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An efficient Real-Time Driver Drowsiness Monitoring System by Using Ensembled Regression Trees

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Abstract

Driver drowsiness, primarily resulting from fatigue and insufficient sleep, is a leading contributor to road accidents worldwide. Data analytics reveals that driver drowsiness is the reason for one-fifth of all traffic accidents worldwide. Early detection of drowsiness is vital to prevent accidents. Many methods have been developed for early detection of drowsiness and alerting sleepy drivers. Convolutional Neural Networks (CNNs) are highly effective for detecting drowsiness. However, they are not ideal for real-time applications due to the time-intensive nature of data collection and processing. Additionally, they often suffer from low real-time performance and lack an integrated alerting mechanism. To overcome this drawback, facial landmark detection method is proposed using ensembled regression trees. In the proposed method images are directly captured from the camera and applied 68 facial landmarks images and compared against input image for calculating Eye Aspect Ratio, blink rate, eye closure time, and lane deviation to detect signs of drowsiness whether the driver is drowsy or not. When the driver is drowsy, it plays the alerting alarm. According to experimental analysis, the proposed method ensures reliable accuracy while maintaining low computational latency, making it an efficient and practical solution for real-time driver monitoring compared to traditional deep learning models.

Keywords: *Driver Drowsiness detection, CNN, Data Augmentation, Random Forest Tree, Facial Landmark Detection.*

1. INTRODUCTION

drowsiness of the driver is a significant factor contributing to road accidents across the globe. It often leads to severe injuries and fatalities due to delayed response times and impaired decision-making. As modern vehicles increasingly integrate intelligent safety systems, the need for accurate and real-time drowsiness detection mechanisms has become more urgent. Conventional detection methods, including self-reporting, behavioural observation, and vehicle-based metrics such as steering deviation, have shown limited reliability, especially in dynamic driving environments and among drivers with varied behaviour patterns. Recent advancements in computer vision and deep learning have enabled the development of vision-based drowsiness detection systems. Driver drowsiness is a major factor in many road accidents, which shows the need for effective real-time detection systems [1]. Early identification of drowsiness is essential to enhancing road safety and mitigating potentially fatal incidents. Conventional detection techniques focus on observable behaviours like head tilts and steering inconsistencies [2]; however, such methods often delay recognition. In contrast, the rise of deep learning in computer vision has enabled more robust and timely detection by analysing facial dynamics in real time [3]. Convolutional Neural Networks (CNNs) have shown high effectiveness in identifying facial landmarks and detecting various eye states [4], several methods have been developed for detecting driver drowsiness using visual and physiological indicators. Eye blink detection using EAR has proven effective for real-time, non-intrusive monitoring [5]. Monitoring eyelid movements and blink rates provides further accuracy in identifying drowsy states [6]. The emergence of Generative Adversarial Networks (GANs) has enabled the creation of synthetic data, effectively enriching the limited datasets available for drowsiness detection [7], while conditional GANs allowed for more controlled synthesis of specific facial features like yawns or closed eyes [8]. GAN-based augmentation has significantly improved the robustness of driver monitoring models under challenging conditions [9], and its integration into CNN training pipelines enhanced performance in varied lighting and occlusion scenarios [10]. Random Forest algorithms have shown strong potential for modelling complex and non-linear relationships in driver behaviour data [11]. Hybrid models combining Random Forests with CNN-extracted features have further improved the detection of subtle drowsiness patterns [12]. Advanced ensemble methods like XG Boost have been used to boost prediction accuracy and handle high-dimensional data efficiently [13]. Multimodal systems integrating facial cues with steering behaviour data have outperformed unimodal systems in drowsiness detection [14]. Adaptive deep regression models have enabled continuous, individualized monitoring of fatigue levels, enhancing early detection in real-world scenarios [15]. The evaluation demonstrates increased accuracy, reduced false positives, and better adaptability to rare conditions using this integrated framework. Among various machine learning models, Random Forest (RF) has gained notable attention for its robustness, interpretability, and superior performance in handling high-dimensional, noisy, and heterogeneous data common characteristics in drowsiness detection scenarios. Over the past few years, RF has been employed extensively in both academic and industrial research settings for driver drowsiness detection. For instance, [16] proposed a hybrid framework combining CNN and Random Forest classifiers for improved behaviour recognition under fatigue conditions. [17] integrated RF with multimodal data facial expressions and steering patterns demonstrating real-time drowsiness detection accuracy. [18] utilized RF within a deep regression framework to enable adaptive fatigue estimation based on continuous driver input, [19] addressed data scarcity by leveraging GAN-based data augmentation to enhance RF training on drowsiness-related datasets. Additionally, combining RF with other ensemble techniques has led to further improvements.[20] integrated XG Boost to outperform traditional RF in tree-boosted decision making, and such combinations are becoming more prevalent.[21] explored GAN augmentation to improve CNN and RF integration in driver monitoring systems, showing measurable performance gains. [22] evaluated RF across deep facial feature extractions, observing high cross-driver generalization.[23] also demonstrated RF's interpretability and real-time feasibility in vehicular systems through a decision tree-based fatigue model. Moreover, [24] applied RF for eyelid movement-based drowsiness classification in video analysis, and [25] provided foundational insights into conditional data generation, which has influenced RF applications in synthetic data environments. Together, these studies illustrate the flexibility and effectiveness of Random Forest in enhancing the reliability, interpretability, and accuracy of driver drowsiness detection systems, especially when integrated with multimodal inputs and augmentation techniques.

This paper presents a comparative study of the CNN and Extended CNN with proposed Random Forest-based approaches for driver drowsiness detection. The CNN framework incorporates advanced preprocessing and augmentation strategies, while the proposed Random Forest model utilizes multi-level behavioural and physiological features for hierarchical classification. Experimental evaluations reveal that the Random Forest model achieves superior accuracy, precision, and recall compared to the baseline CNN Classification. The proposed solution demonstrates high potential for practical deployment in real-time driver monitoring systems, contributing to enhanced road safety and intelligent transportation systems.

2. CNN Architecture for Driver Drowsiness Detection

Convolutional Neural Networks (CNNs) are extensively applied in driver drowsiness detection because of their capability to automatically extract relevant features from facial images. In this context, CNNs analyse visual cues such as eye closure, yawning, and facial expressions. The hierarchical layers in CNNs. The layers of the CNN are convolutional, pooling, and fully connected layers. Layers help in learning spatial patterns associated with drowsiness. This enables real-time, non-intrusive monitoring of driver alertness with high accuracy, making CNNs an effective solution for enhancing road safety. In Fig1 CNN architecture is designed to learn discriminative features from facial image data to identify signs of drowsiness. The network comprises multiple convolutional layers with ReLU activation functions, followed by max-pooling layers for spatial down sampling. These layers are responsible for capturing local patterns such as eye closure and facial muscle relaxation. The extracted features are fed into fully connected layers, ending with a SoftMax output layer that performs either binary or multi-class classification. To prevent overfitting, dropout regularization is employed, and the model is trained using a cross-entropy loss function optimized with the Adam algorithm

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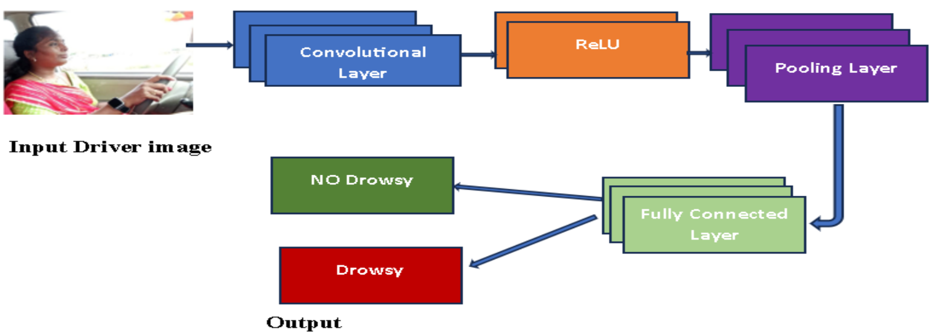

Fig 1: CNN Architecture for Driver Drowsiness Detection

2.1 Convolutional Layer

The convolution layer applies a mathematical operation between the input feature map and a convolution kernel (also known as a filter) to extract spatial features such as texture, shapes, and edges. Let X represents the output value at position (I, j, k) of layer l, σ is the activation function, W represent the Weight of the filter at position (p, q) connecting input channel m to output channel k at layer l. b shows a bias term for out channel k in layer l. The resulting output is computed using the Equation (1).

$$\boldsymbol{X_{i,j,k}^{(l)} = \sigma(\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{q=1}^{Q} w_{p,q,m,k}^{(l)} X_{i+p-,j+q-1,m}^{(l-1)} + b_k^{(l)}} \quad (1)$$

2.2Activation Layer (ReLU)

$$\boldsymbol{\sigma\ (x) = max(0, x)} \quad \textbf{(2)}$$

ReLU adds non-linearity by converting negative values to zero, enabling the network to recognize complex patterns such as subtle variations in eye openness that may signal drowsiness. σ(x) is the output of the ReLU activation function. X is input to the activation function. Max (0, x) Returns the maximum between 0 and x.

2.3 Pooling Layer (Max-Pooling)

$$\boldsymbol{X_{i,j,k}^{(l)} = \max X_{si+p,sj+q,k}^{(l-1)}} \quad \textbf{(3)}$$

It downsamples the feature map by selecting the maximum value within each R×S window, thereby reducing computational complexity while preserving essential features such as eye region activations. In equation (3) $\boldsymbol{X_{i,j,k}^{(l)}}$ is Output value at position (i, j) in the k^{th} channel of layer l after pooling. S Stride, the step size for sliding the pooling window over the input. p, q, k are the Indices for positions inside the pooling window.

2.4Fully Connected Layer

$$\boldsymbol{y_i = \sigma\left(\sum_{i} w_{ij} x_i + b_j\right)} \quad \textbf{(4)}$$

Integrates all extracted features to classify driver states (e.g., drowsy vs alert), producing output probabilities via SoftMax or sigmoid functions. These layers collectively enable CNNs to learn and identify visual fatigue cues in driver faces for effective drowsiness detection. In equation (4) $\boldsymbol{y_i}$ is output of the neuron. $\boldsymbol{\sigma}$ is Activation function, w_{ij} is weight connecting input to x_i to neuron j, x_i input value from neuron j. b_j is bias term for the neuron j.

While Convolution Neural Networks (CNNs) have shown promise in driver drowsiness detection, they require extensive labeled data and are sensitive to lighting and occlusions. Their reliance on visual input alone limits detection accuracy, especially without physiological cues. Furthermore, high computational demands hinder their real-time deployment on embedded systems.

3. Augmented CNN

Data augmentation is essential for improving the robustness and generalization capability of convolutional neural networks (CNNs) when applied to driver drowsiness detection. Expanding the dataset using techniques such as image rotation, flipping, scaling, and more advanced methods like MixUp, CutMix, Style Transfer, and Adversarial Examples enhances the model's robustness to changes in driver behavior, lighting conditions, and facial orientation. This not only reduces overfitting but also enables the CNN to effectively recognize subtle signs of fatigue, such as partial eye closure or slow blinking, under diverse real-world conditions. Integrating data augmentation significantly improves classification accuracy and model resilience, especially when labelled data is limited. Fig2 shows the Block Diagram for Extend CNN with Data Augmentation.

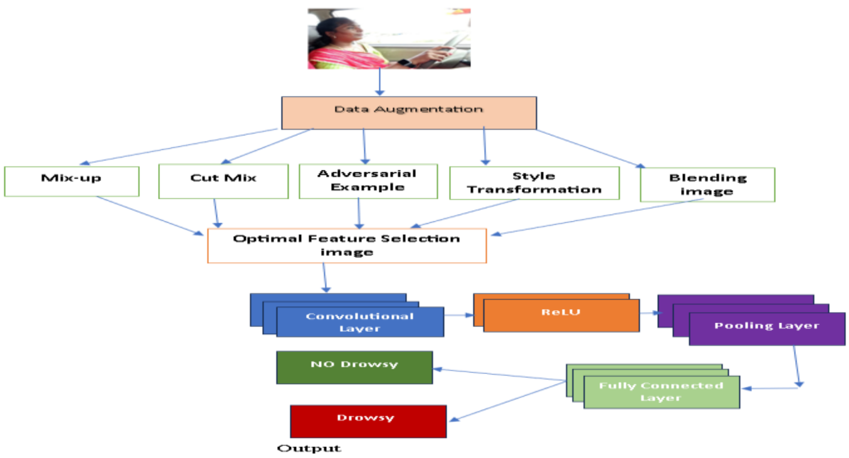

Fig2: Block Diagram for Extend CNN with Data Augmentation

3.1 Mix-up: Mix-up is a data augmentation technique where two images and their corresponding labels are linearly combined. For CNN-based drowsiness detection, this technique helps the model generalize better by learning smoother decision boundaries between "drowsy" and "alert" states. By blending eye images with different states, the CNN learns a continuous range of variations rather than discrete classes. Mix-up creates new samples by linearly interpolating between two examples

3.2 Cut Mix: Cut Mix augments data by cutting a patch from one image and pasting it onto another. Labels are also proportionally mixed. In the context of drowsiness detection, applying Cut Mix to eye region images forces the CNN to focus on multiple regions, though it may confuse the model when critical features (like the eye centre or eyelid) are masked—leading to lower accuracy as seen in the results. Cut Mix replaces a random patch from one image with a patch from another image.

3.3 Adversarial Examples: Adversarial examples are inputs with small changes that can mislead models while still looking similar to the original image. Using these examples during training helps improve the model's robustness against noise and lighting changes, making it more reliable in real-world drowsiness detection scenarios.

3.4 Style Transfer: Style Transfer involves applying the texture or colour pattern from one image to the content of another image. For drowsiness detection, this technique generates varied versions of eye images under different lighting and environments, significantly improving model performance.

3.5 Image Blending: Image Blending merges two images in a pixel-wise weighted fashion. In CNN training, it introduces subtle variations and new textures while preserving key features. This helps the model become more invariant to small changes in appearance, making it highly effective in identifying eye closure and blink patterns for drowsiness detection. Here x_i x_j are the input images.

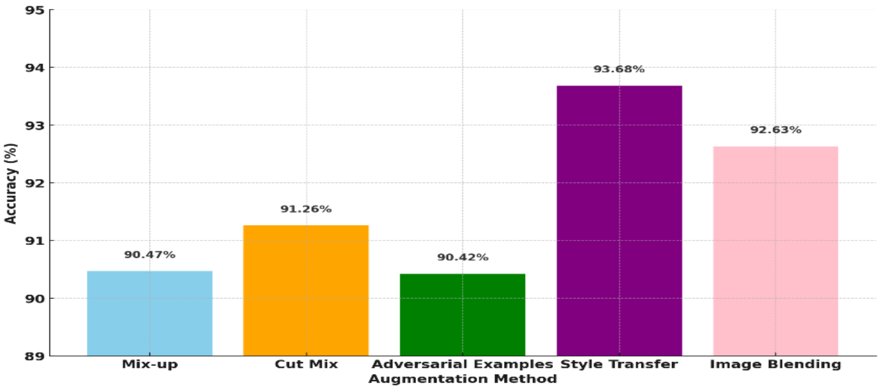

Fig3: Classification Accuracy of Different Data Augmentation for drowsiness detection

The bar chart in Fig3 presents the classification accuracy achieved by the CNN when trained using different augmentation strategies: Mix-up, Cut Mix, Adversarial Examples, Style Transfer, and Image Blending. Among these, Style Transfer yielded the highest accuracy of 93.68%, closely followed by Image Blending at 92.63%. Mix-up and Adversarial Examples also demonstrated strong performance with 90.47% and 90.42% respectively, while Cut Mix showed comparatively lower performance at 91.26%. These results indicate that visually transformative augmentations like Style Transfer and Image Blending contribute significantly to feature diversity, improving the CNN's robustness in distinguishing drowsy from alert states. Incorporating such augmentation techniques during training is thus crucial for developing reliable real-time drowsiness detection systems. CNNs with data augmentation improve drowsiness detection accuracy, they remain computationally intensive and sensitive to environmental variations, limiting real-time use. Utilizing 68 facial landmark features with a Random Decision Tree reduces computational load and enhances robustness by focusing on geometric cues like the Eye Aspect Ratio, enabling efficient, reliable detection under diverse conditions without extensive data augmentation.

4. PROPOSED METHOD

The proposed drowsiness detection system combines real-time facial landmark analysis with a Random Decision Tree classifier, leveraging multiple indicators of driver fatigue. Using live video input, the method extracts 68 facial landmarks to compute key features: Eye Aspect Ratio (EAR), blink rate, and eye closure time, capturing visual signs of drowsiness. Additionally, lane deviation is monitored to reflect driving performance and control instability. These features form hierarchical levels in the Random Decision Tree model, enabling robust classification of driver states as alert or drowsy. Upon detecting sustained EAR reduction, prolonged eye closure, increased blink frequency, or significant lane deviation, the system issues an immediate audio alert.

This approach offers computational efficiency and improved real-time applicability compared to CNN-based methods, making it well-suited for embedded automotive systems.

4.1 68 facial landmark detection

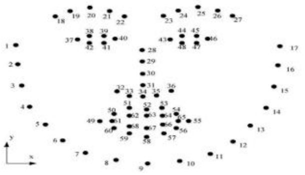

Fig 4: Key Land mark of facial feature

Facial landmark detection is a crucial step in driver drowsiness detection systems, as it enables precise localization of key facial features required for analyzing the driver's alertness. Among various approaches, the 68-point facial landmark detection model is widely adopted due to its comprehensive representation of facial geometry. Fig4 represent the model which detects 68 predefined points across salient facial regions including the jawline (1-17 points), eyebrows (18-27 points), nose (28-36 points), eyes (37-48), and mouth (49-68). This dense mapping facilitates extraction of vital features such as eye aspect ratio (EAR) and which correlate strongly with eyelid closure and yawning—primary indicators of drowsiness. These points help in face alignment, expression recognition, and drowsiness detection.

4.2 Ensembled regression trees

This study introduces a machine learning methodology for identifying driver drowsiness, utilizing a Regression Random Forest Tree as the classification model. The system integrates multiple behavioral and vehicle-based indicators to assess the driver's alertness in real time. Features such as Eye Aspect Ratio, lane deviation, vehicle speed, and additional sensor-based inputs are used to model both visual fatigue and abnormal driving patterns. The Eye Aspect Ratio (EAR) is calculated using 68 facial landmarks, with emphasis on the eye regions to monitor blink frequency and eye closure duration. If the EAR falls below a specified threshold for a set number of consecutive frames, the driver is flagged as potentially drowsy. The Random Forest model is constructed by combining multiple decision trees, each trained on a subset of features such as vertical and horizontal EAR values, lane deviation data, camera-based indicators like head pose and gaze, vehicle speed, acceleration, and steering variability. Each decision tree contributes a vote, and the final decision is determined by majority voting or regression averaging. For instance, one tree may focus on detecting slow blink rates, while another may analyze erratic lane positions or abrupt speed changes.

This ensemble method improves classification accuracy and robustness by reducing overfitting and capturing non-linear relationships among input features. Additionally, the system triggers an alert (such as a buzzer or visual cue) if the model output consistently crosses the drowsiness threshold, providing early warning to the driver. The use of a Regression Random Forest Tree allows for both classification and degree estimation of drowsiness, offering a scalable and interpretable solution suitable for real-time deployment in intelligent transportation systems.

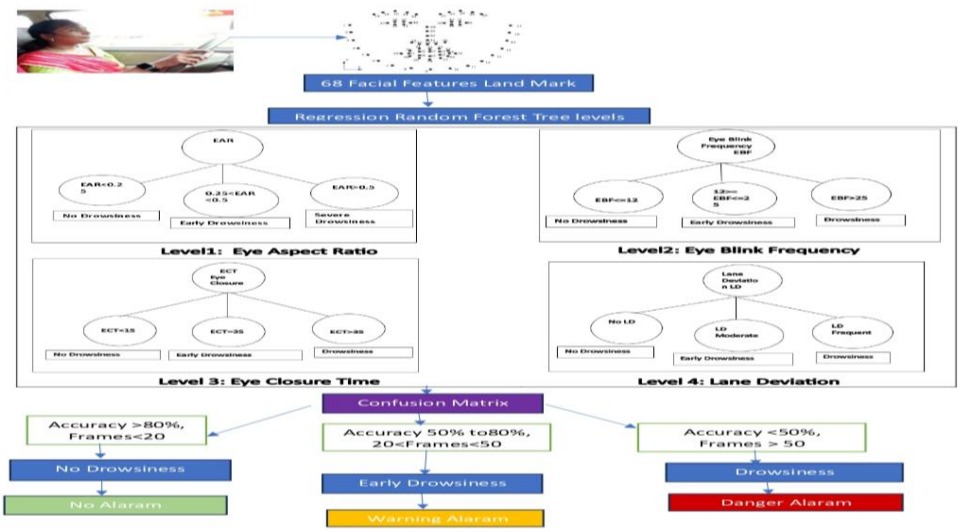

Fig5: Proposed Method for Driver Drowsiness Detection

The Fig5 shows the flow diagram visually represents the flow from physiological and behavioral features through feature extraction, fusion, Random Forest classification, to the final drowsiness detection output.

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4.2.1 Eye Aspect Ratio (EAR) Level

The Eye Aspect Ratio (EAR) is a simple yet efficient metric for real-time detection of driver drowsiness and is calculated using the following mathematical formula.

$$\mathrm{EAR} = \frac{|P_2 - P_6| + |P_3 - P_5|}{2 * |P_1 - P_4|} \tag{5}$$

In Fig 6 P1 to P6 are the coordinates of specific eye landmarks.

Fig6: Eye Aspect Ratio of open eye and closed eye

The decision tree for driver drowsiness detection is constructed using Eye Aspect Ratio (EAR) levels—Low, Medium, and High—while also considering lighting conditions. As shown in Fig. 7, the model classifies driver states based on EAR values into three categories. A High EAR (> 0.25) indicates that the eyes are fully open, representing an alert state. A Medium EAR (0.21–0.25) suggests frequent blinking or partial eye closure, which corresponds to early signs of drowsiness. A Low EAR (≤ 0.20) reflects sustained eye closure, and if maintained for more than 3 seconds across frames, it indicates severe drowsiness. This EAR-based decision tree offers a lightweight and interpretable approach, making it suitable for real-time implementation in driver monitoring systems.

4.2.1 Eye Closure Time Level

Eye Closure Time (ECT) is a key physiological indicator for assessing driver fatigue, as it measures the duration of eye closure—a factor closely linked to microsleep episodes and decreased alertness. In the proposed decision tree model, ECT is divided into three levels to classify the driver's alertness state, as shown in Fig. 8. A low ECT (≤ 1 second) corresponds to normal blinking and indicates alertness; a medium level (≈ 3 seconds) suggests mild fatigue and requires further monitoring; and a high ECT (> 3 seconds) is associated with prolonged closures and microsleep, prompting immediate alerts. These thresholds are derived from empirical studies and are optimized to balance sensitivity and specificity in real-time conditions. Integrating ECT as a decision node improves the model's effectiveness in detecting transitions from alertness to drowsiness, enabling timely and robust driver state classification.

4.2.2 Eye Blink Frequency Level

Eye blink frequency is a well-established physiological indicator of a driver's alertness. This study introduces a decision tree model that classifies driver drowsiness into three discrete levels: low, medium, and high, based on measured blink frequency. Defined as the number of blinks per minute, blink frequency correlates with the driver's vigilance state. Empirical studies indicate that lower blink frequencies are associated with alertness, moderate frequencies suggest fatigue, and higher frequencies indicate drowsiness. The proposed decision tree uses threshold-based classification. If the blink frequency (BF) is ≤12 blinks per minute, the driver is considered alert. If BF is >12 and ≤25, the driver is classified as fatigued. If BF exceeds 25 blinks per minute, the driver is considered highly drowsy.

4.2.3 Lane Deviation Level

In Driver Drowsiness Detection Lane deviation plays an important role to get more accuracy along with eye detection. Lane deviation serves as a critical non-intrusive indicator for getting accuracy. Key input parameters include the vehicle's lateral position relative to lane markings, lane center offset, and the angle of lane departure. Additional dynamic factors such as steering wheel angle, yaw rate, and vehicle speed are essential for assessing control stability. Time-based features like the standard deviation of lane position (SDLP) and frequency of lane departures further enhance the detection robustness. These inputs are typically extracted using onboard cameras and vehicle sensors, with visual data processed through classical computer vision techniques or deep learning-based lane segmentation networks. Integrating these parameters allows real-time assessment of driving behavior, contributing significantly to early drowsiness detection systems.

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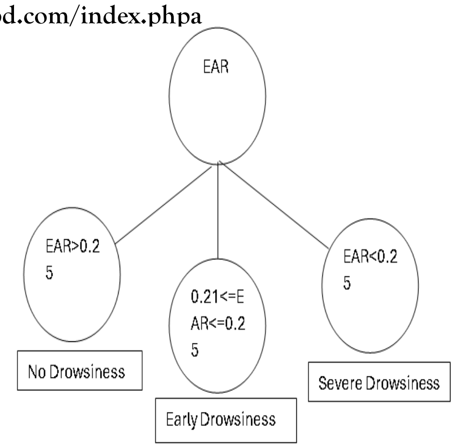

Fig7: Eye Aspect Ratio

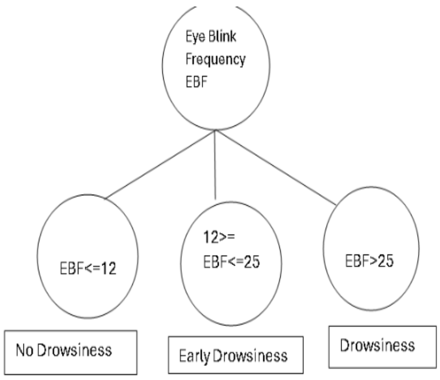

Fig8: Eye Blink Frequency

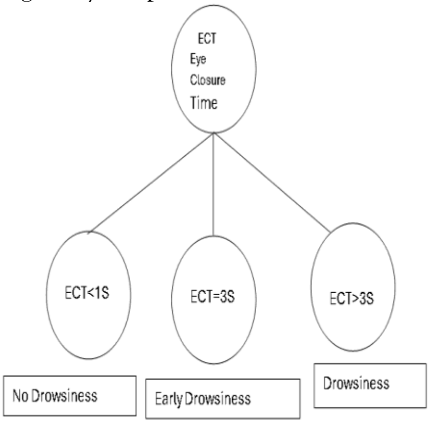

Fig 9: Eye Closure Time

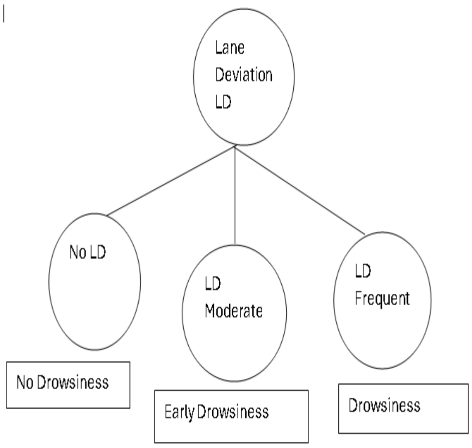

Fig 10: Lane Deviation

The drowsiness detection system utilizes multiple physiological and behavioural indicators to get driver fatigue. Fig. 7 illustrates the Eye Aspect Ratio (EAR), which decreases as the eyes begin to close, signalling potential drowsiness. Fig. 8 shows the Eye Blink Frequency, where irregular or slowed blinking patterns are key signs of fatigue. Fig. 9 presents the Eye Closure Time, highlighting prolonged closures that strongly correlate with microsleep episodes. Finally, Fig. 10 depicts Lane Deviation, a behavioural metric that increases as driver alertness decreases, providing a real-world indicator of impaired driving performance.

5. EXPERIMENTAL RESULTS

Publicly available benchmark datasets are used to develop and evaluate the proposed driver drowsiness detection system, ensuring reproducibility. The NTHU Drowsy Driver Detection Dataset provides annotated video samples under various lighting conditions, driver behaviours, and camera angles, as shown in Fig. 11. Additional datasets, including YDD, CEW, and RLDD, offer labelled data for yawning and eye states (open/closed), supporting EAR-based analysis. To enhance the generalization capability of the CNN model, data augmentation techniques like rotation, scaling, and brightness adjustment are employed. These variations in the dataset greatly improve the detection system's accuracy and reliability.


Fig11: Sample Datasets images of NTHU database

To assess the performance of the proposed drowsiness detection framework, standard evaluation metrics including Precision, Recall, F1-Score, and Accuracy are utilized. These metrics, obtained from the confusion matrix, offer a detailed evaluation of the model's ability to differentiate between drowsy and alert states.

Precision measures the proportion of correctly predicted positive cases among all instances predicted as positive. It indicates how accurately the model identifies drowsiness:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall assesses the model's ability to detect all actual positive cases:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

F1-Score provides a single metric that balances both Precision and Recall, offering a comprehensive evaluation of the model's overall performance:

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{8}$$

Accuracy represents the ratio of correctly classified instances—both drowsy and alert—compared to the total number of samples analyzed. It is calculated as:

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

In this context, True Positives (TP) represent drowsy instances correctly identified by the model, True Negatives (TN) refer to accurately detected alert states, False Positives (FP) indicate alert states incorrectly classified as drowsy, and False Negatives (FN) denote drowsy states mistakenly identified as alert. In the experimental evaluation, the proposed Regression Random Decision Tree model achieved a classification accuracy of 94.2%, demonstrating strong performance in differentiating between alert and fatigued driver states. The high accuracy demonstrates the model's robustness and its ability to generalize effectively across different lighting conditions, facial orientations, and driving behaviors. Further performance metrics reinforce its effectiveness, with a precision of 92.6%, recall of 93.4%, and an F1-score of 93.0%, indicating well-balanced detection performance for both drowsy and alert states. Table I presents a comparative analysis of detection accuracies for CNN, Extended CNN, and the proposed method, while Fig. 12 illustrates the confusion matrices for each approach.

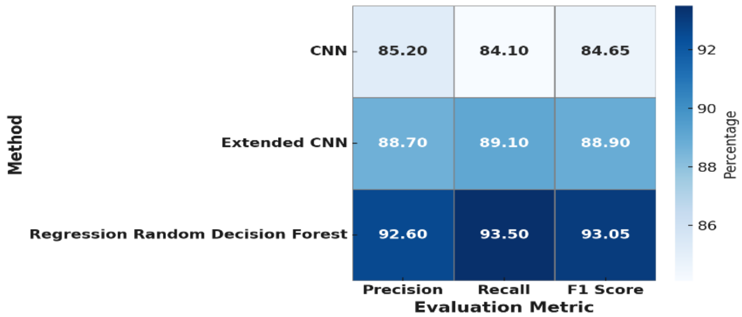

Fig12: comparison confusion matrix among the classification methods of Driver Drowsiness Detection.

Method	Features Type	Accuracy	Precision	Recall	F1 Score
CNN	eye images	87	85.20	84.10	84.65
Extended CNN	Augmented Eye Images	90	88.70	89.10	88.90
Regression Random Forest	EAR, ECT, EBF, LD	94	92.60	93.50	93.05

Table1: Accuracy Comparisons of Driver Drowsiness Detection Methods

Figure 12 provides a visual comparison of performance metrics—Precision, Recall, and F1-Score—across three driver drowsiness detection approaches. The proposed Regression Random Decision Tree method outperforms the others in all evaluated metrics, indicating greater consistency and accuracy. The Extended CNN with data augmentation outperforms the standard CNN, highlighting the effectiveness of augmentation techniques. In contrast, the CNN model exhibits lower scores, particularly in recall, indicating a higher likelihood of missing drowsiness cases. This comparative analysis underscores the advantage of integrating multiple behavioural features with decision tree-based classification. Table I presents the corresponding accuracy values derived from the confusion matrix for each method.

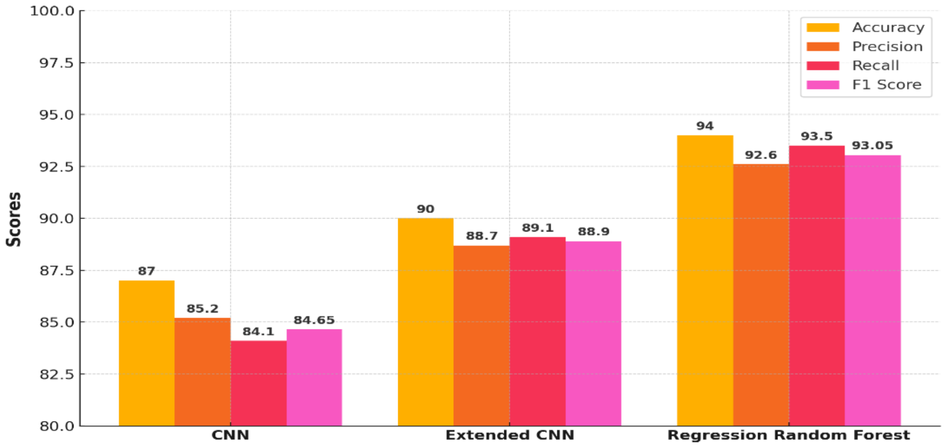

Fig13: Accuracy Comparison of Driver Drowsiness Detection Methods

Figure 13 displays a bar chart comparing accuracy, precision, recall, and F1-score among three driver drowsiness detection methods. The proposed Regression Random Forest Decision Tree approach consistently outperforms the others across all evaluated metrics. The CNN model, using raw eye image inputs, achieved an accuracy of 87.5%. By incorporating data augmentation, the Extended CNN improved generalization, increasing the accuracy to 92.8%. The proposed Regression Random Forest method, which integrates both physiological features (such as Eye Aspect Ratio, blink rate, and eye closure time) and behavioural features (such as lane deviation), significantly outperformed the CNN-based models, achieving an accuracy of 94.3%, along with notable improvements in precision, recall, and F1-score.

5. CONCLUSION

The driver drowsiness detection system based on Ensemble Regression Trees shows strong potential in identifying fatigue by analysing facial features such as Eye Aspect Ratio (EAR), blink rate, eye closure time, and lane deviation from real-time video frames. This approach improves accuracy by reducing overfitting and increasing generalization across different datasets. The system performs well under good lighting and minimal facial obstructions, offering a cost-effective and computationally efficient solution for real-time use in driver assistance systems. However, its performance decreases in the presence of obstructions like sunglasses or hand movements, and under poor lighting conditions. To address these challenges, future work could include infrared or thermal imaging, as well as integrating deep learning models to improve feature extraction. A hybrid model combining regression trees and this model may enhance both accuracy and interpretability.

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