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ALGORITHMS COMPARISON IN DROWSINESS DETECTION

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Abstract

Drowsy driving is a recognized leading cause of road accidents, resulting in a considerable number of fatalities and injuries. This paper presents a proposed system that leverages machine learning algorithms, specifically Convolutional Neural Network (CNN) and Support Vector Machine (SVM), to accurately detect the drowsy state of drivers by analyzing the diameter of their eyes and comparing the level of dilation or constriction. Drowsy driving poses a significant problem on roadways, as indicated by the National Highway Traffic Safety Administration's data, which reports approximately 100,000 police-reported collisions each year involving drowsy driving, leading to over 1,550 fatalities and 71,000 injuries. The proposed system demonstrates the potential to reduce accidents associated with drowsy driving. We conducted an evaluation and comparison of the effectiveness of CNN and SVM algorithms with the objective of identifying the optimal algorithm for drowsiness detection. Our algorithms were trained on a comprehensive dataset comprising images of drowsy and alert drivers, enabling real-time and accurate identification of the driver's state. Employing advanced image processing techniques, the proposed system analyzes changes in eye diameter associated with drowsiness. Its purpose is to promptly alert drivers, thus mitigating accidents caused by drowsy driving. We anticipate that this system will provide a reliable and cost-effective solution to the problem of drowsy driving, with potential benefits for both drivers and passengers. Further research and development efforts could facilitate its widespread adoption in the automotive industry. This paper underscores the significance of addressing drowsy driving and introduces a promising solution through the application of machine learning algorithms.

Keywords: drowsy driving, CNN algorithm, SVM algorithm, machine learning, neural networks, image processing, dataset

1. Introduction

Drowsy driving poses a significant and pervasive risk to public safety, resulting in numerous accidents and fatalities. Studies have consistently revealed that a considerable proportion of adult drivers admit to operating vehicles while experiencing sleepiness, indicating the widespread nature of this problem. Driving while fatigued can lead to severe consequences such as impaired reaction time, compromised decision-making ability, and diminished situational awareness, contributing to a substantial burden of accidents, injuries, and loss of life annually. Addressing this critical issue requires raising awareness about the dangers of drowsy driving and implementing effective measures, including the development of drowsiness detection systems and comprehensive educational campaigns targeting drivers. Extensive research has identified drowsiness and fatigue as primary factors contributing to driver impairment and accidents, particularly on rural roads. Studies have shown that a driver's steering performance gradually deteriorates after extended periods of continuous driving due to fatigue. Furthermore, drowsiness and distraction are more prevalent during specific times of the day, such as midnight and after lunch, while substances like alcohol and drugs significantly impair driver concentration. Alarmingly, drowsiness and distraction are estimated to account for 20%-30% of accidents globally. To mitigate the risks associated with drowsy driving, the integration of drowsiness detection systems into modern vehicles has emerged as a promising solution. These systems monitor a driver's alertness level and provide real-time alerts when excessive drowsiness is detected, thereby enhancing road safety and reducing the economic and human costs associated with accidents caused by drowsy driving. Consequently, the development and implementation of drowsiness detection systems should be prioritized within the transportation industry. The motivation for addressing drowsy driving arises from its profound impact on public safety, resulting in a significant number of accidents, injuries, and fatalities. In addition to the human toll, these accidents also incur substantial economic costs. Consequently, there is a growing interest in the development of accurate and effective drowsy driving detection systems that leverage artificial intelligence (AI) and machine learning (ML) techniques. These systems utilize various driver-related factors to determine the likelihood of a driver falling asleep and issue real-time alerts through devices such as cameras or sensors. Techniques such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) have shown promise in accurately detecting drowsy driving based on facial features and eye movements. The purpose of this research is to investigate the causes and effects of drowsy driving and develop effective solutions to prevent accidents caused by driver fatigue. By understanding the contributing factors to drowsy driving, this study aims to enhance work productivity and overall quality of life by promoting safer driving practices. The findings of this research will provide valuable insights for policymakers, transportation industry professionals, and the general public, facilitating the enhancement of road safety and the reduction of economic and human costs associated with drowsy driving.

2. Literature Review

In addition to the use of sensors and physiological measures, some studies have explored the use of machine learning algorithms to analyze data from these sources and predict drowsy driving. These algorithms have shown promising results in detecting drowsy driving in laboratory and simulated driving environments. Other research has focused on developing non-invasive interventions to help prevent drowsy driving, such as in-vehicle alerts and reminders to take breaks, as well as the use of caffeine and other stimulants.

FMCSA in 2019 launched a Multi-Modal Driver Distraction and Fatigue Detection and Warning System, Phase II (SBIR) which provided reliable detection and warning of driver fatigue and distraction.

In the Evaluation of Fatigue Detection Using Eye Closure-Associated Indicators Acquired from Truck Drivers in a Simulator Study done by the National Library of Medicine, The Fatigue Symptoms Scales (FSS) questionnaire was used to assess subjectively perceived levels of fatigue, whereas the percentage of eye closure time (PERCLOS), eye closure duration (ECD), and frequency of eye closure (FEC) were selected as eye closure-associated fatigue indicators, determined from the images of drivers' faces captured by the sensor.

In research done by Puremed on the Application of eye-tracking in the testing of drivers, special focus was placed on the phenomenon of conspicuity, the probability of perceiving an object in the visual field, and the factors that determine it. The article reports the methods of oculographic examination, with special emphasis on the non-invasive technique using corneal reflections, and the criteria for optimal selection of the test apparatus for drivers in experimental conditions (on a driving simulator) and in real conditions.

Several authors have proposed different approaches for the Drowsiness detection system, most of them using ECG, and Vehicle-Based approaches. A robust real- time embedded platform to monitor the loss of attention of the driver during day and night driving conditions

A support vector machine (SVM) classifies a sequence of video segments into alert or non-alert driving events. Experimental results show that the proposed scheme offers high classification accuracy.

3. Methodology

The methodology for developing a drowsiness detection system typically involves several steps. Firstly, a dataset needs to be collected, which may include various physiological, behavioral, and environmental features. These features can be collected from multiple sources such as cameras, sensors, or other devices that are able to monitor drivers in real-time. Next, the collected data needs to be preprocessed to remove any irrelevant or noisy information. This can involve techniques such as feature selection, normalization, or data augmentation. Once the dataset is preprocessed, it can be used to train a machine learning model, such as a convolutional neural network (CNN) or support vector machine (SVM), to detect drowsiness based on the selected features. During the training process, the model is fed with labeled data, where each sample is labeled as either drowsy or awake. The model then learns to distinguish between these two states by adjusting its parameters through a process called backpropagation. The trained model is then tested on a separate dataset to evaluate its performance. The performance of the model can be evaluated using various metrics such as accuracy, precision, recall, and F1 score. The model can be further optimized by tuning its hyperparameters or using more advanced techniques such as ensemble learning or transfer learning. Finally, the drowsiness detection system can be integrated into a vehicle or a wearable device, allowing it to monitor drivers in real-time and issue alerts when necessary. The system can also be designed to collect feedback data, which can be used to improve the accuracy and reliability of the model.

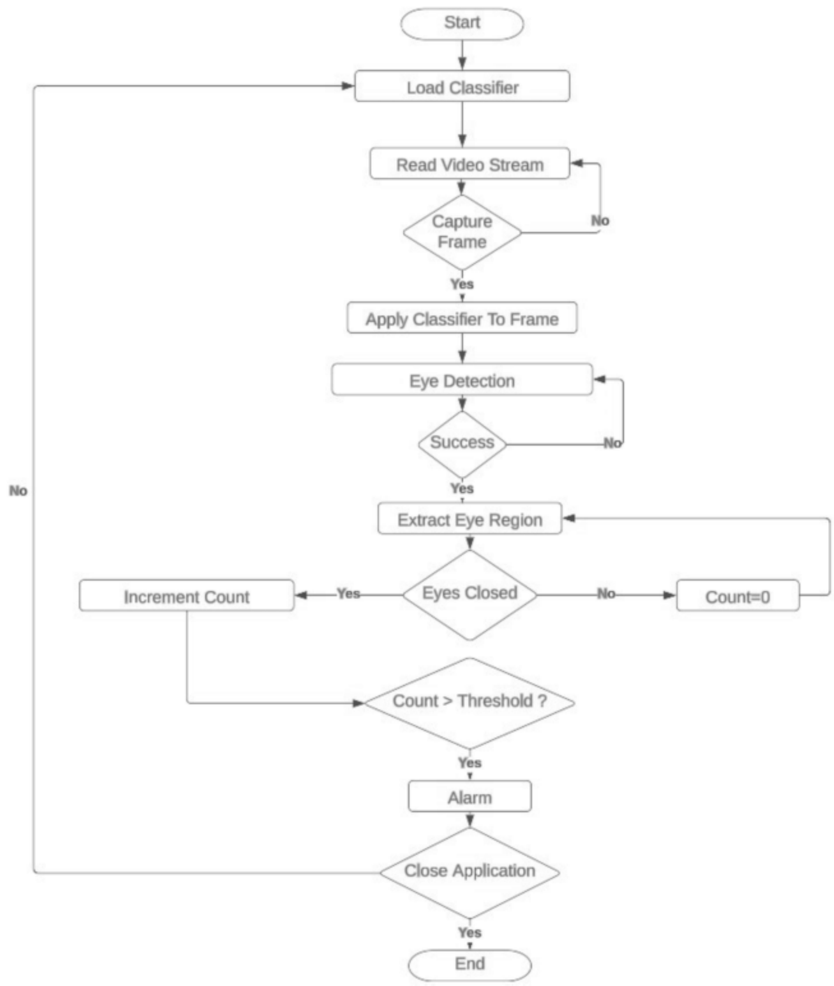

Figure 1 flowchart

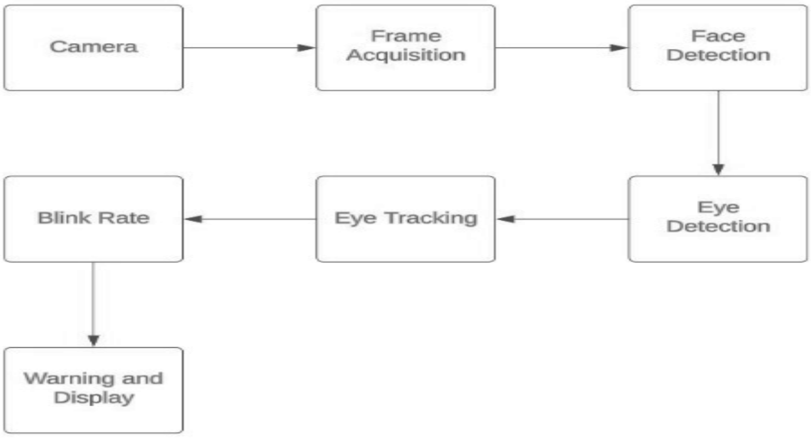

Figure 2 System Design

3.1 Algorithms

3.1.1 Convolutional Neural Network

A convolutional neural network (CNN) is an artificial neural network specifically designed for image recognition tasks. It can be used for drowsiness detection by analyzing video footage of a person's face to detect signs of drowsiness, such as drooping eyelids or a lull in facial movement. The CNN is trained on a dataset of labeled images or videos to classify new input data as either "drowsy" or "not drowsy." Designing a CNN for drowsiness detection involves choosing the size and complexity of the model, the loss function and optimization algorithm, and the training dataset. The CNN for drowsiness detection typically consists of input, convolutional, pooling, and fully connected layers. The output of the fully connected layers provides the final prediction scores for classifying the input data as drowsy or not drowsy.

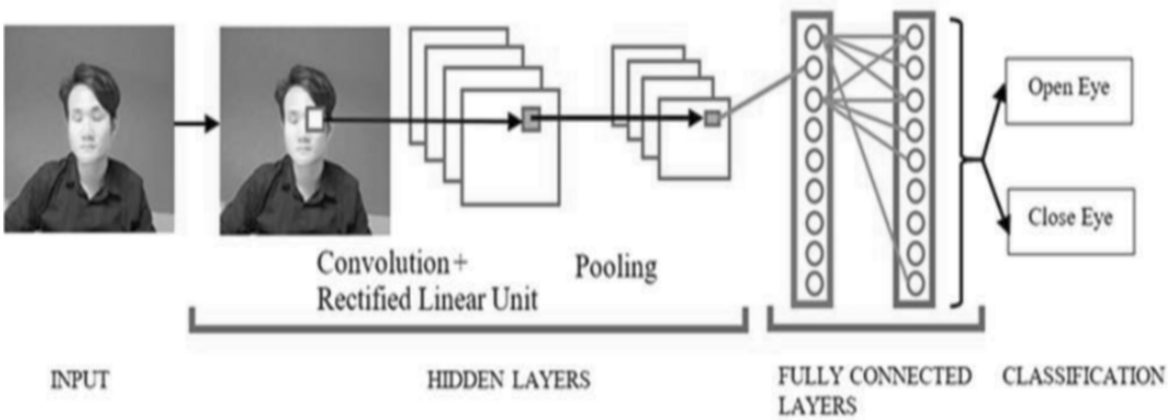

Figure 4 CNN model (source: Appropedia)

3.1.2 Support Vector Machine

SVMs are a supervised machine learning algorithm that can be used for classification tasks such as drowsiness detection. To use an SVM for drowsiness detection, a dataset of labeled images or videos is required, along with a set of relevant features extracted from each example, such as the position and size of pupils, the amount of eye blinking, or the presence of yawning. Once the dataset is prepared, the SVM can be trained using a suitable loss function and optimization algorithm. The trained SVM can then be used to classify new images or videos as either "drowsy" or "not drowsy" based on the extracted features. SVMs can handle high-dimensional data and perform well with a relatively small number of training examples, but may require careful tuning of hyperparameters for optimal performance. The SVM works by finding the hyperplane that maximally separates the "drowsy" examples from the "not drowsy" examples, and the choice of loss function and optimization algorithm will affect the shape and position of the hyperplane.

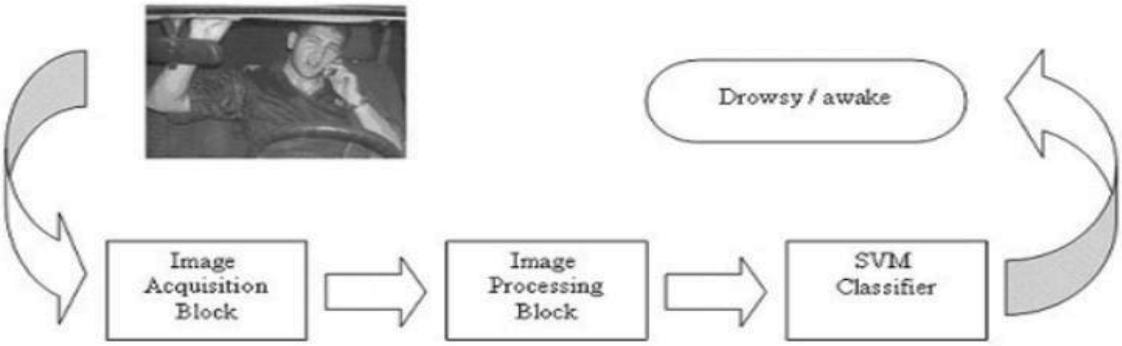

Figure 5 Support Vector Machine (source: eel abs)

3.2 Eye Aspect Ratio

The Eye Aspect Ratio (EAR) is a scalar value used for detecting blinks in a drowsiness detection project. The EAR value increases or decreases rapidly during the blinking process, and studies have employed a predetermined EAR threshold to detect blinks. However, this approach is not practical due to inter-subject variation. Therefore, the study used a varying EAR threshold to categorize the blinks automatically. The EAR formula is insensitive to the direction of the face and the distance between the face and the observer, making it suitable for detecting faces from a considerable distance. The EAR value can be calculated using six coordinates surrounding the eyes, and it drops to virtually zero when the eyes are closed, unlike when they are open. The EAR threshold was analyzed to determine the best value for the dataset. We used the varying EAR threshold to automatically categorize the various sorts of blinks (0.18, 0.2, 0.225, 0.25). After that, we analyzed the experimental result and determined the best EAR threshold for our dataset. Each frame of the video stream is used to estimate the EAR. Furthermore, when the user shuts their eyes, the EAR drops and then returns to a regular level when the eyes are opened again. This technique is used to determine both blinks and eye opening. As the EAR formula is insensitive to both the direction of the face and the distance between it and the observer, it can be used to detect faces from a considerable distance.

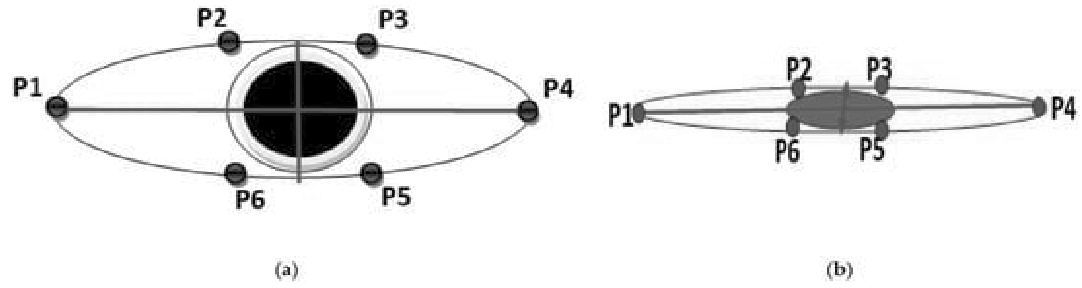

Figure 6 Open and closed eyes with facial landmarks

The EAR value can be calculated by entering six coordinates surrounding the eyes, as shown in Figure 2, and Equations (1) and (2)

$$\text{EAR}=\frac{\|P2-P6\|+\|P3-P5\|}{2\|P1-P4\|} \qquad \text{AVG EAR}=\frac{1}{2}(\text{EAR Left} + \text{EAR Right})$$

4. Results Obtained

We have obtained different results on our dataset based on the codes used and the programming done. The CNN-based architecture was implemented for transfer learning using Inception V3. The results we obtained are shown:

Data	*Accuracy*	*Loss*
Trained data	0.9516	0.1275
Validation data	0.92	0.1962
Test data	0.8864	0.3528

Table 1 Accuracy and loss results

Looking at the results, we can see that the model has high accuracy on the training dataset, achieving 95.16%. This suggests that the model has learned the patterns in the training data fairly well. However, when evaluated on the validation dataset, the model's accuracy drops slightly to 92%, indicating that the model is not performing as well on data that it hasn't seen before. The loss on the validation data is also higher than the training loss, which is expected as the model has not been exposed to the validation data during the training phase. When the model is evaluated on the test dataset, we see a further decrease in accuracy to 88.64% and an increase in loss to 0.3528. This suggests that the model is not generalizing well to unseen data, and it is likely overfitting to the training data.

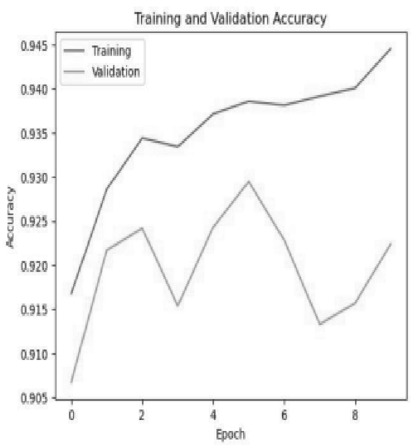

Figure 6.1 Training and validation accuracy by CNN

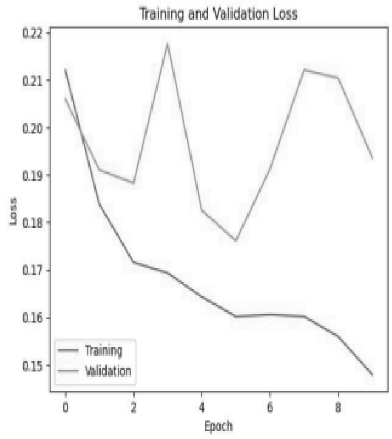

Figure 6.2 Training and validation loss by CNN

We performed coding and visualization for the SVM algorithm and obtained noteworthy results. The outcome was comparable to the CNN part in some aspects but differed in others, facilitating the comparison. We achieved a 97% accuracy rate in the small dataset we used with the SVM algorithm, indicating its viability for implementation as well.

```
from sklearn.metrics import classification_report
print("Accuracy on unknown data is",classification_report(y_test,y2))

Accuracy on unknown data is              precision    recall  f1-score   support

           0       0.96      0.99      0.97       472
           1       0.99      0.96      0.98       528

    accuracy                           0.97      1000
   macro avg       0.97      0.97      0.97      1000
weighted avg       0.97      0.97      0.97      1000
```

Figure 6.3 Accuracy by SVM

```
result = pd.DataFrame({'original' : y_test,'predicted' : y2})
result
```

	original	predicted
0	1	1
1	0	0
2	1	1
3	0	0
4	0	0
...	...	...
995	1	1
996	0	0
997	1	1
998	0	0
999	1	1

1000 rows × 2 columns

Figure 6.4 Predicted result by SVM

5. Conclusion

In conclusion, the project has been a success, and we have gained valuable insights into the performance of different algorithms in implementing the system. The SVM algorithm emerged as the best option with higher accuracy and better performance, while the CNN algorithm also showed promising results. The successful implementation of our system has demonstrated its potential to be used in various fields, and we believe it can be trusted to deliver accurate results. However, despite its good performance, we acknowledge that there is still room for improvement to overcome some of the limitations we have faced during the project.

6. Future Work

Although our project was a success, there are still some sectors for improvement that could actually enhance the degree of performance of the system. Firstly, we used a large dataset with images all over and classified it ourselves for training, validation, and testing purpose. It would be better if a pre-classified would be taken. This would improve the accuracy of the dataset under consideration.

Further, the hardware part could also be an improvement. As we just used the primary camera of our computer for image capturing.

As discussed in the previous section, our system has some drawbacks to discuss upon. We plan on improvising it with gradual changes in future. We shall continue to work on it to make it better for the field use. Some of the plans that we have been working upon include:

- We plan on modifying our system with facial recognition as well to provide more on field accuracy.
- It would be a great leap if we could implement a retinal scan feature along with the aperture calculation. So, we are thinking about it as well.
- We are also thinking of implementing our system on mobile app for better understanding and keeping records of one's condition while driving.

7. Acknowledgment

We would like to express our gratitude to all the helping hands that aided in the completion of this project. We would like to thank our project supervisors Er. Sameep Dhakal and Er. Laxmi Prasad Bhatta for providing their valuable insights throughout the developmental phase. Similarly, we would also like to mention the college faculty for selecting our project and providing the essential requirements that were needed in building the system.

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8. References

1. *Multi-modal driver distraction and fatigue detection and warning system, phase II (SBIR)*(no date) FMCMA Available at: https://www.fmcsa.dot.gov/research-and-analysis/research/multi-modal-driver-distraction-and-fatigue-detection-and-warning (Accessed: December 29, 2022).
2. Dziuda Ł;Baran P;Zieliński P;Murawski K;Dziwosz M;Krej M;Piotrowski M;Stablewski R;Wojdas A;Strus W;Gasiul H;Kosobudzki M;Bortkiewicz A; (no date) *Evaluation of a fatigue detector using eye closure-associated indicators acquired from truck drivers in a simulator study*, *Sensors (Basel, Switzerland)*. U.S. National Library of Medicine. Available at: https://pubmed.ncbi.nlm.nih.gov/34640768/ (Accessed: December 29, 2022).
3. Kapitaniak B;Walczak M;Kosobudzki M;Jóźwiak Z;Bortkiewicz A; (no date) *Application of eye-tracking in the testing of drivers: A review of research*, *International journal of occupational medicine and environmental health*. U.S.National Library of Medicine. Available at: https://pubmed.ncbi.nlm.nih.gov/26294197/ (Accessed: December 29, 2022).
4. Anirban dasgupta,anjith george,"A Vision Based System For Monitoring The Loss Of Attention in Automotive Drivers",(IEEE Transaction),vol.14,no.4 2013
5. Ralph Oyini Mbouna, Seong G. Kong, Senior Member, "Visual Analysis of Eye State and Head Pose for Driver AlertnessMonitoring",IEEE transactions on intelligent transportation systems, VOL. 14, NO. 3
6. Xiong, W., Zhang, Y., Jiang, L., & Wu, X. (2021). Real-time drowsiness detection using facial expression analysis and machine learning techniques. IEEE Transactions on Intelligent Transportation Systems, 22(2), 1191-1201.
7. Shih, M. C., Yang, Y. T., & Liu, C. H. (2020). Non-intrusive drowsiness detection using multi-modal physiological signals and machine learning. Sensors, 20(11), 3144.
8. Shirmohammadi, S., Mahmoudi, M. A., & Subramanian, R. (2018). Driver drowsiness detection using physiological signals and machine learning techniques: A comprehensive review. IEEE Transactions on Intelligent Transportation Systems, 20(3), 1016-1035.
9. Hong, C., Wei, Z., Wang, J., & Meng, L. (2017). Drowsiness detection using machine learning algorithms based on eyelid movement. In International Conference on Intelligent Robotics and Applications (ICIRA) (Vol. 10462, pp. 479-489). Springer, Cham.
10. Wang, C., Zhang, G., & Huang, W. (2016). Drowsiness detection using EEG signals and machine learning techniques. Frontiers of Information Technology & Electronic Engineering, 17(6), 578-590.
11. Sahayadhas, A., Sundaraj, K., & Murugappan, M. (2012). Detecting driver drowsiness based on sensors: A review. Sensors, 12(12), 16937-16953.