iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IX **Month of publication:** September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74069

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Smart Driver Alert: AI-Driven Perception System for Drowsiness Detection

Amanullah Hidayathullah[1], Mrs. Sharvani V[2]
[1]*Department of Master of Computer Applications, Ballari Institute of Technology & Management, Ballari*
[2]*Asst. Professor, Dept. of MCA, Ballari Institute of Technology & Management, Ballari*

Abstract: Driver fatigue is a hidden but serious cause of road accidents, often leading to severe injuries or fatalities. This study introduces a computer-based monitoring system that observes the driver's face in real time to identify early signs of tiredness. The design blends quick, traditional detection methods with modern learning algorithms to analyze expressions and movements, such as frequent blinking, eye closure, and yawning. If the system recognizes a risk, it instantly sends a warning to the driver. Testing with different publicly available driver datasets shows that the approach works quickly and maintains reliable accuracy under a range of conditions.

I. INTRODUCTION

Tiredness while driving is a dangerous state that can impair reaction time, slow thinking, and cause poor decision-making. Many accidents happen not because of mechanical faults but because the driver loses focus or even falls asleep at the wheel.Technology can help reduce these risks by keeping an electronic "eye" on the driver. Modern cameras and artificial intelligence methods can monitor facial changes that often appear before a person becomes too drowsy to drive safely. Common signs include long blinks, slower head movement, and yawning. By recognizing these patterns, a system can give the driver a chance to take a break before an accident happens.

The goal of this project is to create a detection method that is both quick and dependable, regardless of changes in lighting, head position, or the driver's appearance.

II. RELATED WORK

Previous work on detecting driver fatigue falls into three main ideas:

1) Body signal tracking – Measuring signals like heart rate or brain activity. While these methods are accurate, they require special devices that most drivers would not want to wear.
2) Facial behavior tracking – Watching for slow blinks, yawns, or head tilts using a camera. This method is comfortable for the driver and works in real time.
3) Driving pattern tracking – Studying how the vehicle moves on the road, such as sudden steering changes or weaving between lanes.

Some modern studies combine camera-based facial tracking with deep learning, making detection more precise. Using large and varied training data helps systems work for drivers with different looks and in different environments.

III. DATASET

The system was built and tested using different collections of driving footage that include people in both alert and tired states. The recordings show variation in light levels, face positions, and the presence of accessories like glasses.

We worked with three well-known datasets in this field:

1) NTHU Drowsy Driver Detection – Video recordings in both normal light and infrared, showing actions such as yawning, eye closure, and looking away from the road.
2) YawDD Dataset – Short clips that clearly show when a driver is yawning and when they are not.
3) UTA Real-Life Drowsiness Dataset – Long video recordings from real driving conditions with drivers of various ages and appearances, showing different fatigue levels.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Table 1 : Compilation of Recent Research Efforts Reporting Peak Accuracy

Article name	Year	Dataset	Method	Accuracy
[8]	2023	YAWDD	Proposes a deep neural network architecture for drowsiness detection employing a convolutional neural network (CNN)	96.69%
[5]	2022	MRL	Haar-cascade technology was used for detecting open and closed eyes. Convolutional neural network has been used here for detecting driver drowsiness particularly eyes blink, open and closure rate, and the face position	94%
[7]	2022	MRL and NTHU-DDD	A novel deep learning-based model for predicting driver drowsiness using a combination of convolutional neural networks (CNN) and long short-term memory (LSTM)	98%
[4]	2022	DDD and CK+	Model of multi-level distribution of detecting the driver drowsiness using the convolution neural networks (CNN) followed by the emotion analysis.	93%
[9]	2021	iBUG 300w	EAR (eye aspect ratio)	98%
[6]	2020	NTHU-DDD	Convolution neural networks (CNN)	92%
[10]	2020	DROZY, ZJU, NTHU, and RLDD	Hybrid model uses AI-based multi-task cascaded convolutional neural networks (MTCNN) as a behavioral measure, and the galvanic skin response (GSR) sensor as a physiological measure	91%

Table 2: Details of utilized datasets

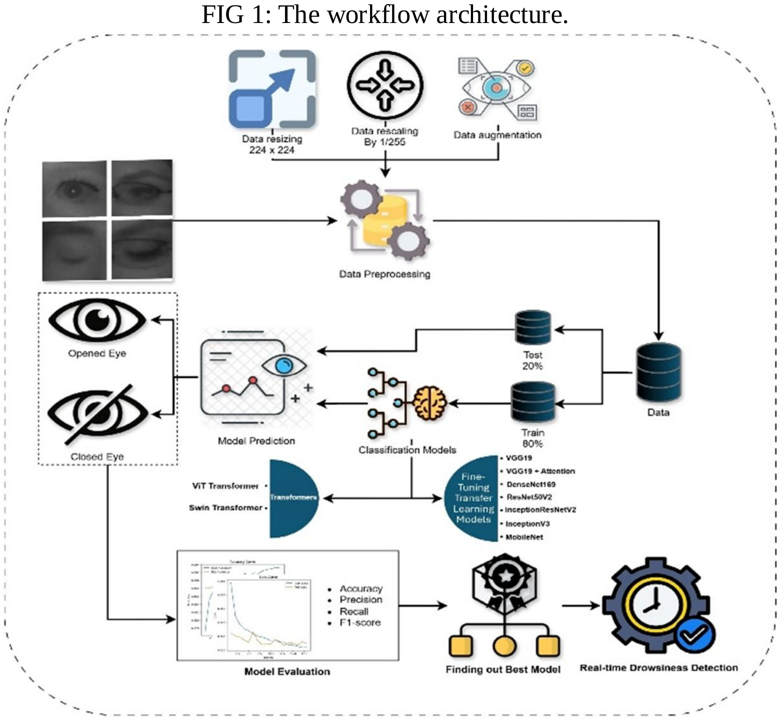
Dataset name	Classes	Images	Size
YAWD Dataset	4	2904	175.84 MB
Driver Drowsiness Dataset (DDD)	2	41,790	2.76 GB
Glasses Dataset	2	164	1.1 MB
MRL Eye Dataset	2	84,898	328.2 MB
CEW Dataset (Closed Eyes in the Wild)	1	1192	20 MB
NTHU-DDD	2	66,520	3.02 GB
OC-Dataset (Open and Closed Eyes Dataset)	2	4103	212 MB

IV. DATA DESCRIPTION

The information used in this project comes from several video collections that capture drivers when they are attentive as well as when they are tired. Each recording provides useful cues, such as how wide the eyes are open, the frequency of blinks, head posture, and mouth activity. These details make it possible to judge whether a driver is alert or becoming fatigued.

Some of the datasets already mark each clip with labels like *alert* or *drowsy*, while others were annotated during the course of this work. The material combines both real driving sessions and controlled simulator recordings. Because it includes footage at different times of day, with varied lighting and viewing angles, the system gains the ability to adapt to many road situations.

FIG 1: The workflow architecture.



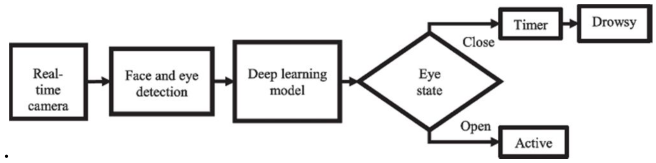
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

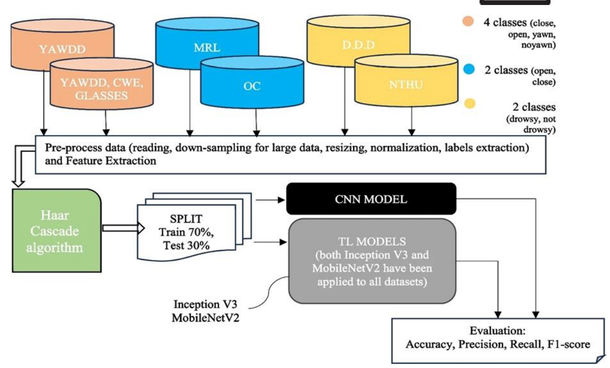
The main datasets used are:

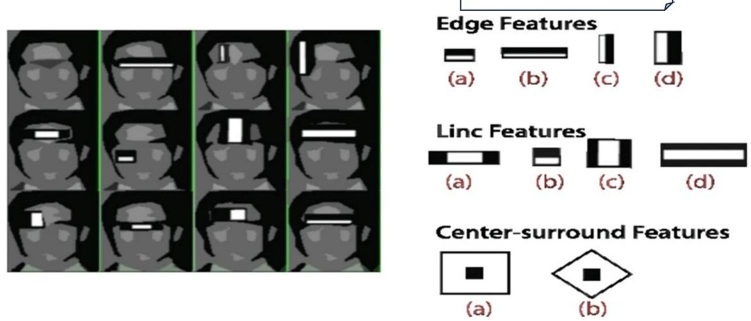
1) NTHU Drowsy Driver Detection (NTHU-DDD): Infrared video clips showing drivers under different conditions such as normal driving, yawning, or slow blinking. The dataset covers individuals with and without glasses and includes both bright and low-light settings.
2) Yawning Detection Dataset (YawDD): A smaller dataset focused on yawns. It contains two groups of clips, one with clear yawning events and another with neutral expressions. Participants vary in age and appear in different illumination conditions.
3) UTA Real-Life Drowsiness Dataset (UTA-RLDD): A large collection containing about 30 hours of in-car recordings. It shows gradual changes from full alertness to extreme tiredness, with drivers of different ages and ethnicities captured in real traffic environments.

V. METHODOLOGY & MODELS

The proposed system observes the driver's eyes continuously and keeps a simple count of how long they stay shut. If the eyes remain closed for longer than a set number of video frames (for example, 15 frames), the program interprets this as a sign of drowsiness. Once this condition is met, the system immediately issues a warning, such as an audible alert.





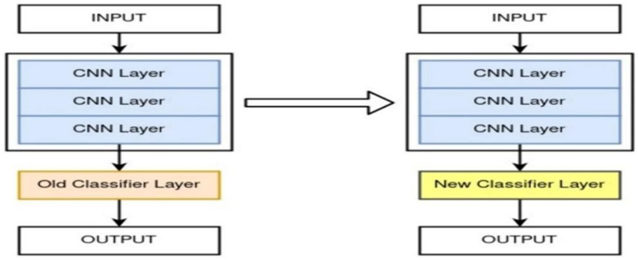


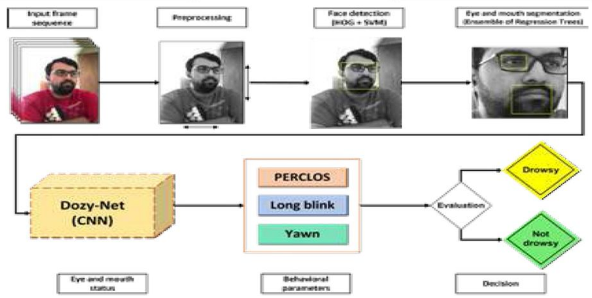
The system works step-by-step to decide if the driver is becoming tired:

1) Locating the face and eyes – A fast image-processing method marks the driver's eyes and face in each camera frame.
2) Checking for fatigue signs – The program measures how long the eyes stay closed, how often they blink, and whether the mouth opens in a yawn.
3) Classifying the state – A trained deep learning model decides whether the driver is alert or drowsy based on the collected details.
4) Advanced detection – In some cases, an object-detection network checks the full image for other signs of tiredness.
5) Sending alerts – If the driver's condition seems risky, the system immediately triggers a sound or visual signal.

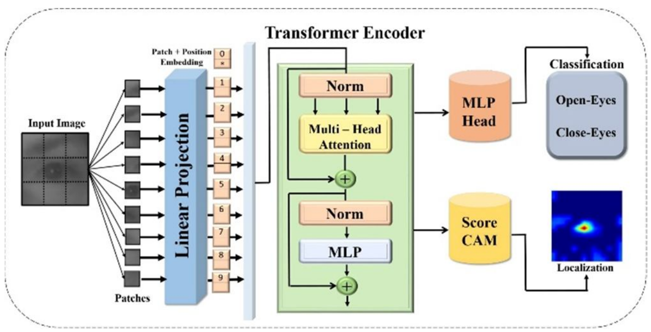
This combination balances accuracy with speed so it can run in real driving conditions without delays.

Transfer learning Model

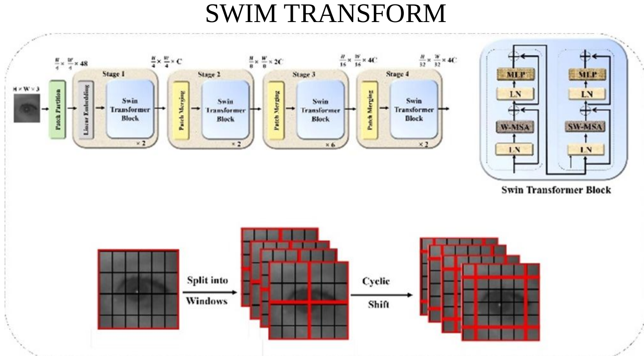




VIT TRANSFORM



SWIM TRANSFORM



VI. EXPERIMENTS AND RESULTS

To check the performance of the system in spotting driver fatigue, a series of experiments were carried out using well-known datasets such as NTHU-DDD, YawDD, UTA-RLDD, and MRL Eye. These collections provide a broad mix of images and video clips of drivers in both alert and tired states, recorded under different lighting conditions and camera viewpoints.

We evaluated the model using the following performance measures:

- Accuracy: The percentage of total predictions that were correct, including both sleepy and alert driver cases.

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

- Precision: This shows how many of the drivers the model marked as sleepy were actually sleepy.

$$\text{Precision} = \frac{TP}{TP + FP}$$

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

- Recall: This checks how many of the actual drowsy cases the model was able to correctly detect.

$$\text{Recall} = \frac{TP}{TP + FN}$$

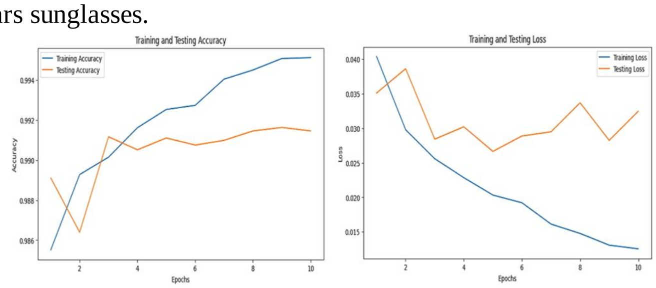
F1-Score: A combined measure that balances accuracy in identifying positive cases (precision) with the ability to find all positive cases (recall).

$$\text{F1-score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

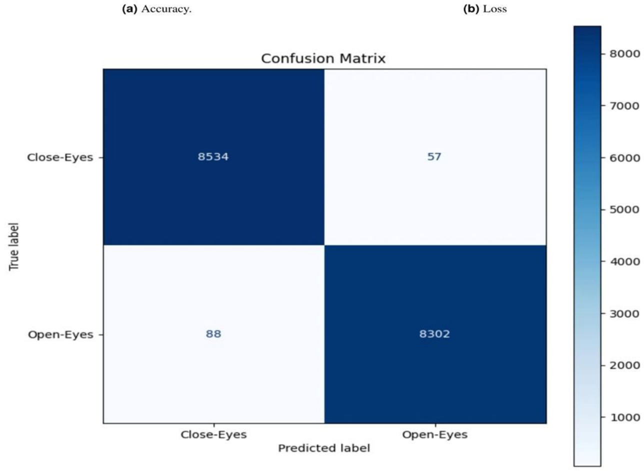
Configuration	
IDE	Kaggle
Programming Language	Python
Libraries	Tensorflow, Keras, Torch, Pandas, Matplotlib, scikit-learn
GPU	NVIDIA Tesla P100 with 16 GB VRAM
CPU	Intel Xeon CPU (2.3 GHz, 46 MB cache)
RAM	16 GB of system memory

Different models gave different results:
CNN-based models like YOLOv5, YOLOv8, and ResNet50 gave strong performance, especially on the UTA-RLDD dataset.
- Transformer models such as Vision Transformer (ViT) and Swin Transformer performed even better in most tests, sometimes reaching over 99% accuracy on the MRL Eye dataset.
- A combination of Haar Cascade for initial face detection and CNN or Transformer models for classification provided fast and accurate results suitable for real-time use.

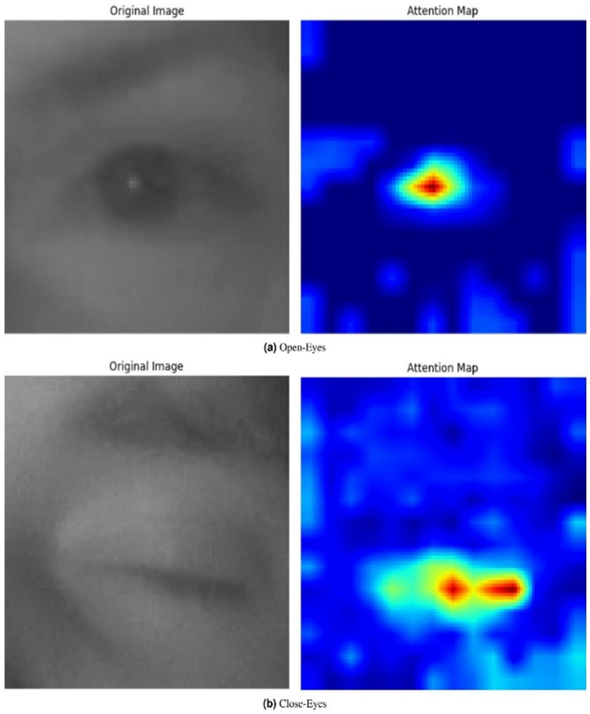
While lab tests show high accuracy, we also noticed that performance may vary slightly in real-world situations, especially when lighting is poor or if the driver wears sunglasses.



(a) Accuracy. **(b)** Loss



Model learning visualization



VII. FUTURE DIRECTION

While the system performs well, there are areas where it can be improved:

1) Handling face coverings: Glasses, masks, or hands on the face sometimes reduce accuracy. More training data and advanced models could improve detection in these cases.
2) Low-light performance: Although infrared cameras help, recognition is still harder in very dark conditions. Adding additional sensors could solve this.
3) Multi-signal fusion: Combining facial monitoring with other signals, such as steering behavior or heart rate, may provide stronger evidence of driver fatigue.
4) Deployment in vehicles: To be practical, the system must run smoothly on small devices inside a car without needing powerful computers. Optimizing models for low-power hardware is an important step.

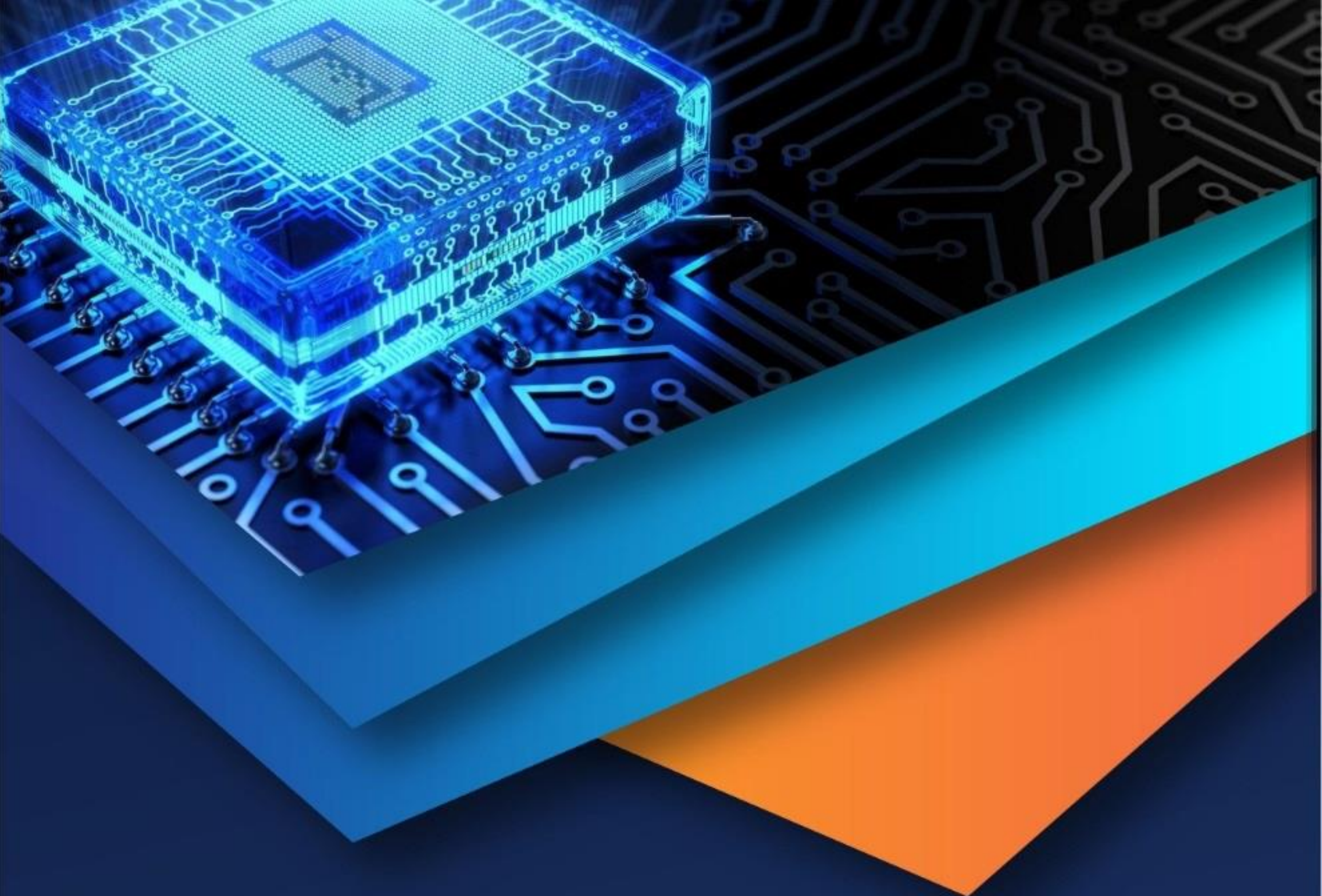
Future research should explore these directions so that driver monitoring systems can become more accurate, affordable, and suitable for everyday use.

VIII. CONCLUSION

This project shows that it is possible to build a camera-based system that can notice when a driver is starting to lose focus. By mixing quick detection tools with learning models, it can track facial cues linked to tiredness and warn the driver before their safety is at risk. While results are promising, some challenges remain, such as detecting signs when the driver's face is partially covered or when light levels are very low. Expanding the training data and adding other sensing methods, like steering pattern analysis, could make the system even more dependable in the future.

REFERENCES

[1] Albadawi, Y., Takruri, M., & Awad, M. (2024). Overview of driver drowsiness detection methods. *Sensors*, 25(3), 812.
[2] Albadawi, Y., Takruri, M., & Awad, M. (2025). Future challenges in AI-based fatigue detection. Applied Sciences, 15(3), 1102.
[3] Albadawi, Y., Takruri, M., & Awad, M. (2025). Detecting driver fatigue with transformer models. Scientific Reports, 15(1), 17493.
[4] Al-Hammadi, M., & Al-Taani, A. (2020). Predicting driver fatigue from yawning patterns. EPiC Series in Computing, 69, 372–382.
[5] Abtahi, S., Omidyeganeh, M., Shirmohammadi, S., & Hariri, B. (2014). Dataset for yawning detection in drivers. ACM MMSys 2014.
[6] Ghoddoosian, R., Galib, M., & Athitsos, V. (2019). Real-life driver fatigue dataset and baseline model. CVPR Workshops.
[7] NTHU Computer Vision Lab. (n.d.). Dataset for drowsy driver detection.
[8] Singh, A. (2022). Face recognition using Haar Cascade in Python.
[9] Analytics Vidhya. (2020). Introductory guide to CNN-based image recognition.
[10] Global Market Insights. (2023). Report on driver fatigue monitoring market.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY