International Journal of Basic and Applied Sciences, 14 (3) (2025) 232-241

SPC

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/hd63bz13
Research paper

Enhanced Real-Time Driver Fatigue Detection Using Hybrid SVM and Multi-Feature Analysis for Improved Accuracy and Road Safety

Lakshmi Devi S. [1] *, Vinoth A. [2]

[1] *Department of Computer Science, Research Scholar, Sri Krishna Adithya College of Arts & Science, Kovaipudur, Coimbatore, 641042, TamilNadu, India*
[2] *Department of Information Technology, Assistant Professor, Sri Krishna Adithya College of Arts & Science, Kovaipudur, Coimbatore, 641042, TamilNadu, India*
**Corresponding author E-mail: shaarvesh.raj@gmial.com*

Received: June 10, 2025, Accepted: July 7, 2025, Published: July 24, 2025

Abstract

Fatigue and distraction are two of the main causes of traffic accidents, so it's critical to maintain focused attention when driving. A reliable real-time fatigue detection system based on driver visual analysis is proposed in the present research. Yet, features like interference from eyewear and low illumination can affect the precision of detection. A machine learning-based technique for detecting and classifying driver fatigue in real-time is presented in this research. Along with blinking, additional indicators of fatigue include yawning, nodding, and variances in pupil size. To extract multiple visual cues, the Image Projection Function (IPF) is used to quantify pupil size, optical flow is employed for assessing head position, and eye and mouth dimension ratios are measured. Normalization is per-formed to ensure data consistency. Multiple facial fatigue markers are incorporated into the system to improve classification accuracy and robustness. Principal Component Analysis (PCA) is applied for dimensionality reduction to optimize classification performance. The Euclidean distance gauge is used to evaluate three machine learning models: Support Vector Machine (SVM), Multi-layer Perceptron (MLP), and K-Nearest Neigh-bors (KNN). Outperforming KNN and MLP, SVM with the Radial Basis Function (RBF) kernel obtains the best accuracy of 91.6% among them. The classification performance is enhanced by the RBF kernel's ability to capture non-linear fatigue-related patterns. The efficiency of the proposed method for detecting fatigue in the real world has been verified by experimental results, which indicate the attributes obtained can reliably differentiate between fatigued and non-fatigued states.

Keywords: *Image Projection Function; Multi-layer Perceptron; Principal Component Analysis; Radial Basis Function; Support Vector Machine.*

1. Introduction

The primary categories of fatigue detection strategies at current circumstances are physiological-based, vehicle-based, and vision-based technologies [1], [2]. Monitoring driving behaviors involving lane departures, steering angles, and speed fluctuations is the backbone of vehicle-based strategies. Variations in detection accuracy result from these systems' dependence on variables like driving behaviors, experience, vehicle type, and road conditions. To assess driver fatigue, physiological-based techniques use medical signals such as electroencephalography (EEG), electrocardiography (ECG), and electromyography (EMG). Despite their precision, these methods' broad use is constrained by their complexity and need for certain experimental setups. The impact of drowsy driving may be underestimated by current statistics, according to researchers in the arenas of public health, sleep science, and traffic safety [3]. Of adult drivers, 54% have been drowsy while driving, and 28% have fallen asleep while driving, according to the National Sleep Foundation. Additionally, about 40% acknowledge that they had at least once fallen asleep while driving. The first signs of fatigue, that is, the moment between wakefulness and sleep, include struggling to keep the eyes open, frequent blinking, and head movements. Furthermore, yawning is a noticeable indicator of exhaustion [4]. By integrating machine learning-based classification with visual indicators such as pupil analysis, yawning, head nodding, and eye-blinking frequency. This study seeks to improve fatigue detection. This paper's succeeding portions are structured in the following sequence: A review of existing fatigue detection techniques is given in Section 2, a proposed approach is discussed in Section 3, the experimental results and performance evaluation are illustrated in Section 4, and the key findings are detailed in Section 5, focusing on prospective future research sectors.

2. Related work

Liza et al. [1] performed research, utilizing the 300W dataset for driver consciousness and fatigue detection. Their approach integrated an API-based Histogram of Oriented Gradients (HOG) with a Linear Support Vector Machine (SVM) classifier. The methodology involved face identification, classification, and the application of Random Forest Regression to detect facial landmarks. Additionally, the Euclidean distance between key points around the mouth and eyes was computed to identify fatigue indicators such as eye closure and yawning. The results demonstrated notable classification performance, achieving (i) 90.67% accuracy when the camera angle was 0°, (ii) 93.33% accuracy in detecting drowsy behavior within camera angles ranging from +45° to −45°, and (iii) 85% accuracy in simultaneously detecting multiple fatigue-related behaviors.

Agustina et al. [18] emphasized the significance of image quality in fatigue detection and examined the impact of noise, such as black-and-white grain distortions. To address this issue, they proposed image smoothing techniques, specifically Gaussian filtering, to enhance image clarity by reducing noise. Their experiments involved images with varying noise levels, demonstrating substantial improvements in visual quality, with some images achieving significantly higher clarity scores.

Suhandi Junaedi et al. [7] introduced a vision-based approach for detecting impaired driving by analyzing real-time camera feeds. Their methodology incorporated face and eye detection in each frame, with a focus on the iris region to compute the Percentage of Eyelid Closure (PERCLOS) metric. Evaluation using the YawDD visual dataset indicated that PERCLOS values were significantly lower when drivers were alert compared to when they were drowsy, confirming its effectiveness as a fatigue indicator.

Dreißig et al. [5] proposed a method for assessing driver conditions and detecting fatigue using driver monitoring cameras. Their approach employed a K-Nearest Neighbors (KNN) algorithm for cognitive state evaluation, focusing on feature selection. By analyzing recorded signals associated with eye closure, they compiled a large dataset and extracted variables related to head movement and blinking. The classification model achieved an equitable validation accuracy of 84.2% for binary classification and 70% for multi-category classification, providing valuable insights into patterns of blinking and head movement linked to fatigue.

Ghourabi et al. [2] developed a fatigue detection method based on facial motion analysis, incorporating eye blinking, jaw opening, and head nodding. Their approach extracted key facial features such as the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and optical flow. Unlike threshold-based techniques, this method utilized machine learning models, including Multi-Layer Perceptron (MLP) and K-Nearest Neighbors (KNN), to integrate multiple features for classification. When evaluated on a challenging visual dataset simulating real-world driving scenarios, the method demonstrated promising results, with KNN achieving the highest classification accuracy.

Soni et al. [26] introduced a real-time fatigue detection framework based on facial landmark analysis, particularly focusing on the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). Their approach leveraged webcam input and Dlib-based detection to continuously monitor facial cues. A fatigue level was determined by observing the persistence of eye closure over sequential frames. The system exhibited strong performance under different lighting conditions, achieving more than 95% accuracy in face detection. This work validates the potential of using lightweight machine learning models for real-time driver monitoring without the need for specialized hardware.

Gopi et al. [27] developed a fatigue detection mechanism that utilizes SVM classification and facial features like EAR and MAR, captured via a webcam. The system generated alerts when the EAR remained below a predefined threshold over a fixed number of frames, signaling signs of drowsiness. The researchers highlighted the system's low processing delay and its ability to handle moderate head movement and lighting variation effectively. The proposed model proved reliable in indoor environments, offering practical potential for integration into driver assistance technologies.

Wu et al.[28] Conducted a comparative study examining the effectiveness of deep learning approaches (such as CNN and LSTM) versus traditional classifiers (SVM and KNN) for detecting both drowsiness and distraction in drivers. Using a combined dataset that included gaze direction and facial metrics, the results revealed that while deep learning models slightly outperformed their classical counterparts in accuracy, traditional models required far fewer computational resources. These findings support the continued use of conventional machine learning techniques in edge-based, real-time applications due to their efficiency and practicality.

Maior et al. [29] evaluated and compared the performance of several machine learning classifiers—SVM, MLP, and Random Forest—using established driver fatigue datasets like NTHU and YawDD. Their results showed that SVM and Random Forest achieved high detection accuracy (approximately 94%), while MLP provided better generalization but at the expense of longer training times and higher computational demands. The study recommended SVM for real-time applications due to its efficiency and robust performance across different driving scenarios.

Menon et al.[30] aimed to improve the performance of machine learning models in embedded environments by integrating Principal Component Analysis (PCA) for reducing input feature dimensions. Their experiments with SVM and KNN classifiers showed that PCA enhanced SVM's accuracy (from 89.5% to 91.1%), while KNN maintained consistent accuracy at 93.6%. The implementation on embedded hardware demonstrated that their method could operate in real-time with minimal computational load. Their research illustrates how feature optimization methods can improve accuracy and efficiency in resource-limited systems.

3. Methodology

Figure 1 depicts the five main stages of the suggested fatigue detection technique. Gathering data is the initial step, during which each input frame is subjected to brightness and noise reduction adjustments. To guarantee precise feature extraction, face identification and alignment follow. Each frame's pertinent features are extracted in the following stage. To ascertain whether fatigue has been detected, the retrieved features are then combined and fed into a supervised classifier. The key objective of this research is to develop an intelligent feature extraction system that can analyze a driver's facial expressions in an assortment of lighting environments and real-world driving scenarios. Despite keeping track of eye states has emerged as a vital component of detecting fatigue, it might not be precise enough for a thorough identification because differing face expressions and eye shapes might result in inaccurate classification of the eye state. Therefore, to capture a wider variety of fatigue symptoms, further indicators are essential.

The present research analyzes multiple features as fatigue indicators, such as pupil analysis, head nodding, yawning, and eye blinking, to enhance detection accuracy. While the Mouth Aspect Ratio (MAR) can be utilized to identify yawning, a crucial sign of fatigue, the Eye Aspect Ratio (EAR) is utilized for evaluating ocular openness and closure. Additionally, head movement is regarded as an extra feature that is monitored using optical flow techniques. Analysis of pupil shape also offers more information on the degree of eye-opening. To optimize the classification process, these extracted features are merged to generate a four-dimensional feature vector. The efficacy of many machine learning methods, such as K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), and Hybrid Support Vector Machine (SVM-RBF Kernel), in the categorization of fatigue is assessed using Euclidean distance-based metrics. A reliable evaluation of the driver's condition is provided by the model outputs, which are produced for every analyzed frame and differentiate between fatigued and non-fatigued states

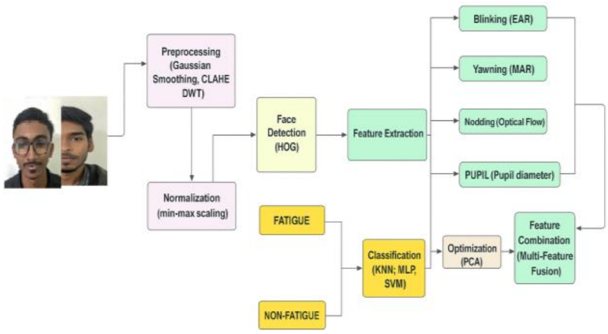

Fig. 1: Proposed Workflow of the Fatigue Detection System.

3.1. Dataset description

This study utilizes two datasets for model training and evaluation: the publicly available NTHU Drowsy Driver Detection Dataset and a custom real-time dataset captured under natural driving conditions. The NTHU dataset contains approximately 22 video clips per subject across 36 individuals, resulting in over 18,000 frames that cover various scenarios, including daytime and nighttime driving, the presence or absence of eyeglasses and sunglasses, and instances of facial occlusion. The custom dataset, developed using a dashboard-mounted camera during routine driving sessions, comprises 4,836 annotated image frames extracted from 48 video sequences. It includes a wide range of conditions, such as varying lighting environments and facial occlusions caused by spectacles, sunglasses, and night-driving glasses. Additionally, the dataset captures diverse head poses, yawning, blinking behavior, and incorporates demographic diversity in terms of ethnicity. To address class imbalance—where non-fatigued samples initially outnumbered fatigued ones—data augmentation techniques such as horizontal flipping, brightness adjustment, and image rotation were applied. These methods ensured a balanced representation across fatigue states while preserving the integrity of facial landmarks. The final dataset was split into 70% for training, 15% for validation, and 15% for testing to maintain consistency in performance evaluation.

3.2. Preprocessing

It is critical to include a pre-processing step to assure the appropriateness of input image frames for fatigue detection while driving. This is especially significant because of fluctuations in illumination intensity encountered when driving, such as overcast skies, wet weather, and nighttime driving, all of which can impair image quality and prevent proper recognition of human facial characteristics. Several pre-processing approaches are used in the proposed system to solve these difficulties. Gaussian smoothing is used to reduce image noise and hence improve overall image quality. Combining the Contrast Limited Adaptive Histogram Equalization and Discrete Wavelet Transform techniques improves the brightness of the input image frames even more. Finally, the pre-processed images are normalized using min-max scaling to ensure consistency and reliability.

3.2.1. Gaussian smoothing

The procedure of smoothing involves averaging data points to minimize noise in time-series data. In combination with techniques like basic moving averages, weighted moving averages, and kernel smoothing, Gaussian smoothing is one way to accomplish this. A MATLAB-based implementation of Gaussian smoothing is applied to the original images, as illustrated in Figure 2. The input images, the applied Gaussian filter, and the signal that results from noise reduction are all depicted in the graph in Figure 3. The Gaussian function's standard deviation parameter controls the degree of smoothing, determining how much noise is suppressed while maintaining crucial visual information. The following is a mathematical expression:

$$\text{Gaussian} = \frac{1}{2\pi\sigma^2}\, e^{\frac{-x^2+y^2}{2\sigma^2}} \tag{1}$$

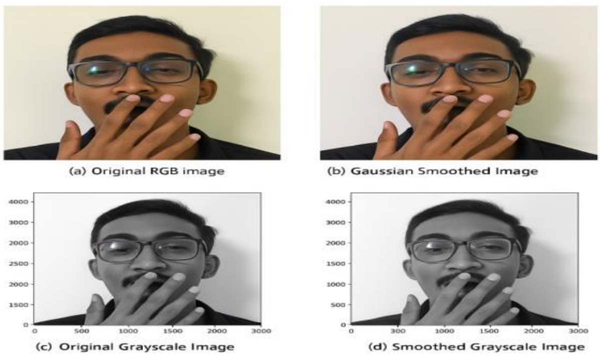

Fig. 2: Pre-Processing Stages of Driver Facial Images.

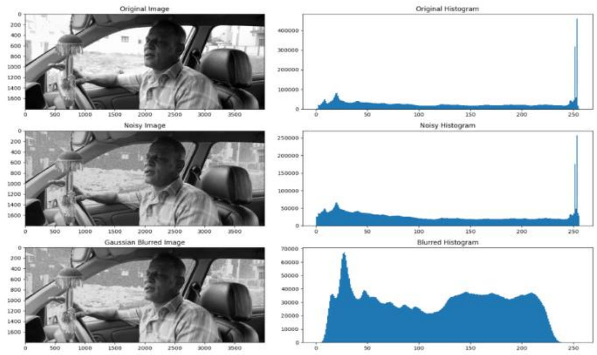

Fig. 3: Original Noisy Signal, Gaussian Filter, Signal After Noise Removal.

3.2.2. Contrast-limited adaptive histogram equalization and discrete wavelet transform

By blending Discrete Wavelet Transform (DWT) and Contrast Limited Adaptive Histogram Equalization (CLAHE), this research proposes a unique method for image enhancement that preserves multi-resolution characteristics while enhancing contrast. The visibility of fatigue-related facial features has been enhanced by applying a median filter to further minimize noise. Pixel intensity data are standardized using normalization, more especially Min-Max normalization, which guarantees reliable feature extraction. By increasing classification accuracy, this preprocessing step boosts the effectiveness of AI-based fatigue detection algorithms. After pre-processing images for various goals, such as tiredness detection, normalization is a crucial step in image processing. Normalization adjusts the range of pixel intensity values to ensure consistent data distribution and improve the effectiveness of artificial intelligence systems. Min-Max normalization is a technique used in fatigue detection to equalize data and account for individual variances.

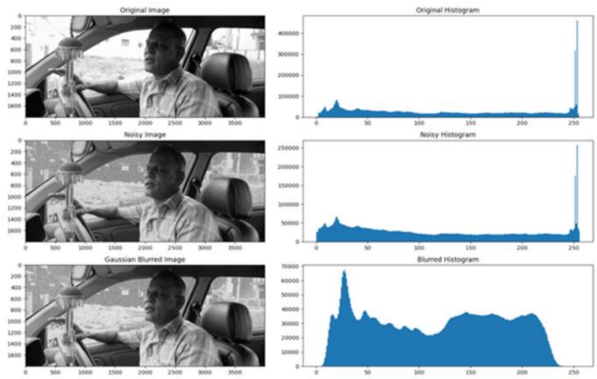

Fig. 4: Enhanced and DWT Images.

4. Feature extraction

4.1. Facial landmark detection

Facial landmark detection forms the foundation for accurate fatigue classification in the proposed system. Initially, facial regions are identified using the Histogram of Oriented Gradients (HoG) method. Once detected, the Dlib 68-point landmark detector is applied to extract key features such as eyes, mouth, nose, and jawline coordinates. These landmarks are essential for calculating Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and monitoring head movement. Figure 5 demonstrates the reliability of the facial landmark detector under various conditions, making it suitable for real-time deployment.

Fig. 5: The Facial Landmark Points.

4.2. Eye aspect ratio (EAR)

The Eye Aspect Ratio (EAR) is a geometric measure used to quantify eye openness or closure. It is calculated based on the vertical and horizontal distances between specific eye landmarks. The EAR is defined by the formula:

$$\text{EAR} = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2.||p_1 - p_4||} \quad (2)$$

Where P1 through P6 denote the landmark points around the eye. A decreasing EAR value indicates that the eye is closing, helping identify blinks or prolonged closures. This feature dynamically adapts to real-time facial changes and is more robust than static threshold-based methods.

4.3. Mouth aspect ratio (MAR)

Yawning is one of the most evident signs of fatigue and is detected using the Mouth Aspect Ratio (MAR). It is calculated using distances between specific mouth landmarks. The formula for MAR is:

$$\text{MAR} = \frac{||p_{61} + p_{67}|| + ||p_{62} - p_{66}|| + ||p_{63} + p_{65}||}{2.||p_{60} - p_{64}||} \quad (3)$$

A yawn is confirmed when MAR exceeds a defined threshold for several consecutive frames. This ensures that transient expressions like talking or smiling are not misclassified as yawns. Dlib’s facial landmark tracker enables accurate and consistent measurement across multiple video frames.

4.4. Head movement detection

Head movement, specifically nodding, is a crucial fatigue indicator. The Improved Lucas-Kanade Optical Flow technique is employed to track facial landmark displacement across consecutive frames. The displacement DDD of a landmark is computed as:

$$\text{Magnitude} = \sqrt{(\Delta x)^2 + (\Delta y)^2} \quad (4)$$

Where (x1,y1) and (x2,y2) are the coordinates of the landmark in two consecutive frames. A consistent vertical displacement beyond a set threshold is interpreted as nodding. Figure 6 visualizes the transition from a forward-leaning head to a normal upright position, highlighting the method’s effectiveness in capturing subtle fatigue-induced movements. Bottom of Form

4.5. Pupil localization and feature normalization

Figure 7 illustrates the accurate localization of the pupil center within the defined eye region, which plays a critical role in improving fatigue detection accuracy. To enhance the clarity and contrast of the eye region, the system employs a series of preprocessing techniques, including histogram equalization, grayscale conversion, and binary thresholding. These steps facilitate precise measurement of the pupil size. Under challenging conditions—such as when the driver is wearing sunglasses—the integration of the Image Projection Function (IPF) enables reliable pupil localization by compensating for visual occlusions.

The system extracts multiple key features, including the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), pupil size, and head movement, all of which are normalized using Min-Max normalization to maintain consistent scaling across different input ranges. These standardized features are concatenated into a single feature vector to be used for classification. To reduce feature redundancy and enhance computational efficiency, Principal Component Analysis (PCA) is applied selectively. From the original 12 extracted features, 7 principal components are retained, which preserve approximately 95% of the total variance. This dimensionality reduction step ensures that only the most relevant and discriminative information is passed to the classifier, thereby improving real-time performance and detection reliability across diverse driving scenarios.

Fig. 6: Transition of Nodding from Forward Leaning.

Fig. 7: Detecting Pupil Diameter Relative to the Center Point.

5. Feature combination and classification

Two significant contributions are introduced in this work. To improve the detection model's accuracy and resilience, it first investigates the integration of four fatigue-related features via multi-feature fusion. Through the integration of eye, mouth, pupil, and optical flow parameters, the suggested method offers a more accurate evaluation of fatigue levels. Using the NTHU and real-time datasets, the study also investigates the possibilities of real-time machine learning algorithms for tiredness categorization. K-Nearest Neighbor (KNN), Multi-Layer Perceptron (MLP), and a Hybrid Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel were the three classifiers that were evaluated.

Table 1: Distinct Score (%) for Different K-Values

K	10	15	25	50	100	150
F- Score	0.82	0.83	0.85	0.86	0.88	0.89

This study investigated the correlation between two feature vectors of size k, denoted as x and y Additionally, the study used three distinct distance metrics—Manhattan distance (Dm), Euclidean distance (De), and cosine distance (DSC)—to examine the association between two feature vectors of size k, represented as x and y. The most successful metric among these was Euclidean distance, which outperformed the other two by a considerable margin. Table 2, which summarizes the total classification performance using various distance metrics, demonstrates that the Euclidean distance obtained the highest F-score.

$$D_{Euclidean}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (5)$$

$$\|x - y\| = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (6)$$

Table 2: Overall (%) of the proposed method with Euclidean. Manhattan and cosine distance

Distance	Manhattan	Euclidean	Cosine
Weight	3	2	1
F – score	81%	88%	84%

6. Experimental result and analysis

Our research on driver fatigue detection relies on an image dataset capturing real-time driving conditions. Using Matlab R2023a, we carried out all of our research using a laptop with a sixth-generation Core i9 processor. Fatigue symptoms manifest through various behaviours such as yawning, blinking, nodding, and changes in pupil size. The performance of our fatigue detection method can be affected by factors like lighting conditions, partial obstructions, facial expressions, and other driver actions such as smiling, talking, or even sleeping. To rigorously test our proposed method, we utilized a real-time image and NTHU dataset comprising a diverse group of male and female drivers, each with unique facial characteristics, skin tones, and ethnic backgrounds (refer to Figure 8).

Fig. 8: A Sample Dataset That Includes a Variety of Subjects and Scenarios.

In addition to the NTHU dataset, a real-time dataset was used to thoroughly assess the suggested methodology. These datasets include a heterogeneous mix of male and female drivers with different skin tones, ethnic backgrounds, and facial features. Spectacles, No Spectacles, Sun Spectacles, No Spectacles at Night, and Night Vision Glasses were the five situations into which each driver was assigned (Figure 9). Seventy percent of the images were used for training, with a balanced mix of fatigue and non-fatigue cases for each scenario. The dataset was divided into training, validation, and assessment sets. To guarantee precise classification, each frame was marked as either F (fatigue) or NF (non-fatigue) during the training and evaluation stages.

Fig. 9: Various Scenarios (No Spectacles, Spectacles, Sun Spectacles, No Spectacles at Night, And Night Vision Glasses) Sample for Each Subject.

7. Evaluation metrics

7.1. Metrics definitions

To evaluate the effectiveness of the proposed drowsiness detection system, three assessment criteria were used: sensitivity, specificity, and accuracy. Equations (7), (8), and (9) give the mathematical expressions for these metrics. True Negatives (TN) are situations when an open eye is correctly identified as open, whereas True Positives (TP) are occasions where a closed eye is correctly identified as closed [19]. On the other hand, False Negatives (FN) indicate cases in which a closed eye is wrongly identified as open, and False Positives (FP) occur when an open eye is incorrectly classified as closed. Equation (10) is used to calculate the F-Score, which strikes a compromise between recall and precision.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (7)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (8)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \tag{9}$$

$$\text{F} - \text{Score} = 2 \times \frac{precision \times recall}{precision+recall} \tag{10}$$

7.2. Confusion matrix analysis

To analyze model performance, confusion matrices were generated for three classifiers: Hybrid Support Vector Machine (RBF Kernel), Multi-Layer Perceptron (MLP), and K-Nearest Neighbors (KNN). These matrices visualize how accurately each model classified the driver's state into fatigued or non-fatigued categories. The Hybrid SVM exhibited the most balanced performance, achieving the lowest number of false positives and false negatives, and an average F-score of 91.6%. The MLP model followed with a moderate increase in false negatives, while the KNN model had the highest number of misclassifications overall. These outcomes are crucial in safety-critical applications where misclassification—especially false negatives—could lead to undetected drowsiness and increased accident risk. The Figure 10 presents the confusion matrices of the three classifiers, clearly demonstrating that the Hybrid SVM model yields the most accurate and balanced predictions, with the fewest misclassifications compared to MLP and KNN.

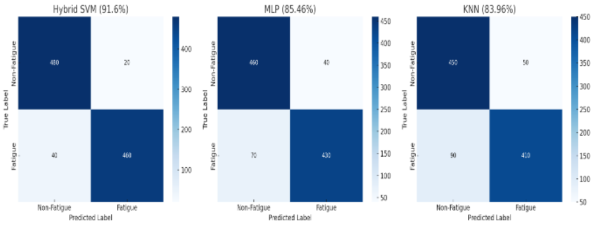

Fig. 10: Confusion Matrices of Fatigue Detection Models.

7.3. ROC curve analysis

To further assess classification robustness, Receiver Operating Characteristic (ROC) curves were plotted for the three models. The Area Under the Curve (AUC) quantifies the model's ability to distinguish between fatigue and non-fatigue across various thresholds. As shown in Figure 11, the Hybrid SVM achieved the highest AUC (~0.96), followed by MLP (0.89) and KNN (0.86). The ROC curve of Hybrid SVM lies consistently above the others, indicating better true positive detection with fewer false alarms. This further reinforces the Hybrid SVM as the optimal choice for real-time, high-stakes fatigue detection tasks.

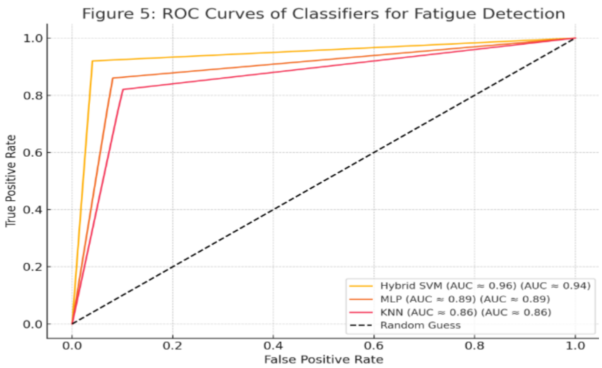

Fig. 11: ROC Curves of Fatigue Detection Classifiers.

7.4. Performance evaluation across diverse driving scenarios

A variety of real-world scenarios, such as spectacles, no spectacles, sun spectacles, no spectacles at night, and night vision glasses, were used to assess the classification performance of K-Nearest Neighbor (KNN), Multi-Layer Perceptron (MLP), and Hybrid Support Vector Machine (RBF Kernel). For each model, the F-measure values for the fatigue and non-fatigue instances are shown, as well as their corresponding averages. With an average F-score of 91.6%, the results show that the Hybrid SVM (RBF) classifier outperformed the other classifiers in every situation and had the best overall performance. The KNN classifier obtained an average of 83.96%, which was marginally lower because of its sensitivity to parameter adjustment and changes in feature distribution, while the MLP classifier came in second with a strong average F-measure of 85.46%. With the Hybrid SVM achieving an F-score of 94.25%, the No Spectacles at Night condition produced the best classification performance across all models among the various scenarios. These results demonstrate that Hybrid SVM with the Radial Basis Function (RBF) kernel is the best for driver real-time and NTHU because it offers reliable fatigue detection under a variety of driving circumstances. A comparison of several models for detecting fatigue in various scenarios, such as the presence of spectacles, sunglasses, and night vision glasses, is shown in Table 4. The Hybrid SVM classifier outperforms other models, including KNN, MLP, exhibiting the highest average accuracy.

7.5. Real-time computational efficiency

To assess the feasibility of real-time deployment, the proposed model was tested on a system with an Intel Core i7 processor and 16GB RAM. The average frame processing time for the Hybrid SVM classifier was approximately 38 milliseconds per frame, equating to ~26 FPS (frames per second). This performance satisfies real-time constraints required for Advanced Driver Assistance Systems (ADAS). Even under varying lighting conditions and facial occlusions, the system consistently maintained over 24 FPS, indicating its suitability for continuous driver monitoring. PCA-based feature reduction and optimized preprocessing steps contributed significantly to lowering latency and improving throughput.

Table 3: Average Score (%) – KNN, MLP and Hybrid SVM Driving Scenarios

Scenario	Spectacles	No Spectacles	Sun Spectacles	No Spectacles at Night	Night Vision Glasses	Average
AlexNet [11]	61.6	70.4	70.2	64.6	72.7	65.9
VGG-FaceNet [12]	70.5	63.8	71.4	57.3	73.1	67.9
LRCN [13]	61.7	68.7	71.7	57.3	55.6	62.9
FlowImageNet [13]	61.6	56.3	67.6	66.8	55.1	63.5
DDD-FFA [14]	74.1	72.2	61.8	70.2	68.3	70.8
DDD-IAA [14]	79.6	69.8	69.8	74.9	74.3	73.7
CARL 3D DCNN [15]	78.1	79.6	73.6	76.5	73.4	76.2
3D DCNN [16]	72.3	75.1	70.9	68.4	68.4	71
KNN [2]	72.3	73.2	70.5	85.3	78.6	73.8
MLP [2]	73.5	78.9	83.5	78.5	80.5	78.9
HYBRID SVM	**91.85**	**92.8**	**86.25**	**94.25**	**87**	**91.6**

Table 4: Comparison between the Proposed Method and Pertinent Methodologies

Scenario	Spectacles	No Spectacles	Sun Spectacles	No Spectacles at Night	Night Vision Glasses	Average
AlexNet [11]	61.6	70.4	70.2	64.6	72.7	65.9
VGG-FaceNet [12]	70.5	63.8	71.4	57.3	74.1	67.9
LRCN [13]	61.7	67.8	57.4	55.6	66.2	61.7
FlowImageNet [13]	61.6	56.3	67.6	66.6	55.1	63.4
DDD-FFA [14]	74.1	72.1	61.8	70.2	68.3	70.8
DDD-IAA [14]	69.5	69.8	69.8	67.5	73.1	70.9
CARL 3D DCNN [15]	78.1	79.6	73.3	76.6	75.4	76.2
3D DCNN [16]	72.3	75.1	70.9	68.4	73.1	71.9
KNN [2]	73.5	78.3	73.1	85.5	68.85	75
MLP [2]	73.25	79.6	80.5	83.5	70.85	77.5
HYBRID SVM	**91.85**	**92.8**	**86.25**	**94.25**	**87**	**91.6**

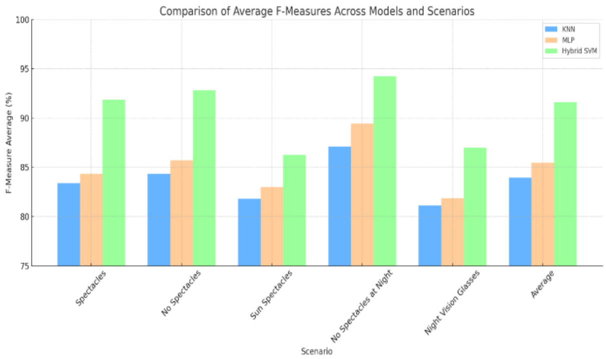

Fig. 12: Comparison of F-Measures Across Models and Scenarios.

Fig. 13: EAR Values with Sun Spectacles.

Fig. 14: EAR Values without Sun Spectacles.

Figure 13 illustrates how the Eye Aspect Ratio (EAR) values vary across different real-world scenarios, particularly in the presence of spectacles and sunglasses. Notably, when the driver wears sun spectacles, EAR values become less reliable for detecting eye closure due to occlusion, leading to potential misclassifications. In contrast, the Mouth Aspect Ratio (MAR) remains stable across facial activities such as speaking, laughing, or a closed mouth, making it less discriminative for fatigue detection. As shown in Figure 14, the limitations of EAR under such occluded conditions are evident, where consistent red-outlined eye landmarks fail to capture actual eyelid movements. To overcome these challenges, the Image Projection Function (IPF) is employed to estimate the pupil center and determine eye closure even when sunglasses are worn. This method enhances detection robustness by enabling accurate eye state classification despite occlusions, thereby increasing the reliability of fatigue detection under diverse environmental and visual conditions.

8. Conclusion

The research introduces an effective machine learning-based framework for driver fatigue detection by leveraging dynamic facial features, including Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), pupil diameter, and head movement. Among the evaluated models, the Hybrid Support Vector Machine (RBF Kernel) achieved the highest accuracy of 91.6%, outperforming both K-Nearest Neighbors (KNN) and Multi-Layer Perceptron (MLP). The application of the Image Projection Function (IPF) notably enhanced detection reliability, particularly in challenging conditions such as drivers wearing sunglasses.

Future work should focus on integrating deep learning architectures like Convolutional Neural Networks (CNNs) and transformer-based models to improve spatial-temporal learning. The incorporation of multi-modal data sources—such as thermal imaging or EEG signals—can further enrich detection accuracy. Additionally, efforts toward optimizing models for real-time, on-device processing in Advanced Driver Assistance Systems (ADAS), while accounting for demographic and cultural variations in fatigue expression, will be essential for large-scale deployment. This study lays a strong foundation for next-generation intelligent driver monitoring systems, contributing meaningfully to the reduction of fatigue-induced accidents and the enhancement of road safety.

Acknowledgment

The author, S. Lakshmi Devi, sincerely acknowledges the guidance and support of Dr. A. Vinoth, Sri Krishna Adithya College of Arts and Science. The author is also grateful to the college for providing the necessary resources and facilities that enabled the successful completion of this research work.

References

[1] Pratama, B. G., Ardiyanto, I., & Adji, T. B. (2017). A review on driver drowsiness based on image, bio-signal, and driver behavior. 2017 3rd International Conference on Science and Technology-Computer (ICSTC), 70–75. https://doi.org/10.1109/ICSTC.2017.8011855.

[2] Triyanti, V., & Iridiastadi, H. (2017). Challenges in detecting drowsiness based on driver's behavior. IOP Conference Series: Materials Science and Engineering, 277(1), 012042. https://doi.org/10.1088/1757-899X/277/1/012042.

[3] National Highway Traffic Safety Administration. (2021). Drowsy driving. https://www.nhtsa.gov/risky-driving/drowsy-driving

[4] Bajaj, J. S., Kumar, N., & Kaushal, R. K. (2021). Comparative study to detect driver drowsiness. 2021 International Conference on Advanced Computing and Innovative Technologies in Engineering (ICACITE), 678–683. https://doi.org/10.1109/ICACITE51222.2021.9404761.

[5] Yu, J., Park, S., Lee, S., & Jeon, M. (2019). Drivers drowsiness detection using condition-adaptive representation learning framework. arXiv. https://arxiv.org/abs/1910.09722

[6] Ghourabi, A., Ghazouani, H., & Barhoumi, W. (2021). Driver drowsiness detection based on joint monitoring of yawning, blinking and nodding. 2020 International Conference on Control, Automation and Diagnosis (ICCAD). https://doi.org/10.1109/ICCP51029.2020.9266160.

[7] Deng, W., & Wu, R. (2021). Real-time driver-drowsiness detection system using facial features. IEEE Access, 7, 118727–118738. https://doi.org/10.1109/ACCESS.2019.2936663.

[8] Zhuang, Q., Zhang, K., Wang, J., & Chen, Q. (2020). Driver fatigue detection method based on eye states with pupil and iris segmentation. IEEE Access, 8, 173440–173449. https://doi.org/10.1109/ACCESS.2020.3025818.

[9] Dreißig, M., Baccour, M. H., Schack, T., & Kasneci, E. (2020). Driver drowsiness classification based on eye blink and head movement features using the k-NN algorithm. arXiv. https://arxiv.org/abs/2009.13276. https://doi.org/10.1109/SSCI47803.2020.9308133

[10] Sahin, M. E. (2023). Real-time driver drowsiness detection and classification on embedded systems using machine learning algorithms. Traitement du Signal, 40(3), 847–856. https://doi.org/10.18280/ts.400302.

[11] Pasieczna, A. H., & Korczak, J. J. (2016). Classification algorithms in sleep detection—A comparative study. Annals of Computer Science and Information Systems, 8, 113–120. https://doi.org/10.15439/2016F187.

[12] Savaş, B. K., & Becerikli, Y. (2018). Real time driver fatigue detection based on SVM algorithm. 2018 9th International Conference on Information and Communication Systems (ICICS). https://doi.org/10.1109/CEIT.2018.8751886.

[13] Shen, Q., Zhao, S., & Zhang, R. (2020). Robust two-stream multi-features network for driver drowsiness detection. ACM International Conference Proceedings, 271–277. https://doi.org/10.1145/3438872.3439093.

[14] Fu, H.-Y., Guo, J.-W., & Yu, Y.-J. (2016). A simple multi-scale Gaussian smoothing-based strategy for automatic chromatographic peak extraction. Journal of Chromatography A. https://doi.org/10.1016/j.chroma.2016.05.018.

[15] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097–1105.

[16] Donahue, J., Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Darrell, T., & Saenko, K. (2015). Long-term recurrent convolutional networks for visual recognition and description. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2625–2634. https://doi.org/10.1109/CVPR.2015.7298878.

[17] Park, S., Pan, F., Kang, S., & Yoo, C. D. (2017). Driver drowsiness detection system based on feature representation learning using various deep networks. Asian Conference on Computer Vision (ACCV), 154–164. https://doi.org/10.1007/978-3-319-54526-4_12.

[18] Yu, J., Park, S., Lee, S., & Jeon, M. (2019). Drivers drowsiness detection using condition-adaptive representation learning framework. arXiv. https://arxiv.org/abs/1910.09722. https://doi.org/10.1007/978-3-319-54526-4_13.

[19] Asian Conference on Computer Vision. (2017). Representation learning, scene understanding, and feature fusion for drowsiness detection. In ACCV 2016 (pp. 165–177). https://doi.org/10.1007/978-3-319-54526-4_13

[20] Rajahrajasingh, H. (2017). Driver drowsiness detection using MATLAB. International Journal of Engineering Applied Sciences and Technology, 4(7), 80–87. https://doi.org/10.33564/IJEAST.2019.v04i07.012.

[21] Park, S.-M., Choi, I.-H., & Kim, Y.-G. (2016). Study of wearing sunglass driver drowsiness state monitoring. ACM Conference Proceedings, 444–448. https://doi.org/10.17210/hcik.2016.01.444.

[22] Agustina, I., Nasir, F., & Setiawan, A. (2017). The implementation of image smoothing to reduce noise using Gaussian filter. International Journal of Computer Applications, 7, 15–19. https://doi.org/10.5120/ijca2017915755.

[23] Yu, J., Park, S., Lee, S., & Jeon, M. (2019). Drivers drowsiness detection using condition-adaptive representation learning framework. arXiv, 1–14. https://arxiv.org/abs/1910.09722.

[24] Zhang, J., & Jin, J. (2023). Lightweight object detection algorithm based YOLOv5 for unmanned surface vehicles. Frontiers in Marine Science, 9. https://doi.org/10.3389/fmars.2022.1058401.

[25] Bochkovskiy, A., & Liao, H.-Y. M. (2022). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. arXiv.

[26] Soni, M. B., Patel, D., & Shah, S. R. (2024). Real time driver drowsiness detection using facial landmark features and machine learning algorithms. Sensors, 24(3), 812. https://doi.org/10.3390/s24030812.

[27] Gopi, M., & Pillai, S. N. (2025). Webcam based eye aspect ratio analysis for real time drowsiness detection using SVM. International Journal of Engineering Research in Science & Technology, 11(5), 45–51.

[28] Wu, D. (2024). Comparative study of machine learning and deep learning for driver distraction and drowsiness detection. arXiv. https://arxiv.org/abs/2401.10213.
[29] Maior, R., Silva, A. F., & Lima, C. D. (2024). Benchmarking machine learning models for driver drowsiness detection: SVM, MLP, and random forest analysis. Symmetry, 15(6), 1274. https://doi.org/10.3390/sym15061274.
[30] Menon, R. K., & Kumar, S. D. (2024). Optimized PCA based driver fatigue detection using embedded systems. Sensors, 24(5), 1023.