International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

REAL TIME DROWSINESS DETECTION ALGORITHM WITH INDIVIDUAL DIFFERENCE CONSIDERATION

Manjula K[1], Vyshnavi L[2]

[1]Assistant Professor, Department of Electronics and Communication engineering, S J C Institute of Technology Chickballapur, India, manjulak@sjcit.ac.in

[2]UG Student, Department of Electronics and Communication engineering S J C Institute of Technology Chickballapur, India, vyshnavilokesh362@gmail.com

ABSTRACT –

Developing an algorithm that can detect drowsiness in real-time while considering individual differences. Drowsiness detection is crucial for ensuring the safety of individuals, especially in situations like driving or operating heavy machinery. The algorithm takes into account the fact that different people exhibit drowsiness in various ways. It considers individual characteristics such as eye movement patterns, facial expressions, and physiological signals to accurately identify signs of drowsiness. By incorporating individual differences, the algorithm can provide personalized and more accurate drowsiness detection. This can help prevent accidents and improve overall safety. The real-time aspect of the algorithm ensures that drowsiness can be detected and alerted promptly, allowing individuals to take necessary actions to prevent accidents or mitigate the effects of drowsiness.

Keywords - Drowsiness detection, Eye blinking patterns, Driver alertness, Yawning detection, Head falling detection, Road safety.

INTRODUCTION

Drowsy driving can have a big impact on how well we drive and overall safety on the road. According to statistics, the main causes of drowsy driving are when drivers become less alert and attentive. One of the most effective ways to detect drowsiness is by using a combination of deep learning and computer-vision algorithms. These algorithms can analyze visual data and learn complex patterns to create robust and accurate drowsiness detection systems. Focusing on drowsiness detection based on eye-blinking patterns. By analyzing how our eyes blink, we can identify signs of drowsiness. Deep learning algorithms have proven to be powerful tools for this task because they can automatically learn from the data we provide and extract important features. This helps us create reliable drowsiness detection systems that can keep us safe on the road.

There are various possible applications for classifying eye conditions, such as detecting tiredness or evaluating psychological conditions. Many studies have already been published in this field, using different neural network algorithms and achieving good results. In real-time applications, convolutional neural networks (CNNs) are commonly used to achieve high accuracy and speed.[2]

However, detecting drowsiness at an early stage is crucial for preventing accidents. To automate drowsiness detection, we can leverage the power of artificial intelligence (AI). AI allows us to assess more cases in less time and at a lower cost. In this paper, we propose a CNN model for categorizing the state of the eyes, using modern techniques in deep learning (DL) and digital image processing (DIP). We tested our model on three different CNN architectures: VGG16, VGG19, and 4D.

Most vehicle accidents occur because drivers become drowsy while driving. To prevent accidents caused by drowsiness, there are ongoing studies that propose different methods to detect drowsiness in drivers before it's too late. There are mainly four measures for drowsiness detection. One measure involves analyzing the vehicle, specifically the steering wheel angle and lane deviation. Another measure involves analyzing bio-signals like electrocardiography (ECG), electroencephalography (EEG), and electrooculogram (EOG). While bio-signals provide accurate results, they can be invasive for drivers. The third measure focuses on image analysis, specifically examining the eyes, mouth, and head position. This measure is widely used because it is non-invasive and doesn't cause any discomfort to the driver.

Fig. 1: Detection of Drowsiness [6].

LITERATURE SURVEY

Real-Time Deep Learning-Based Drowsiness Detection:
Leveraging Computer-Vision and Eye-Blink Analyses for
Enhanced Road Safety

Authors: Furkat Safarov, Farkhod Akhmedov, Akmalbek Bobomirzaevich Abdusalomov, Rashid Nasimov and Young Im Cho.

Abstract: This paper explains how they collected custom data for training their model and presents the results obtained for different participants. They used landmarks to track the blinking of the eyes and mouth region. Computer vision techniques were employed to analyze the rate of eye blinking and changes in mouth shape in real-time. The experimental analysis demonstrated a correlation between yawning and closed eyes, indicating drowsiness. The overall performance of the drowsiness detection model was 95.8% accuracy for detecting drowsy eyes, 97% for detecting open eyes, 0.84% for yawning detection, 0.98% for right-sided falling, and 100% for left-sided falling. Additionally, their proposed method enabled real-time analysis of eye rates and classified them into two states: "Open" and "Closed" based on a threshold.[1].

4D: A Real-Time Driver Drowsiness Detector Using
Deep Learning

Authors: Israt Jahan, K. M. Aslam Uddin, Saydul Akbar Murad, M. Saef Ullah Miah, Tanvir Zaman Khan, Mehedi Masud, Sultan Aljahdali and Anupam Kumar Bairagi.

Abstract: This paper describe the process of developing a comprehensive drowsiness detection system. This system

predicts the condition of a driver's eyes to assess their level of drowsiness and issues alerts to prevent potential risks to road safety.[2]

A CNN-Based Approach for Driver Drowsiness Detection
by Real-Time Eye State Identification.

Authors: Ruben Florez, Facundo Palomino-Quispe, Roger
Jesus Coaquira-Castillo, Julio Cesar Herrera-Levano,
Thuanne Paixão and Ana Beatriz Alvarez.

Abstract: This paper discuss a method for detecting drowsiness in drivers, with a specific focus on the eye region. Eye fatigue is often one of the initial signs of drowsiness. They used Mediapipe, a highly accurate and robust tool, to extract the eye region. Three deep learning neural networks, namely InceptionV3, VGG16, and ResNet50V2, were evaluated. The NITYMED database, consisting of videos of drivers exhibiting varying levels of drowsiness, was used for analysis. The performance of these networks in terms of accuracy, precision, and recall for detecting drowsiness in the eye region was assessed. The study revealed that all three convolutional neural networks achieved high accuracy in detecting drowsiness in the eye region. Notably, the ResNet50V2 network demonstrated the highest accuracy, averaging at a rate of 99.71%. To better understand the algorithms' classification process, the Grad-CAM technique was employed for enhanced data visualization.[3]

Real-Time Machine Learning-Based Driver Drowsiness
Detection Using Visual Features

Authors: Yaman Albadawi, Aneesa AlRedhaei and Maen Takruri.

Abstract: The system we developed utilizes facial landmarks and face mesh detectors to pinpoint specific areas of interest. From these areas, we extract features such as mouth aspect ratio, eye aspect ratio, and head pose. These features are then inputted into three different classifiers: random forest, sequential neural network, and linear support vector machine classifiers. Through evaluations conducted on the driver drowsiness detection dataset from National Tsing Hua University, our system has demonstrated the ability to accurately detect and alert drowsy drivers, achieving an impressive accuracy rate of up to 99%.[4]

TECHNOLOGIES USED IN HEALTHCARE

Facial Landmark Detection: Facial landmark detection is a technology used in drowsiness detection systems to track and analyze specific points on a person's face. These points, known as landmarks, correspond to key facial features such as the eyes, eyebrows, nose, and mouth. By accurately detecting and tracking these landmarks in real-time, the system can monitor changes in facial expressions and movements that indicate drowsiness. For drowsiness detection, facial landmark detection algorithms can track the movement of the eyes, including the blinking rate and duration of eye closure. By analyzing these eye-related

landmarks, the system can identify signs of drowsiness, such as prolonged eye closure or a decrease in the frequency of blinking. Facial landmark detection is a crucial component in drowsiness detection algorithms as it provides valuable information about the driver's facial expressions and eye movements. This technology enables the system to accurately assess the driver's level of drowsiness and issue timely alerts to prevent potential accidents on the road.

Eye Aspect Ratio (EAR): Eye Aspect Ratio (EAR) is a metric used in drowsiness detection algorithms to assess the level of eye openness or closure. It is calculated based on the relative positions of specific facial landmarks around the eyes. To calculate the EAR, the algorithm measures the distances between landmarks such as the inner and outer corners of the eyes and the top and bottom points of the eye. By comparing these distances, the algorithm can determine the ratio of eye opening. In a drowsiness detection system, a lower EAR value indicates a higher likelihood of drowsiness or eye closure. As the eyes become more closed, the EAR value decreases. By continuously monitoring the EAR in real-time, the system can detect when the eyes are getting drowsy or closing for an extended period, prompting alerts or interventions to prevent accidents. The Eye Aspect Ratio is a useful and widely used feature in drowsiness detection systems as it provides a quantitative measure of eye openness, allowing for accurate and timely detection of drowsiness based on eye movements.

Support Vector Machines (SVM): Support Vector Machines (SVM) is a machine learning algorithm commonly used in drowsiness detection systems. It is a supervised learning algorithm that can classify data into different categories based on labeled training examples. In the context of drowsiness detection, SVM can be trained using features extracted from data such as eye movements, facial expressions, or physiological signals. These features are used to create a model that can distinguish between drowsy and alert states. During real-time drowsiness detection, the SVM algorithm takes in the extracted features as input and predicts whether the individual is drowsy or not.

The algorithm uses a decision boundary to separate the two classes, and new data points are classified based on their position relative to this boundary. SVM is a popular choice for drowsiness detection because it can handle high-dimensional feature spaces and is effective in dealing with complex decision boundaries. It can generalize well to unseen data and provide accurate predictions. By using SVM in drowsiness detection systems, it becomes possible to analyze and classify data in real-time, allowing for timely alerts or interventions to prevent accidents caused by drowsy individuals.

Convolutional Neural Networks (CNNs): They are a type of deep learning algorithm specifically designed for image and pattern recognition tasks. In the context of drowsiness detection, CNNs can analyze images or video frames of a person's face to identify patterns and features related to drowsiness. The network consists of multiple layers, including convolutional layers that perform feature extraction and pooling layers that reduce the dimensions of the extracted features.

During training, the CNN learns to recognize specific patterns associated with drowsiness. This is done by presenting the network with a large dataset of labeled images or video frames, where the labels indicate whether the person is drowsy or not. The network adjusts its internal parameters to minimize the difference between its predictions and the true labels. Once trained, the CNN can be used in real-time drowsiness detection by feeding it with new images or video frames. The network analyzes the input and produces a prediction indicating the likelihood of drowsiness. CNNs are effective in drowsiness detection because they can automatically learn and extract relevant features from images or video frames without the need for manual feature engineering. This makes them highly adaptable and capable of capturing complex patterns associated with drowsiness. Using CNNs in drowsiness detection systems allows for accurate and efficient monitoring of drowsiness levels, enabling timely interventions to prevent accidents on the road.

Electroencephalography (EEG): Electroencephalography (EEG) is a technique used for drowsiness detection! It involves measuring the electrical activity of the brain using electrodes placed on the scalp. During drowsiness, the brain's electrical activity exhibits specific patterns that can be captured by EEG. These patterns, such as alpha and theta waves, can indicate the level of alertness or drowsiness of an individual. In drowsiness detection systems, EEG signals are recorded and processed to extract features that are indicative of drowsiness. These features can include power spectral density, coherence, or other statistical measures derived from the EEG data. Machine learning algorithms, such as Support Vector Machines (SVM) or Artificial Neural Networks (ANN), can be trained using these extracted features to classify the level of drowsiness. The trained model can then be used to analyze real-time EEG signals and determine the drowsiness level of an individual. By using EEG in drowsiness detection, it becomes possible to directly measure the brain's activity and identify the physiological markers of drowsiness. This allows for more accurate and objective assessment of drowsiness, leading to improved safety measures and interventions to prevent accidents caused by drowsy individuals.

WHY CNNs IN DROWSINESS DETECTION?

CNNs are particularly effective in image recognition tasks because they can automatically learn and extract relevant features from images without the need for manual feature engineering. This makes them highly adaptable and capable of capturing complex patterns and relationships within the data.

Automatic Feature Extraction: Unlike traditional methods that rely on hand-crafted features, CNNs can automatically learn relevant features for drowsiness detection directly from the input images or video frames. This is crucial as drowsiness manifests differently in individuals (blinking patterns, head tilt variations). CNNs can capture these subtleties through the learning process.

Superior Pattern Recognition: CNNs excel at recognizing complex patterns in image data. This allows them to identify subtle changes in facial features, like drooping eyelids or minor head tilts, which might be missed by simpler algorithms. This is particularly important for drowsiness detection as individuals might exhibit varying degrees of these signs.

Adaptability to Individual Differences: By training a CNN on a diverse dataset that includes examples from people with different facial features and blinking patterns, the network can learn to generalize and become more accurate in detecting drowsiness across a wider population.

BLOCK DIAGRAM

- **Pre-processing:** The video or image data undergoes initial processing like noise reduction and scaling for better CNN performance.
- **Calibration (Optional):** In this step, the system might collect data from the user during alert and drowsy states. This data can be used to train a personalized CNN model that considers the user's specific blinking patterns or head movements.

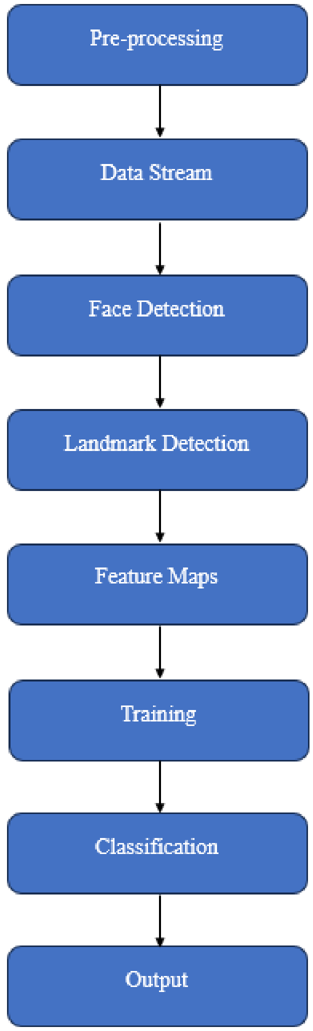

Fig. 1: Block diagram

- **Data Stream:** The real-time video or image data is fed into the system.
- **Face Detection:** The system identifies a human face within the frame.
- **Landmark Detection:** Facial landmarks like eyes, eyebrows, mouth, and nose are pinpointed using FLD.
- **Feature Maps:** Based on the landmarks, relevant features like eye aspect ratio and head pose are extracted and converted into feature maps suitable for CNN processing.
- **Training (Optional):** If calibration was done, the user's data is used to train a CNN model specifically for that user.
- **Classification:** The CNN analyses the feature maps and classifies the user's state as drowsy or alert based on the learned patterns.
- **Output:** The system generates an output based on the classification. This could be an alert signal or a warning message if drowsiness is detected.

APPLICATIONS

Transportation: This is a primary application. In-vehicle systems can monitor driver alertness and trigger warnings (vibrations, audio alerts) when drowsiness is detected. Personalized thresholds based on individual blinking patterns or head movements can improve accuracy.

Long haul truck drivers are particularly susceptible to fatigue. Real-time monitoring can ensure driver safety and prevent accidents.

Public Safety: These systems can be used in professions like construction, mining, or operating heavy machinery, where fatigue can lead to serious accidents. Personalized drowsiness detection can provide additional safety measures.

Aviation: Real-time drowsiness detection can be integrated into cockpits to monitor pilot alertness during long flights, potentially preventing pilot fatigue-related incidents.

Healthcare and Wellness: These devices can track sleep patterns and alert users if they experience excessive drowsiness during the day. Personalized detection can account for individual sleep needs and blinking habits. Drowsiness can be a precursor to epileptic seizures. These algorithms can be used to develop wearable devices that monitor drowsiness and potentially warn users of impending seizures.

General Applications:

Educational Settings: These systems can be used to monitor student alertness in classrooms, particularly during long lectures. Personalized detection can account for individual blinking patterns and attention spans.

Work from Home Monitoring: For desk jobs with long computer screen time, drowsiness detection systems can prompt users to take breaks and prevent fatigue-related productivity loss.

CONCLUSION

A real-time drowsiness detection algorithm that considers individual differences is crucial for accurate and personalized drowsiness detection. By taking into account factors such as age, sleep patterns, and individual variations in brain activity, the algorithm can provide more precise and tailored results. This type of algorithm utilizes techniques like Electroencephalography (EEG) to measure the electrical activity of the brain and extract features indicative of drowsiness. Machine learning algorithms, such as Convolutional Neural Networks (CNNs), can then be trained to classify the level of drowsiness based on these features. Considering individual differences allows the algorithm to account for variations in brain activity and drowsiness patterns among different individuals. This leads to more accurate and reliable drowsiness detection, enhancing safety measures and preventing accidents caused by drowsy individuals. By continuously monitoring and analyzing real-time data, the algorithm can provide timely alerts or interventions when drowsiness is detected, helping individuals take necessary actions to stay awake and alert.

FUTURE SCOPE

Focusing on Increased Accuracy and Personalization:

- **Advanced Machine Learning Techniques:** Utilizing deeper learning architectures or exploring explainable AI (XAI) can lead to more accurate drowsiness classification and a better understanding of the system's decision-making process.

Expanding Applications and User Base:

- **Integration with Advanced Driver-Assistance Systems (ADAS):** Drowsiness detection can be seamlessly integrated with ADAS features like lane departure warnings or automatic emergency braking for a more comprehensive safety approach.
- **Accessibility Features for Diverse Users:** The development of algorithms that consider variations in facial features due to ethnicity, age, or eyewear usage can broaden the user base.
- **Enhanced Physiological Signal Integration:** Incorporating biometrics like EEG (brainwaves) or blood pressure readings alongside facial recognition can provide even more personalized drowsiness detection.

REFERENCES

1. Furkat Safarov et al., "Real-Time Deep Learning-Based Drowsiness Detection:Leveraging Computer-Vision and Eye-Blink Analyses for Enhanced Road Safety" – volume 15, 17 July 2023.
2. Israt Jahan et al.," 4D: A Real-Time Driver Drowsiness Detector Using Deep Learning" – 3 January 2023.
3. Ruben Florez et al.," A CNN-Based Approach for Driver Drowsiness Detection by Real-Time Eye State Identification" – 4 July 2023.
4. Yaman Albadawi et al.," Real-Time Machine Learning-Based Driver Drowsiness Detection Using Visual Features" – volume 11, 29 April 2023.
5. https://images.app.goo.gl/yBNWbaoWsXZesgoq7 accessed on 29 April 2024.
6. Weng, C.H et al., "Driver drowsiness detection via a hierarchical temporal deep belief network",Vol.20–24 November 2016;
7. Abtahi, S et al., "A yawning detection dataset",19 March 2014, pp. 24–28.

8. Fusek, R, “Pupil localization using geodesic distance”, Vol.11241, pp. 433–444.
9. Ghoddoosian et al., “A realistic dataset and baseline temporal model for early drowsiness detection”, 16–20 June 2019.
10. Petrellis, N et al., “Software Acceleration of the Deformable Shape Tracking Application”,19–21 November 2021; pp. 51–57.