A Implementation on Deep Learning Techniques for Detecting Driver Fatigue

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Abstract - Driver fatigue is a significant contributor to road accidents worldwide. This paper introduces a smart and reliable method for detecting driver drowsiness through a combination of eye blink rate and yawning analysis. The system captures the driver's facial expressions using a camera positioned within the vehicle. Initially, the driver's face is detected and monitored using advanced image processing algorithms. Subsequently, the regions around the eyes and mouth are isolated for further analysis to identify signs of sleepiness. These indicators are then integrated in a decision-making module to assess the driver's alertness level. If drowsiness is confirmed, an alert is triggered to notify the driver. Experimental evaluations demonstrate that the proposed system performs effectively in real-time scenarios.

Key Words: Driver monitoring, drowsiness detection, image processing, face analysis, fatigue recognition, alert system.

1. INTRODUCTION

Drowsiness poses a serious threat to road safety, as it impairs a driver's focus, delays reaction times, and reduces vehicle control. It is a transitional state between full alertness and sleep, during which the likelihood of accidents increases significantly. Studies have shown that fatigue contributes to approximately 12% of traffic accidents and 10% of near-accidents, with drowsy drivers being nearly four times more likely to be involved in such incidents. In fact, fatigue-related behaviors have been implicated in 22% to 24% of crash and near-crash events. These statistics highlight the urgent need for intelligent driver monitoring systems that can detect signs of

fatigue and promptly issue warnings to help prevent accidents.

In this study, we present a hybrid approach that improves the accuracy of drowsiness detection by combining eye closure and yawning analysis. The system utilizes visual cues from the driver's face, captured by a camera mounted in the vehicle. A key strength of the proposed method is its subject-independent design, making it suitable for integration into real-world commercial applications.

The remainder of this paper is structured as follows: Section II discusses related research in the field. Section III describes the proposed drowsiness detection framework in detail. In Section IV, experimental results demonstrate the effectiveness of our system in identifying fatigue symptoms. Finally, Section V concludes the paper with a summary and potential directions for future work.

2. LITERATURE SURVEY

In recent years, driver monitoring systems have gained significant attention for their potential to detect drowsiness and issue timely alerts to prevent road accidents. Various strategies have been explored to assess driver fatigue. One approach involves monitoring head posture to identify significant tilts that may indicate the driver is dozing off [3]; however, this signal often appears too late in the drowsiness cycle to be effective. Another technique on analyzing behavioral patterns comparing the driver's current response times with their baseline performance to detect abnormalities. While this method can be effective, it is highly dependent on individual driving styles and typically requires a training phase to adapt to each user [4, 5]. Speech-based detection is another possibility,



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analyzing voice patterns for signs of fatigue, but such systems are complex and not always reliable in a noisy vehicle environment [6].

Physiological monitoring methods also exist, using wearable sensors or embedded devices in the vehicle to measure biometric signals like heart rate or body posture [7]. While these systems can be accurate, they are often considered invasive and may lead to driver discomfort. A widely accepted and less intrusive alternative is facial feature monitoring through invehicle cameras. These systems track signs such as prolonged eye closure, yawning, and unusual head movements to assess the driver's state of alertness [8-10]. Some versions employ infrared or stereo cameras for enhanced accuracy in low-light conditions [11]. Although considerable progress has been made in this field, no universal standard currently exists for fatigue detection, and individual indicators may sometimes be unreliable.

To address these challenges, our proposed system leverages a fusion-based approach that combines multiple facial indicators—specifically eye closure and yawning—to improve detection accuracy. Our method is designed to be independent of both the driver and environmental conditions, increasing its practicality and reliability. Additionally, the system relies on lightweight image processing algorithms, ensuring suitability for real-time implementation in commercial vehicles.

3. PROPOSED SYSTEM

The proposed system for detecting driver drowsiness operates in four main stages to ensure accurate, real-time monitoring. The first stage involves detecting the driver's face within the input image using a facial detection algorithm. Once the face is successfully located, the system proceeds to identify key facial featuresspecifically the eyes and mouth—which are critical indicators of fatigue. By focusing on these regions, the system enhances detection accuracy, as the eve and mouth regions help cross-validate each other's status. In the third stage, the system analyzes these features for behavioral signs of drowsiness. Prolonged eye closure and yawning are the primary indicators used to assess the driver's state. These behaviors are carefully monitored and interpreted by the system to infer fatigue. In the final stage, a decision-making module integrates the analysis results to determine whether the driver is indeed drowsy. If drowsiness is detected, an alert or warning signal is issued to prompt the driver. To maintain continuous vigilance, the system also incorporates face-tracking techniques, allowing it to follow the driver's movements in subsequent video frames for ongoing assessment. Each component of the framework is interconnected, creating a cohesive and effective solution for enhancing driver safety through fatigue detection. Would you like a visual flowchart of this system?

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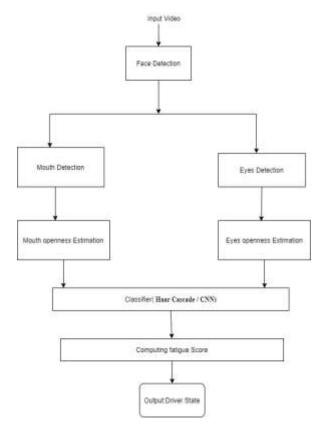


Figure 1. The proposed drowsiness detection system.

3.1. Face Detection

The goal of this step is to locate the driver's face in the frame, regardless of lighting, facial orientation, skin tone, or occlusions such as glasses or facial hair. A reliable face detection method must handle diverse appearances and conditions. Our system identifies skin-colored regions using specific thresholds in both **YCbCr** and **HSV** color spaces, similar to the method described in [15]:

1.5862	20
0.3448	76.2069
1.15	301.75
4.5652	234.5653
2.2857	432.85
25	

230 The first five rules apply to Cr and Cb values using logical AND, while the last two, based on the H channel, use logical OR. After identifying the skin region, we convert it into a binary format—white for detected skin and black for background. Morphological operations are then used to clean the result, and the largest, uppermost component is selected as the likely face. If this component fails later stages (e.g., eye or mouth not found), the system selects the next candidate component.

3.2 Eyes Detection

We detect the eye region using Structural Similarity Index Measure (SSIM), which evaluates similarity between image patches based on luminance, contrast, and structure, and is more aligned with the human visual system than traditional metrics like MSE or PSNR [19].

The SSIM is defined as:

 $SSIM(x, y) = \left[(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_x^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + \sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left[(\mu_x^2 + \mu_y^2 + c_2)(\sigma_y^2 + c_2) \right] / \left$ $+ c_2)$

Where:

- μ_x , μ_y : Means of images x and y
- σ_x , σ_y : Variances of x and y
- σ_{xy} : Covariance between x and y
- c₁ and c₂: Constants to stabilize the equation

We use this similarity metric alongside template matching to locate eyes, and confirm accuracy with an "eye map" technique as described in [16].

3.2.1 Eye Openness Detection

Once eyes are identified, their horizontal intensity projection is analyzed. A central peak in the projection indicates closed eyes. Vertical projections help align the detection, showing a distinct pattern with a central peak and flanking dips.

3. 3 Mouth Detection



Figure 3.1 Output

For mouth localization, we use a simplified method based on **YCbCr** color space, inspired by [16]. A "mouth map" computed, thresholded, and cleaned with morphological operations. largest The resulting component is assumed to be the mouth.

3.3.1 Yawn Detection or Mouth Openness Detection

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Figure 3.2: Output

Yawning is determined by calculating the mouth's aspect ratio—if it exceeds a predefined threshold(0.65), a yawn is detected. Additionally, we verify whether the mouth map contains internal holes, further confirming a yawn.

3.4. Decision-Making

Fusion can occur at different stages in recognition systems: during feature extraction, similarity scoring, or decision-making [18]. Our system applies fusion at the decision level. A drowsy state is determined under any of the following conditions:

- Simultaneous eye closure and yawning
- Continuous eye closure for more than 1 second
- Repeated yawning within a 1-second time frame

We define three levels of drowsiness:

- State 0 (Alert): Normal blinking and no yawning
- State 1 (Slightly Drowsy): Occasional yawns, increased blink frequency
- State 2 (Drowsy): Prolonged eye closure and frequent yawns

```
nt probablity of yawn:
take Uniii
    rent probablity of yawn: 53.14%
Make Up!!!
Current probablity of yawn: 52.71%
Length of yawnCounter: 63
   ke Uplii
   rrent probablity of yawn: 63.34%
ngth of yawnCounter: 63
        'yawn
      detected
Make Up!!!
    ment probablity of yawn: 56.89%
Make Up!!!
    ent probablity of yawn: 55.22%
```

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5. SYSTEM ARCHITECTURE

The architecture of the proposed system is designed to ensure efficiency, reliability, and user engagement. It consists of several components:

3.5. Face Tracking

To maintain consistent detection, we apply SSIM between the current frame and the previously identified face region. The most similar area is selected as the new face candidate. If eyes and mouth are correctly detected within it, this region becomes the updated face template. If not, a broader search area is scanned.

3.6. Experimental Evaluation

We tested our system on ten video sequences, each containing 10,000 frames, featuring different subjects, lighting setups, and angles. The videos were captured at 30 fps with resolutions of 480x640 and 320x568. Face detection achieved a 98% accuracy on the dataset [20]. After identifying the face, the system proceeded with eye and mouth extraction, and detected signs of drowsiness based on previously described algorithms. Sample outputs for eye and mouth detection are shown in Figures 6 and 3.2& 3.1.

Face tracking examples are provided in **Figure 8**, demonstrating how SSIM effectively identifies the matching face region with minimal computational cost.

Finally, the driver's drowsiness level is classified using both current and historical detection results for eye closure and yawning. An example scenario showing detection and classification is presented in **Figure 9**.

4. OBJECTIVES

The increasing number of traffic accidents due to a diminished driver's vigilance level has become a serious problem for society. Statistics show that 20 percent of all the traffic accidents are due to drivers with a diminished vigilance level. Furthermore, accidents related to driver hypo-vigilance are more serious than other types of accidents, since sleepy drivers often do not take correct action prior to a collision. For this reason, developing systems for monitoring driver's level of vigilance and alerting the driver, when he is drowsy and not paying adequate attention to the road, is essential to prevent accidents. The prevention of such accidents is a major focus of effort in the field of active safety research.

1. Data Acquisition

- Camera Module
 - Captures real-time video of the driver
 - o Positioned to get a clear view of the face

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2. Preprocessing

- Frame Extraction
 - o Converts video stream into image frames
- Grayscale Conversion
 - Converts images to grayscale (required for Haar detection)
- Noise Reduction
 - o Optional Gaussian blur or histogram equalization for clarity

3. Face, Eye & Mouth Detection (Haar Cascade)

- Haar Cascade Classifiers
 - Pre-trained XML files used for detecting:
 - Face
 - Eves
 - Mouth
- Extract **ROI** (**Region of Interest**) for eyes and mouth from the detected face region.

4. Feature Classification (CNN)

- CNN 1 Eye State Classifier
 - o Input: Cropped eye image
 - Output: Open / Closed eye classification
- CNN 2 Mouth State Classifier
 - o Input: Cropped mouth image
 - o Output: Yawning / Not Yawning classification

5. Fusion & Drowsiness Decision

- Combines predictions from CNNs:
 - If eyes are closed > 1.5 seconds, mark as drowsy
 - o If **yawning frequency is high**, mark as drowsy
 - o If **both** occur simultaneously → High confidence drowsiness
- Decision is based on frame history and time thresholds.



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6. Alert System

- Generates alert when drowsiness is detected
 - o Buzzer / Alarm Sound
 - Dashboard visual alert

7. Face Tracking (Optional)

- Tracks face using:
 - o Kalman Filter or
 - o Optical Flow or
 - Repeated Haar detection in consecutive frames

6. IMPLEMENTATION

- **Dataset Collection:** Gather images/videos of drivers in different conditions (day/night, various angles, lighting variations).
- Model Training: Train VGLG (VGG16-LGBM) with labeled drowsy and alert driver data. The Haar cascade classifier processes the image to locate the driver's face.
- **Performance Testing:** Measure accuracy, precision, recall, and F1-score.
- **Simulation & Deployment:** Test in real-time using simulators and in-vehicle systems.

7. RESULTS AND FUTURE SCOPE



Figure 8.1:



- The system improves detection by recognizing tired or sluggish facial expressions in drowsy drivers.
- If Moving the head up and down, often due to sleepiness. the head is a clear sign that a driver is feeling drowsy.
- This system aims to monitor the driver's facial condition and help prevent accidents.
- The driver fatigue is the major problem in today's world, because due to the downiness problem day by day accidents are increased. In the future work it further implemented with the help of Neural Network and other real time sensor devices. So that more accuracy is achieved.
- For school bus driver the system was very useful.

8. CONCLUSION

The increasing number of traffic accidents due to a diminished driver's vigilance level has become a serious problem for society. Statistics show that 20 percent of all the traffic accidents are due to drivers with a diminished vigilance level. Furthermore, accidents related to driver hypo-vigilance are more serious than other types of accidents, since sleepy drivers often do not take correct action prior to a collision. For this reason, developing systems for monitoring driver's level of vigilance and alerting the driver, when he is drowsy and not paying adequate attention to the road, is essential to prevent accidents. The prevention of such accidents is a major focus of effort in the field of active safety research. People in fatigue show some visual behaviors easily observable from changes in their facial features like eyes, head, mouth and face.

The driver fatigue detection is considered as one of the most prospective commercial applications of automatic facial expression recognition. Automatic recognition (or analysis) of facial expression consists of three levels of tasks: face detection, facial expression information extraction, and expression classification. In these tasks, the information extraction is the main issue for the feature based facial expression recognition from an image sequence. It involves detection, identification and tracking facial feature points under different illuminations, face orientations and facial expressions.

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