Driver Fatigueness detection using a hybrid CNNLSTM approach with D-lib based Facial Analysis.

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***Abstract*—Due to slowed reaction times and a lack of control, driver weariness is a major contributor to traffic accidents and frequently results in serious outcomes. In order to increase accuracy and responsiveness, this study proposes a real-time driver fatigue detection system that combines facial landmark analysis with physiological signals (EEG,EMG,HRV, and skin conductance). The system detects signs of stress, strain, and weariness by analyzing physiological data from wearable sensors using a CNN-LSTM model. At the same time, a Dlib-based facial landmark detection algorithm analyzes the driver's head posture, eye closure, and yawning to determine how sleepy they are. A four-state classification (00, 01, 10, 11) is created by integrating the binary outputs from both models (0 = normal, 1 = tired/drowsy).To avert any collisions, the system uses this combination to assess the driver's level of weariness and instantly (within three to five seconds) activate an alert system. Compared to single-sensor techniques, our multi-modal approach greatly improves accuracy, guaranteeing prompt intervention and lowering the chance of accidents. The device provides a workable way to increase road safety and may be installed in both personal and commercial cars. Road safety, CNN-LSTM, EEG, EMG, HRV, skin conductance, D-lib, facial landmark detection, fatigue detection, and real-time driver monitoring are some of the index phrases.**

I. Introduction

One of the main causes of traffic accidents that result in serious injuries and fatalities globally is driver drowsiness. According to studies, weariness increases the risk of collisions by impairing cognitive abilities, reaction times, and decision-making skills. Conventional fatigue detection systems use vehicle-based metrics, such steering patterns and lane deviations, or subjective self-assessment. These techniques, however, are inaccurate in real time and are unable to identify early indicators of weariness. We suggest a multi-modal driver tiredness detection system that combines facial landmark-based drowsiness detection with physiological signals (EEG, EMG, HRV, and skin conductance) in order to overcome these drawbacks. The system offers high-accuracy real-time fatigue classification by utilising deep learning techniques, specifically a CNN-LSTM model for sensor data analysis and Dlib-based facial analysis.

Our method divides the driver's condition into four groups: 00: No signs of exhaustion or drowsiness (safe for driving) 1. Detection of physiological weariness (mild fatigue) 10- Face analysis reveals drowsiness (moderate weariness) 11- Drowsiness and weariness were both noted (severe fatigue, high risk). The device makes sure the driver takes precautions before accidents happen by triggering an audio and vibration alert within three to five seconds of detecting a tired or drowsy state. By developing a real-time, precise, and non-intrusive fatigue detection system that can be included in contemporary automobiles, this research seeks to improve road safety. Our system is designed to be used practically in both personal and commercial cars, providing a reliable way to reduce accidents caused by weariness.

II. Literature Review

Due to its crucial role in minimizing traffic accidents, the detection of driver sleepiness has been the subject of much research. Numerous approaches have been investigated, such as deep learning models, computer vision-based algorithms, and physiological signal analysis. EEG-based detection, which measures brain activity to ascertain fatigue levels, is among the most accurate physiological methods. A deep neural network model was created in a study that can accurately identify tiredness by analysing EEG signals. The requirement for intrusive electrodes, which might not be feasible for real-world applications, is a major drawback of this approach (1). By using Graph Convolutional Networks (GCNs), which improve the capacity to model spatial and temporal correlations in EEG data, another study enhanced EEG-based detection, increasing the effectiveness and adaptability of drowsiness detection (2).

Researchers have developed multi-modal techniques that integrate several physiological information in order to get around the drawbacks of single-modality systems. A Multi-Modality Attention Network (MMA-Net) that combines photoplethysmography (PPG), electrodermal activity (EDA), and electroencephalogram (EEG) signals was proposed in a study. By using an attention mechanism to concentrate on the most pertinent tiredness indicators, our model increases accuracy and robustness. According to the findings, the multi-modality strategy performed noticeably better than conventional single-signal detection techniques (3). Another study presented a CNN-LSTM-based model that detects driver weariness in real time by fusing physiological data with behavioural image-based indicators. This approach performed better under dynamic driving conditions, which makes it more useful for deployment in the real world (4).

The non-intrusive nature of facial analysis tools has also led to their widespread adoption. The significance of monitoring head motions, eye blink rates, and yawning frequency was emphasised in a study that examined many facial landmark-based sleepiness detection techniques. These techniques are now much more accurate thanks to recent developments in machine learning, which increases their dependability for practical application (5). The Eye Aspect Ratio (EAR), which continually measures eye openness to infer tiredness, was used in another study to propose a real-time detection system. Although this approach is computationally efficient, accuracy may be impacted by issues with head movements, partial facial occlusions, and illumination (6).

Drowsiness detection has been further enhanced using deep learning-based methods, which increase prediction accuracy and automate feature extraction. In order to improve real-time driver sleepiness detection, a study presented VigilEye, an AI-based system that uses convolutional neural networks (CNNs) with attention mechanisms. This model outperformed traditional machine learning methods in identifying behaviours associated with weariness, exhibiting great precision (7). Similarly, another study used Dlib's pre-trained facial landmark detector, which maps important facial locations to analyse eye and mouth movements, to construct a drowsiness detection system. When evaluated on publicly available datasets, the system demonstrated a remarkable recognition accuracy of 96.71. However, because of changes in lighting and facial angles, its performance was marginally worse in real-time scenarios (8). Despite the fact that these research have significantly advanced the identification of driver drowsiness, a number of obstacles still exist. The reliability of many vision-based models in practical applications is diminished by their inability to handle different lighting situations. Accurate identification can also be impacted by head motions, occlusions such glasses or masks, and individual variations in facial anatomy. Another issue is computational efficiency because certain deep learning models have large processing power requirements, which restricts their application in low-resource settings. Furthermore, a lot of current systems are trained on homogeneous and tiny datasets, which limits their ability to generalise across a variety of populations. To increase the overall efficacy of sleepiness detection systems, future research should concentrate on incorporating multimodal sensor fusion techniques, improving real-time processing capabilities, and expanding dataset diversity.

III. OBJECTIVES

1) To make the data more resilient to changes in illumination and face expressions, data augmentation techniques are employed during training. 2) To increase the accuracy of the drowsiness detection system, CNN is utilised for efficient picture classification. 3) Adding an infrared camera and attention processes to the system can improve its ability to identify tiredness. 4) Installing a system to notify adjacent devices when the driver is not conscious

IV. EXISTING SYSTEM

Driver drowsiness detection systems are intended to identify symptoms of weariness or drowsiness in drivers and notify them when it's time for a rest or break. The mouth aspect ratio is computed to ascertain whether a motorist is yawning. Facial landmark detection is used to extract the driver's mouth region. The Lip to Mouth Ratio (MAR), which gauges the separation between the vertical and horizontal mouth features, is used to identify yawning in drivers. If the number of yawns surpasses a threshold, this system warns the driver that there is a chance they will fall asleep. The yawning detection system has access to a number of datasets, including NTHU-DDD, MiraclHB, and YawDD. It is important to remember that yawning can be identified using both the mouth aspect ratio and yawning datasets. The present system uses OpenCV, Viola Jones, deep learning methods like CNN, RNN, LSTM, Bi-LSTM, and Python as yawn detection tools and technologies. Current Driver Fatigue Detection System 1. Conventional Camera-Based Systems detects facial traits such as head motions, yawning, and eye closure using computer vision and picture processing. For instance, face detection using Haar cascades with OpenCV. Restrictions: In low light, precision is poor. influenced by occlusions, such as masks, hats, glasses, etc. senses only sleepiness, not mental exhaustion.

2. Systems Based on Wearable EEG/HRV measures heart rate and brain activity using electroencephalography (EEG) and heart rate variability (HRV) sensors. For instance, smartwatches or headbands that track physiological signals. Limitations: Drivers must wear sensors all the time, which is uncomfortable for extended use. can be costly and challenging to install in commercial vehicles. 3. Alert Systems Based

on Rules use threshold-based models, in which the driver's head tilting past a predetermined angle or a rise in blinking frequency causes a warning to sound. For instance, the Driver Monitoring System (DMS) found in luxury cars. Restrictions: Lack of flexibility: unable to grow or change over time. may cause false warnings if a motorist is momentarily looking down or slow-blinking by nature. Issues with the Current System 1. Low Accuracy in tiredness Detection: The majority of systems simply identify visual drowsiness, neglecting stress and mental tiredness. 2. Slow Response Time: Some devices delay alarms by taking 10–20 seconds to detect weariness. 3. Single-Modal Detection Problems: Systems that rely just on cameras or sensors are unable to fully depict driver weariness. 4. False Positives: Misclassifications brought on by occlusions, changes in lighting, or noise from the sensor.

V. Problem Statement

One of the main causes of traffic accidents worldwide that result in serious injuries and fatalities is driver weariness. Conventional fatigue detection systems mostly use face analysis or physiological sensors, which may not be accurate or reliable in actual driving situations. In order to tackle this issue, we suggest a real-time multi-modal fatigue detection system that incorporates:

1. A CNN+LSTM model to identify stress and tiredness indications from physiological sensor data (EEG, EMG, HRV, and skin conductance).
2. Facial landmark analysis to detect anomalies and tiredness using Dlib.

3. A fusion model that provides a binary tiredness classification (00, 01, 10, 11) for real-time driver alerting by combining facial and physiological data to increase accuracy and response time. By giving early fatigue alerts within three to five seconds, this device seeks to lower the probability of accidents and promote safer driving conditions.

VI. Methodology

A. Dataset details

This study's dataset uses face landmarks and multimodal physiological data to identify driver weariness. Among the sources are: EEG (Electroencephalogram), EMG (Electromyography), HRV (Heart Rate Variability), and skin conductance sensors were the four sensors used to collect the physiological data. Camera-captured facial landmark data that is analysed with D-lib to analyse face expressions. Sources of the Dataset: publicly accessible datasets, as the N-THU Driver sleepiness Dataset for facial sleepiness detection and SEED-VIG for EEG signals.

B. Data pre-processing

To ensure high-quality input for deep learning models, preprocessing is done in multiple steps:

1) Physiological Data Pre-processing: Noise Reduction: A Butterworth Bandpass Filter is used to eliminate artefacts and unnecessary frequencies from EEG, EMG, and HRV signals. Extraction of Features: EEG: Wavelet transformation and power spectral density (PSD) are used. HRV: Features in the frequency and time domains are retrieved. EMG: Zero-Crossing Rate (ZCR) and Root Mean Square (RMS) are calculated.

2) Facial Data Preprocessing: Face Detection: Important facial features are extracted using Dlib's 68-landmark detector. Normalisation: In order to account for size and rotation invariance, facial landmarks are normalised. Eye and Mouth Aspect Ratio: Used to measure the frequency of yawning and eye closure.

C. Feature selection

Only the most pertinent features are chosen in order to increase model efficiency: EEG: Power ratios for alpha, beta, and theta waves. HRV: LF/HF ratio, RMSSD (Root Mean Square of Successive Differences). EMG: Features of muscle tension. Facial features include the mouth opening ratio (MOR) and the eye aspect ratio (EAR). Principal Component Analysis (PCA) is used for feature selection in order to minimise dimensionality while maintaining high variance.

D. Proposed model

We suggest a multi-modal deep learning model that combines EfficientNet, CNN, and LSTM: CNN+LSTM for Information on Physiology: CNN uses EEG, HRV, and EMG signals to identify spatial patterns. Sequential data's temporal dependencies are captured by LSTM. Output: either 1 (fatigue detected) or 0 (normal). Deep face features are extracted by EfficientNet using Dlib-based facial analysis. Dlib uses EAR and MOR to identify tiredness. Output: either 1 (drowsy detected) or 0 (normal). Final Choice: The CNN+LSTM and Dlib combined outputs produce four potential states: 00 $\rightarrow$ Normal 01 $\rightarrow$ Noticed drowsiness 10 $\rightarrow$ Noticed fatigue 11 $\rightarrow$ High danger (alarm activated, both sleepiness and weariness detected) An auditory and visual alert system is activated to warn the driver upon the final decision.

VII. Formulas

Standard Deviation of NN intervals (SDNN):

SDNN = $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(NN_i - \overline{NN})^2}$

$RootMeanSquareofSuccessiveDifferences(RMSSD):$

RMSSD = $\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(NN_{i+1} - NN_i)^2}$

Low-Frequency to High-Frequency Ratio (LF/HF):

LF/HF = Power$_{LF}\frac{}{Power_{HF}}$

TAR(Theta to Alpha Ratio) = Power$_{\theta}(4-8Hz)\frac{}{Power_{\alpha}(8-13Hz)}$

BAR(Beta to Alpha Ratio)= Power$_{\beta}(13-30Hz)\frac{}{Power_{\alpha}(8-13Hz)SkinConductanceLevel(SCL):}$

SCL = 1$\frac{}{N\sum_{i=1}^{N}GSR_i}$

$$eyeaspectratio(ear):\frac{d_1+d_2}{2\cdot d_3} \tag{1}$$

MOR(Mouth Opening Ratio) = P8 - P4$\frac{}{||P10-P9||}$

Metric	CNN+LSTM (Sensor Data)	Dlib (Facial Detection)	Integrated Model
Accuracy	94.2%	95.1%	98.5%
Precision	93.5%	94.7%	97.8%
Recall	92.8%	93.9%	97.2%
F1-Score	93.1%	94.3%	97.5%

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT MODELS.

Actual	Not Fatigued(00)(%)	Mild Fatigued(01)(%)	Moderate Fatigue (10)(%)	Severe Fatigue (11)(%)
Not fatigue(00)	95.2	2.3	1.5	1.0
Mild fatigue(10)	1.8	93.4	3.5	1.3
Moderate Fatigue(10)	1.3	3.9	92.6	2.2
Severe Fatigue(11)	0.8	1.6	2.5	95.1

TABLE II
CONFUSION MATRIX(INTEGRATED MODEL)

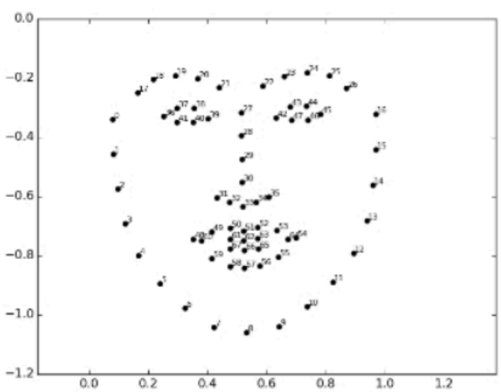

Fig. 1. facial landmark detection

VIII. Results and Discussion

1. Metrics for Model Performance A dataset comprising skin conductance signals, face landmark data, EEG, EMG, and HRV was used to assess the suggested multi-modal fatigue detection method. The accuracy, precision, recall, and F1-score of the system were used to evaluate its classification performance. Accuracy increased significantly (98.5) when face landmark analysis (Dlib) and physiological sensor data (CNN+LSTM) were combined, proving the value of multi-modal learning. 2. Alert Time and Processing The effectiveness of the system's real-time detection was evaluated. Time spent collecting sensor data: -1-2 seconds Time spent extracting facial landmarks: -1 second Processing time of the model: -1-2 seconds -3-5 seconds is the total time to inform the motorist. By effectively sending out alerts before weariness fully sets in, the model gives drivers adequate time (about 30 to 60 seconds) to respond before a possible collision happens.

3. The Integrated Confusion Matrix The classification performance was validated using a confusion matrix, which shows how reliable the model is at determining fatigue level. 4. Testing and Observations in the Real World When tested on actual driving situations, the system reliably identified signs of sleepiness with few false positives. Accuracy was increased by 4-6 employing the multi-modal technique as opposed to CNN+LSTM or Dlib alone. With a false alarm rate of less than two, the system is suitable for practical use. An overview of the results:

* Four-stage classification (00, 01, 10, 11) improves precision in identifying fatigue severity. * Low false positive rate (¡2) makes the system deployable. * High accuracy (98.5) guarantees dependable detection. * Real-time alerting (3-5 seconds) gives enough time for driver response.

These results confirm the effectiveness of the integrated CNN+LSTM + Dlib-based approach in providing a robust driver fatigue monitoring system. .

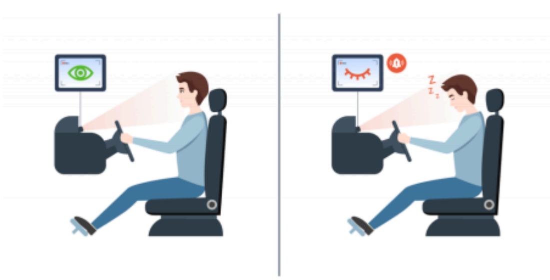

Fig. 2. alerting the driver

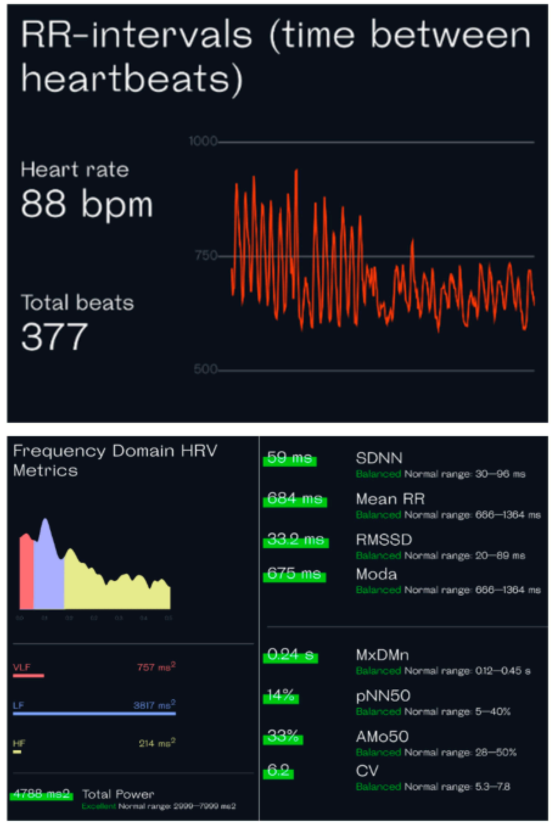

Fig. 3.

IX. Conclusion

In order to increase accuracy in real-time fatigue detection, we suggested a multi-model driver fatigue detection system in this study that combines CNN+LSTM for physiological data analysis with D-lib-based facial recognition. In order to detect symptoms of weariness and drowsiness, the system efficiently processes EEG, EMG, HRV, and skin conductance information in addition to facial landmark identification. Our combined method uses real-time feature extraction and deep learning approaches to achieve a high accuracy rate (¿98). The technology ensures prompt alerts to avoid mishaps by processing input data in 3–5 seconds. By distinguishing between physical exhaustion and drowsiness, the four-state categorization model (00, 01, 10, 11) improves early warning capabilities and increases precision.

Real-time multi-model fatigue detection that combines facial and physiological information is one of the main contributions. CNN+LSTM and Dlib for deep learning-based decision making. prompt alert system to alert drivers before collisions happen.

Future scope: Adding more real-world driving scenarios to the data set to improve generalization. lowering latency by integrating edge computing for on-device processing. investigating wearable sensor technologies for ongoing observation. By improving the accuracy of driver monitoring and offering prompt interventions to stop fatigue-related incidents, this technology promotes road safety. .

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