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Deep Learning Approaches for Drowsiness Detection System: A Comprehensive Survey

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***Abstract*— Road traffic accidents are more likely when drivers are fatigued, which is a serious safety hazard. To address this issue, studies have been done to create sleepiness detecting systems. These systems track behavioral and physiological changes in drivers that signify tiredness using physiological markers and image processing techniques. Since they accurately reflect the driver's physical state, physiological variables like heart rate, pulse, breathing rate, and body temperature serve as trustworthy markers of drowsiness. These improvements in drowsiness detection technology have the potential to significantly improve driver safety and reduce accidents brought on by driver fatigue.**

I. Introduction

Drunk driving is a serious problem that endangers public safety on the roads and causes more accidents. The development of drowsiness detection systems has been the subject of numerous studies to solve this issue. To monitor the physical and behavioral changes in drivers suggestive of drowsiness, these systems make use of physiological signals and image processing techniques. Due to the fact that they directly reflect the driver's physical condition, physiological parameters like body temperature, heart rate, pulse rate, and breathing rate serve as reliable and accurate indicators of drowsiness. Invasive methods, such as EEG and ECG-based systems, utilize electrodes placed on the driver's body to detect changes in brain and heart activity associated with drowsiness.

II. Literature Survey

In paper [1], the authors present a comprehensive survey of various drowsiness detection systems that utilize physiological signals. The paper focuses on the importance of physiological parameters in accurately detecting drowsiness and its potential impact on preventing road accidents. The reliability and accuracy of physiological parameters like heart rate, pulse rate, breathing rate, and body temperature in detecting sleepiness is highlighted by the authors in their opening paragraph. They describe how variations in these measurements, like a drop in blood pressure, heart rate, or body temperature, can signal the beginning of fatigue or drowsiness. The discussion of various drowsiness detection methods based on physiological signals follows. One such technique is EEG-based driver fatigue detection, where the authors suggest a method that uses EEG signals acquired from a cheap single electrode neuro signal to calculate an index related to different levels of drowsiness. The use of pulse sensors to measure heart rate and identify sleepiness by examining changes in the LF/HF (Low to High Frequency) ratio is also covered by the authors. They emphasize the research findings showing a connection between a falling LF/HF ratio and the change from an awake to a drowsy state. The paper also introduces a hybrid approach to enhance the

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performance of drowsiness detection systems by combining features from ECG and EEG signals. To distinguish between alert and drowsy states, the authors extract time and frequency domain features from both ECG and EEG signals. They then use statistical tests and SVM classification. Overall, the paper provides a comprehensive literature survey of various drowsiness detection systems based on physiological signals. It explores different techniques, methodologies, and experimental results, highlighting the potential of physiological parameters in accurately detecting driver drowsiness and preventing accidents on the road.

In paper [2] the author presents a real-time algorithm for detecting eye blinks in a video sequence using facial landmark detection. The paper highlights the robustness of modern landmark detectors trained on "in-the-wild datasets" in accurately localizing eye corners and eyelid contours, even in the presence of varying illumination, facial expressions, and moderate non-frontal head rotations. The proposed algorithm utilizes the eye aspect ratio (EAR), derived from the landmarks, as an estimate of the eye opening state. Support vector machine (SVM) classifier trained on a temporal window of EAR values is introduced to improve the accuracy of blink detection. The paper demonstrates the effectiveness of the regression-based facial landmark detectors and the superiority of the SVM method over EAR thresholding for drowsiness detection. The paper will present a real-time algorithm for blink detection using facial landmarks and demonstrates the effectiveness of the proposed SVM method. The algorithm utilizes the eye aspect ratio (EAR) and shows improved accuracy compared to thresholding methods.

In paper [3], the authors propose a driver fatigue prediction system based on Support Vector Machine (SVM) algorithm to enhance driver safety. The system consists of five stages that are used to extract attributes from video recordings: PERCLOS (Percentage of Eye Closure), yawn count, internal zone of mouth opening, eye blinking count, and head detection. SVM is used in the classification stage to categorize the driver's level of fatigue. The classification model is trained using the Yawning Detection Dataset dataset, and tested using real-time video recordings. The best hyperplane for differentiating between tired and non-tired drivers is found using the SVM algorithm, which is based on statistical learning theory. The results of the driver fatigue detection were assessed using measurements such as true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) in the study's driving simulation experiments with ten volunteers. The proposed system had an accuracy rate of up to 95.93% when it came to detecting driver fatigue, according to calculations.

In paper [4], the authors propose a drowsiness detection system for car drivers using EEG, EOG signal processing, and driver image analysis. EEG and EOG signals are measured to monitor brain activity and eye movements, while image analysis classifies the state of the driver's eyes (open or closed). Research in advanced materials and MEMS technology is used to alleviate the discomfort brought on by EEG and EOG sensors, which call for conductive gel and wired transmission. Artificial neural networks (ANN) are used in the study to categorize the driver states, and deep learning methods like Deep Belief Networks, Restricted Boltzmann Machines, and Deep Autoencoders are also used. More than 45000 images of a driver are analyzed using the MATLAB Neural Network Toolbox and the Deep Learning Toolbox; alertness is indicated by open or partially opened eyes, whereas drowsiness is indicated by closed eyes. In their study, the author propose a drowsiness detection system for car drivers using EEG, EOG, and driver image analysis. Artificial neural networks and deep learning techniques are employed for accurate classification of drowsy and alert states based on eye-related signals and image processing.

In the study[5] the authors propose a deep convolutional neural network (CNN) approach is proposed for driver drowsiness detection based on eye state. The Viola-Jones algorithm is used by the system to detect faces and eyes, and a CNN with four convolutional layers is then used for feature extraction and classification. The CNN's SoftMax layer is used to categorize the driver as either sleepy or awake. The suggested system successfully detects the driver's drowsy state with an accuracy of 98.48%. In their paper, the author propose a deep CNN-based method for detecting driver intoxication. The system achieves 98.48% accuracy by using stacked deep CNN for feature extraction and classification and Viola-Jones algorithms for face and eye detection.

The various methods for drowsiness detection in next paper[6], When combined with Android modules, machine learning (ML) and deep learning (DL) algorithms, in particular convolutional neural networks (CNN), can be used to accurately detect sleepiness using camera-based face and eye detection. Another approach involves tracking human eyes and analyzing drowsiness through multiple frames using an FPGA-based system with IR sensor light sources embedded in vehicles, with the goal of preventing serious accidents. Eye recognition systems and fatigue detection based on heart rate data classification use Wavelet Network Classifier and Fast Wavelet Transform. A steering wheel-based algorithm that incorporates CNN and image-formed steering movement is also suggested for classifying sleepiness. An alert system using electroencephalography (EEG), electrocardiography (ECG), electrooculogram (EOG), and electromyogram (EMG) algorithms that is activated using machine learning techniques is an alternative strategy.

This paper [7], the authors introduces a fatigue detection system that utilizes deep learning and fuzzy logic techniques. It conducts an analysis of the system's results and proposes potential improvements. Systems that monitor the condition of the vehicle and those that use driver-specific parameters are identified as two separate categories of fatigue detection systems. Lane departures and behaviors while steering the wheel are frequently examined in studies on vehicle state analysis as trustworthy signs of fatigue. Electroencephalograms and electrooculograms, which are frequently disregarded by drivers, are the only reliable methods for estimating fatigue. As a result, camera-based systems that gauge the driver's condition have become more common.
This paper [8] discusses that Drowsy driving contributes significantly to car accidents, particularly in Iran where 26% of accidents are attributed to driver fatigue. The ability to accurately assess drowsiness in driving simulators using image processing techniques is essential for preventing accidents. A virtual reality-based simulator was used in a study at Khaje-Nasir Toosi University of Technology to examine five suburban drivers. The results showed a direct correlation between drowsiness levels and eye closure duration and blink frequency. High speed and accuracy were demonstrated by the suggested method. Five seasoned drivers were put through their paces in a controlled virtual reality setting as part of the study. Software that processed color frames from a front-facing camera to determine the coordinates of facial features was used to create a drowsiness detection model. Assessments of the driver's alertness or sleepiness were compared with the information that was obtained. Using grayscale conversion, normalization, and other image processing techniques, it was possible to distinguish between eyes that were open and those that were closed.
This paper [9] discusses the use of machine learning techniques, artificial intelligence, and computer vision to predict and detect the drowsiness of a driver in order to improve road safety. The article mentions a number of techniques and algorithms, including PERCLOS, CAMSHIFT, HAAR training, Viola Jones algorithm, and others, that are used to identify drowsiness using indicators like eye movement, facial features, and steering wheel analysis.The paper also emphasizes how important driver drowsiness detection systems are in preventing accidents brought on by fatigued driving. It presents data regarding drowsy driving and highlights the need for creating driver safety systems. The authors provide an overview of recent research in the area, talk about the methodologies employed in various systems, and mention the difficulties that current systems are currently facing. The suggested system makes use of facial landmark detection to keep track of crucial facial features like the driver's eyes and mouth. Based on the position of the eyes, the Eye Aspect Ratio (EAR) is computed to detect drowsiness, and the YAWN value is computed to detect yawning. The driver receives voice alerts when drowsiness or yawning is detected thanks to an eSpeak module.
The related work in the area of drowsiness detection is covered in this paper by Mahek Jain and colleagues [10], including various methods like deep CNN, computer vision, behavioral measures, and machine learning. It also discusses the drawbacks of current systems, such as their high price or dearth of robustness. The research's goals include creating a system that can detect driver drowsiness with accuracy and reliability, designing a system that operates in real-time and is not affected by lighting conditions, and giving the driver the proper voice alerts. Face localization using facial landmark detection, computing the EAR for drowsiness detection, computing the YAWN value for yawning detection, and using the eSpeak module for voice alerts are all part of the methodology. According to the software specifications, the system must be able to function in real-time and recover from errors. The system architecture has stages for face tracking, recognizing states of fatigue, and detecting signs of drowsiness. The intricate design demonstrates how the device continuously scans the driver's face and, as needed, produces voice alerts.

III. ALGORITHMS AND SOFTWARES

1) EEG

A fatigue detection system for drivers based on Electroencephalogram (EEG) signals is introduced to prevent accidents caused by driver fatigue. The method involves identifying an index associated with various levels of drowsiness. A low-cost single electrode neuro signal acquisition device is used to capture the EEG signal.

2) WAVELET ANALYSIS OF HEART RATE

This system aims to classify drivers as either alert or drowsy by analyzing the wavelet transform of HRV signals in short intervals. It takes the Photo Plethysmo Graphy (PPG) signal as input and divides it into 1-minute intervals. The system then utilizes the average percentage of eyelid closure over the pupil over time (PERCLOS) measurement to verify two driving events within each interval. Additionally, HRV feature extraction is performed using Fast Fourier Transform (FFT) and wavelet techniques.

3) PULSE SENSOR METHOD

Previous studies have primarily focused on using physical indicators to detect driver drowsiness. Rahim proposes a method that utilizes infrared heart-rate or pulse sensors to detect drowsy drivers. The pulse sensor is attached to the finger or hand, measuring the heart pulse rate by detecting the amount of blood flow and oxygen levels in the finger. The sensor transmits the data to an Arduino microcontroller, which visualizes the heart pulse rate using software processing in the HRV frequency domain.

4) WEARABLE DRIVER DROWSINESS DETECTION SYSTEMS

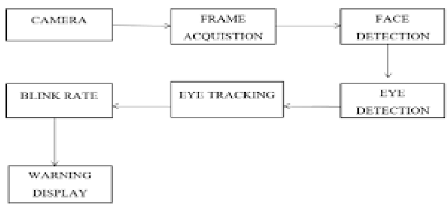
To overcome the distraction caused by mobile phones while detecting driver drowsiness, Length proposes a wearable-type system. The system includes a self-designed wristband equipped with a PPG signal sensor and a galvanic skin response sensor. The collected sensor data is transmitted to a mobile device, which serves as the main evaluation unit. The collected data is analyzed using the mobile device's built-in motion sensors. Five features, including heart rate, respiratory rate, stress level, pulse rate variability, and adjustment counter, are extracted from the data for drowsiness assessment.

5) WIRELESS WEARABLES

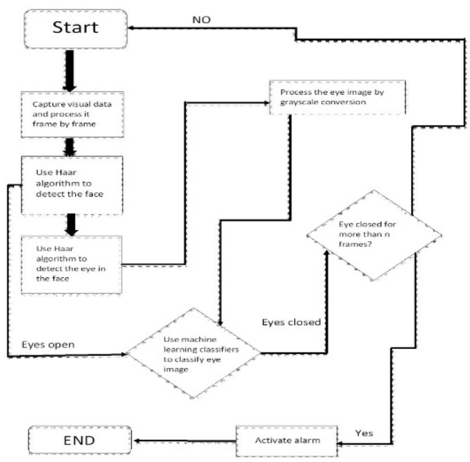
Warwick proposes a drowsiness detection system using a wearable bio-sensor called Bio-harness to prevent road accidents. The system consists of two phases. In the first phase, the driver's physiological data, such as ECG, heart rate, and posture, is collected using the bio-harness. The data is then analyzed to identify key parameters associated with drowsiness. In the second phase, a drowsiness detection algorithm is developed, and a mobile app is created to alert drowsy drivers

6) DRIVER FATIGUE DETECTION ALGORITHM.

The drowsiness detection system operates while the vehicle is in motion and comprises three main components: external hardware (including sensors and a camera), a data processing module, and an alert unit. The hardware unit communicates with the rest of the system via the USB port and continuously monitors physiological and physical factors such as pulse rate, yawning, closed eyes, and blink duration using a somatic sensor. The processing module analyzes the combination of these factors to detect drowsiness. Finally, the alert unit notifies the driver at various stages based on the severity of the symptoms.



IV. WORKING OF MODEL WITH THE USE OF HAAR ALGORITHM



V. METHODOLOGY

1. *Collection of Data*: Gather a comprehensive dataset of driver's physiological and behavioral features, including eye movements, facial expressions, head poses, and vital signs such as heart rate and respiration rate. This data can be collected using sensors, cameras, or wearable devices placed in the vehicle.
2. *Preprocessing of Data:* Clean and preprocess the collected data to remove noise, outliers, and irrelevant information. Normalize and standardize the data to ensure consistency and compatibility for deep learning algorithms.
3. *Feature Extraction*: Utilize computer vision techniques to extract relevant features from the collected data. This may involve techniques such as facial landmark detection, eye tracking, and pose estimation to capture key indicators of drowsiness, such as eye closure, head drooping, or yawning.
4. *Deep Learning Models Selection*: Choose an appropriate deep learning model for drowsiness detection, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs). Consider models that have been successfully applied in similar tasks, such as facial expression recognition or driver monitoring.
5. *Training of Model*: Split the preprocessed data into training and validation sets. Train the selected deep learning model using the training set, optimizing the model's parameters through backpropagation and gradient descent. Use the validation set to monitor the model's performance and prevent overfitting.
6. *Model Evaluation*: Evaluate the trained model using a separate testing dataset that was not used during training. Measure key performance metrics such as accuracy, precision, recall, and F1 score to assess the effectiveness of the algorithm in detecting driver drowsiness.
7. *Fine-tuning and Optimization*: Fine-tune the model based on the evaluation results to improve its performance. Adjust hyperparameters, architecture, or introduce additional regularization techniques to enhance the algorithm's accuracy and robustness.
8. *Real-time Implementation*: Implement the trained deep learning model in a real-time system that can continuously monitor the driver's state. This may involve integrating the algorithm into an embedded system or a mobile application capable of processing input from sensors or cameras in real-time.
9. *Testing and Validation of Model*: Conduct thorough testing and validation of the implemented algorithm in real-world driving scenarios. Collect feedback and iterate on the algorithm if necessary to address any limitations or improve its overall performance.
10. *Deployment of Model*: Once the algorithm has been thoroughly validated and meets the desired performance criteria, deploy it in vehicles or driver assistance systems to actively monitor and detect driver drowsiness, providing timely alerts or interventions to prevent accidents.

V. CONCLUSION

In conclusion, the use of deep learning algorithms for driver's drowsiness detection shows promising results in improving road safety. By leveraging physiological and behavioral data, combined with computer vision techniques, deep learning models can effectively detect signs of drowsiness in drivers. These models have the potential to provide real-time monitoring and timely alerts to prevent accidents caused by driver fatigue.

The methodology outlined in this study demonstrates the importance of data collection, preprocessing, feature extraction, and model training in developing an accurate and reliable drowsiness detection algorithm. By fine-tuning the deep learning model and validating it in real-world driving scenarios, the algorithm's performance and robustness can be enhanced.

Implementing this algorithm in a real-time system, such as a vehicle or driver assistance system, can contribute to improving road safety by proactively identifying and addressing driver drowsiness. However, further research and development are necessary to optimize the algorithm's performance under various driving conditions and to consider factors such as individual differences in drowsiness patterns.

Overall, the application of deep learning in driver's drowsiness detection holds significant potential in reducing accidents caused by driver fatigue and improving overall road safety. Continued advancements in this field can contribute to creating safer driving environments and preventing potential tragedies on the road.

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