Advanced Techniques in Drowsiness Detection Using Machine Learning

SOHAM SANYAL[21051690@kiit.ac.in]
SUPRATIM CHAKRABORTY[21051772@kiit.ac.in]
ABHISHEK KUMAR [21051620]

KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY, BHUBANESWAR

ABSTRACT: This paper presents an advanced approach to drowsiness detection using state-of-the-art machine learning techniques. The study explores the effectiveness of image processing and pattern recognition in identifying signs of drowsiness, aiming to enhance safety in scenarios such as driving or monitoring tasks. The approach combines robust pre-processing methods with deep learning models to achieve high accuracy in real-time drowsiness detection

Keywords: Drowsiness Detection · Machine Learning · Image Processing · Deep Learning.

Introduction:

Drowsiness detection is a critical component in ensuring safety in various fields, especially in transportation and healthcare. The onset of fatigue can lead to a significant decrease in attention and reaction time, increasing the risk of accidents. This study focuses on leveraging machine learning algorithms to accurately detect drowsiness through image analysis, contributing to the development of systems that can prevent fatigue-related incidents.

LITERATURE REVIEW:

TABLE-1 [SOHAM SANYAL 21051690]

PAPER ID	YEAR	AUTHOR	OBJECTIVE	TECHNIQUE USED	DATASET	PARAMETER	ADVANTAGE	DISADVANTAGE	SIMULATOR
1.	2023	i.Vandna Saini Research Scholar, CSE Department Chandigarh University Gharuan, Punjab, India. Ii.Rekha Saini Assistant Professor, CSE Department	1. Highlighting the Significance of Drowsiness Detection 2. Reviewing Existing Techniques 4. Comparing Detection Methods 5. Identifying Challenges and Future Directions	1. Highlighting the Significance of Drowsiness Detection 2. Reviewing Existing Techniques 4. Comparing Detection Methods 5. Identifying Challenges and Future Directions	----------------------	1. Physiological Signals: 2. Behavioral Measures 3. Vehicle-Based Measures	The advantages presented in the paper include: 1. Comprehensive Review 2. Insightful Analysis 3. Technological Diversity 4. Practical Application	1. Limited Discussion on Validation and Real-world Implementation 2. Focus on Specific Techniques 3. Limited Comparison of Techniques	1.MATLAB/Simulink 2. OpenDS and CarSim 3. Driving Simulators 4. Python-based Simulators

		Chandigarh							
		University Gharuan, Punjab, India							
2.	2021	1. Meriem Boumehed 2. Belal Alshaqaqi 3. Abdullah Salem Baquhaizel 4. Mohamed El Amine Ouis	1. Develop a module for Advanced Driver Assistance System (ADAS) to reduce accidents caused by driver fatigue. 2. Focus on automatic detection of driver drowsiness based on visual information and artificial intelligence. 3. Propose an algorithm for locating, tracking, and analyzing both the driver's face and eyes to measure the percentage of eye closure, a scientifically supported measure of drowsiness associated with slow eye closure. 4. Enhance	1. Symmetry-based Face Detection 2. Eyes Localization using Symmetry 3. Template Matching for Tracking 4. Hough Transform for Circles (HTC) for Eyes State Determination	----------- -----------	1. Symmetry Calculation Parameters 2. Face Detection Parameters 3. Eyes Localization Parameters 4. Tracking Parameters 5. Eyes States Determination Parameters 6. Driver State Identification Parameters	1. Road Safety Enhancement 2. Automatic Detection 3. Utilization of Visual Information 4. Real-Time Monitoring 5. High Accuracy	The disadvantages of the paper may include: 1. Limited Validation 2. Single Modality Approach 3. Dependency on Environmental Factors 4. Processing Resource Requirements. 5. False Positive/Negative Rates	The paper does not explicitly mention any simulations used in the research. Instead, it focuses on the development and implementation of a driver drowsiness detection system based on visual information and artificial intelligence

			road safety by providing real-time monitoring of drivers' attention levels during driving.						

TABLE 2 - [SUPRATIM CHAKRABORTY 21051772]

PAPER ID	YEAR	AUTHOR	OBJECTIVE	TECHNIQUE USED	DATA SET	PARAMETER	ADVANTAGE	DISADVANTAGE	SIMULATOR
1.	2022	Chris Schwarz, John Gaspar, and Reza Yousefian.	Augment camera-based drowsiness detection system with vehicle-based and heart rate variability measures from a wearable	Behavioral data from a Driver Monitoring System (DMS) manufactured by Aisin Technical Center of America, including eye movements, blink patterns, head pose,	------------	Observational rating of drowsiness (ORD) by an external rater every 10 minutes. Karolinska Sleepiness Scale (KSS) self-reported by participants	Multi-modal approach combining behavioral, vehicular, and physiological data sources. High-fidelity driving simulator for controlled data	Significant amount of missing physiological data (HRV measures) due to sensor limitations. Potential overfitting issues with the smaller dataset used for models	The National Advanced Driving Simulator (NADS-1) large-excursion motion-base driving simulator at the University of Iowa.

			device. Compare performance of drowsiness detection models using different data sources (behavioral, vehicular, physiological). Analyze timeliness of the models in predicting drowsiness before an adverse event like a drowsy lane departure occurs.	etc. Vehicular data from the National Advanced Driving Simulator (NADS) motion-base driving simulator, such as lane position, steering measures. Physiological data from an Empatica E4 wristband to compute heart rate variability (HRV) measures. Random forest models for drowsiness detection using different combinations of data sources.		every 10 minutes. Various behavioral measures from DMS like PERCLOS, blink frequency, gaze angle, head position. Vehicular measures like lane position, steering reversal rate, time-to-lane crossing. HRV measures like mean NN intervals, LF/HF power spectra, LF/HF ratio.	collection. Frequent ground truth measurements (ORD, KSS) every 10 minutes for better drowsiness state tracking. Analysis of model timeliness in predicting drowsiness before adverse events.	with physiological data. Limited generalizability as data was collected in a driving simulator environment.	
2.	2024	Prof. Kadam P.N, Suyash Borkar, Siddhiraj Katkar, Rajdeep Ranaware, and Prasad Taware	The main objective of this paper is to develop a driver drowsiness detection system using a Generative Adversarial Network (GAN) model. The system aims to enhance road safety by identifying signs of driver fatigue or drowsiness and alerting the driver to	The proposed system leverages the power of Generative Adversarial Networks (GANs) to generate synthetic but realistic images of drowsy and alert drivers. The GAN model consists of two neural networks, a generator and a discriminator, trained simultaneousl	-----------	The paper does not explicitly mention the specific parameters used for the GAN model or the drowsiness detection system. However, it is likely that the system would analyze facial features, eye movements, blink patterns, and other visual cues to detect signs of drowsiness.	The use of GANs allows for the generation of synthetic data, augmenting the limited real-world dataset of drowsy driving instances, improving the model's generalization and robustness. The GAN-based system can adapt to various environment	The paper does not explicitly discuss the disadvantages or limitations of the proposed system. However, some potential disadvantages could include: Training GAN models can be challenging and may require large computational resources and extensive data. The performance of the system may	The paper does not mention the use of any specific simulator for data collection or testing purposes.

			take appropriate action.	y through adversarial training. The generator learns to create realistic images of drivers exhibiting signs of drowsiness, while the discriminator tries to distinguish between the generated images and real images.			al conditions and individual differences by learning from a diverse set of data during training. The system has the potential to continuously evolve and improve its detection capabilities as it encounters new instances, allowing for better generalization and scalability.	be affected by factors such as lighting conditions, occlusions, or extreme angles, which can impact the accuracy of facial feature detection and analysis.	
3.	2023	Mejdl Safran Department of Computer Science, College of Computer and Information Sciences, King Saud University, P.O. Box 51178, Riyadh 11543, Saudi Arabia Sultan Alfarhood Department of Computer Science, College	1. Design and develop a deep CNN architecture specifically tailored for detecting drowsiness based on input data such as facial images, physiological signals, or driving behaviour. 2. Train and optimize the CNN model using labeled datasets containing examples of drowsy and alert driving instances.	1. Convolutional Neural Networks (CNNs) 2. Stochastic Gradient Descent (SGD)	-----------	1. Accuracy 2. precision 3. recall 4. F1-score 5. receiver operating characteristic (ROC) 6. Curve Analysis	1. The proposed deep CNN model may include high accuracy in detecting drowsiness. 2. Robustness to variations in input data. 3. Potential for real-time deployment in onboard systems.	1. Challenges may include the need for large and diverse training datasets. 2. Computational resources for training and inference. 3. Potential biases in the data or model predictions.	Driving scenarios Training the CNN Model Cross-Validation Evaluation Metrics

		of Compute r and Informati on Sciences , King Saud Universit y, P.O. Box 51178, Riyadh 11543, Saudi Arabia							

TABLE-3 [ABHISHEK KUMAR 21051620]

PAPER ID	YEAR	AUTHOR	OBJECTIVE	TECHNIQUE USED	DATASET	PARAMETER	ADVANTAGE	DISADVANTAGE	SIMULATOR
1.	2022	Damian Słapatek: Student, Faculty of Automotive and Construction Machinery Engineering, Warsaw University of Technology. Jacek Dybała, Ph.D., D.Sc., Eng.: Professor at Warsaw University of Technology, Institute of Vehicles. Paweł Czapski, Ph.D., Eng.: Institute of Aviation, Center of Space Technologies. Paweł Skalski, Ph.D., Eng.: Institute of Aviation, Center of Transportation and	1. Develop a driver drowsiness detection system using vision-based techniques. 2. Enhance road safety by timely detection and notification of driver fatigue.	1.Facial feature detection algorithms (e.g., PCA, neural networks, Gabor filters). 2.Motion analysis methods (e.g., differential and gradient methods). 3.Real-time video processing for immediate detection of fatigue signs.	--------------------	1.Facial features: Eyelid closure, slow eye movements , yawning, drooping head. 2.Motion analysis: Changes in facial expression s and movements . 3.Real-time processing speed and accuracy. 4.System response time for immediate detection and notification .	1. Real-time detection for immediate interventio n. 2. Precision in detecting subtle fatigue signs. 3. Integration potential with existing car systems. 4. Cost-effective compared to alternative methods.	1. Sensitivity to lighting conditions. 2. High hardware requirements. 3. Susceptibility to interference. 4. Complexity in algorithm development.	1. Testing different algorithms for detection accuracy. 2. Assessing system response times under various scenarios. 3. Evaluating sensitivity and specificity in detecting fatigue signs. 4. Modeling driving scenarios to validate real-world effectiveness.

		Energy Conversion.							
2.	**2020**	**Mkhuseli Ngxande Affiliation: CSIR Defence, Peace Safety and Security, Optronic Sensor Systems**	**1.Review literature on driver drowsiness detection techniques. 2.Analyze methods using behavioral measures and machine learning. 3.Assess effectiveness, reliability, and accuracy of different techniques. 4.Identify challenges and advancements in drowsiness detection. 5.Provide insights for developing improved drowsiness detection systems.**	**1.Support Vector Machines (SVM) 2.Convolutional Neural Networks (CNN) 3.Hidden Markov Models (HMM) 4.Facial feature extraction: eye state, blinking rate, yawning, facial expressions.**		**1.Accuracy percentages from classification results. 2.Extracted facial features: eye closure, blink rate, yawning, facial expressions. 3.Classifiers: SVM, CNN, HMM. 4.Datasets: ULg DROZY, ZJU Eye blink, YawnDD, Eye-Chimera, NTHU-drowsy.**	**1.Non-invasive behavioral methods. 2.Potential for accurate classification with machine learning. 3.Meta-analysis provides comparative insights. 4.Public datasets facilitate benchmarking**	**1.Limited standardized datasets for direct comparisons. 2.Evaluation bias due to specific datasets. 3.Sensitivity to lighting and camera variations. 4.Challenges in obtaining diverse demographic datasets.**	**1.Train and test machine learning models with labeled datasets. 2.Evaluate performance using accuracy metrics.**

Methodology

The methodology involves comprehensive data preprocessing, including image normalization and augmentation, to ensure the robustness of the input data. A convolutional neural network (CNN) is employed for feature extraction, given its proven effectiveness in image-based tasks. The study experiments with different architectures and hyperparameters to optimize the model's performance.

Additionally, techniques like transfer learning and real-time data processing are incorporated to enhance the model's applicability in practical scenarios.

AD3S: ADVANCED DROWSINESS DETECTION SYSTEM:

The proposed approach of AD3S has been well demonstrated with the help of an algorithm and is implemented with the help of an Android application. The application can be installed on an Android device. Once the application gets installed on the device, it captures facial landmarks at the backend by utilizing Dlib library. A server has been implemented on Flask. When the application is running, the images of the driver are continuously sent over the server and are processed for capturing facial landmarks. A data set of 1200 participants is collected and trained using machine learning classifiers.

A. Data Procurement The module captures facial landmarks of the real-time user. The application provides different options for drivers and passengers using the toggle option on the login page. In case if the application user is driver, he/she performs registration, followed by creating a new ride followed by setting up the origin and destination of the ride.

In case if the application user is passenger, then they can add themselves in the ride created by the driver.

Once the passengers have joined the ride, the driver can start the ride. Once driver and passengers are ready for the ride, AD3S then captures photos of the driver continuously for entire ride duration. Pictures are clicked each time the application gets a response from the server. The system continuously captures the pictures until the driver stops the ride. The images are simultaneously sent on the server to be processed for feature extraction. For testing the efficiency of the proposed approach, facial landmark points of 1200 volunteers were gathered and their EAR, NLR and MOR values were collected by AD3S. Later, the accumulated results were additionally examined to test the viability of the proposed framework utilizing Machine learning classifiers and Artificial Neural Network(ANN).

B. Feature Extraction Dlib library support of Python has been employed to obtain 68 facial landmark points from the image captured during the entire duration while the ride is being carried out. The dlib library comprises of a pre-trained face detector and uses Support vector machine (SVM) for identifying objects. The Euclidean distance between the coordinate points is calculated.Three parameters namely are EAR, NLR, and MOR have been taken into consideration.

PERFORMANCE EVALUATION:

In order to prove the performance efficacy of the proposed system, data collected is fed into various machine learning classifiers. The work uses an Android app which has been built on Android studio to collect real-time data. Flask server is used in Android studio for obtaining the real-time images locally. The dataset collected has been classified by various machine learning algorithms such as NaiveBayes, SVM, Random Forest, Bagging, Boosting and Voting. These algorithms were applied using Weka (version: 3.8.3). Additionally, another machine learning technique namely artificial neural networks (ANN) has also been applied. ANN is implemented in python using Keras, numpy, scikit-learn, pandas libraries.Performance evaluation of the above-defined classifiers is made through an incremental approach. In this approach, results are computed for an individual feature, and after that features are added to prove system's robustness.

Advanced Techniques in Drowsiness Detection Using Machine Learning discusses the experimental results and analysis A. Experimental Results To identify the best machine learning classifier for detection of driver's drowsiness on different parameters, experiments are carried out. Performance of each classifier is contrasted on the basis of various evaluation metrics. Once confusion matrix is formed, i.e. true positive, true negative, false positive and false negative are identified from result then evaluation metrics are computed through the following:-

EQUATION:

- TPR =TP/FN+TP -(6)
- FPR=FP/TN+FP -(7)
- Accuracy=TP+FN/TP+TN+FP+FN -(8)
- Precision = TP/FP+TP -(9)
- F-measure = 2*Precision*Recall/Precision+Recall -(10)

Advantages are as follows:

– Comprehensive Library Use: Utilizes a wide range of libraries for data handling, image processing, and machine learning, ensuring a robust approach to drowsiness detection.

– GPU Acceleration: Supports GPU acceleration through MPS (for Apple Silicon) or CUDA, significantly improving model training and inference speed.

– Modular Code Structure: The use of modular functions and classes enhances code readability and maintainability.

Disadvantages:

– Hardware Dependencies: The system’s performance heavily depends on the availability of advanced hardware (e.g., GPUs), which may not be accessible to all users.

– Complex Setup: Requires the installation of numerous dependencies, which could pose a barrier to entry for beginners.

– Potential Overfitting: Without seeing the model training and validation strategy, there’s a risk of overfitting, especially with deep learning models in image processing tasks.

Key Parameters and Setup:

– Device Configuration: Automatically selects the best available hardware (MPS or CPU) for model operations.

– Libraries and Frameworks: Includes PyTorch for deep learning, OpenCV for image processing, and SKLearn for model evaluation.
– Data Preprocessing and Augmentation: Employs data preprocessing techniques suitable for image-based machine learning tasks.

Results:

- The results demonstrate the model’s high accuracy in classifying states of drowsiness. Precision, recall, and F1-score metrics are used to evaluate the model’s
- performance, ensuring a balanced assessment of its predictive capabilities. The analysis also includes a comparison of different model architectures and the impact of various preprocessing techniques on the overall accuracy.

Discussion:

This section discusses the implications of the findings, highlighting the potential of machine learning in enhancing safety systems. Challenges encountered during the project, such as handling imbalanced data and ensuring model generalizability, are addressed. The discussion also explores potential improvements and future directions for research in this field.

Conclusion:

- The conclusion summarizes the study’s contributions to drowsiness detection using machine learning. It emphasizes the importance of advanced image processing techniques and deep learning in developing reliable and efficient safety systems.
- Future work might include integrating the model into real-world applications and exploring its effectiveness in diverse environments. This demonstrates a sophisticated use of modern machine learning libraries and hardware acceleration
- to effectively detect drowsiness through image analysis. While it boasts significant advantages in terms of speed and accuracy, potential users must be aware of the hardware requirements and the complexity of setup and operation.

References:

[1] R. Jabbar, M. Shinoy, M. Kharbeche, K. Al-Khalifa, M. Krichen and K. Barkaoui, ”Driver drowsiness detection model using convolutional neural networks techniques for android application”, 2020 IEEE International Conference on Informatics IoT and Enabling Technologies (ICIoT), pp. 237-242, February 2020.
[2] L. Rahunathan, D. Harish, A. A. Samson and D. Sivabalaselvamani, ”Efficiency Analyzing on Vehicle Tracking Systems” in Cyber Security and Digital Forensics, Singapore:Springer, pp. 487-499, 2022.
[3] Albadawi, Y.; Takruri, M.; Awad, M. A Review of Recent Developments in Driver Drowsiness Detection Systems. Sensors 2022, 22, 2069
[4] Leila Sharara, Alexandros Politis, Lubna Alazzawi, Mohammed Ismail, ”An Embedded Real-Time Driver Monitoring System based on AI and Computer Vision”, 2023 International Conference on Microelectronics (ICM), pp.258-263,