DRIVER DROWSINESS DETECTION

Under the Supervision
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Abstract
Driver drowsiness can be caused by various reasons such as sleep deprivation, long hours of driving , monotonous roads such as highways, alcohol and substance use, time of day, poor work life balance.This can result in fatal accidents, as drowsy drivers have reduced reaction times, impaired judgment, and are more likely to fall asleep , leading to collisions with other vehicles, pedestrians, or roadside obstacles. Such accidents often occur at high speeds and can be devastating, causing severe injuries or death to both the driver and others involved. Drivers can avoid these accidents if they are warned in time.
There are various methods for detecting drowsiness, and this paper proposes a deep learning approach using convolutional neural networks to detect drowsiness in drivers by analyzing their face and eye regions.

Introduction

Driver drowsiness is a state of extreme fatigue or sleepiness which is experienced by a driver, due to which they are unable to stay alert, cannot focus on the road and are unable to react effectively to driving conditions they face at the road. This is usually caused due to lack of sleep, long hours of driving and monotonous driving on roads like highways and inadequate breaks during long trips. Also, use of alcohol,drugs and sedatives, heavy use of medications which affect sleep quality also contribute to drivers feeling sleepy. Work life imbalance like irregular and hectic work schedules, shift work, driving during the body's natural sleep cycle (late night or early morning), mental fatigue caused due to unrealistic amounts of workload can lead to driver feeling fatigued[3]. Many employees returning after work have secretion of melatonin after long shifts of work. Melatonin is a hormone that signals the body to prepare for sleep, making drivers feel more tired and less alert. It increases naturally during nighttime or in low-light conditions, leading to drowsiness. Not paying attention to health like dehydration, poor diet, stress, untreated sleep disorders like sleep apnea, narcolepsy, or restless leg syndrome are also a major reason for driver drowsiness.

Drowsy driving can have serious consequences which can be life threatening. Drivers may take longer amounts of time to respond to sudden blockages on the road which can cause delays in braking or steering. If the driver is not in the right state of mind due to medication or substance use, this can lead to impaired decision making increasing the probability of accidents. This also reduces the ability to focus on the road. Drowsy drivers are more likely to cause collisions due to missed lights, not following speed limits, lack of control on the vehicle. They may shift to the wrong lanes on the road. Extreme fatigue and lack of attention can lead to involuntary periods of sleep lasting 15-20 seconds which are also a major cause of accidents when truck drivers fall asleep driving at night. Straight stretches of road with no visual stimulations reduces mental engagement which makes it harder to focus while driving. A drowsy driver is unable to remember the last few stretches he has driven. This makes it difficult for the driver to stay focused or respond to new situations. This cognitive decline can put the driver and also others on the road at risk of fatal accidents especially in situations where raised awareness and rapid actions are required.

The data from the Yamuna Expressway Industrial Development Authority shows that over 44% of accidents on the 165.5 km long, six-lane Yamuna Expressway from January 2012 to March 2023 were due to drivers dozing off at the wheel, while around 18% were caused by overspeeding. In 2015, the Ministry of Road Transport and Highways (MoRTH) recorded 3,081 accidents due to driver fatigue, resulting in 706 fatalities and 3,383 injuries. Highway patrol authorities estimate that sleep-deprived drivers are involved in roughly 40% of road accidents[4].
Also, these numbers might not be accurate as it’s really difficult to predict if the accident was caused due to driver drowsiness and lack of sleep. This shows the urgent need for enhanced safety strategies, including better tracking of fatigue-related incidents and measures to mitigate drowsy driving.

Due to advancements in technology and developments in the field of Artificial Intelligence, it is possible to detect if the driver is drowsy and also alert them which can prevent the occurrence of road accidents. This includes leveraging a combination of various techniques, such as computer vision, machine learning and physiological monitoring which helps assess the driver’s alertness in real time. A key indicator of drowsiness is facial expressions, facial movements like eye blinking rate, eyelid closure and head positioning to identify signs of fatigue. AI can recognize changes in mouth shape or size which indicates yawning. Algorithms can also be used to detect partially closed eyes which helps assess alertness. Drowsy drivers can also drift their gaze from the road which can also be detected using such systems. This can be implemented using Computer vision-based systems to identify specific facial features and movement patterns and Deep learning models for facial recognition like convolutional neural networks. The system analyzes these patterns and, once a threshold is reached, it can trigger an alert, helping to keep the driver awake and aware.

In addition to facial recognition, some systems even monitor driving patterns like sudden lane shifts, irregular steering or inconsistent speed which may indicate driver drowsiness. AI systems that use cameras and sensors can detect when the vehicle crosses lane markings. Models can analyze steering patterns and detect erratic or delayed steering inputs. AI can process data from speed sensors to identify unusual speed variations.

Beyond visual and driving pattern recognition, advanced AI-based systems are using biometric sensors that track physiological data such as heart rate variability, temperature of skin or brain activity to detect fatigue through wearable devices or built-in car sensors. This can help gain deeper insights into the driver's level of alertness. Heart rate tends to decrease when the driver is drowsy and increased fatigue leads to lower skin conductance which can be detected using wearable devices or sensors in the seat of the vehicle. Some advanced AI systems also use electroencephalography(EEG) sensors[5] integrated into headbands and caps which monitor brain activity and can help detect fatigue.

When signs of drowsiness are detected using these AI systems, these systems can release immediate warnings through sounds, vibrations, alarms ,visual alerts like dashboard notifications, physical interventions like vibrations on the seat of the vehicle or resistance on steering wheel. In long periods of driving ,the AI systems may recommend rest breaks or take control as well in semi-autonomous vehicles. These warnings alert the driver to rest or take necessary precautions, thus reducing the risk of accidents caused by driver fatigue significantly.

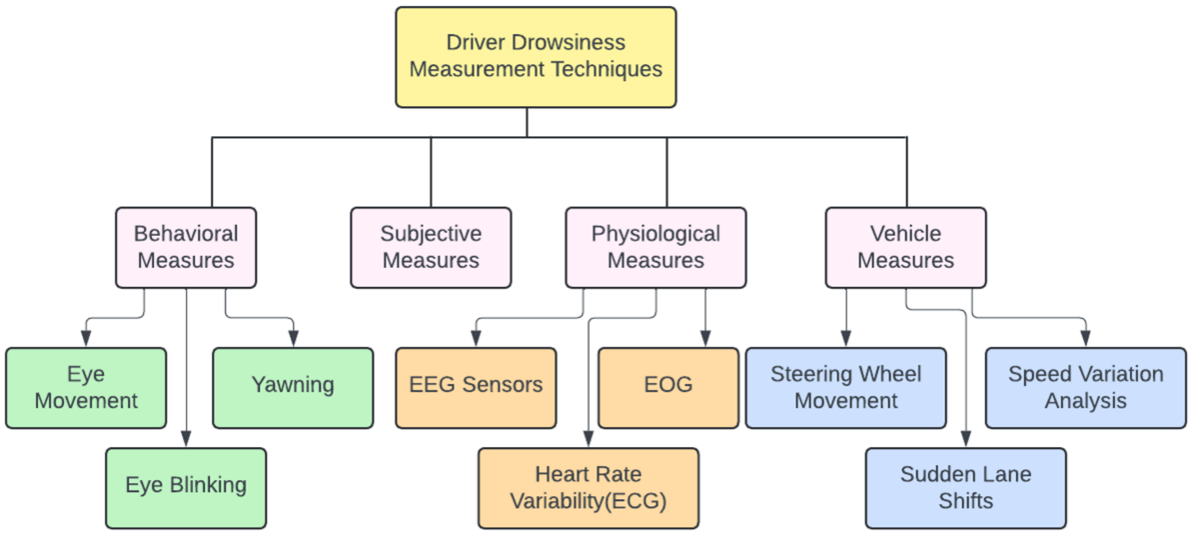

Fig 1 : DRIVER DROWSINESS MEASUREMENT TECHNIQUES

MOTIVATION OF THE WORK:

Drowsy driving is a significant cause of accidents globally, responsible for countless injuries, fatalities, and substantial economic costs each year. With fatigue impairing driver alertness and response times, studies show that a high percentage of road accidents are directly linked to drowsiness. Current detection methods, however, often depend on complex, multi-factor systems that are difficult to implement for real-time use in typical driving conditions. This research aims to address this gap by focusing on two primary indicators- eye movement and yawning , enabling a more streamlined, efficient, and accurate approach. Utilizing deep learning, this simplified system can continuously monitor drowsiness in real-time, potentially preventing accidents before they occur, thus enhancing overall road safety and reducing the heavy toll of drowsy driving.

LITERATURE REVIEW

Numerous studies have been conducted to address the critical issue of driver drowsiness detection, a few of which are reviewed below.

S.NO	Authors	Classification Methods	Drowsiness Measures	Dataset	Performance
1.	Guo et al. (2016) [6]	Bayesian Network (BN)	Heart rate, pulse rate, eyelid movement, gaze, head movement	21 participants car simulator for 110 min	Accuracy = 79.50%
2.	Bakheet ang Al Hamadi, (2021)[7]	Histogram of Oriented Gradient (HOG) features	Driver image, eye pair region	NTHU-DDD dataset	Accuracy = 85.62%
3.	Chen et al. (2021)[8]	LSTM, CNN	Eye, face area	THU-DDD dataset	Accuracy = 93.30%
4.	Guo and Markoni, (2018) [9]	Hybrid CNN, LSTM	Facial landmark (eye and mouth)	Public drowsy driver dataset	Accuracy = 84.85%
5.	Wijnands et al. (2019)[10]	3D neural networks	Yawning, nodding, looking aside, talking, laughing, closing eye	DDD dataset	Accuracy = 80.8%
6.	Rajamohana et al. (2021)[11]	CNN, BILSTM	Facial image, eye blink, eye closure	Eye data, 1104 images	Accuracy = 96.00%
7.	Jabbar et al. (2020)[12]	CNN	Yawning, slow rate blinking, sleepy head movements	NTHU-DDD dataset	Accuracy = 88.00%
8.	Deng W, Wu R (2019)[13]	Multiple CNN-kernelized correlation filters method	Mouth and Eye	CelebA dataset, YawDD dataset	Accuracy = 92.00%

9.	Zhao Z, Zhou N, Zhang L, Yan H, Xu Y, Zhang Z (2020)[14]	CNN	Eye and mouth	Driving image dataset from Biteda company	Accuracy = 93.62%
10.	Moujahid A, Dornaika F, Arganda-Carreras I, Reta J (2021)[15]	SVM	Eye, head, and mouth	NTHUDDD public dataset	Accuracy = 79.84%
11.	Celecia A, Figueiredo K, Vellasco M, González R (2020)[16]	Mamdani fuzzy inference system	Eye and mouth	300-W dataset	Accuracy = 95.5%
12.	Maior CBS, das Chagas Moura, M. J., Santana, J. M. M., & Lins, I. D. (2020)[17]	Multilayer perceptron, RF, and SVM	Eye	DROZY dataset	SVM: 94.9%

Gao et al. (2019) [18] introduces a recurrence network-based convolutional neural network (RN-CNN) model that utilizes electroencephalogram (EEG) signals to identify driver fatigue. By constructing a multiplex recurrence network (RN) from EEG data and applying a convolutional neural network (CNN) to learn and classify features, the model achieves an impressive average accuracy of 92.95%. Future research could focus on integrating this method into real-time systems and enhancing its adaptability for practical applications across various driving conditions.

De Naurois et al. (2018) [19] address the challenge of monitoring driver drowsiness, which is often impacted by high inter-individual variability affecting detection accuracy. To improve performance, the authors trained Artificial Neural Networks (ANNs) using data from 20 drivers, creating two models: one for minute-by-minute drowsiness detection and another for predicting the time to moderate drowsiness. The adapted models achieved approximately 40% better prediction accuracy and 80% improved detection rates. Future research could refine these models for real-time applications and enhance their adaptability across varying driving conditions.

Zhang et al. (2020) [20] presented a method for detecting driver drowsiness by identifying facial landmarks in video frames. It uses a residual-based deep 3D convolutional neural network (CNN) to classify these facial sequences and output drowsiness probability values, which are then processed by a recurrent neural network. Achieving an accuracy of 88.6% on a public dataset, this approach demonstrates the effectiveness of 3D CNNs in capturing spatiotemporal features. Future research could enhance real-time application and robustness in varying driving conditions.

Dua et al. (2020) [21] tackle the issue of drowsy driving, which accounts for about 20% of drivers, as noted by the National Sleep Foundation. They propose a detection system utilizing four deep learning models - AlexNet, VGG-FaceNet, FlowImageNet, and ResNet to analyze RGB videos of drivers. The models assess features such as hand gestures and facial expressions, classifying states into non-drowsiness, drowsiness with eye blinking, yawning, and nodding. The system achieves 85% accuracy with an ensemble algorithm and a SoftMax classifier.Future research could focus on enhancing model accuracy and adaptability for real-time monitoring in diverse driving environments.

Siddiqui et al. (2021) [22] classifies drowsy and non-drowsy driver states using non-invasive impulsive radio ultra-wideband (IR-UWB) radar to detect respiration rates. Data were collected from 40 subjects, and various machine learning models—including Support Vector Machine (SVM), Decision Tree, Logistic Regression, and Multilayer Perceptron—were trained on the dataset. The SVM achieved the highest accuracy of 87% and an F1-score of 73%. Future work could focus on integrating real-time data monitoring to enhance driver drowsiness detection and improve overall road safety.

Gwak et al. (2020) [23] classify driver alertness states using a driving simulator, measuring physiological signals and behavioral indices to assess drowsiness. They applied various machine learning models, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF), with the ensemble algorithm achieving an accuracy of 95.4% in distinguishing between alert and moderately drowsy states. These results demonstrate the potential for effective early detection systems for driver drowsiness. Future research could focus on refining these models for real-time applications and testing across a wider range of drivers to improve reliability.

Yu et al. (2019) [24] present a condition-adaptive framework for detecting driver drowsiness using a 3D deep convolutional neural network (3D-DCNN). The framework employs spatio-temporal representation learning and feature fusion to classify driving conditions, such as the presence of glasses and facial movements, yielding a more discriminative representation. Evaluation on the NTHU drowsy driver detection dataset achieved an accuracy of 76.20% and an F1-score of 76.50%. Future research may aim to improve the framework's accuracy and applicability in real-time across diverse driving environments.

PROBLEM STATEMENT

Driver drowsiness poses a serious threat to road safety, as it greatly heightens the likelihood of accidents by slowing reaction times, diminishing concentration and impairing judgment. Fatigued drivers frequently miss crucial road signals, drift from their lanes and even fall asleep momentarily, all of which can result in serious accidents, especially when traveling at high speeds. In India, the situation is even more critical, as data from the Ministry of Road Transport and Highways indicates that fatigue among drivers contributes to more than 40% of accidents on highways[25]. These incidents often lead to severe injuries and deaths, highlighting the pressing necessity for effective methods to identify and mitigate driver drowsiness.

The critical nature of this problem is further highlighted by studies showing that drowsy drivers exhibit impairments comparable to those of individuals under the influence of alcohol, with research indicating that they are nearly as impaired as drunk drivers in terms of reaction times and decision-making abilities. Drowsy driving is associated with approximately 100,000 reported crashes annually in the United States alone[3], leading to significant loss of life and long-term injuries. Addressing this problem is vital not only for reducing preventable accidents but also for enhancing overall road safety.

Despite the existence of various drowsiness detection methods, many of these approaches rely on multiple visual and non-visual indicators, requiring complex and costly setups. Techniques that monitor physiological signals, such as heart rate or EEG[5], or assess vehicle behavior through specialized sensors can be invasive and difficult to implement on a broad scale. The process of integrating multiple sensors and hardware is complex, making widespread adoption difficult and challenging for drivers and fleet operators.

This paper proposes a streamlined approach focusing on eye closure and yawning, two easily observable and effective visual indicators of drowsiness. A Convolutional Neural Network (CNN)[26] is used to classify images as either eyes open/closed or yawning/not yawning. This offers a cost-effective and non-intrusive alternative that requires only standard camera input. This simplification reduces the technological barriers associated with traditional drowsiness detection methods and enhances the practicality and accessibility of implementation in vehicles. This study aims to contribute significantly to the development of effective drowsiness detection systems by concentrating on these visual factors, hence addressing the critical issue of driver fatigue and its associated risks.

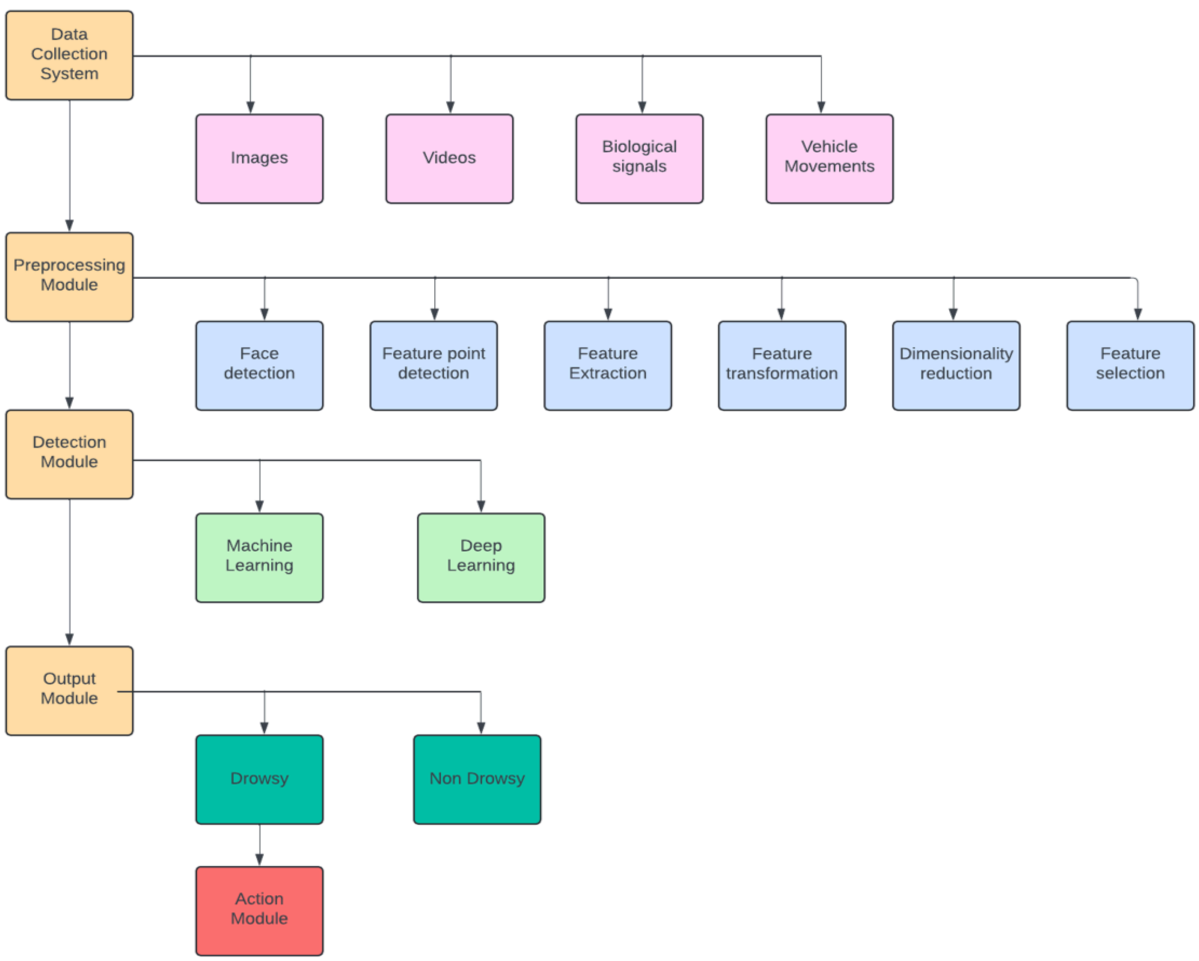

Fig 2 : GENERAL FLOW IN DRIVER DROWSINESS DETECTION SYSTEMS

DATASETS

There exist several standardized datasets that researchers have used for drowsiness detection.

Ref./Year	Dataset Name	Description
[2], 2020	YawDD	Videos of drivers showing drowsiness signs, captured from two camera angles in various scenarios.
[27], 2016	DROZY	Contains synchronized data from 14 individuals, including EEG and eye-tracking information.
[1], 2014	CEW	Includes 2423 subjects eye images, focusing on open and closed eye detection.
[28], 2016	NTHUDDD	Contains 36 subjects in various driving scenarios, focusing on drowsiness indicators like yawning.
[29], 2015	CelebA	A large dataset of 200K celebrity images with 40 binary attribute labels per image.
[30], 2018	MRL Eye	Comprises 84,898 images depicting various eye states and lighting conditions from 37 individuals.
[31], 2020	ZJU Gallery	Multi-view dataset of dynamic human videos recorded under different lighting conditions.
[32], 2013	300-W	Includes 600 images (300 indoor and 300 outdoor) with 68 facial landmark annotations.
[33], 1999	MIT/BIH EEG Database	Records physiological signals during sleep, focusing on the effects of CPAP on sleep apnea.
[34], 2000	Sleep-EDF	Whole-night sleep recordings with various physiological signals and hypnograms.
[35], 2019	UTA-RLDD Dataset	30 hours of RGB footage of 60 subjects classified into alertness, low vigilance, and drowsiness.

This paper utilizes two of these datasets. The first is the YawDD Video dataset [2], which comprises videos recorded by a camera mounted on a car dashboard. This dataset includes male and female drivers, some wearing glasses and others without. It features a collection of videos captured by an in-car camera, showcasing real drivers engaged in various activities such as talking, singing, yawning and more. The drivers represent diverse facial features, including different ethnicities and the presence of glasses or sunglasses. The second dataset used is the Closed Eyes in the Wild (CEW) dataset [1]. This dataset contains 2423 subjects, with 1192 people having closed eyes and 1231 people with open eyes.

METHODOLOGY

1.DATA PREPROCESSING

Data augmentation [38] is a process that improves the generalization of a model by creating variations of the original image data. In our case, these two data augmentation techniques are implemented. Random cropping is used to randomly crop a section of the image and resize it to the original size of the image. This technique helps the model to learn features from different parts of the image and hence makes it more robust to variations in the position of the eyes or the face in the image. Horizontal flipping is used to flip the image horizontally. This technique helps the model to learn features from different orientations and hence makes it more robust to variations in the orientation of the head or face in the image. By using data augmentation, the model can learn to identify drowsiness under various conditions, such as different lighting conditions, different head and eye positions and different driver appearances.

The data transformation preprocesses images to ensure uniformity. Images are loaded from structured directories containing categories like "yawn," "no_yawn," "closed eye," and "open eye." For yawning detection, Haar cascade classifiers are utilized to detect facial regions. These classifiers work by applying a sliding window approach and evaluating regions against pre-trained Haar features, isolating facial areas of interest. Detected faces are cropped and resized to 145x145 pixels using OpenCV’s resizing functions. For eye data, images undergo direct resizing to the same dimensions, maintaining consistency across datasets. The preprocessed facial and eye data are then combined into a unified array, enabling analysis of yawning and eye closure patterns.

To enhance the model's robustness, additional data augmentations such as zooming (±20%), rotation (up to 30 degrees), and horizontal flipping, are applied using TensorFlow. This ensures the model can adapt to various lighting conditions, head angles, and individual driver traits. The processed data is split into training and testing sets, with a 70-30 split. Normalization is performed by scaling pixel values to the [0, 1] range, which helps in achieving faster and more stable convergence during model training by ensuring that the input features are on a similar scale.

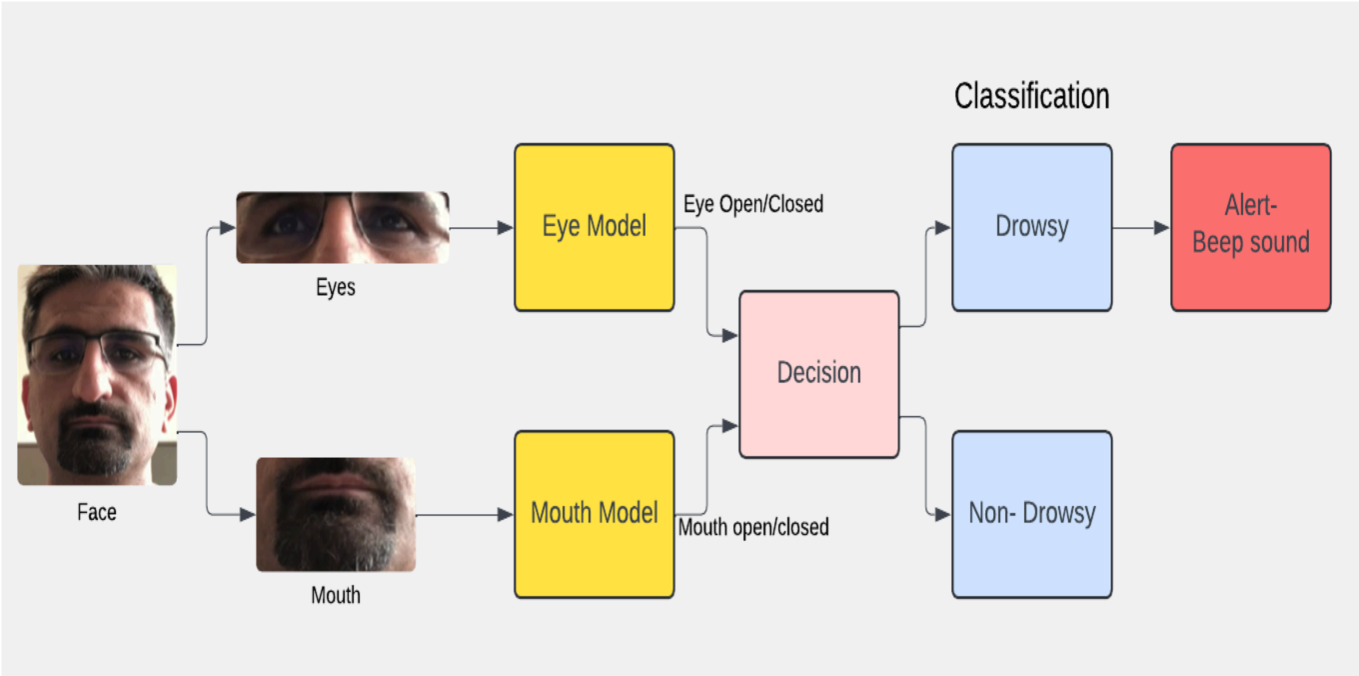

Fig 3: Workflow of the Driver Drowsiness Detection System

2. MODEL DESCRIPTION

The Convolutional Neural Network (CNN) [26] used for driver drowsiness detection is designed for efficient and scalable image classification. The input layer processes 4D tensors with dimensions corresponding to the batch size, image height, width (145x145 pixels), and color channels (RGB). The architecture begins with a convolutional layer featuring 512 filters and a 3x3 kernel, employing the ReLU activation function [36]. This operation extracts local features, such as edges and textures, crucial for identifying drowsiness-related cues. Each convolutional layer is followed by max-pooling layers with a 2x2 pool size, reducing spatial dimensions and minimizing computational overhead while preserving essential features.

The network deepens progressively, employing additional convolutional layers with 512 and 256 filters, which capture increasingly abstract patterns. The hierarchical feature extraction culminates in a Flatten layer [37], converting the 3D feature maps into a 1D vector suitable for dense layers. This transformation bridges the convolutional layers with the fully connected layers, where high-level relationships in the data are modeled.

To prevent overfitting, a Dropout layer [42] with a dropout rate of 50% is integrated before the dense layers. Dropout stochastically disables neurons during training, preventing over-reliance on specific pathways and encouraging the model to generalize better. The fully connected section includes two dense layers with 128 and 64 neurons, respectively, both using ReLU activation function to capture non-linear dependencies. The final output layer uses a softmax activation function [39], producing a probability distribution over the four classes: yawn, no yawn, closed eyes, and open eyes.

The model is compiled with the categorical cross-entropy loss function [40], optimal for multi-class classification tasks, and the Adam optimizer [41], which dynamically adjusts learning rates for faster convergence. Training incorporates a mini-batch gradient descent, processing batches of augmented data. Additionally, the model architecture, implemented using TensorFlow's Sequential API, is designed to allow seamless backpropagation and optimization. This CNN architecture, designed for efficiency in training and evaluation, is well-suited to the task of detecting driver drowsiness from images, providing a robust framework for real-time image classification.

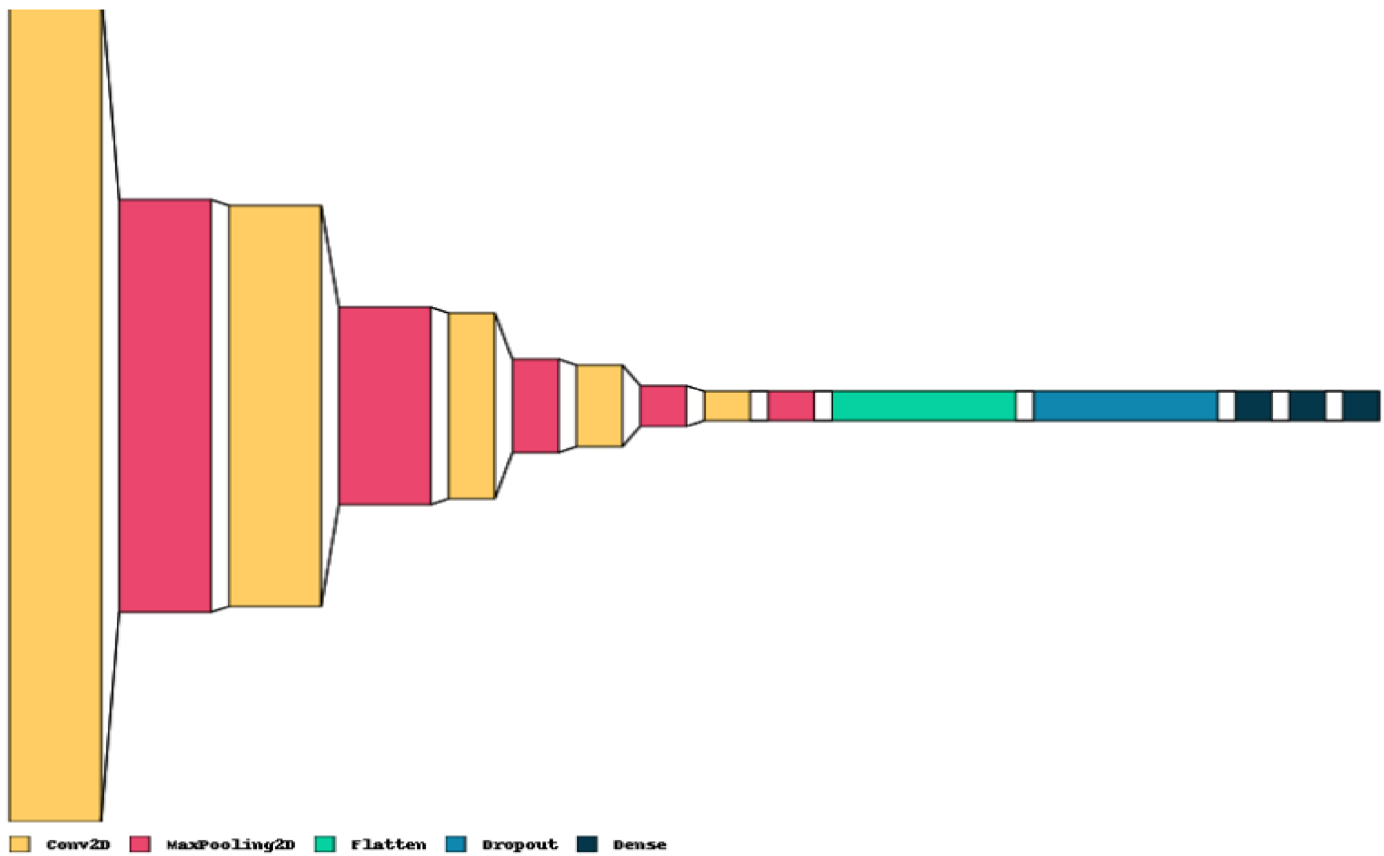

Fig 4: Network Architecture Diagram

RESULTS

The network is trained on an augmented dataset over 30 epochs, achieving a training accuracy of 96.21% and a testing accuracy of 96.54%. To assess the model's performance, training and testing loss and accuracy are plotted using Matplotlib as shown in figure.

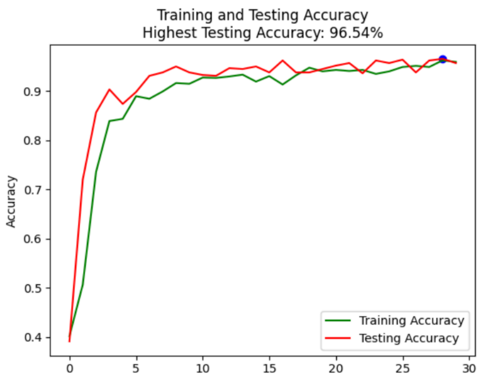

Fig 5: Training and testing accuracy

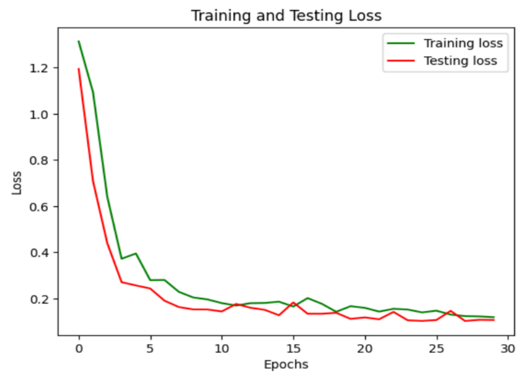

Fig 6: Training and testing loss

The model exhibits excellent precision and recall for all four classes, showing especially strong results in detecting Closed and Open eye labels, with F1-scores of 0.95 and 0.96 respectively. The weighted average F1-score is 0.94, while the macro average F1-score is 0.92, indicating the model's strong capability in identifying driver drowsiness.
The weighted average Recall(Sensitivity) is 94.10% and the weighted average specificity comes out to be 97.95% .

	precision	recall	f1-score
yawn	0.88	0.84	0.86
no_yawn	0.87	0.97	0.92
Closed	0.98	0.93	0.95
Open	0.96	0.97	0.96
accuracy			0.94
macro avg	0.92	0.93	0.92
weighted avg	0.94	0.94	0.94

Specificity for each class:
yawn: 0.9864
no_yawn: 0.9782
Closed: 0.9862
Open: 0.9716

Macro Average Specificity: 0.9806
Weighted Average Specificity: 0.9795

Fig 7: Performance Characteristics

The results indicate that the developed system has the potential to be used in real-world applications, such as in vehicles equipped with a camera to monitor the driver's state. The system can provide an alert to the driver in case of drowsiness, which can help prevent accidents and improve road safety.

Comparison with base paper:

	Base paper[44]	Proposed paper
Methodology	MTCNN	Haar Cascade and CNN
Dataset	IT Company - Biteda	YAWDD and CEW
Accuracy	93.623%	96.54%
Sensitivity	93.643%	94.10%
Specificity	60.882%	97.95%
Parameters	Eye and Mouth	Eye and Mouth

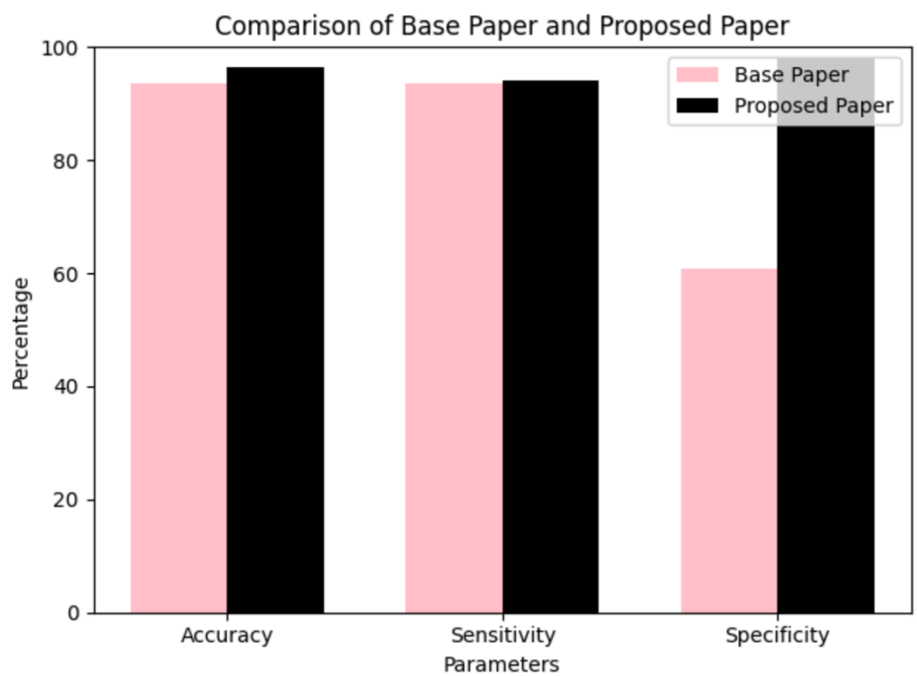

Fig 8: Comparison of parameters in base paper and proposed paper

HARDWARE AND SOFTWARE REQUIREMENTS

1.Hardware Requirements

1. GPU: Two NVIDIA T4 units on Kaggle for efficient training and inference.
2. CPU: Standard CPU for local execution; longer processing times without GPU.
3. RAM: Minimum of 16 GB for effective data processing and training.
4. Storage: At least 50 GB for datasets, model files, and outputs.

2.Software Requirements

1. Operating System:
   1.1. Windows for local development.
2. Cloud Environment:
   2.1. Kaggle Notebook for cloud execution.
3. Python:
   3.1. Version 3.6 or higher.
4. Libraries:
   4.1. TensorFlow: Model building and training.
   4.2. Keras: High-level API for model construction.
   4.3. OpenCV: Image processing, including face detection.
   4.4. NumPy: Numerical computations and image data handling.
   4.5. scikit-learn: Data preprocessing and encoding.
   4.6. Matplotlib: Visualizing training progress.

Future Work and Conclusion

The driver drowsiness detection system was successfully developed using a Convolutional Neural Network (CNN) architecture, achieving a maximum testing accuracy of 96.54% on the YawDD and CEW datasets. These datasets contributed to the robustness of the model, as YawDD includes varying levels of drowsiness and CEW provides a range of emotional expressions, enabling the system to perform effectively across different driver states. This research highlights the potential of deploying CNN-based drowsiness detection in real-world applications, where vehicles equipped with cameras could use the system to monitor drivers and issue alerts when drowsiness is detected, ultimately helping to reduce accidents and enhance road safety.

Future research in deep learning-based driver drowsiness detection systems can expand on these findings through several key directions. First, integrating multimodal data, such as combining facial cues, eye gaze tracking, head movement analysis, and physiological signals (e.g., heart rate, brain activity), could improve the system's depth of understanding. Advanced fusion techniques, such as multi-stream networks or attention mechanisms, can be used to selectively attend to the most relevant signals, creating a more holistic representation of drowsiness.

Improving model generalization across diverse populations and environmental conditions remains essential for effective deployment. Current models, often trained on specific datasets, may struggle to perform reliably in real-world scenarios with variations in demographics, lighting, and camera angles. Future work could address these challenges through domain adaptation, data augmentation, and adversarial training, which would help create models that are robust under varied conditions.

Efficient, real-time implementation is another critical focus. Practical deployment requires optimization techniques like model compression, quantization, and the use of hardware accelerators to reduce computational demands. Developing lightweight architectures specifically designed for drowsiness detection can further ensure low-latency processing, allowing for quick alerts and maximizing safety on the road.

Finally, transfer learning offers a promising approach to overcoming the limitation of annotated drowsiness datasets. By pre-training on larger, general datasets and then fine-tuning on domain-specific data, models can leverage learned features to improve performance, even with limited labeled samples. This approach can enhance robustness and generalizability, addressing data scarcity issues.

By advancing these aspects-multi-modal integration, improved generalization, efficient real-time processing, and data-efficient transfer learning-future research can drive significant improvements in driver drowsiness detection systems. These enhancements will lead to more practical, reliable, and accessible systems, further contributing to road safety and reducing the risks associated with drowsy driving.

REFERENCES

[1] Song F, Tan X, Liu X, Chen S (2014) Eyes closeness detection from still images with multi-scale histograms of principal oriented gradients. Pattern Recogn 47(9):2825–2838
[2] Abtahi S, Omidyeganeh M, Shirmohammadi S, Hariri B (2014) YawDD: a yawning detection dataset. In: Proceedings of the 5th ACM multimedia systems conference, pp 24–28
[3]UCLA Health. (n.d.). Drowsy driving.
[4]Times of India. (2023). No data on driver fatigue-related accidents reveals RTI reply.
[5]NHS. (n.d.). Electroencephalogram (EEG).
[6]Guo, W., Zhang, B., Xia, L., Shi, S., Zhang, X., She, J., 2016. Driver drowsiness detection model identification with Bayesian network structure learning method. Chin. Control Decision Conf. (CCDC) 2016, 131–136 .
[7]Bakheet, S., Al-Hamadi, A., 2021. A Framework for Instantaneous Driver Drowsiness Detection Based on Improved HOG Features and Naïve Bayesian Classification. Brain Sci. 11, 240.

[8]Chen, S., Wang, Z., Chen, W., 2021. Driver Drowsiness Estimation Based on Factorized Bilinear Feature Fusion and a Long-Short-Term Recurrent Convolutional Network. Information 12, 3.
[9]Guo, J.-M., Markoni, H., 2019. Driver drowsiness detection using hybrid convolutional neural network and long short-term memory. Multimed. Tools Appl. 78 (20), 29059–29087.
[10]Wijnands, J.S., Thompson, J., Nice, K.A., Aschwanden, G.D.P.A., Stevenson, M., 2020. Real-time monitoring of driver drowsiness on mobile platforms using 3D neural networks. Neural Comput. & Applic. 32 (13), 9731–9743
[11]Rajamohana, S.P., Radhika, E.G., Priya, S., Sangeetha, S., 2021. Driver drowsiness detection system using hybrid approach of convolutional neural network and bidirectional long short term memory (CNN_BILSTM). Mater. Today:. Proc. 45 (2), 2897–2901
[12]Jabbar, R., Shinoy, M., Kharbeche, M., Al-Khalifa, K., Krichen, M., Barkaoui, K. (2020). Driver Drowsiness Detection Model Using Convolutional Neural Networks Techniques for Android Application. ICIoT 2020, Doha, Qatar. Hal-02479367.
[13]Deng W, Wu R (2019) Real-time driver-drowsiness detection system using facial features. Ieee Access 7: 118727–118738
[14]Zhao Z, Zhou N, Zhang L, Yan H, Xu Y, Zhang Z (2020) Driver fatigue detection based on convolutional neural networks using EM-CNN. Comput Intell Neurosci 2020
[15]Moujahid A, Dornaika F, Arganda-Carreras I, Reta J (2021) Efficient and compact face descriptor for driver drowsiness detection. Expert Syst Appl 168:114334
[16]Celecia A, Figueiredo K, Vellasco M, González R (2020) A portable fuzzy driver drowsiness estimation system. Sensors 20(15):4093
[17]Maior CBS, das Chagas Moura, M. J., Santana, J. M. M., & Lins, I. D. (2020) Real-time classification for autonomous drowsiness detection using eye aspect ratio. Expert Syst Appl 158:113505
[18]Gao, Z.-K., Li, Y.-L., Yang, Y.-X., Ma, C., 2019. A recurrence network-based convolutional neural network for fatigue driving detection from EEG. Chaos: An Interdisciplinary. J. Nonlinear Sci. 29 (11)
[19]De Naurois, C.J., Bourdin, C., Bougard, C., Vercher, J.-L., 2018. Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness. Accid. Anal. Prev. 121, 118–128.
[20]Zhang, X., Wang, X., Yang, X., Xu, C., Zhu, X., Wei, J., 2020. Driver Drowsiness Detection Using Mixed-effect Ordered Logit Model Considering Time Cumulative Effect. Analytic Methods in Accident Research. 26, 100114.
[21]Dua, M., Shakshi, Singla, R., Raj, S., Jangra, A., 2021. Deep CNN models-based ensemble approach to driver drowsiness detection. Neural Comput. Applic. 33 (8), 3155–3168.
[22]Siddiqui, H.U.R., Saleem, A.A., Brown, R., Bademci, B., Lee, E., Rustam, F., Dudley, S., 2021. Non-Invasive Driver Drowsiness Detection System. Non-Invasive Driver Drowsiness Detection System. Sensors 21 (14), 4833.
[23]Gwak, J., Hirao, A., Shino, M., 2020. An Investigation of Early Detection of Driver Drowsiness Using Ensemble Machine Learning Based on Hybrid Sensing. Appl. Sci. 10 (8), 2890

[24]Yu, J., Park, S., Lee, S., Jeon, M., 2019. Driver Drowsiness Detection Using ConditionAdaptive Representation Learning Framework. IEEE Trans. Intell. Transp. Syst. 20 (11), 4206–4218.
[25]The Hindu. (2022). Sleep-deprived drivers responsible for 40% of road accidents,
[26]MathWorks. (n.d.). Introduction to deep learning: What are convolutional neural networks.
[27].Massoz Q, Langohr T, François C, Verly JG (2016) The ULg multimodality drowsiness database (called DROZY) and examples of use. In: 2016 IEEE winter conference on applications of computer vision (WACV). IEEE, pp 1–7
[28]Weng CH, Lai YH, Lai SH (2016) Driver drowsiness detection via a hierarchical temporal deep belief network. In: Asian conference on computer vision. Springer, Cham, pp 117–133
[29]Liu Z, Luo P, Wang X, Tang X (2015) Deep learning face attributes in the wild. In: Proceedings of the IEEE international conference on computer vision, pp 3730–3738
[30]Fusek R (2018) Pupil localization using geodesic distance. In: International symposium on visual computing. Springer, Cham, pp 433–444
[31]Zhou K, Wang K, Yang K (2020) A robust monocular depth estimation framework based on light-weight erf-pspnet for day-night driving scenes. In: Journal of physics: conference series, vol 1518, no 1. IOP Publishing, pp 012051
[32]Sagonas C, Tzimiropoulos G, Zafeiriou S, Pantic M (2013) 300 faces in-the-wild challenge: the first facial landmark localization challenge. In: Proceedings of the IEEE international conference on computer vision workshops, pp 397–403
[33]Ichimaru Y, Moody GB (1999) Development of the polysomnographic database on CD-ROM. Psychiatry Clin Neurosci 53(2):175–177
[34]Kemp B, Zwinderman AH, Tuk B, Kamphuisen HA, Oberye JJ (2000) Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG. IEEE Trans Biomed Eng 47(9): 1185–1194
[35]Ghoddoosian R, Galib M, Athitsos V (2019) A realistic dataset and baseline temporal model for early drowsiness detection. In: Proceedings of the ieee/cvf conference on computer vision and pattern recognition workshop
[36]BuiltIn. (n.d.). ReLU activation function
[37]Deeplizard. (2019). Exploring the ReLU activation function.
[38]Hoh, S. (2020). Exploring data augmentation techniques for image datasets.
[39]Pinecone. (n.d.). Softmax activation function.
[40]DataCamp. (n.d.). The cross-entropy loss function in machine learning.
[41]Built In. (n.d.). Adam optimization.
[42]Keras. (n.d.). Dropout.
[43]Built In. (n.d.). Transfer learning.
[44]ILT In. (n.d.). Adam optimization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshop*. Wiley.