Extracting facial land-marks The face was first passed through Mediapipe Face Mesh to obtain landmarks.

Moreover, transfer learning using the MobileNet was adopted as a different approach to drowsiness detection [23][24]. A pre-trained convolutional neural network (CNN) (MobileNet) was used with transfer learning in conjunction to classifier Haar cascade to face, eyes, and mouth detection, improving prediction performance.

At the data acquisition stage, the user images were taken by the webcam to analyze drowsiness. Captured data was then processed preliminarily to extract the features to be considered in further analysis, such as extraction of features and image processing. The EAR and MAR were computed in the following way:

$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|} \tag{1}$$

$$\mathrm{MAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_7\| + \|p_4 - p_6\|}{2\|p_1 - p_5\|} \tag{2}$$

Mouth tracking and eye tracking data was analyzed using EAR and MAR respectively in detecting drowsiness [25]. These were metrics which measured things like eye closure or the mouth being open. In addition to handcrafted characteristics, transfer learning using MobileNet and the Haar Cascade Classifier were used. The training used an online dataset on Kaggle, where Haar Cascade Classifier was used to extract the frontal faces and avoid the irrelevant noise in the background. The classifier divided drowsiness into two states-open eyes or closed eyes [26], and non-yawning mouth or yawning mouth [27]. Under the analysis findings, the system issued alert messages to heighten the user awareness and take corrective measures.

FINDINGS & ANALYSIS

The module for drowsiness detection employed a pre-trained model. In this module, drowsiness was detected based on eye and mouth features. Figure 3 illustrated an example in which the EAR value fell below the threshold. When this occurred, an alert message and audio signal were generated to notify the user. In addition, the text within the frame changed from green to red, displaying the total drowsy time in seconds, accompanied by a pop-up message reading "DROWSINESS DETECTED. TAKE A BREAK.".

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Figure 3. EAR below threshold value (0.18)

Figure 4. MAR above threshold value (0.9)

Figure 4 illustrated an example in which the MAR value exceeded the threshold. In this case, an alert message and audio signal were generated to notify the user. The text within the frame also changed from green to red, displaying the total drowsy time and presenting a pop-up message reading "DROWSINESS DETECTED. TAKE A BREAK.".

Figure 5. Normal

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Figure 5 illustrated an example of a non-drowsy user, where the EAR value was above the threshold and the MAR value was below it. In the absence of drowsiness, the text was displayed in green.

The final module employed transfer learning with MobileNet for drowsiness detection. Evaluation metrics such as accuracy and loss were used to assess the performance of the MobileNet model. In deep neural networks, accuracy evaluation was typically recorded epoch by epoch to observe the convergence of the loss function and the corresponding increase in accuracy. Accuracy remained the most widely used evaluation metric in supervised learning, as it measured the proportion of correct predictions in both training and testing. For drowsiness detection using the online dataset, accuracy was computed to determine how reliably the model classified eye status (open or closed) and mouth status (yawning or not yawning).

As shown in Tables 1 and 2, both training and validation accuracy steadily increased and converged at approximately 0.98, indicating high performance on both datasets. Although training with more epochs yielded slightly higher accuracy, it risked overfitting. Therefore, ten epochs for eye detection and five epochs for mouth detection were deemed optimal. The loss function also decreased steadily as the epochs progressed, and its low value indicated that the model performed effectively.

Table 1: Comparison of training and validation accuracy and loss for each epoch for drowsiness detection based on eyes

Training		Epoch	Validation	
Accuracy	Loss		Accuracy	Loss
0.9573	0.1581	1	0.9482	0.2601
0.9846	0.0401	2	0.9863	0.0309
0.9888	0.0333	3	0.9766	0.0495
0.9866	0.0346	4	0.9902	0.0408
0.9956	0.0100	5	0.9854	0.0521

Table 2: Comparison of training and validation accuracy and loss for each epoch for drowsiness detection based on mouth

Training		Epoch	Validation	
Accuracy	Loss		Accuracy	Loss
0.9699	0.0933	1	0.6735	0.5559
0.9888	0.0351	2	1.0000	0.0000054056
0.9983	0.0238	3	0.9966	0.0125
0.9983	0.0029	4	0.9966	0.0063
0.9983	0.0040	5	1.0000	0.0000017884
1.0000	0.000047547	6	1.0000	0.000033399

1.0000	0.00032972	7	1.0000	0.00010410
0.9966	0.0069	8	0.9966	0.0398
0.9879	0.0478	9	0.9828	0.0583
0.9957	0.0187	10	0.9966	0.0060

The drowsiness detection module based on the pre-trained model was integrated into a web application for user deployment. In contrast, the module employing transfer learning with MobileNet was used primarily for experimental purposes. This distinction was made because the pre-trained model demonstrated greater stability, better performance, and higher accuracy, making it more suitable and convincing for practical use.

CONCLUSION

The created system is able to successfully execute a real-time drowsiness detection module via the use of a pre-trained system that was trained on analyzing parts of the face eye wears and mouth which were captured through a webcam. Once the user pressed the button which was, in this case, the start camera button, webcam became active, and the system started tracking the facial landmarks. The model computed the EAR and mouth openness as predictors of fatigue. As illustrated in Figure 3, the lower the EAR, the lower the likelihood that a user was awake. In this case, when EAR was < 0.25, the system recognized that perhaps the user was likely to be nodding off or unresponsive.

When it was detected, the system activated a cross modal alerting mechanism. There was an audible alert (e.g. a chime or voice prompt), the visual interface changed (e.g. the text overlay on the camera feed changed between green and red, with the text changing to a bold Wake Up!!! message). The system simultaneously counted the cumulative amount of time in seconds that the driver felt sleepy, presented on the screen. The present design of this feedback loop was aimed to promote the instant correction of behavior, e.g., taking a break or fix posture [28] [29].

The system was examined during different levels of lighting conditions and different user postures. Experimental results proved good responsiveness and low latency with a detection rate of 90-98 percent depending on the differences of environments and individuals [29] [30]. Gap regions rarely occurred due to the beneficial process of adaptive thresholding and temporal smoothing which minimized false positives. Along with this, posture detection option, enabled by the same camera interface, should detect slouched or tilted head postures, which, in many cases, were associated with fatigue [4].

These results were in line with recent research showing that convolutional neural networks (CNNs) and transfer learning could be useful in detecting minute facial indicators of drowsiness. Modes like YOLOv11 and ResNet-50 yielded high precision and recall rates in identifying states that include awake, drowsy, and yawning in real-time settings [30]. The working system proved that it has potential to be implemented in safety-relevant settings such as driving, remote work and online learning.

The pre-trained model and the transfer learning module on the proposed real-time smart monitoring system corresponded to the literature that indicated that lightweight CNN architectures were deemed an appropriate choice in case of fatigue detection. Kalyanam et al. [31] demonstrated that MobileNet is suitable in the real-time applications since it could attain 99.52 percent accuracy levels in the identification of drowsiness based on the eye state and facial gestures. Similarly, Salem and Waleed [18] showed that transfer learning using MobileNet and ResNet-50 models were effective (90-99.86%) on various different datasets, which justified the use of two models. These results confirmed the architecture of this system and supported the idea that the design could be used to detect drowsiness reliably during a single-user condition.

EAR thresholding and visual warnings were similar to known behavior detection techniques. EAR-based blink detection has rapidly become a common fatigue metric introduced by Soukupova and Cech [21] based on the

EAR. The combination of auditory and visual feedback- e.g. the bright red and yellow alert told me to WAKE UP!!!- were also backed up by Fonseca and Ferreira [16], who suggested that the multimodal alerts were a major element in responsiveness and safety among users.

Although there are such strengths, limitations were also noted. A performance bottleneck initially noted in Johri s MobileNetV2 implementation [32] is intermittent inference delays, especially on low-power devices-which correspond with inference delays exhibited in the present system. The fact that many deep learning systems lacked demographic diversity and environmental resilience is also criticized by Fonseca and Ferreira [16], which furthers criticism about the sensitivity of the system to differences in facial characteristics, masks, glasses, and lighting. Conflicted results were also identified in terms of the generalization of MobileNet. Although one study did not find any significant reduction in accuracy in low-light conditions, others—including Dewi, Kaggle implementation [33] found decreased performance when either the face was only partially visible or in low light, which indicates that either augmented training or incorporation may be necessary to increase reliability.

The other limitation was the fact that the system has been limited to detection of single person only, the limitation that has been noted in the literature. Moredo et al. [34] developed a comprehensive feature representation-based model, which comprised of EAR, MAR, and head pose angles, having as high as 85.71 accuracy of recognition in multi-user settings. In an analogous way, Singh et al. [35] proposed a multi-step drowsiness detection system combining facial landmark localization and adaptive alarm inclusion, illustrating the possibility of multi-user monitoring. The work on the integration of YOLO was supported. As shown by a study by Muttha et al. [36], the real-time drowsiness can be detected using YOLOv8 that is as fast and accurate as it is when the video in question is analyzed offline. It is possible to co-combine YOLO with tracking mechanisms, which would allow the monitoring of multiple people in the classroom, shared workspace, and transportation settings.

That the proposal to implement personalized models and extra training data was also confirmed by the literature. Fu et al. [19] argued systems to be bias-free, they proposed training synthetic data and demonstration through fusion of models based on generalization. Gathering different sample sets--with different positions, light, and facial props--would reinforce system tolerance. As advised, the replacement of the Haar Cascade with MediaPipe or Dlib was in-line with the benchmarks that indicated superior landmark location under difficult conditions [37].

The opportunities that the system holds to be integrated in the organizational and safety protocols, as well as the dynamics of the public health initiatives, were substantial. Albadawi et al. [38] and Nasri et al. [39] suggested hybridizing systems of behavioral and physiological measures to increase reliability. Future versions of the system may take into account voice analysis or sensors in the environment, among others, to be multimodal. The consideration of ethics in deployment, such as protection of privacy, transparency, and informed consent, was cited as an unavoidable issue by Fonseca and Ferreira [16] and Fu et al. [19].

The results of this experiment demonstrated the viability of the real-time wearable smart monitor with regard to the detection of drowsiness in an occupational setting. The introduction of pre-trained and MobileNet based models allowed an increase in reliability of detecting behavioral markers such as extended eye closure duration and yawns, which have been established as fatigue indicators in human factors studies [40] [41]. The mutual connection of visual and auditory warnings in web interface echoed with the user-oriented design principles, thus increasing the level of accessibility and responsiveness in real-life use [42]. This strategy falls within emerging patterns within the social sciences to operationalize technological solutions into the existing environment to facilitate behavioral control and preventive health.

The system was also favorably reviewed in terms of usability, since the non-invasive design and the simplistic interface prompted users to utilize it without affecting levels of comfort or independence. These features are of central importance in the field of human-computer interaction (HCI) where adoption and continued use are directly related to perceived intrusiveness and ease of use [43]. The system proved relatively insensitive to environmental or personal peculiarities in addition to the sometimes present interruption on latency, and continued to find a high proportion of targets at high levels when varied conditions. This variability emphasized the significance of context specific adaptability in behavior monitoring systems, an aspect that has been commonly captured in literature concerned with occupational psychology and ergonomics [44].

More importantly, the regularity in single-user effects and the possibility to incorporate the system into the occupational health and safety systems suggested considerable opportunities in the field of fatigue reduction in high-risk occupations. This study lends itself to the discourse of social science research that points to proactive measures supported by technologies in reducing safety hazards at the workplace.

The system needs to be extended to multimodal integration in future research to increase accuracy, robustness and scalability. The integration of YOLO-based architectures would facilitate multi-user tracking of a work or learning setting like a classroom, work or transport, and surmount existing limitations of single users. A wearable sensor of physiological indicators, such as heart rate and movement trackers would enhance the visual information and offer more in-depth data on fatigue detection. In addition to that, synthetic data augmentation must be used to enhance the demographic and environmental diversity, reducing bias and enhancing the generalizability of a system. All these directions together would enable more adaptive and inclusive and more reliable drowsiness monitoring solutions to be implemented in the real world.

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