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DRIVER DROWSINESS DETECTION USING PYTHON AND MACHINE LEARNING

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Abstract - This work presents a new driver drowsiness detection system implemented with Python and machine learning (ML) methods for improved road safety. The system makes use of the eye aspect ratio (EAR) as the major measure to detect drowsiness, supplemented by yawn detection (through mouth aspect ratio, MAR) and eye focus monitoring (through gaze tracking and blink frequency analysis). The method uses real-time video processing with OpenCV, dlib-based facial landmark detection, and an SVM-trained ML classifier based on extracted features. Experimental testing with 20 volunteer drivers under different conditions (daylight, nighttime, and simulated drowsiness) resulted in a 92% accuracy of drowsy state detection with a false positive rate minimized by 15% through multi-feature integration. The findings highlight the potential for real-world deployment of the system, though areas of improvement include low-light performance (85% accuracy) and computational loads. The research makes a scalable, cost- effective contribution to the field of intelligent transportation, with future improvements suggested in the form of larger data sets and hardware integration.

***Key Words*:** driver safety, drowsiness detection, machine learning, eye aspect ratio, Python, real-time monitoring.

1. INTRODUCTION

A. Background Information

Driver fatigue continues to be a major global issue, responsible for about 20% of road crashes and causing more than 1.2 million deaths every year, according to the World Health Organization's report of 2024.
Conventional countermeasures, including drinking coffee or taking rest stops, prove to be insufficient because there is a lack of early perception of fatigue. The latest advances in computer vision and machine learning have made it possible to create automatic systems to identify drowsiness in real-time, providing a proactive solution to preventing accidents. These systems are often based on non-intrusive means, such as observing facial features or driving behavior,that can be easily adopted in most vehicles.

B. Research Problem or Question

The main challenge tackled in this research is the creation of a robust, non-intrusive drowsiness detection system with the help of available programming platforms (Python) and ML algorithms. The questions are: Can a multi-metric system incorporating EAR, yawn detection, and eye focus monitoring outperform single- metric systems? How can the system generalize across different environmental conditions (e.g., lighting, occlusions) and driver profiles (e.g., age, ethnicity)? These questions necessitate a strong, generalizable solution.

C. Significance of the Research

The value of this study is that it has the potential to decrease traffic accidents by offering a low-cost, real- time drowsiness detection system. Implementing such a system in cars could save lives, reduce insurance premiums, and enable the development of intelligent transportation systems. Moreover, the open-source implementation using Python promotes further innovation and accessibility for developers and researchers globally.

LITERATURE REVIEW

Overview of Relevant Literature

There has been intensive research on detecting drowsiness, with methodologies varying from analysis of physiological signals (e.g., electroencephalography, EEG) to computer vision methods. Soukupová and Čech (2016) set the precedent in using EAR to detect eye blink in real time, laying a basis for assessing drowsiness. Viola and Jones (2001) proposed a boosted cascade classifier to detect facial features at high speeds, which was used extensively in later systems. Later research has also investigated multi-modal methods, merging visual information with steering or heart rate variability, but these tend to necessitate specialized equipment.

D. Key Theories or Concepts

The conceptual framework of this research is founded on a number of major concepts:

- Eye Aspect Ratio (EAR): The ratio of vertical eye landmark distance to horizontal distance, with smaller values below a certain threshold (e.g., 0.25) suggesting closed eyes.
- Mouth Aspect Ratio (MAR): Computed likewise for the mouth, utilized for the detection of yawning as a secondary drowsiness sign.
- Gaze Tracking: Examines patterns of eye movement to measure driver attention and concentration.
- Machine Learning Classification: Uses algorithms such as SVM to categorize drowsy vs. alert states from feature inputs.

2. METHODOLOGY

A. Research Design

This research employs an experimental research design, with the creation and iterative testing of a real- time drowsiness detection system. The design focuses on a software-based approach using Python, with controlled experiments to test performance metrics like accuracy and false positive rates.

B. Data Collection Methods

Data was gathered from 20 volunteer drivers between the ages of 20-50, with diverse ethnic backgrounds. A standard webcam captured video under two conditions: daylight (natural light) and nighttime (low-light with artificial lighting). Drivers were asked to mimic alert and drowsy conditions (e.g., by sleep deprivation or extended driving), with annotations by an observer for ground truth labeling. Sessions were 30 minutes long, resulting in about 10 hours of video data.

C. Sample Selection

The sample was purposefully drawn to comprise a variety of genders, ages and ethnicities to guarantee the system's generalizability. The inclusion criteria demanded that participants possess a valid driver's license and no previous history of extreme sleep disorders. The sample size, although limited, was adequate for initial testing, with intentions to expand in subsequent studies.

D. Data Analysis Techniques

Data analysis comprised a few steps:

- Facial Landmark Detection: The 68 facial landmark predictors from the dlib library was utilized to detect eyes, mouth, and other features in every video frame.
- Feature Extraction: EAR was calculated as eye height to width ratio, MAR as mouth height to width ratio, and gaze direction was monitored with the help of coordinate shifts.
- ML Model Training: The model was trained with an SVM classifier on 5,000 labeled frames (drowsy, alert), features normalized via z- scores.
- Performance Evaluation: Accuracy, precision, recall, and confusion matrices were computed to measure the performance of the model.

3. RESULTS

A. Presentation of Findings

The system proved 92% accurate for state detection drowsy over the test dataset, with EAR thresholds (for example, <0.25 for 3 successive frames) correctly detecting eye closures in 88% of instances. Yawn detection using MAR was 85% accurate and eye focus monitoring minimized false positives as it correctly identified 15% of misclassified alert states.
A test confusion matrix had 450 true positives, 40 false positives, 30 false negatives, and 480 true negatives out of 1,000 test frames.

B. Data Analysis and Interpretation

Statistical analysis of correlation between EAR values and subject-reported fatigue indicated a high correspondence (r =0.89), substantiating its utilization as a core indicator. Combined and MAR attention metrics enhanced reliability in general, with a composite feature model enhancing accuracy over EAR-only models by 12%. Nighttime performance fell to 85% when landmark visibility fell to decreased, indicating one of the most significant limitations.

C. Support for Research Question or Hypothesis

The outcome confirms the hypothesis that multi-feature ML can provide better drowsiness detection accuracy. The adaptability of the system to various conditions and the minimization of false positives correspond to the research question, although low-light conditions require further optimization.

4. DISCUSSION

A. Interpretation of Results

The 92% accuracy suggests a strong basis for real-world deployment, with the multi-feature method offering a more comprehensive drowsiness evaluation than single- metric systems. The 85% nighttime performance implies that illumination conditions have a significant effect on feature extraction, requiring sophisticated preprocessing methods.

B. Comparison with Existing Literature

In comparison to Soukupová and Čech's EAR-based system (80% accuracy), the multi-feature design of this study provides a 12% improvement. It is, however, behind EEG-based systems (95% accuracy) in terms of precision, although it does not have the intrusiveness of wearable sensors. The emphasis on Python and open- source tools also increases accessibility over proprietary solutions.

C. Implications and Limitations of the Study

The system's implications involve possible commercial implementation in cars, with substantial safety advantages. Limitations involve the computational requirement (need for a mid-range processor for real- time computation) and the small sample size, which could be non-representative of global driver populations. These should be addressed in future work with hardware optimization and larger data sets.

5. CONCLUSION

A. Summary of Key Findings

This study designed a Python-based drowsiness detection system with 92% accuracy using EAR, MAR, and eye focus tracking. The system successfully detected drowsy conditions under varied conditions, albeit with varying performance under lighting.

B. Contributions to the Field

The research adds a scalable, multi-feature ML solution to drowsiness detection, providing a cost- competitive solution compared to alternatives and facili tating the development of intelligent transportation systems.

C. Recommendations for Future Research

Future work should include real world verification with larger, more diverse datasets, tuning the system for low-light environments, and integrating it with vehicle hardware (e.g., dashboard cameras) for easy deployment.

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