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Hypovigilance detection based on analysis and binary classification of brain signals

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ABSTRACT

Road safety has now become a priority for drivers and citizens alike, given its considerable impact on the economy and human life, which is reflected in the increase in the number of accidents worldwide. This increase is linked to a number of factors, drowsiness being one of the main causes that can lead to tragic consequences. Various systems have been developed to monitor the state of alertness. The main idea adopted in this paper is based on the integration of a biosensor to acquire the cerebral signal, then the processing and analysis of the characteristics required to detect the two states of the driver using intelligent machine learning algorithms. Two models were chosen to carry out this binary classification: The K-nearest neighbour (KNN) and logistic regression (LR) classifiers. The experimental simulation results show that the first model outperforms the second in terms of accuracy, with a percentage of 97.83% for k=3. This could lead to the development of a new safety machine brain system based on classification to control vehicle speed deceleration or activate self-driving mode in the event of hypovigilance.

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1. INTRODUCTION

Hypovigilance is a transitory state characterised by a drop in attention and concentration due to drowsiness, fatigue, or health problems [1]. This reduction in vigilance can lead to difficulties in analysis and observation during driving, which can subsequently be one of the factors responsible for fatal accidents [2]. Monitoring and early detection of hypovigilance are critical for saving lives, as studies show that hypovigilance is responsible for approximately 20% of road accidents worldwide, with over 1.2 million fatalities annually according to the World Health Organization [3]. In Morocco, where traffic accidents are particularly frequent, the financial burden in 2022 reached an estimated €1.6 billion, representing about 1.2% of gross domestic product (GDP), largely due to factors like sleep disorders, stress, and substance use [4], [5]. The inclusion of statistical data on road accidents worldwide and in Morocco highlights the urgency of tackling driver drowsiness and hypovigilance, which are major factors in road accidents and make the need for early detection systems evident.

To address this issue, two main categories of technology have been developed. The first category targets vehicle behavior by using integrated sensors to monitor speed variation and positional deviation, although these methods are susceptible to inaccuracies due to environmental factors [6], [7]. The second category focuses on driver behavior by detecting signs of drowsiness through methods such as facial recognition (e.g., yawning or blinking) and physiological monitoring using biosensors like electro-oculography (EOG) and electroencephalography (EEG), with EEG being particularly effective for its accuracy, low cost, and non-invasiveness [8], [9].

The EEG signal is chosen as the input to the system proposed in this work, and undergoes two main stages to detect whether the driver is alert or not. The first stage is the processing and selection of relevant information from the analysed signal, and the second stage is classification using the K-nearest neighbour (KNN) and logistic regression (LR) machine learning algorithms. There are other intelligent techniques in the literature that are involved to achieve the same goal, such as the two studies [10], [11] which employ machine learning algorithms such as naives Bayes, machine vector support, decision tree, discriminant analysis, and random forest. Deep learning models is also applied to detect sleepiness, convolutional neural networks, self-evolving recurrent fuzzy neural networks and long-term memories are among them [12]–[14].

The rest of the article is organised as follows: the next section describes the equations and approaches used to obtain an intelligent, accurate, and robust model. It details the methodologies applied in the study to ensure the reliability and precision of the results. The third part is devoted to the results of the training and testing of the classifiers, providing an in-depth analysis of their performance. The final section represents the summary, limitations, and prospects of this work, highlighting the key findings and future directions for research.

2. METHOD

The proposed system comprises three modules, illustrated in Figure 1. The acquisition and processing module, based on importing the raw EEG signal and eliminating artefacts by filtering. The second module, used to decompose the filtered signal into brain waves and extract the necessary characteristics. The last module, used to classify and evaluate performance using two classifiers, KNN and LR. Each module plays a crucial role in the overall system. The operation of each module will be detailed in the following subsections, providing a comprehensive understanding of the processes involved.

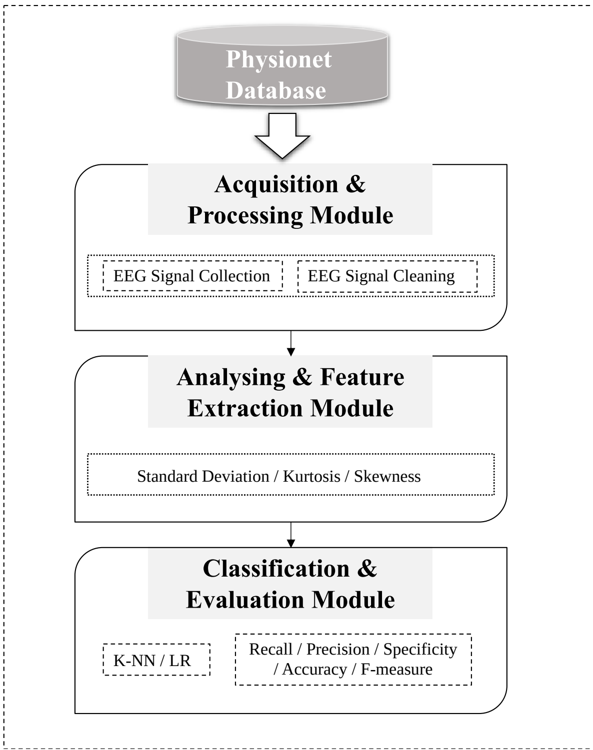

Figure 1. A flow chart of the various stages involved in identifying a hypovigilance state

2.1. Acquisition and processing module

Generally, during the acquisition phase, the brain signal generated always contains artefacts, so it is important to apply filtering to eliminate noise, which can affect the significant information in the signal and subsequently lead to false classification interpretations. In this case, a low-pass filter is considered a suitable solution for smoothing the raw signal, with a frequency band [0-30Hz] because the alpha, beta, delta, and theta brain waves lie in this interval [15], [16]. The general filter equation is expressed as follows:

$$|H(jf)| = 1 / \sqrt{([1 + \varepsilon^2 (f / f_c)]^{2n})} \quad (1)$$

Where:
f: operating frequency
f_c: cut-off frequency
ε: bandwidth transmission for maximum variation
n: order of the filter

2.2. Analysing and feature extraction module

After the processing phase, the filtered signal will be analysed to extract the maximum property necessary to detect the state of alertness. Data extraction is performed on the time domain, focusing on three key characteristics: standard deviation, kurtosis, and skewness. The calculation of these parameters is straightforward and less complex, making them sensitive and suitable for capturing rapid changes in the signal over time [12].

Standard deviation (S_D) represents the average variability of the EEG signal for each period. It provides a measure of how much the signal varies from its mean value. This parameter is crucial for identifying significant fluctuations in the brain activity that may indicate a state of alertness or drowsiness [17]:

$$S_D = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi - M_e)^2} \quad (2)$$

$$M_e = \frac{1}{N}\sum_{n=1}^{N} Xn \quad (3)$$

Where:
M_e: the mean value
N: the length of the EEG data
$\{X1, \ldots, Xn\}$: the values of signal

Kurtosis (k_u) and Skewness (S_k) are also calculated to further analyze the signal's properties. Kurtosis measures the level of asymmetry of the distribution of a signal, while skewness assesses the degree of distortion from a normal distribution. Together, these characteristics help in understanding the overall behavior of the EEG signal and contribute to the accurate detection of the driver's state of alertness. These are expressed by (4) and (5).

$$k_u = \frac{\sum_{i=1}^{N}(Xi - M_e)^4}{N{S_D}^4} \quad (4)$$

$$S_k = \frac{\sum_{i=1}^{N}(Xi - M_e)^3}{N{S_D}^3} \quad (5)$$

2.3. Classification and evaluation module

The classification stage is crucial for obtaining an effective and suitable learning model for predicting the state of alertness. The statistics extracted in the previous section are prepared to be trained and tested in order to evaluate the performance of the KNN and LR classifiers. The binary classification performance is analysed using metrics such as sensitivity, accuracy and specificity, which are represented in Table 1.

Table 1. The performance metrics for assessing learning models

Metric	Formula
Precision	TP/(FP+TP)
Specificity	TN/(FP+TN)
Recall (Sensibility)	TP/(FN+TP)
Accuracy	(TN+TP)/(FP+FN+TN+TP)
F-measure	(2*Recall*Precision)/(Recall+Precision)

Where: TP: true positive TN: true negative FP: false positive FN: false negative

KNN is a non-linear machine learning model that measures the distance between different features in a dataset in order to assign them to a data cluster [10]. The distance is calculated using (6):

$$D(y_{i,}y_j) = \sqrt{\sum_i (y_{i-}y_j)^2} \quad (6)$$

LR is a supervised algorithm used to analyse data by finding relationships between two data parameters. It is powerful and widely used for binary classifications [18]. The logistic function is expressed in (7):

$$L_f = {}^{1}/_{1+e^{-x}} \quad (7)$$

Here x is the input variable.

3. RESULTS AND DISCUSSION

The EEG signals used in this paper come from the Physionet database [19], they are processed and classified into two classes: normal state and drowsy state, the result of the KNN classifier is displayed in Table 2, shows that the learning model is very accurate for all K values, with a negligible difference. The best accuracy obtained is for K=3, at 97.831%, with a low overall error of 2.17%. The Kappa parameter is between 0.8 and 1, which also indicates very high reliability and almost perfect classification agreement.

Table 3 describes the different performance indicators, the KNN managed to detect 98.5% of normal cases and 95.1% were identified as drowsy. As illustrated in the Figure 2, this model still managed to capture 98.8% and 94% of both true states of alertness respectively, which means that it minimises the number of false positives. The good F-measure values reflect that there is a very good balance and compromise between accuracy and sensitivity, making the model more reliable and efficient.

Table 2. The KNN model's performance across a range of K

KNN classifier	Overall accuracy (%)	Error (%)	Cohen's Kappa	Correctly classified	Incorrectly classified
K=1	97.41	2.59	0.919	1617	43
K=2	97.47	2.53	0.918	1618	42
K=3	97.831	2.17	0.932	1624	36
K=4	97.59	2.41	0.923	1620	40

Table 3. Binary classification of the vigilance state by KNN and LR based on performance parameters

Classifiers	State	TP	FP	TN	FN	Recall (Sen)	Pr	Spe	F-measure	Acc (%)
KNN	Normal	1,313	20	311	16	0.988	0.985	0.94	0.986	97.83
	Drowzy	311	16	1313	20	0.94	0.951	0.988	0.945	
LR	Normal	1,936	28	478	48	0.976	0.986	0.945	0.981	96.95
	Drowzy	478	48	1936	28	0.945	0.909	0.976	0.926	

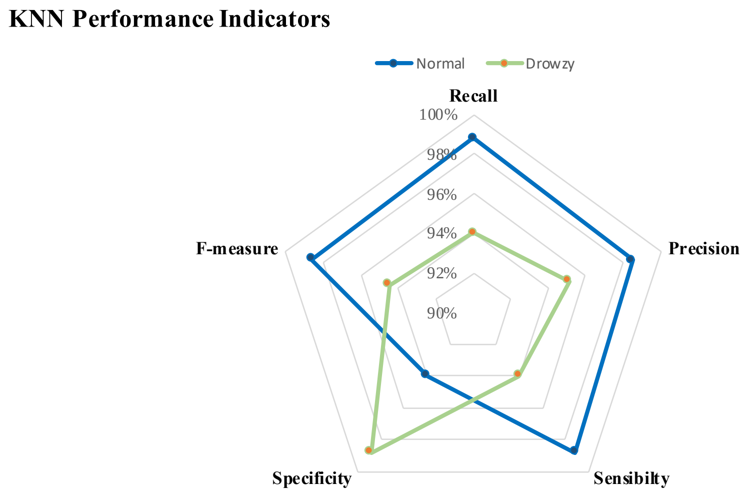

Figure 2. The radar of the KNN model based on key performance indicators (KPI's)

The radar displayed in Figure 3 shows the performance of the LR model in detecting the two states, the LR classifier demonstrates significant accuracy and specificity similar to KNN, especially in the "normal" class and the same sensitivity for the "drowzy" class, indicating that they have the same proportion of correct predictions as well as reflecting a good ability to identify true negatives and positives. In addition, the F-measure indicator provides an excellent balance between the different metrics for the same class, with negligible superiority over the KNN for the drowzy class. However, the LR has a lower sensitivity than the KNN for the 'normal' case, and the values of the other KPI's are lower than those of the KNN, i.e. the measures of the LR classifier are generally closer to those of the first model, with a slight decrease in accuracy (90.9%) and F-measure (92.6%) for the drowsiness cases. Overall, this difference is very insignificant, confirming the capacity of the two models to establish very meaningful and satisfactory performances for binary classification.

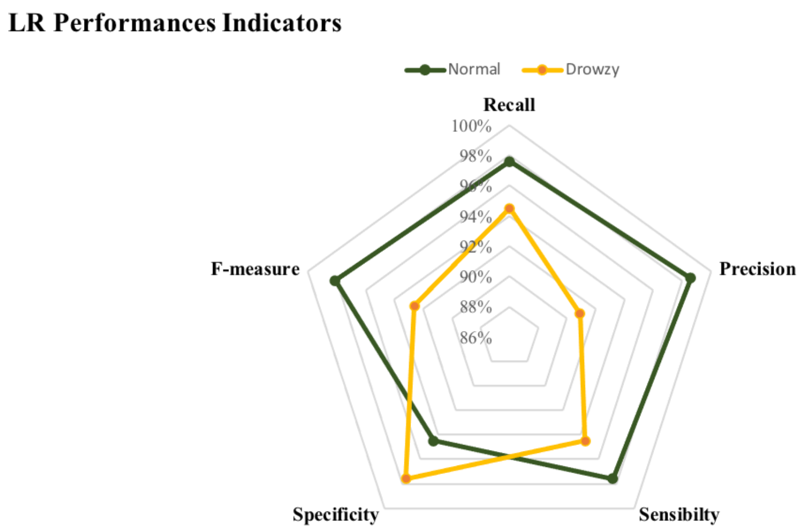

Figure 3. The radar of the LR model based on indicators

The two classification models presented in Figure 4 performed well in terms of overall accuracy, 96.95% for LR and 97.83% for KNN, with a minor outperformance for the second model. These results show that they have a high capacity to predict both positive and negative classes. This excellent ability proves that the KNN and LR models are highly effective and accurate at detecting hypovigilance and wakefulness. The high accuracy rates demonstrate the robustness of these models in real-world applications, suggesting their potential for integration into safety systems to prevent accidents caused by driver drowsiness.

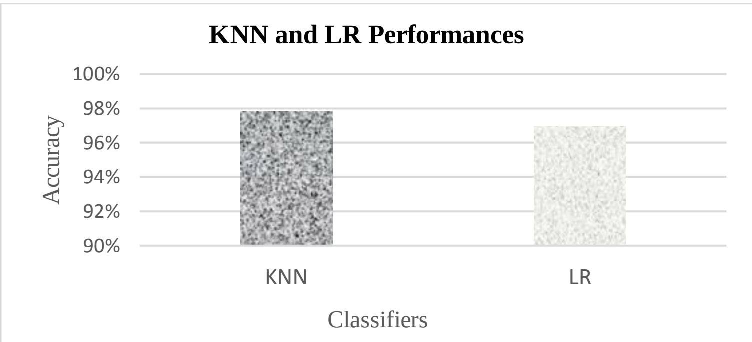

Figure 4. A comparative representation of the two models adopted in terms of accuracy

Table 4 offers a comparison of the proposed work with existing studies, based on the measurement tools, classification method and overall accuracy. The final results for the identification of the state of vigilance also validate the good performance of the system adopted in this study, compared with works that suggest machine learning and deep learning models. As the findings show, the two KNN models and the LR model outperform models based on convolutional neural network, common spatial patern (CSP), support vector machine (SVM) and extra trees, and using various acquisition tools such as ECG, EOG and camera for facial recognition. This confirms the excellent accuracy and robustness of the two models relative to binary hypovigilance classification.

Table 4. Comparison between the findings of the proposed method and existing studies

Studies	Measurement device	Classification method	Global accuracy (%)
Boudaya *et al*. [20]	EEG	CNN	93.94
Venkat and Chinara [21]	EEG	Extra trees	94.45
Murugan *et al*. [22]	EOG	Ensemble ML	90.9
Dua *et al.* [23]	Camera	Deep-CNN-based ensemble	85
Rahma and Rahmatillah [24]	EEG	CSP	91.67
Kiashari *et al*. [25]	Thermal camera	SVM and KNN	90
Kundinger *et al*. [26]	ECG	Ensemble ML	92
Proposed work	EEG	KNN (3) / LR	97.83/96.95

3.1. Remark

In real-world applications, KNN and LR models could be integrated into embedded driver assistance systems that, upon detecting hypovigilance, would trigger alerts for the driver or activate automated safety measures, such as speed reduction or lane-keeping assistance. These practical applications hold significant potential for reducing accident rates associated with drowsiness and decreased vigilance while driving. However, the performance of these models may be limited by external factors, such as road conditions, ambient noise that could interfere with EEG signal capture, and individual variability in physiological responses to fatigue. To address these limitations, future research could focus on testing the models in varied driving environments, including different weather and road conditions, and exploring model adaptability to each driver’s unique physiological characteristics. Additionally, improvements in real-time EEG signal processing capabilities will be essential for rapid detection and intervention, enhancing the responsiveness and reliability of assistance systems in diverse practical scenarios.

4. CONCLUSION

In the context of safety and the prevention of fatal accidents, this work was carried out to highlight an intelligent approach to the detection of hypovigilance. It is based on a set of modules comprising EEG signal acquisition and filtering, then analysis and extraction of the relevant features to establish a binary classification of hypovigilance state and normal state based on performance metrics. The prediction result obtained in this paper is very significant and proves that the KNN classifier outperforms the LR model, with an overall accuracy of 97.83%, which explains why this system can be an effective drowsiness detection tool not only for car drivers, as well as being exploited in work environments, the air traffic control domain and medical surveillance. On the other hand, despite the good classifier performance, these findings could be improved in future work, by developing tests on other data and applying other machine learning or deep learning algorithms in real time and moving straight on to the on-board implementation phase.

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REFERENCES

[1] S. A. El-Nabi, W. El-Shafai, E. S. M. El-Rabaie, K. F. Ramadan, F. E. A. El-Samie, and S. Mohsen, “Machine learning and deep learning techniques for driver fatigue and drowsiness detection: a review,” *Multimedia Tools and Applications*, vol. 83, no. 3, pp. 9441–9477, 2024, doi: 10.1007/s11042-023-15054-0.

[2] A. El Hadiri, L. Bahatti, A. El Magri, and R. Lajouad, “Brain signals analysis for sleep stages detection using virtual instrumentation platform,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 2, pp. 761–771, 2023, doi: 10.11591/ijeecs.v29.i2.pp761-771.

[3] I. A. Fouad, “A robust and efficient EEG-based drowsiness detection system using different machine learning algorithms,” *Ain Shams Engineering Journal*, vol. 14, no. 3, 2023, doi: 10.1016/j.asej.2022.101895.

[4] A. Karkouch, H. Mousannif, and H. Al Moatassime, "CADS: A connected assistant for driving safe," *Procedia Computer Science*, vol. 127, pp. 353–359, 2018, doi: 10.1016/j.procs.2018.01.132.
[5] A. El Hadiri, L. Bahatti, A. El Magri, and R. Lajouad, "A hybrid analysis approach of physiological signals based on excessive sleepiness and distraction state detection," *Automatic Control and Emerging Technologies*, pp. 299–311, 2024, doi: 10.1007/978-981-97-0126-1_27.
[6] A. Marois *et al.*, "Psychophysiological models of hypovigilance detection: A scoping review," *Psychophysiology*, vol. 60, no. 11, 2023, doi: 10.1111/psyp.14370.
[7] A. El Hadiri, L. Bahatti, A. El Magri, and R. Lajouad, "A novel brain-machine safety system based on drowsiness detection using the PNN and MLP algorithms," *IFAC-PapersOnline*, vol. 58, no. 13, pp. 823–828, 2024, doi: 10.1016/j.ifacol.2024.07.584.
[8] M. Ramzan, H. U. Khan, S. M. Awan, A. Ismail, M. Ilyas, and A. Mahmood, "A survey on state-of-the-art drowsiness detection techniques," *IEEE Access*, vol. 7, pp. 61904–61919, 2019, doi: 10.1109/ACCESS.2019.2914373.
[9] A. El Hadiri, L. Bahatti, A. El Magri, and R. Lajouad, "Profound sedation detection based on brain waves analysis," *International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD'2023)*, pp. 1–10, 2024, doi: 10.1007/978-3-031-52385-4_1.
[10] M. P. Hosseini, A. Hosseini, and K. Ahi, "A review on machine learning for EEG signal processing in bioengineering," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 204–218, 2021, doi: 10.1109/RBME.2020.2969915.
[11] J. Gwak, M. Shino, and A. Hirao, "Early detection of driver drowsiness utilizing machine learning based on physiological signals, behavioral measures, and driving performance," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, pp. 1794–1800, 2018, doi: 10.1109/ITSC.2018.8569493.
[12] Pawan and R. Dhiman, "Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review," *Measurement: Sensors*, vol. 28, 2023, doi: 10.1016/j.measen.2023.100823.
[13] D. D. Chakladar, S. Dey, P. P. Roy, and D. P. Dogra, "EEG-based mental workload estimation using deep BLSTM-LSTM network and evolutionary algorithm," *Biomedical Signal Processing and Control*, vol. 60, 2020, doi: 10.1016/j.bspc.2020.101989.
[14] C. J. D. Naurois, C. Bourdin, C. Bougard, and J. L. Vercher, "Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness," *Accident Analysis and Prevention*, vol. 121, pp. 118–128, 2018, doi: 10.1016/j.aap.2018.08.017.
[15] A. Chaddad, Y. Wu, R. Kateb, and A. Bouridane, "Electroencephalography signal processing: a comprehensive review and analysis of methods and techniques," *Sensors*, vol. 23, no. 14, 2023, doi: 10.3390/s23146434.
[16] A. El Hadiri, L. Bahatti, A. El Magri, and R. Lajouad, "Sleep stages detection based on analysis and optimisation of non-linear brain signal parameters," *Results in Engineering*, vol. 23, 2024, doi: 10.1016/j.rineng.2024.102664.
[17] M. E. Elidrissi, E. Essoukaki, L. B. Taleb, A. Mouhsen, and M. Harmouchi, "A new hybrid and optimized algorithm for drivers' drowsiness detection," *IAES International Journal of Artificial Intelligence*, vol. 11, no. 3, pp. 1101–1107, 2022, doi: 10.11591/ijai.v11.i3.pp1101-1107.
[18] M. C. Guerrero, J. S. Parada, and H. E. Espitia, "EEG signal analysis using classification techniques: Logistic regression, artificial neural networks, support vector machines, and convolutional neural networks," *Heliyon*, vol. 7, no. 6, 2021, doi: 10.1016/j.heliyon.2021.e07258.
[19] B. Kemp, A. Zwinderman, B. Tuk, H. Kamphuisen, and J. Oberyé, "Sleep-EDF database expanded," *PhysioNet*, 2013. Accessed: Mar. 07, 2022. [Online]. Available: https://www.physionet.org/content/sleep-edfx/1.0.0/
[20] A. Boudaya, B. Bouaziz, S. Chaabene, L. Chaari, A. Ammar, and A. Hökelmann, "EEG-based hypo-vigilance detection using convolutional neural network," *The Impact of Digital Technologies on Public Health in Developed and Developing Countries*, pp. 69–78, 2020, doi: 10.1007/978-3-030-51517-1_6.
[21] P. B. Venkata and S. Chinara, "Automatic classification methods for detecting drowsiness using wavelet packet transform extracted time-domain features from single-channel EEG signal," *Journal of Neuroscience Methods*, vol. 347, 2021, doi: 10.1016/j.jneumeth.2020.108927.
[22] S. Murugan, P. K. Sivakumar, C. Kavitha, A. Harichandran, and W. C. Lai, "An electro-oculogram (EOG) sensor's ability to detect driver hypovigilance using machine learning," *Sensors*, vol. 23, no. 6, 2023, doi: 10.3390/s23062944.
[23] M. Dua, Shakshi, R. Singla, S. Raj, and A. Jangra, "Deep CNN models-based ensemble approach to driver drowsiness detection," *Neural Computing and Applications*, vol. 33, no. 8, pp. 3155–3168, 2021, doi: 10.1007/s00521-020-05209-7.
[24] O. Rahma and A. Rahmatillah, "Drowsiness analysis using common spatial pattern and extreme learning machine based on electroencephalogram signal," *Journal of Medical Signals and Sensors*, vol. 9, no. 2, pp. 130–136, 2019, doi: 10.4103/jmss.JMSS_54_18.
[25] S. E. H. Kiashari, A. Nahvi, H. Bakhoda, A. Homayounfard, and M. Tashakori, "Evaluation of driver drowsiness using respiration analysis by thermal imaging on a driving simulator," *Multimedia Tools and Applications*, vol. 79, no. 25–26, pp. 17793–17815, 2020, doi: 10.1007/s11042-020-08696-x.
[26] T. Kundinger, N. Sofra, and A. Riener, "Assessment of the potential of wrist-worn wearable sensors for driver drowsiness detection," *Sensors*, vol. 20, no. 4, 2020, doi: 10.3390/s20041029.

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