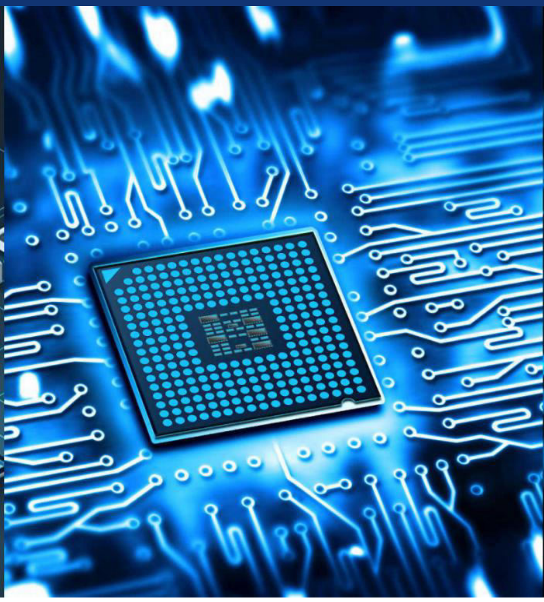
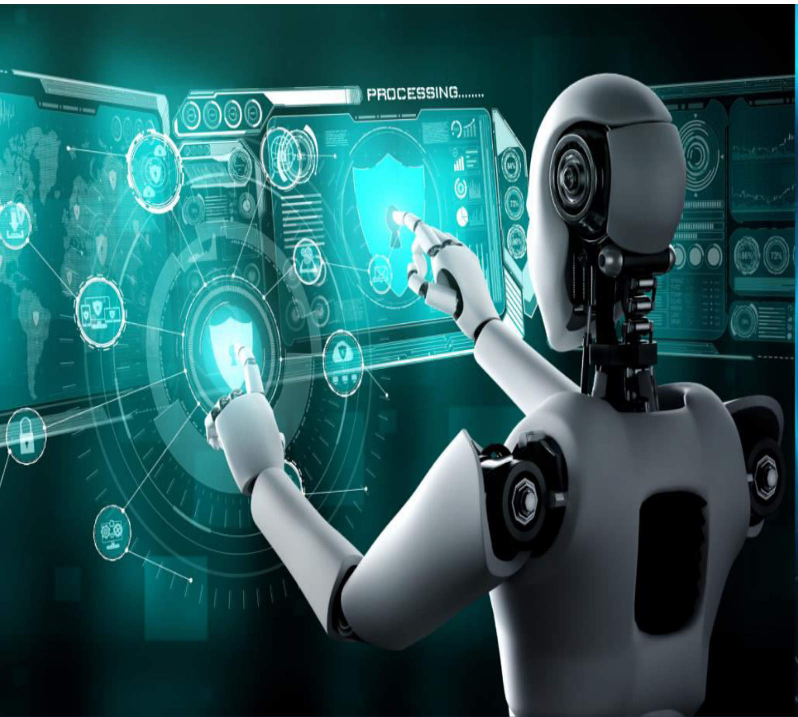
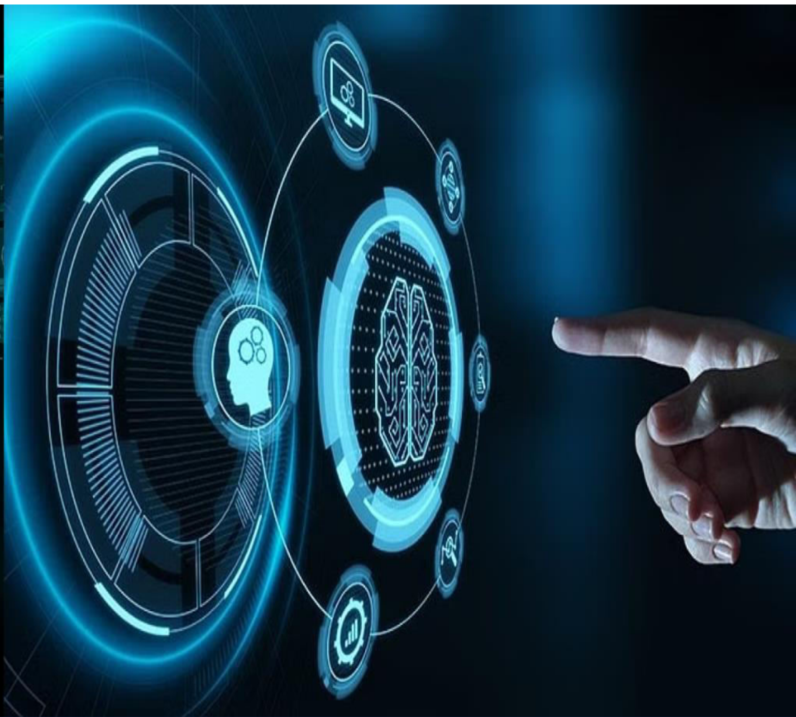
ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 13, Issue 4, April 2025

www.ijircce.com ijircce@gmail.com +91-9940572462 +91 63819 07438

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI:10.15680/IJIRCCE.2025.1304146

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Drowsiness Detection System using CNN and Python Flask

Ch. Neha kamal[1], D. Jyothi kavya sri[2], M. Jay Shankar[3], T. Anand kumar[4], Ch Sai Siva Durga[5]

U G Students, Dept. of CSE-DS, SRK Institute of Technology, Enikepadu, Vijayawada, Andhra Pradesh, India[1-4]

Assistant Professor, Dept. of CSE-DS, SRK Institute of Technology, Enikepadu, Vijayawada, Andhra Pradesh, India[5]

ABSTRACT: Traffic accidents caused by driver fatigue and drowsiness are a significant threat to public safety, leading to serious injuries and deaths worldwide. Traditional detection of drowsiness depends on self-remediation or physiological sensors, which cannot always be practical. This AI -driven system uses computational vision and deep learning techniques to analyze facial resources and eye movement patterns, identifying initial signs of drowsiness and warning the driver immediately. The system employs a convolutional neural network (CNN) and OpenCV to process real time video feeds, detecting important facial reference points, such as eye closure, yawning and head position. A pre-trained deep learning model is used to classify drowsiness levels based on extracted visual bands. Flask serves as a back-end structure, allowing an easy-to-use web app where users can access real-time monitoring and receive alerts through visual or audio notifications. This solution is designed to improve road safety by providing timely notices, reducing the risk of lonely related accidents.

KEYWORDS: Drowsiness detection system, Machine Learning, CNN Algorithm, Eye Aspect Ratio (EAR), Real-time Processing, Fatigue Monitoring.

I. INTRODUCTION

The purpose of our project is to reduce traffic accidents caused by driver drowsiness. Fatigue behind the wheel is one of the main contributors to traffic collisions, as private sleep drivers are more likely to lose focus or fall asleep while driving. To solve this problem, we propose a machine learning -based application that can detect real -time drowsiness and issue timely alerts to avoid accidents and increase road safety.

Our project, titled "Drowsiness Detection System using Flask CNN and Python", is designed to monitor driver alerting using computational vision and deep learning techniques. The system employs convolutionary neural networks (CNNS) to detect important facial characteristics such as eye closure, yawning and mouth movement. Using OPENCV for video and balloon processing for the back -end web application, the system analyzes live video feeds to track behaviors associated with drowsiness. The distance between the driver's eye iris and the mouth opening is calculated using the Euclidean distance formula to determine the levels of drowsiness. Real -time alerts are generated through visual or audio tips to wake the driver and reduce the risk of accidents

The paper is structured as follows: Section II discusses related work, highlighting previous studies in ML-based drowsiness detection system. Section III provides a detailed background on the algorithms used in the project. Section IV introduces the proposed system, detailing the methodology and model architecture. Section V presents comparative results using graphical visualizations, and Section VI concludes the study with insights and future research directions.

II. RELATED WORKS

Detect drowsiness as a field of significant research due to the dangerous number of accidents caused by the fatigue and cautious deficiency of the driver. Several techniques have been proposed to monitor the driver's behavior, such as the closure of the eyes, analyzing yawning frequency and head movements Several systems depend on IoT devices, facial milestones and computational vision algorithms to detect signs of drowsiness. In one study, the researchers proposed a night driver monitoring system, while others developed IoT -based portable devices to track the movement of the eyelids. Some approaches are focused on detecting real eyes using HAAR and DLIB, while others combine various

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

facial features such as eye closure and yawning for more accurate detection. Despite the variety of techniques, there are still limitations such as sensitivity to lighting, need for constant connectivity and hardware dependence

S.no	Paper Information	Description	Limitations/Inference
1.	Vidhu Valsan A; Paul P Mathai; Ierin Babu [1]	Developed Night -based driver drowsiness monitoring using computer vision.	Performance is affected by lighting conditions
2.	Menchie Miranda et al. [2]	Proposed IoT-based eyelid movement monitoring device.	Requires continuous internet connectivity.
3.	Maheswari, V. Uma, et al. [3]	Used image processing techniques such as perclos, EAR. It combines facial analysis and gesture using CNN.	External factors such as bad lighting, face occlusion and sunglasses affect accuracy.
4.	T. Soukupova and J. Cech [4]	Presented Eye blink detection using facial landmarks.	Considers only blinking, not other cues like yawning.
5.	Adrian Rosebrock [5]	Applied Eye blink detection with OpenCV, Python, and dlib	Not a complete drowsiness alert system.
6.	Li, Yongkai, et al [6]	Proposed a system based on wearable glasses using a light CNN (LGN) to detect drowsiness, tracking eyelid movements.	limited participants. Real-world performance is unverified, and the wearable's size may affect comfort and usability.
7.	Tejasweeni Musale and Pansambal [7]	Introduced Raspberry Pi-based facial feature detection system.	It is hardware-dependent and not easily scalable.

III. BACKGROUND

1. Machine learning Algorithms
   1.1 Adaboost

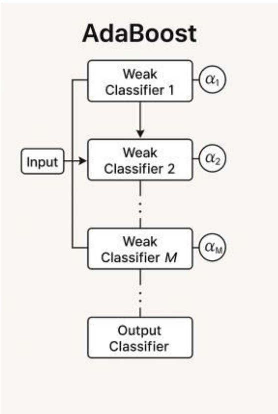


Fig1: Adaboost

Figure 1 Adaboost, brief for adaptive reinforcement, is a machine learning algorithm that is used to improve the performance of a weak classifier. In terms of the detection of the driver's drowsiness, the adaboost plays an important role in increasing the accuracy of the object detection, especially when the HAAR waterfall is integrated into the classifier. It works by mixing multiple weak classifiers in a strong, which helps in reliable detection of facial features such as the eyes and face. These characteristics are necessary to assess whether the driver is sleep or alert.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

1.2 CNN (Convolutional Neural Network)

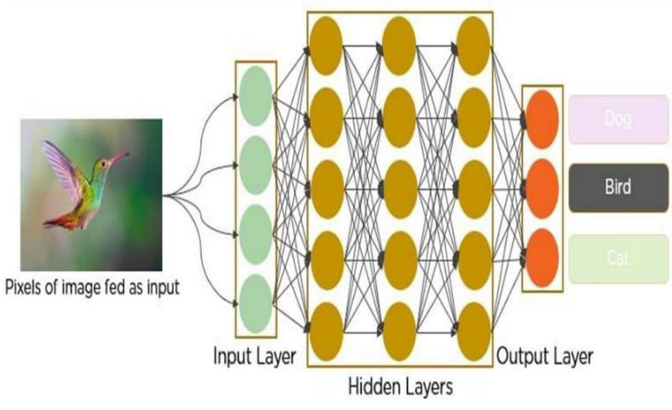


Fig2: CNN

Figure 2: (CNNs) are deep learning algorithms, especially suitable for image classification and resource extraction. In this application, CNN is used to classify the position of the eye as open or off based on the exhaust image frame. CNN conversion processes the input image through the algorithm, where the image is grouped and completely associated with layers to identify the pattern and differentiate between different states. By training CNN in an open and closed eye set, the model can make precise predictions in real time. This classification is important for calculating eye ratio (EAR), which is used to determine the level of drowsiness.

2. Computer Vision Algorithms

2.1 HAAR (HAAR Cascade Classifier)

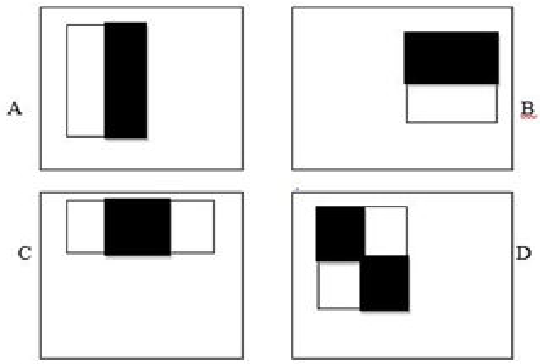


Fig3: Haar Cascade

Fig 3 The Haar Cascade classifier is an object detection technique used to identify objects in images or videos. It is particularly effective for face detection and an eye on real time, which is critical in a driver drowsiness detection system. This classifier is trained using positive and negative images to recognize specific resources such as eyes, nose and mouth. Here the sum of pixel values in the white rectangles is subtracted from those in the gray rectangles. This differential approach helps to detect visual structures such as edges and lines quickly and efficiently. To increase detection accuracy, especially in varied lighting conditions or angles, the Region of Interest (ROI) is used. A temperature-like variable is computed as:

$$T= [100-|FC/2|]/100$$

where (FC) is the face degree, and (T) helps refine detection thresholds dynamically based on the driver's face orientation.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI:10.15680/IJIRCCE.2025.1304146

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

2.2 Drowsiness Detection Algorithm (includes EAR - Eye Aspect Ratio)

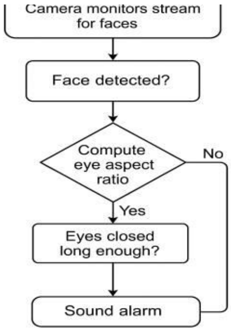


Fig4: CNN

Fig 4 The algorithm of core drowsiness detection depends on the calculation of the aspect ratio (EAR) of the eye, a method that measures the ratio of distance between major eye sites. If the eyes remain closed for a period of over - determined range (continuously indicated by low ear value), the system explains it as drowsiness. The ear is calculated for both eyes and average to get a strong estimate. When jointly (using the mar -mouth aspect ratio) with the mouth detection for yawning, the algorithm becomes more reliable. If either the eye closed or yawning is detected for a long time, there is an alarm trigger to alert the driver. This approach enables a non-intrusive, real-time monitoring system that increases road safety by preventing accidents caused by fatigue.

3. Dataset

A Drowsiness Detection dataset with the following attributes is taken for analysis to perform the prediction, as shown in table 1.

Origin Type	**Description**	**Contribution to Application**
Simulated data generation	artificially created acceleration data, covering various steering scenarios.	It allows controlled model tests under various conditions, such as speed, road and behaviour.
Sets of public steering data sets	open-source data sets with vehicle sensor data (not always labelled).	Provides real -world steering patterns; It can be noted manually for the drowsiness states.
Custom data collection	using sensors or accelerometers in the vehicle for real -time data record.	Allows specific data collection in defined scenarios; Guarantees relevance of the model.
Research collaborations	Data collected through partnerships with academic and research institutions that work on drivers' security. These contributions include images and videos noted from driver states under various conditions.	Access to proprietary and high-quality data sets with diversified driver behaviour and vehicle responses.
Annotation and marking	manual of data segments marking in alert/drowsiness states.	Essential for supervised learning; Provides a fundamental truth for model training and validation.
Increased data	by introducing variations in collected data (eg climate, lighting).	Increases the diversity of the database and helps create a robust and generalizable model.
Continuous data collection	mechanisms for long -term data acquisition in real time.	It helps to model the evolution of steering patterns and ensures the sustainability of the detection system.
Preparation of balanced data set	ensuring the equal representation of warning and drowsiness states.	It prevents the model bias and ensures precise detection in both scenarios.

Table 1 The table describes various sources and methods to obtain data used in the development of a drowsiness

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

detection system. Includes simulated data, public data sets, smartphone applications and custom data collection approaches. Each source is described along with its specific contribution to the application, such as improving model robustness, ensuring real time accuracy, allowing supervised learning through annotation and maintaining a balanced data set. These various data acquisition strategies collectively improve the performance and adaptability of the drowsiness detection model in real scenarios in the world.

IV. PROPOSED SYSTEM

1.Architechture

Fig. 5 illustrates the architecture of the proposed machine learning System design for drowsiness detection system. System design has been introduced to create an efficient and automated way to detect driver drowsiness using image - based analysis. The process begins when the user's face is captured as an input image. This image suffers pre-processing, specifically gray scale conversion to simplify data to better resource extraction. In the next step, important resources, such as facial landmarks, are extracted from the image. These features are then compared to trained data using a neural neural Network (CNN) algorithm to verify if there are similarities and standards related to drowsiness. If the system detects closed or fallen eyes, it confirms signs of drowsiness. Finally, the system activates an alarm and sends an alert to the driver, ensuring safety, preventing drowsiness -related accidents.

Drowsiness-detection System Architecture

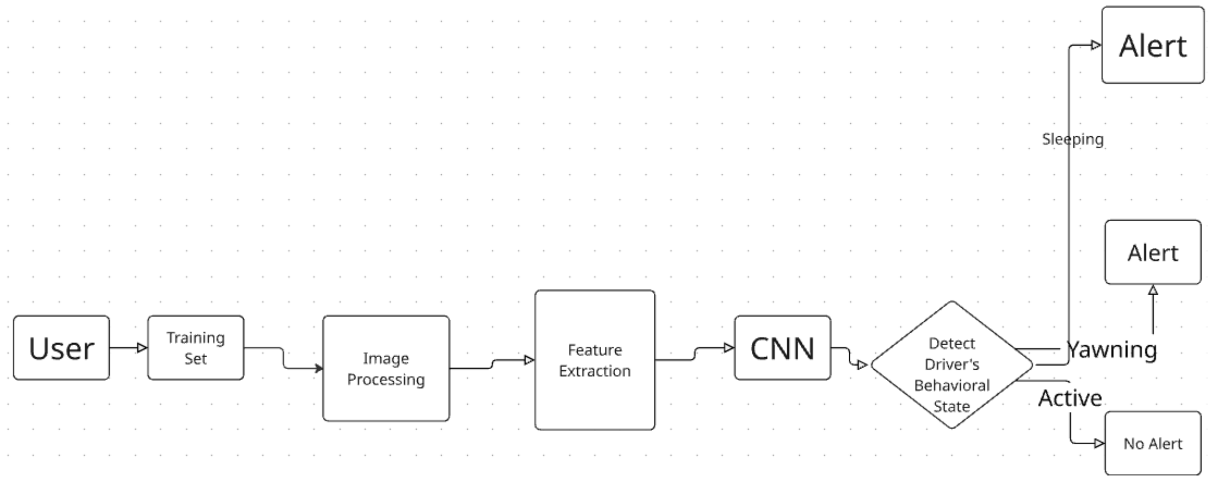


Fig5: Drowsiness – detection system Architecture

.2.Workflow

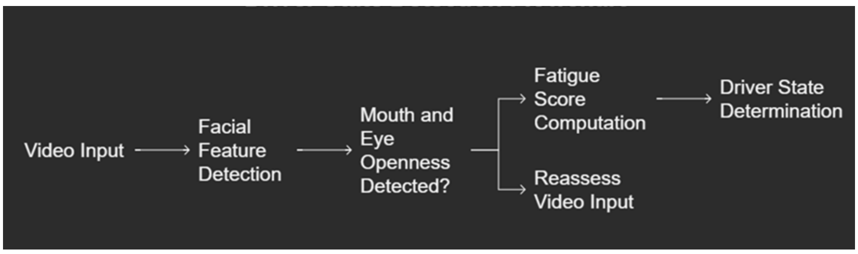


Fig 6: Drowsiness – detection system workflow

Fig. 6 5 illustrates the workflow for drowsiness detection system. The architecture outlines a system designed to assess whether a driver's eyes are open or closed, as well as to detect mouth movements, in order to closely monitor signs of fatigue. These observations are crucial for estimating the driver's level of alertness.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The subsequent phase involves calculating a fatigue score based on the data collected from the eyes and mouth. A classifier, such as the Haar Cascade and the Convolutional Neural Network (CNN), analyzes these inputs to determine whether the driver is involved or sleepy. If the system identifies drowsiness indications, activates notices and visual signs to alert the driver. Architecture guarantees continuous surveillance and offers immediate notifications to avoid fatigue accidents.

3.Data Collection and Preprocessing

3.1 Data Collection:

The system gathers data from multiple sources including public drowsiness-related datasets, real-time camera streams, simulated EAR variations, and sensor data from mobile apps or in-vehicle systems. This data includes facial landmarks, eye movement or closure duration, and mouth positions. These features are essential for building a rich dataset that represents both alert and drowsy states for training and evaluating the model

3.2 Data Preprocessing:

Collected data undergoes several preprocessing steps to ensure accuracy and consistency. Face detection is done using HAAR Cascades or Dlib, followed by extracting facial landmarks, particularly around the eyes and mouth. Images are normalized, frames are labeled as alert or drowsy, and the dataset is balanced to avoid bias. Data augmentation techniques such as changes in lighting and angles are also applied to improve model robustness.

3.3 Machine learning/Deep learning model Selection:

Various models are evaluated to determine the best-performing architecture for drowsiness detection. Convolutional Neural Networks (CNNs) help extract spatial features from facial images, while Long Short-Term Memory (LSTM) networks track temporal eye closure patterns. Hybrid models like CNN-LSTM with attention mechanisms offer enhanced performance. Depending on hardware constraints, lightweight models like MobileNet or more accurate ones like VGG16 and EfficientNet can also be used.

3.4 Real-Time Alert System:

In real-time, the system continuously processes video frames to detect faces and calculate the Eye Aspect Ratio (EAR). If the EAR stays below a set threshold for a specific duration, an alarm is triggered to alert the driver. This system relies on OpenCV for video handling and can be deployed on edge devices like Raspberry Pi to ensure immediate, on-device alerts without latency.

3.5 Testing and Validation:

The model is tested using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix evaluations. Validation involves testing the system under diverse real-world conditions, including different lighting and driver behaviors. The model's performance is compared with baseline approaches like simple EAR thresholding to confirm its reliability before deployment.

V. RESULTS AND DISCUSSIONS

1. Comparative analytic table

Model Name	**Accuracy (%)**	**Algorithm/Technique Used**
Traditional ML Models	65–70	Edge detection methods
Eye Aspect Ratio (EAR)	72–78	Geometric feature-based eye analysis
Perclos (Eye closure %)	68–75	Percentage of eye closure over time
HOG + SVM	75–83	Histogram of Oriented Gradients + Support Vector Machine
Early CNN Models	75–85 (approx.)	Basic Convolutional Neural Networks
VGG16-Based Models	85–90	VGG16 Architecture
LSTM + CNN Hybrid	94–97	Combined CNN feature extraction with LSTM sequence modelling

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Modern Deep Learning	89+	Multiple integrated deep learning techniques
ResNet-Based Models	85–90	Residual Networks (ResNet50)
Mobile Net for Edge	90–94	Lightweight MobileNetV3 model
Efficient Net Variants	90–94	Efficient Net family with optimized scaling
Vision Transformers (ViT)	92–96 (est.)	Transformer-based vision models
Hybrid CNN-LSTM + Attention	94–97	CNN + LSTM with Attention Mechanism
Basic CNN	89.2	Standard Convolutional Neural Network

Table2: Different model evaluations

Table 2 presents a comparative analysis of different models used to detect drowsiness, focusing on their accuracy and the algorithms they use. He highlights how advances in technology have improved the ability to detect driver's drowsiness. Traditional methods such as proportion detection (EAR) reached basic precision levels between 65% and 78%. These methods were based on image processing and geometric techniques. With the advancement of technology, machine learning techniques, such as the oriented gradient histogram (HOG) combined with support vector machines (SVM), higher accuracy to about 83%. The introduction of convolution neural networks (CNN) has brought a major improvement in performance. For example, models such as the VGG16 reached accuracy rates between 85%and 90%, while basic CNNs reached an accuracy of 89.2%.

2. Results:

2.1 Accuracy

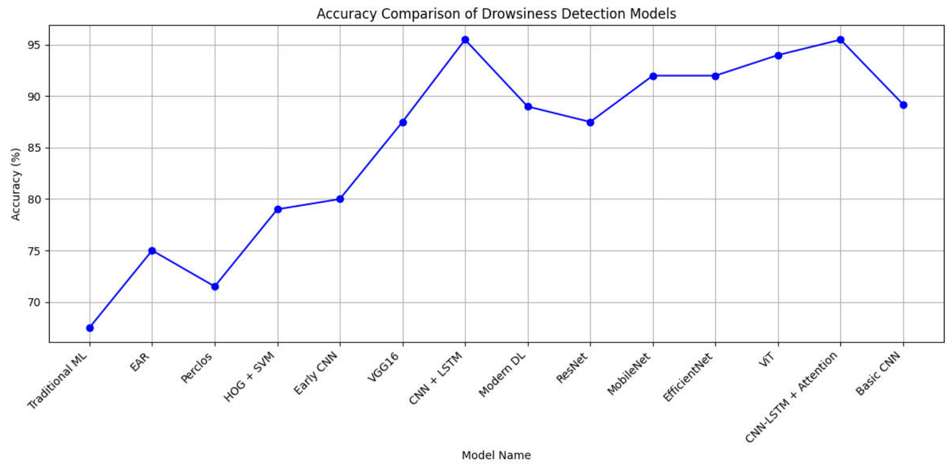


Fig7: Accuracy % for various Models

Fig 7 presents a The line chart presents a comparative analysis of various drowsiness detection models based on its accuracy. It clearly illustrates the progression of traditional machine learning techniques, such as edge detection (less accurately around 68%) for more advanced deep learning methods. Improvements are not observed with the use of Hog + SVM and early CNNs, but the most significant gains are achieved by models such as CNN-LSTM and Hybrid CNN-LSTM + ATTENTION +, both. Models such as Efficient net, Mobile net and Vision Transformers (VIT) also show strong performance, reflecting the growing efficacy of lightweight and based architectures on real -time drowsiness detection tasks.

VI. CONCLUSION

This project highlights machine learning can play a vital role in improving road safety through drowsiness detection systems. When analyzing real visuals and physiological clues, such as eye closure, yawning and mouth movements, machine learning models can detect early drivers' drowsiness signs and issue alerts timely.

Despite of progress, challenges are still remained, such as the need for better accuracy under different lighting conditions, more different facial characteristics with real low power performance. Future improvements can focus on the use of IoT sensors combined with deep learning techniques to make drowsiness detection systems more reliable and create friendly alert systems. With AI and hardware advances, these systems will become more accurate, affordable, making the roads safer and reduce accidents caused by tiredness.

REFERENCES

[1] Valsan, Vidhu, Paul P. Mathai, and Ierin Babu. "Monitoring driver's drowsiness status at night based on computer vision." 2021 international conference on computing, communication, and intelligent systems (ICCCIS). IEEE, 2021.
[2] Menchie Miranda; Portable Prevention and Monitoring of Driver's Drowsiness Focuses to Eyelid Movement Using Internet of Things 3. Kavianpour, Parisa, et al. "A CNN-BiLSTM model with attention mechanism for earthquake prediction." The Journal of Supercomputing 79.17 (2023): 19194-19226.
[3.] Maheswari, V. Uma, et al. "Driver drowsiness prediction based on multiple aspects using image processing techniques." IEEE Access 10 (2022): 54980-54990.
[4.] T. Soukupova and J. Cech "Real-Time Eye Blink Detection using Facial Landmarks," arXiv preprint arXiv:2002020arxiv.org
[5] A Rosebrock -Facial landmarks with dilb, OpenCV, and Python Retrieved on-line at https://www. pyimagesearch. com …, 2017
[6.] Li, Yongkai, et al. "A CNN-based wearable system for driver drowsiness detection." Sensors 23.7 (2023): 3475
[7.] Tejasweeni Musaleand Pansambal, DRIVER DROWSINESS DETECTION TECHNIQUE USING RASPBERRY PI, B.H. Bhivarabai Sawant College of Engineering and Research, Narhe, Pune, India ARTICLE. (2017)
[8.] Chand, H. Varun, and J. Karthikeyan. "CNN Based Driver Drowsiness Detection System Using Emotion Analysis." Intelligent Automation & Soft Computing 31, no. 2 (2022).
[9.] Dua, Mohit, Shakshi, Ritu Singla, Saumya Raj, and Arti Jangra. "Deep CNN models-based ensemble approach to driverdrowsinessdetection." NeuralComputingandApplications 33(2021):3155-3168.
[10.] Hashemi, M., Mirrashid, A. and Beheshti Shirazi, A., 2020. Driver safety development: Real-time driver drowsiness detection system based on convolutional neural network. SN Computer Science, 1(5), p.289.
[11.] Jabbar, Rateb, et al. "Driver drowsiness detection model using convolutional neural networks techniques for android application." 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT).2020.
[12.] Ramli, Rusmawarni, et al. "Raspberry pi-based driver drowsiness detection system using convolutional neural network (cnn)." 2022 IEEE 18th international colloquium on signal processing & applications (CSPA). IEEE, 2022.
[13.] Sinha, Avigyan, R. P. Aneesh, and Sarada K. Gopal. "Drowsiness detection system using deep learning." 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII). IEEE, 2021.
[14.] Dipu, M.T.A., Hossain, S.S., Arafat, Y. and Rafiq, F.B., 2021. Real-time driver drowsiness detection using deep learning. International Journal of Advanced Computer Science and Applications, 12(7).
[15.] Rajmohan, S. P., E. G. Radhika, S. Priya, and S. Sangeetha. "Driver drowsiness detection system using hybrid approach of convolutional neural network and bidirectional long short term memory (CNN_BILSTM)." Materials Today: Proceedings 45 (2021): 2897-2901.