Advances in Reliability, Safety and Security

ESREL 2024
Collection of Extended Abstracts

Enhancing Drowsiness Detection In Monitoring Tasks: Approach Using RESNET50 And Computer Vision

Plínio Ramos, Caio Maior, Márcio Moura, Isis Lins

Center for Risk Analysis, Reliability Engineering and Environmental Modeling, Universidade Federal de Pernambuco, Recife, Brazil

Keywords: drowsiness detection, computer vision, RESNET50, safety-critical environments, advanced deep learning

In recent years, catastrophic accidents in industries such as oil and gas, chemical, and nuclear have underscored the role of human operators in safety-critical operations (Sadeghi & Goerlandt, 2023). Despite advancements in safety measures and reliable equipment, human factors, including fatigue-induced drowsiness, continue to contribute to accidents in high-risk environments. Drowsiness, linked to factors like poor resting habits, sleep deprivation, and night shifts, poses a significant threat to overall performance and safety in critical operations (Ramos et al., 2022).

When facing the challenge of detecting early signs of drowsiness, researchers have explored several methods, including biological approaches such as electroencephalogram (EEG) analysis and computer vision (CV) techniques(Maior et al., 2020). The latter focuses on visual signs associated with drowsiness, analyzing facial expressions, eye movements and other visual characteristics.

Notably, existing studies often rely on traditional machine learning models, and there is limited exploration of advanced models like deep learning in the domain of drowsiness detection. The advent of more advanced models, such as RESNET50, has revolutionized this approach (Nijaguna et al., 2023). RESNET50 is a deep convolutional neural network architecture that stands out for its depth and the use of residual blocks, which facilitate the training of deep networks without facing performance degradation issues. Trained on a representative, public dataset called DROZY (Massoz et al., 2016.) that reflects subject attentional tasks such as those found in critical environments, RESNET50 has the potential to discern intricate visual patterns associated with drowsiness, thereby improving early identification capabilities crucial to sleep prevention. accidents.

Preprocessing plays a crucial role in analyzing video data for drowsiness detection. We will discuss pre-processing steps performed using CV techniques from processed video frames to extract relevant information for further analysis.

- Computer Vision Preprocessing Steps

The preprocessing steps for video data are performed using the cv2 library (Bradski, 2000). Video processing, face detection, facial landmark detection, and image cropping are some steps essential. These preprocessing steps using CV techniques are crucial for isolating and extracting the necessary visual information from the video frames. Through the combination of face detection, facial landmark detection, and image cropping, the preprocessing step prepares the video frames for subsequent analysis, such as classification, improving the overall accuracy and performance of the drowsiness detection system.

- ResNet50

Implementation of the ResNet50 model, using TensorFlow Keras (Abadi et al., 2015.), involves creating an input tensor and instantiating the ResNet50 class. Images are processed with the ResNet50 model, followed by sequential data analysis using an Long short-term memory (LSTM) model. The LSTM model architecture, with 1000 neurons, incorporates dense layers with dropout regularization to prevent overfitting. The model utilizes the Adam optimizer and cross-entropy loss for efficient training and classification. Parameters are initialized using ImageNet (Deng et al., 2009).

This methodology, integrating ResNet50 and LSTM, showcases a comprehensive approach to drowsiness detection, leveraging advanced CV techniques and deep learning models.

We evaluate the performance of the ResNet50 model using the images extracted from CV-based techniques from the DROZY database. We considered a time window of 5 seconds on each test data to be more comprehensive in detecting facial information. In addition, we disregard the seconds included in each test data time window from the training data in order to ensure that the test data is free of any time overlap with the training data. This approach ensures that the model is evaluated on unseen facial (more specifically, eye crop) images and provides a more accurate assessment of its performance in detecting drowsiness.

We measure the performance of the ResNet50 model using various evaluation metrics, including accuracy, precision, recall and F1 score. These metrics provide information about the model's ability to correctly classify drowsiness and alertness states based on facial features. In addition, we analyzed the model's confusion matrix to understand any misclassifications and identify potential areas for improvement. Thus, the accuracy results of the facial data are presented in Table 1.

Table 1. Results of the accuracy of the facial data.

Subjects	1	2	3	4	5
Accuracy	94.73%	100%	92.86%	76.78%	91.80%

CV-based drowsiness detection results show promising accuracy rates for subject tests. Four out of the five evaluated subjects achieved accuracy levels above 90%. Subject 2 demonstrated a perfect accuracy rate of 100%, indicating that the model correctly classified all cases of drowsiness and alertness. Subjects 1, 3 and 5 also achieved high accuracy rates of 94.73%, 92.86% and 91.80%, respectively, indicating a reliable performance and validating the effectiveness of the CV approach from the model ResNet50. However, Subject 4 continued to show a low accuracy rate (i.e., 76.78%), suggesting some challenges in accurately classifying drowsiness in this specific case.

Acknowledgements

The authors thank the Brazilian research funding agencies ‘Agência Nacional de Petróleo (ANP)’, ‘Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq): 305696/2018-1’ and ‘Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES)’ - Finance Code 001 - for the financial support through research grants.

References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., et al. Research, G. (n.d.). TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. www.tensorflow.org.

Bradski, G. 2000. The openCV library. Dr. Dobb’s Journal: Software Tools for the Professional Programmer 25(11), 120–123.

Deng, J., Dong, W., Socher, R., Li, L.-J., Kai Li, Li Fei-Fei. 2009. ImageNet: A large-scale hierarchical image database. 2009 IEEE Conference on Computer Vision and Pattern Recognition, 248-255. https://doi.org/10.1109/CVPR.2009.5206848

Maior, C. B. S., Moura, M. J. das C., Santana, J. M. M., Lins, I. D. (2020). Real-time classification for autonomous drowsiness detection using eye aspect ratio. Expert Systems with Applications, 158. https://doi.org/10.1016/j.eswa.2020.113505

Massoz, Q., Langohr, T., François, C., Verly, J. G. (n.d.). The ULg Multimodality Drowsiness Database (called DROZY) and Examples of Use. http://www.drozy.ulg.ac.be

Nijaguna, G. S., Babu, J. A., Parameshachari, B. D., de Prado, R. P., Frnda, J. 2023. Quantum Fruit Fly algorithm and ResNet50-VGG16 for medical diagnosis. Applied Soft Computing, 136, 110055. https://doi.org/10.1016/j.asoc.2023.110055

Ramos, P. M. S., Maior, C. B. S., Moura, M. C., Lins, I. D. 2022. Automatic drowsiness detection for safety-critical operations using ensemble models and EEG signals. Process Safety and Environmental Protection, 164, 566–581. https://doi.org/10.1016/j.psep.2022.06.039

Sadeghi, R., & Goerlandt, F. 2023. Validation of system safety hazard analysis in safety-critical industries: An interview study with industry practitioners. Safety Science, 161. https://doi.org/10.1016/j.ssci.2023.106084