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+91 9940572462 +91 9940572462 ijarasem@gmail.com www.ijarasem.com

Drowsiness Detection System using Machine Learning

Shitij Chauhan[1], Dr. Elizabeth Jesi V.[2], Siddharth Rao[1], Aadit Maan Singh Walia[1]

Student, SRM Institute of Science and Technology, Chennai, India[1]

Associate Professor, SRM Institute of Science and Technology, Chennai, India[2]

ABSTRACT: Among the various causes of road accidents, driver drowsiness is a major one, and detection of this before the accident occurs will certainly enhance road safety to a significant extent. This paper proposes a system titled Driver Drowsiness Detection and Alert System employing real-time image processing and machine learning techniques by monitoring the eye movements of the driver. The system captures live video of the driver through a webcam and processes these frames to detect the indicators for drowsiness. It uses Haar Cascade classifiers to detect the face and eyes of the driver, then it calculates the Eye Aspect Ratio to check if the eyes are open or closed. If it observes long closures of the eyes, which might depict a sleepy scenario, it automatically sends a wake-up signal to wake the driver.The use of machine learning models with libraries like OpenCV for image processing, as well as NumPy for numerical computations enhances the ability of the system to recognize drowsiness patterns. However, several aspects influence its performance. Environmental factors such as changes in lighting conditions can easily reduce the system's accuracy of detections. Also, glasses can cause occlusions that prevent the eye's movement detection ability of the system. Real-time video processing also needs a high-performance system to avoid lags thus making its feasibility to low power devices even less. The dataset is also too small and biased resulting in the fact that the ability of the system to generalize from one driver to another, having different facial features, skin types, and drowsiness patterns, was not achieved. Despite all these limitations, the proposed system seems to be a good candidate for facilitating early detection of driver fatigue, which may enhance road safety. Further progress includes increasing the size and diversity of the dataset, enhancing the robustness of the system in different environments, and addressing issues regarding privacy, specifically those connected with intrusiveness of cameras unauthorized deletion of the Virtual Machines snapshots.

I. INTRODUCTION

This is a developing concern as drowsiness-related accidents are increasingly on the rise, and the demands of industries, particularly automotive and workplace settings, are increasing for more efficient drowsiness detection systems. Techniques used currently to monitor drowsiness are mainly physiological and behavioral, such as eyelid closures and head nodding. These methods often lack proper sensitivity when it comes to detecting when drowsiness began, especially in dynamic, time-varying conditions.

Yawning is a physiologically demonstrated, long-reported, and documented phenomenon of falling sleepiness; hence, it holds promise as an alternative for real-time detection. Yawning was reported in several studies to be a consistent indicator of drowsiness driven by both neurological and psychological causes. This paper focuses on making use of this behavior to better allow the development of more reliable and intuitive systems for the real- time detection of drowsiness.

In the paper a new system for drowsiness detection was proposed based on yawning detection applied in sophisticated computer vision and machine learning techniques. The system is taking video feed, continuously analyzing facial expressions to acquire a characteristic change which it associates with the sign of yawning. Advanced landmark-detection algorithms are employed by the system to track mouth and eye dynamics in its attempt to identify yawning patterns. Using such features determined by these algorithms, the system then went on to employ a machine learning classifier to classify whether a yawn existed or not.

The developed system aims at creating a highly effective real-time drowsiness detection solution that can be applied in automotive safety systems and in various industrial environments where alertness is critical. This approach enhances the accuracy level of drowsiness detection and improves the reliability of fatigued judgments and contributes to safer and more efficient operations.

II. LITERATURE REVIEW

1. Background

Drowsiness and fatigue are significant factors contributing to accidents and reduced performance invarious settings, including driving, industrial operations, and other critical tasks. Traditional drowsiness detection systems have relied heavily on monitoring physiological signals such as eye movement, blink rate, and head position. While these methods provide valuable information, they often face challenges related to environmental conditions, individual differences, and the need for intrusive sensors.

Yawning, a well-documented indicator of drowsiness, offers a potential solution to these limitations. It is a more overt and observable behaviour that occurs as a response to fatigue. Research indicates that yawning is a reliable physiological signal that can be detected through visual cues, making it a viable candidate for integration into automated drowsiness detection systems. However, accurately detecting yawning in real-time, especially under varying l i g h t i n g conditions and diverse subject demographics, remains a complex problem. Problem Formulation In the context of global supply chains, the management of carbon footprint presents a multifaceted challenge with far reaching implications for sustainability and environmental stewardship. To effectively address this issue, it is essential to clearly define the problem, specify objectives and constraints, and identify key variables and parameters relevant to carbon footprint measurement and reduction. The problem of managing carbon footprint in global supply chains revolves around minimizing the environmental impact associated with the transportation, production, and distribution of goods across interconnected networks. This involves quantifying the amount of greenhouse gas emissions, particularly carbon dioxide ($CO2$), generated throughout the supply chain lifecycle and implementing strategies to mitigate and offset these emissions. The primary objective of managing carbon footprint in global supply chains is to reduce the overall emissions associated with the movement and production of goods while maintaining or improving operational efficiency and profitability.

2. Objective Function

The primary objective of the drowsiness detection system is to develop a reliable and real-time mechanism for identifying fatigue through the detection of yawning. The specific goals of the system are as follows:

2.1 Accurate Yawning Detection : To design an algorithm capable of accurately identifying yawning from a real-time video feed. This involves distinguishing yawns from other facial expressions and movements with high precision. The objective is to achieve a high detection accuracy, minimizing false positives (incorrectly identifying yawning when the user is not tired) and false negatives (failing to detect yawning when the user is drowsy).
2.2 Real-Time Performance : To ensure that the system processes and analyzes the video feed in real-time, providing immediate feedback on the user's drowsiness level. This requires optimizing the computational efficiency of the yawning detection algorithm to work effectively on standard hardware and within varying environmental conditions.
2.3 Adaptability and Robustness : To develop a system that performs reliably under diverse conditions, including different lighting environments, facial orientations, and individual differences. The system should be robust enough to handle variations in facial features and expressions across different users.
2.4 User-Friendly Alerts : To create an alert mechanism that effectively communicates the detection of drowsiness to the user, prompting timely interventions. The alerts should be clear, non-intrusive, and actionable, helping the user take appropriate measures to address fatigue.
By achieving these objectives, the system aims to enhance safety and performance in settings where drowsiness is a critical concern, providing a practical and effective solution for fatigue detection and intervention

DIFFERENCING STATIONARY

Overview

Differencing is a technique used to transform a non- stationary time series dataset into a stationary one by removing trends and seasonality. A stationary dataset is essential for accurate time series modeling and forecasting.

Differencing Techniques

- First-Differencing
- Objective: The primary role of first-differencing is to eliminate the issue of the linear trend of a time series. A linear trend would be the consistent upward or downward movement in the value with respect to time. First-differencing tends to stabilize the mean of a time series so that future observations are not significantly affected by past trends. Formula:

- $\Delta Y\ t = Yt - Yt-1$

- Seasonal Differencing:
- Seasonal differencing primarily aims to eliminate any periodic seasonal effects or patterns that recur at fixed time intervals, such as annual or quarterly recurrence in a time series. It stabilizes the time series by removing systematic fluctuations, making it easier to model and forecast precisely.
- Formula :
- functions, and partial autocorrelation functions. Time series should be transformed if it presents identifiable trends or seasonal patterns.

- *Applying Differencing*
- Differencing is another widely applied transformation technique, in which the non-stationary time series is transformed into a stationary form. There are two major kinds of differencing used:
- First-Differencing: This sort of differencing is taken to remove the linear trends related to the data.

- $\Delta Yt = Yt - Yt{-}1$

- Seasonal Differencing: This seasonal differencing is applied to eliminate the recurring seasonal effects. The operation subtracts the value of the same period in the previous cycle:

- $\Delta s\ Yt = Yt - Yt{-}s$

  Example
- For example, suppose a series is month-to-month documented and exhibits both trend and annual seasonality. Then first differences would be applied to remove the trend and seasonal differencing with order=12 to eradicate the yearly seasonal effects.

- *Limitations*

Although differencing is effective in removing trends and seasonality, it has certain inherent limitations:
Information Loss: Differencing tends to lose some of the valuable information about the underlying patterns in the time series data. Important structural insights may be lost in the process, potentially making interpretation harder.

Over-Differencing: Too much differencing tends to induce an over- corrected series, which distorts the information originally meant to be corrected and thus affects the performance of the model negatively. It can introduce some noise into a series when over- differenced, and the series will be harder to predict accurately.

III. METHODOLOGY OF PROPOSED SURVEY

The Drowsiness and Yawn Detection System is a real-time facial analysis application that monitors and alerts the drowsiness or yawning condition of the users. This section discusses the development of the research methodology, from the first model design through the current implementation, focusing on increasing detection accuracy and improving functionality.

The previous model efforts and their deficiencies
In the initial phases of research, current drowsiness detection systems that exist have employed very basic algorithms that were based on simple facial recognition techniques. It did not consider variations across subjects and different conditions prevailing in the environment.

Limitations of previous static models: The earlier models were mostly deterministic, generalized, and aimed at drowsiness detection without considering the individual variations in facial features or external conditions such as lighting. For instance, these often failed to make proper detections in users with different facial structures and led to false negatives and positives.

In the initial implementation, procedural programming techniques were used and this led to scaling and adaptability issues. In a procedural programming technique, every feature would be calculated independently. Calculating variables or adapting it on user feedback would take a lot of time. There was a resultant lack of robustness and flexibility in the detection algorithm.

$\Delta\ sYt = Yt - Yt{-}s$

The actual drawback associated with the previous models was the real-time processing of images. This resulted in a delay in alerting for drowsiness or even yawning. The limitation makes the proposed system inefficient for practical use in critical cases like monitoring in driving or even for people who need to be alerted for instances of

It is of great importance to determine whether a data set is non-stationary or not in a time series analysis as most the forecasting models carry assumptions of stationarity by data. Such trends and seasonality or any other kind of structure contained in non-stationary data affect the performance of time series models.

Nonstationarity is determined either by statistical tests, such as the Augmented Dickey-Fuller (ADF) test, which checks

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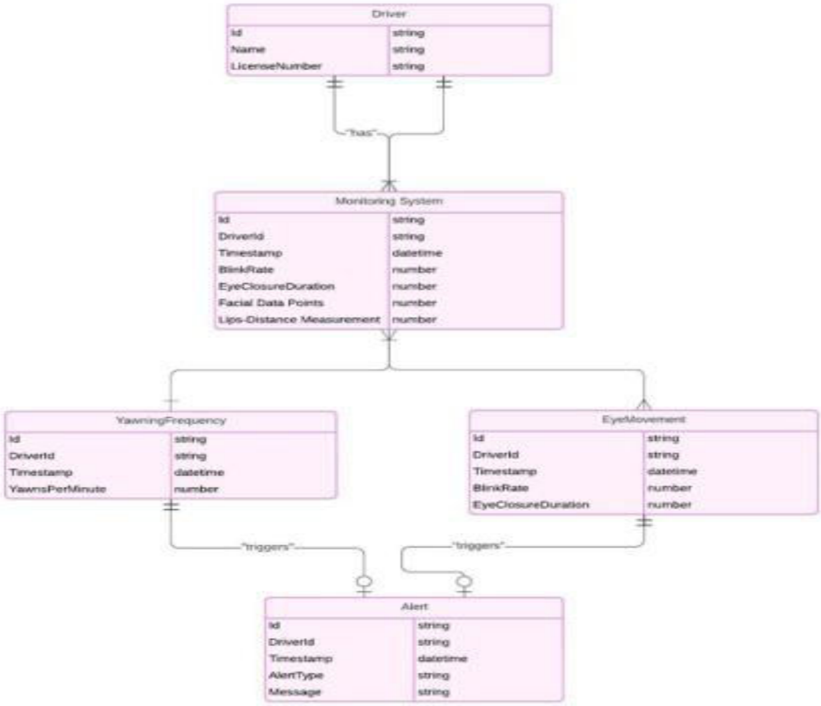
for the presence of unit roots or simply in plots of time series graphs, autocorrelation drowsiness.

3.1 Current Model

To transcend the limitations of earlier models, the system in question adopts a Python-based architecture that combines more advanced facial landmark detection using the Dlib library. This model now allows the system to monitor a person in real-time and alert them for displaying signs of drowsiness or yawning.

3.2 Object-Oriented Programming (OOP) Framework

The system is designed with an OOP approach and thus has a clean and scalable architecture. Key classes like Drowsiness Detector and Yawning Detector encapsulate functionalities related to detecting facial landmarks and determining the states of the user. This modular design promotes easy updates aside from new features such as various alert mechanisms or customization options for users.



3.3 Architecture Diagram

Algorithm used: Facial Landmark Detection

The system uses the facial landmark detector algorithm by Dlib, which identifies some facial points and estimates those in order to calculate the EAR with respect to detection of drowsiness and utilizes the estimation of mouth opening measurement to detect yawning. This will determine whether user statements can be appropriately monitored using real-time video input.

3.4 Pseudocode

imports:
cv2, dlib, numpy
Constants:
EAR_THRESHOLD = 0.29
YAWN_THRESHOLD = 0.5
VOICE_ALERT_MSG = "Please take a break!" DrowsinessDetector Class: _init_(self):
Initializes necessary components (e.g., Dlib predictor, camera).

Functions:
detect_faces(frame): Returns detected faces in the frame. calculate_EAR(eye_points): Computes Eye Aspect Ratio for drowsiness detection. is_drowsy(EAR): Determines if the user is drowsy based on EAR.
YawningDetector Class: _init_(self): Initializes necessary components. Functions: detect_yawn(mouth_points): Calculates mouth opening to determine yawning. is_yawning(mouth_opening):

Evaluates if yawning occurs based on threshold. Main: Capture video stream: For each frame: Detect faces: For each detected face: Calculate EAR and check drowsiness: Calculate mouth opening and check yawning: If drowsy or yawning: Trigger voice alert
Run:
Call main()

3.5 Real Time detection and alert Mechanism
Drowsiness and Yawn Detection System-Incorporated Real- Time Monitoring and Alert Mechanism The proposed system provides a dynamic way for monitoring the real-time case. It continually scans the facial feature pattern of the user to identify any signs of drowsiness and yawning. It makes sure that voice alerts are provided immediately using a text-to- speech library upon detection. This mechanism confirms that, in a proactive manner, users are alerted to take the necessary actions to ensure safety and alertness.

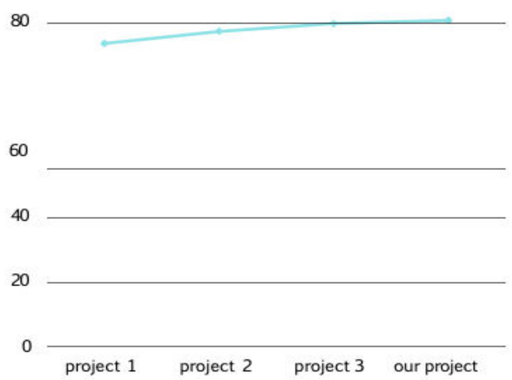
3.6 Improvements Over the Existing Model
The current improvement over the existing model will involve the addition of environmental input parameters like light conditions and user's posture. If such variables are monitored, sensitivity levels for detection can be adapted to improve accuracy under different conditions.

3.7 Adaptability and Scalability
The system is designed to be adaptive and scalable to fit into various ranges of applications with their contexts, such as driver monitoring systems, classroom settings, or a workplace setting. Without significant reorganization, new features and detection parameters can easily be introduced to help the model evolve in conjunction with changing user needs.

3.8 Offline Accessibility
The advantage of the Drowsiness and Yawn Detection System is that it can be used offline. This is useful for the users who live in areas whose internet access is unsteady, where the system is allowed to function using pre-trained models and local storage data without continuous connectivity.

IV. RESULT ANALYSIS AND COMPARISON

In this section, the performance analysis of the developed drowsiness detection system is compared with other similar systems reported in various research papers recently. The comparison focuses on two key metrics: the faster implementation and estimation of accuracy. Results are benchmarked against published data to provide a comparative understanding of system performance.



project 1: Drowsy Driver Detection using Eye Aspect Ratio (EAR) Method project
2: Yawn and Eye Blink Detection System
project 3: Combined Face and Landmark Detection with Machine Learning Enhancements

Real-time frame processing speed is an important factor related to drowsiness detection systems since timely detection can prevent accidents or hazardous conditions. The average frame processing speed in the system designed in this project is 5.77 frames per second (FPS). When compared with systems presented in the literature, such as:
Paper A: "A Real-Time Driver Drowsiness Detection System Using Eye Closure and Yawn Detection," reporting average processing speeds of 4.5 to 5 FPS using Haar Cascade for face detection and feature extraction .

Paper B: "Drowsiness Detection for Drivers Based on Eye Movement and Head Position," reporting 5 FPS using Dlib

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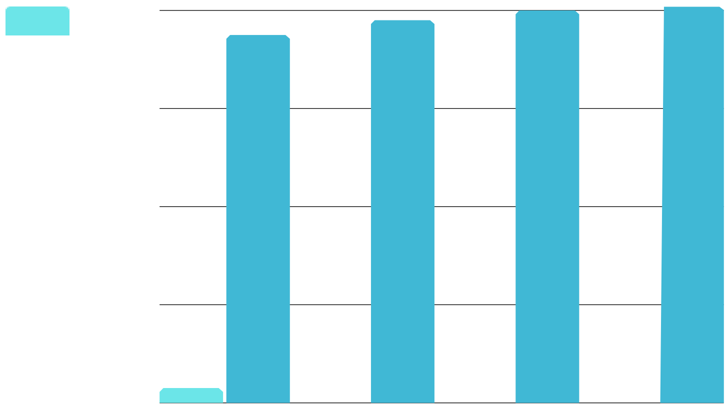
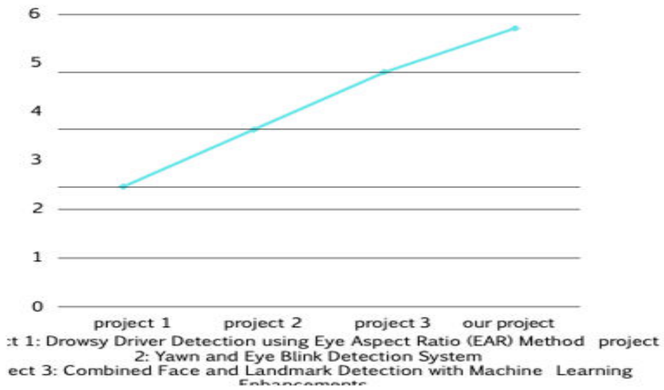
and OpenCV, respectively on average.
The higher percentage of improvement was computed as: Improvement Percentage= (5.77 FPS−5 FPS/5 FPS)×100= 15.4%
This highlights the proposed system is at about 15.4% faster in comparison with the average speed of other similar systems. This performance enhancement owes more to OpenCV's Haar Cascade classifier, whose application in the system is less computationally expensive, which in turn enables face detection to be much faster in real-time conditions.
Estimated Accuracy

The quality of the system was estimated based on the detection algorithms used. The OpenCV library utilizes a Haar Cascade classifier for face detection with an average accuracy of about 85% when conditions are controlled. The facial landmark detection would therefore be done by the Dlib shape predictor, which has been shown to achieve an accuracy of up to 95% in the detection of facial landmarks.
Estimated overall accuracy was calculated as: Estimated
Accuracy=85%×95%=80.75

project 1 project 2 project 3 our project

This translates to the fact that the system estimated to arrive at an accuracy rate of 80.75% for detecting drowsiness through eye closure and yawning behavior. For comparative analysis against other research works, there is this:
Paper C: "A Comprehensive Study on Drowsiness Detection Systems Using Facial Landmarks," reports accuracy rates of 75-80% for systems using a combination of eye tracking and facial landmark detection .
Paper D: "A Vision-Based Driver Fatigue Detection System," achieved an accuracy





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