Drowsiness Detection System Using Image Analysis

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Abstract - Drowsiness while driving continues to be one of the main causes of severe road accidents and fatalities around the world. While traditional drowsiness detection systems that rely on physiological sensors are highly accurate, they tend to be invasive and not practical for regular use in vehicles. In this paper, we introduce a non-intrusive, image-based detection system that uses facial analysis to assess a driver's level of alertness. By analyzing facial landmarks, the system calculates the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), which are strong indicators of eye closure and yawning, respectively. OpenCV and Dlib libraries are used to detect facial landmarks in real-time, and a Convolutional Neural Network (CNN) model is trained using annotated datasets from Kaggle and Roboflow. Our experiments show that while static image analysis has limitations due to changing environmental conditions, it holds significant promise for enhancing road safety through real-time monitoring. Future improvements will focus on making the system more robust and adaptable in real-world settings by incorporating dynamic tracking and IoT integration.

Key Words: Drowsiness Detection, Eye Aspect Ratio, Mouth Aspect Ratio, Image Analysis, OpenCV, CNN, Facial Landmarks.

1.INTRODUCTION

Driver drowsiness is a serious concern for road safety, responsible for thousands of accidents and fatalities every year. The World Health Organization (WHO) has equated the risks of drowsy driving with those of driving under the influence of alcohol, emphasizing the urgent need for early detection and preventive systems. Although EEG and ECG sensors can provide accurate measurements of fatigue by monitoring brain and heart activity, their intrusive nature makes them unsuitable for daily vehicle use. With recent advances in computer vision and machine learning, we now have alternative, non-invasive options for monitoring a driver's alertness in real time. This research focuses on detecting fatigue by analyzing facial features—especially the eyes and mouth—through static images. The method relies on calculating the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) using facial landmarks. We use open-source tools like OpenCV and Dlib for detection, combined with datasets labeled with facial expressions. This paper presents an efficient way to detect early signs of drowsiness in a way that is practical, low-cost, and easy to integrate into vehicles.

1.1 Problem Statement

Despite the progress in fatigue detection, existing solutions often face significant limitations: Intrusiveness: Physiological sensors are uncomfortable and not practical for long-term use. Complexity: Real-time video analysis requires significant computing resources, which makes it unsuitable for devices with limited processing power. Accuracy Issues: Uncontrolled conditions like poor lighting, face obstructions, and movement can lead to inaccurate results. To address these issues, we propose a system based on static images that calculates EAR and MAR using facial landmarks. This approach provides a good balance between accuracy and simplicity, making it suitable for affordable and scalable driver monitoring systems.

1.2 Objectives

This research aims to: Develop a non-invasive, image-based system for detecting drowsiness using facial features. Use labeled datasets to extract key features like EAR and MAR. Build and train a CNN-based model to classify images as either "Drowsy" or "Alert." Test the system's performance under static conditions and assess its limitations in real-world scenarios.

2. Literature Review

Driver fatigue detection methods generally fall into three categories: physiological monitoring, behavioral analysis, and image-based detection. Early systems primarily used EEG and ECG signals to monitor brain waves and heart rate, offering precise fatigue indicators [1]. However, these methods are invasive and not ideal for everyday use. Behavioral methods such as monitoring head position, steering patterns, and driving habits have also been explored. Unfortunately, these approaches tend to lack accuracy and consistency across different users. A major breakthrough came from Soukupova and Cech [2], who introduced the Eye Aspect Ratio (EAR) as a reliable way to detect blinks in real-time using facial landmarks. Following this, several researchers have used CNN models to analyze video frames for signs of eye closure and yawning. These systems showed high accuracy, particularly in well-lit conditions with clearly visible faces. Datasets from platforms like Roboflow and Kaggle [3], [6] have made it easier to train models by providing well-annotated images of various facial expressions and states. While video-based methods offer more data, static image classifiers are more lightweight and easier to deploy. Challenges like low lighting, facial obstructions, and varying head poses still remain.

2.1 Data Collection and Annotation

We used facial image datasets from Kaggle's "Driver Drowsiness Detection" repository [6]. These include both drowsy and alert states of individuals. Roboflow was used for annotation, allowing us to label regions of interest such as the eyes and mouth efficiently [3].

2.2 Feature Selection

- Proper selection of features enhances model accuracy. Important attributes are:
- Area: The larger the property, the more costly it is likely to be.
- Number of Bedrooms and Bathrooms: The greater the number of rooms, the higher the cost.
- Amenities: If the property is close to a school, hospital, or public transport, value increases.

2.3 Feature Extraction

We employed Dlib's 68-point facial landmark detection to map the key parts of the face. From these landmarks, we calculated two main features: EAR and MAR. Eye Aspect Ratio (EAR): EAR=2×∣∣p1−p4∣∣∣∣p2−p6∣∣+∣∣p3−p5∣∣ Where: p1 to p6 are the coordinates of specific eye landmarks. A lower EAR value indicates eye closure. Mouth Aspect Ratio (MAR): MAR=∣∣p60−p64∣∣∣∣p61−p67∣∣ Where: p60 to p67 are the coordinates of mouth landmarks. A higher MAR value is typically associated with yawning or open-mouth expressions.

2.4 Model Design

We developed a CNN model to classify facial images as either "Drowsy" or "Alert." The network consisted of several convolutional layers, followed by max-pooling and dense layers, ending with a sigmoid output layer for binary classification. The dataset was split into 80% for training and 20% for testing.

2.5 Model Evaluation

We evaluated the model based on:

- Accuracy: Overall correctness of predictions.
- Precision/Recall: Specificity and sensitivity in distinguishing drowsy vs. alert images.
- EAR and MAR Thresholds: Used as indicators of fatigue in the test images.

3. Results and Discussion

Our model achieved an overall accuracy of about 92% on the test dataset. Key findings include: EAR values below 0.25 typically indicated closed eyes. MAR values above 0.75 suggested yawning or open-mouth expressions. When both EAR was low and MAR was high, it strongly correlated with a drowsy state. Table 1: EAR and MAR Threshold Analysis Image State Avg. EAR Avg. MAR Classification Alert 0.30 0.55 Alert Drowsy 0.18 0.82 Drowsy Although the model performed well, about 8% of images were misclassified due to issues like poor lighting or facial obstructions. Still, the results confirm that static images can be a useful tool for detecting drowsiness under controlled conditions.

Our findings validate that facial landmarks, particularly EAR and MAR, are effective indicators of driver fatigue. This method is more scalable, affordable, and user-friendly than traditional physiological systems. That said, using static images has its limitations: It can't track blinking frequency or prolonged yawning. Environmental factors like lighting and face orientation affect performance. The dataset had more "Alert" images than "Drowsy" ones, which may impact generalization. Despite these limitations, the approach provides a strong starting point for future systems aimed at improving road safety using AI and computer vision.

4. Conclusion Future Scope

In this paper, we introduced a facial landmark-based system for detecting driver drowsiness using static images. By calculating EAR and MAR, we could accurately classify driver alertness with minimal computational resources, making it suitable for real-time applications on embedded devices. Future enhancements will include: Adding real-time video analysis for better tracking of blinking and yawning. Expanding the dataset to include varied lighting conditions, demographics, and head angles. Deploying the system on IoT devices like Raspberry Pi for practical, on-road use. Combining facial analysis with other data sources such as speech patterns or steering behavior for more comprehensive fatigue detection.

5. References

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