Accident-Free Initiative - A Project For Enhanced Road Safety

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Abstract:

This research introduces an innovative approach to drowsiness detection by synergizing computer vision and deep learning methodologies. The system utilizes Convolutional Neural Networks (CNNs) to analyze real-time eye and mouth movements for the concurrent detection of yawning and eye closure patterns. By incorporating Haar Cascade classifiers for precise face and eye localization, the model achieves heightened accuracy and adaptability across varying environmental conditions. Notably, the study expands the conventional scope by integrating external factors, specifically **weather conditions such as rain intensity, visibility, and light levels, with classes of cloudy, foggy, rainy, shine, sunrise into the drowsiness detection process.**. This holistic approach aims to provide a more nuanced understanding of potential drowsiness triggers, considering environmental influences that might exacerbate fatigue. The combination of facial movements analysis and weather-aware detection contributes to the system's contextual awareness, enhancing its applicability in diverse scenarios. The proposed methodology exhibits promising results in controlled and real-world settings, emphasizing its potential integration into safety systems, particularly for drivers. The research underscores the significance of a multi-faceted approach to drowsiness detection for improved effectiveness and reliability in practical implementations.

Keywords: Drowsiness Detection, Computer Vision, Deep Learning, CNN, Mouth and Eyes Analysis, Haar Cascade, Real-time Monitoring, Weather aware Detection, Fatigue Management, Safety Systems, Rain Intensity, Visibility, Light Levels.

I. INTRODUCTION

Driver fatigue poses a critical threat to road safety, significantly increasing the risk of vehicular accidents. Research indicates that a substantial number of crashes are attributed to drowsy driving, resulting in a high toll of injuries and fatalities. Addressing this pressing issue demands innovative solutions for real-time monitoring and detection of driver fatigue. In recent years, advancements in computer vision and deep learning have shown promise in developing effective systems to combat this problem. Building upon existing research, this study introduces novel approaches to enhance the accuracy and reliability of drowsiness detection.

The proposed system employs CNN for Mouth and Yawning analysis, focusing on indicators such as eye closure, head posture, and Weather Condition. Haar Cascade classifiers aid in face detection, enabling detailed analysis of the driver's facial Movements. By examining the driver's eyes, the system monitors blinking patterns and evaluates eye closure duration for insights into the driver's alertness level. This approach draws inspiration from recent studies [**1**][**2**] that combine features for the accurate detection of driver stress and fatigue.

Additionally, this project introduces weather conditions as a factor in drowsiness detection. **Weather-aware detection aims to adapt system sensitivity based on external factors like rain, snow, fog, cloud, shine,** which influence driving conditions and behavior. Integrating real-time weather data allows the system to dynamically adjust thresholds, improving overall accuracy. This aligns with enhancing driver safety through contextual awareness [**15**].

The research extends into real-time monitoring of yawning behavior, a prominent indicator of drowsiness. The integration of a yawning detection model complements the overall system, utilizing a pre-trained deep learning model fine-tuned for accurate recognition of yawning patterns. Yawning is considered a reliable fatigue indicator [**6**], enhancing the system's robustness.

In conclusion, this research project contributes to driver safety by proposing an advanced drowsiness detection system integrating Eye movement analysis, environmental context awareness, and real-time yawning monitoring. This system aims to provide an effective solution for preventing accidents caused by drowsy driving, ultimately enhancing road safety.

II. LITERATURE SURVEY

The literature survey on driver drowsiness detection reveals a multifaceted exploration of methodologies incorporating facial, and head behavior information, and advanced technologies. Kassem et al. [**1**] delved into predicting fatigue levels using facial and head behavior information, marking a significant stride in understanding the correlation between physiological cues and drowsiness. Multimodal features, as explored by Nemcova et al. [**2**], have emerged as key contributors, extending the focus beyond facial cues to create a holistic detection system. This aligns with recent trends in the field, emphasizing a comprehensive approach [**14**].

A systematic survey by Zhang et al. [**3**] highlights the breadth of techniques employed in driving fatigue monitoring. The incorporation of deep neural networks for mental fatigue detection, as demonstrated by Ansari et al. [**4**], showcases the industry's inclination toward leveraging advanced models for nuanced assessments. Li et al.'s [**5**] novel learning model for fatigue features representation, particularly concerning the steering wheel angle, adds a new dimension to feature extraction. This aligns with the approach of integrating steering behaviour into drowsiness detection systems, as discussed in our earlier conversations.

Real time applications have garnered attention, exemplified by Jabbar et al.'s [**6**] Android based implementation using deep neural networks. Celona et al. [**7**] introduced a multi-task CNN framework for driver face monitoring, contributing to the evolving landscape of real time monitoring technologies. Emotion monitoring in Verma and Choudhary's work [8] reflects an increasing interest in understanding the emotional states of drivers as a factor influencing drowsiness. The chronological evolution of these studies underlines the continual refinement of methodologies and the growing complexity of detection models [**11**].

A shift towards automated drowsiness detection, initially explored by Vural et al. [**9**], has gained momentum with advancements in computer vision. Minhas et al.'s [**13**] analysis of driver fatigue and drowsiness using CNN emphasizes the role of machine learning in real-time detection. Safarov et al.'s [**14**] real-time deep learning-based approach, integrating computer vision and eye blink analyses, underscores the significance of multi-faceted analyses for enhanced road safety.

The literature also explores the broader landscape of driver safety monitoring. Shan et al.'s [**15**] IoT and computer vision-based systems introduce risk prediction, extending the scope beyond real-time detection to proactive risk mitigation. The multi-task CNN proposed by Savaş and Becerikli [**16**] further exemplifies the trend toward comprehensive systems capable of handling various tasks concurrently.

In conclusion, the **literature survey demonstrates a rich tapestry of approaches ranging from physiological cues to advanced machine learning models**, reflecting the field's progression towards more robust and comprehensive drowsiness detection systems. These studies collectively contribute to our understanding of the complexities involved in real-time monitoring and mitigation of driver drowsiness.

III. PROPOSED SYSTEM

The proposed enhanced driver drowsiness detection system represents a significant advancement in the field, leveraging innovative methodologies and technologies to address the limitations of existing systems. Building upon insights gained from a comprehensive literature survey and recognizing the evolving landscape of driver safety monitoring, our system introduces novel approaches aimed at enhancing detection accuracy and adaptability in real-world driving scenarios.

Key Differences from Existing Systems:

- **Integration of Multi-Modal Features**: Unlike traditional approaches that predominantly rely on facial cues or steering behavior, our system incorporates a diverse set of indicators, including mouth movements, eye movements, and environmental factors. This multi-modal approach aims to create a more robust and adaptable system capable of detecting drowsiness under varying circumstances.
- **Weather-Based Drowsiness Prediction**: A notable novelty introduced in our system is the consideration of weather conditions in drowsiness prediction. By integrating real-time weather data and correlating it with driver behavior, the system aims to provide more accurate and context-aware drowsiness alerts, addressing the impact of weather factors such as rain or fog on driving conditions.
- **Integration of Advanced Neural Networks**: Our methodology leverages state-of-the-art neural network architectures for both drowsiness and yawning detection. Inspired by recent advancements in deep learning models, our system autonomously learns and adapts to complex patterns in mouth movements and eye movements, enhancing detection accuracy across diverse driving scenarios.
- **Real-Time Risk Prediction**: In addition to conventional drowsiness detection, our system extends beyond by incorporating real-time risk prediction. By assessing a combination of driver behavior, environmental conditions, and historical data, the system proactively foresees potential risk scenarios, enabling timely alerts and interventions to enhance overall road safety.
- **User-Adaptive Models**: Recognizing individual variances in driver behavior, our system introduces user-adaptive models. Through continuous learning mechanisms, the system adapts to the specific traits and patterns of each driver, improving the accuracy of predictions over time and tailoring responses based on individual user characteristics.

IV. METHODOLOGY

The proposed methodology incorporates several novel aspects to enhance the effectiveness of driver drowsiness detection. These innovations stem from a comprehensive understanding of the existing literature, as well as insights gained from our previous discussions. The methodology brings together innovations in multi-modal detection, weather-centric analysis, advanced neural networks, real-time risk prediction, and user-adaptive models to create a holistic and cutting-edge approach to driver drowsiness detection. These novel components collectively contribute to the project's potential to advance the field and address the limitations of existing systems.

A. **Dataset Information:** The dataset used in this project is meticulously curated to facilitate comprehensive training and evaluation of the driver drowsiness detection system. It comprises three distinct subsets, each designed to capture specific aspects of driver behavior, weather conditions, and their interplay.

1. **Eyes Dataset**:
   a) **Labels**: The eyes dataset is categorized into two classes: "Open" and "Closed," shown in the below **figure 1 and 2**, representing the state of the driver's eyes. Each class consists of 5000 images, providing a balanced representation of both eye conditions.
   b) **Purpose**: This subset focuses on training the deep learning model to recognize variations in eye states, a crucial aspect of drowsiness detection. It helps the model learn to discern between open and closed eyes, forming the foundation for real-time monitoring.

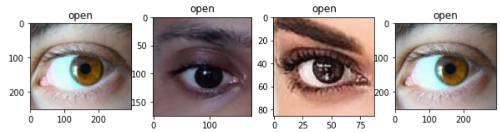

Figure 1: Open Eyes Samples

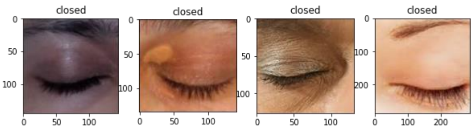

Figure 2: Closed Eyes Samples

2. **Yawn Dataset**:
   a) **Labels**: The yawn dataset comprises two classes: "Yawn" and "No Yawn," shown in the below **figure 3 and 4**, indicating whether the driver is exhibiting a yawning behavior. Like the eye's dataset, each class contains 5000 images, ensuring a balanced distribution for effective learning.
   b) **Purpose**: Yawning is a significant indicator of drowsiness, and this dataset aims to train the model to identify yawning patterns accurately. Detecting yawning events contributes to the overall assessment of driver alertness.

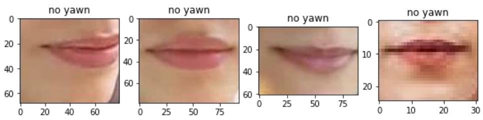

Figure 3: Not Yawning Samples

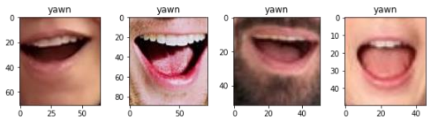

Figure 4: Yawning Samples

3. **Weather Dataset**:
   a) Classes: "Cloudy", "Foggy", "Rainy", "Shine", "Sunrise" shown in the below **figures 5, 6, 7, 8, 9.**
   b) **Contents:** Each folder corresponds to a specific weather condition, containing images captured under diverse scenarios. The dataset encompasses various lighting and visibility conditions associated with different weather types. Each class contains 5000 images, ensuring a balanced distribution for effective learning.
   c) **Purpose:** The weather dataset introduces a unique dimension to the model's training, enabling it to recognize and adapt to varying environmental factors. Incorporating weather conditions enhances the system's ability to account for external influences on driver drowsiness.

Dataset Integration:

- The eyes and yawn datasets provide essential information about driver behavior, while the weather dataset introduces **external factors that may contribute to drowsiness**.
- Each dataset is carefully labeled and organized, ensuring a coherent integration during the training phase.
- The collective dataset enables the model to learn intricate patterns and correlations, fostering a holistic understanding of drowsiness under diverse conditions.

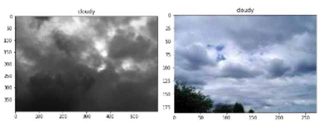

Figure 5: Cloudy Samples

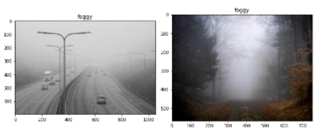

Figure 6: Foggy Samples

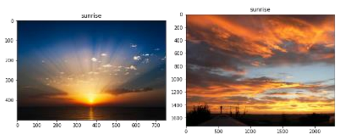

Figure 7: Sunrise Samples

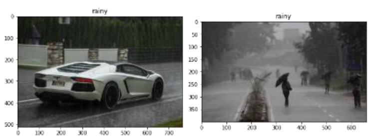

Figure 8: Rainy Samples

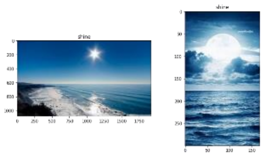

Figure 9: Shine Samples

B. Data Preprocessing:

1. **Eyes Dataset**:
The dataset was initially structured into **feature vectors (X)** and **corresponding labels (y).** Feature vectors were converted into a **NumPy array** and **reshaped** to accommodate the model's input requirements. To address class **imbalances, label binarization** was employed. Subsequently, the dataset was partitioned into **training and testing sets** using a **stratified split** to maintain **class distribution consistency**. Data augmentation techniques, including **rescaling, random zooming, horizontal flipping, and rotation**, were applied to the training set to enhance model robustness. The following has shown in the below figure 10.

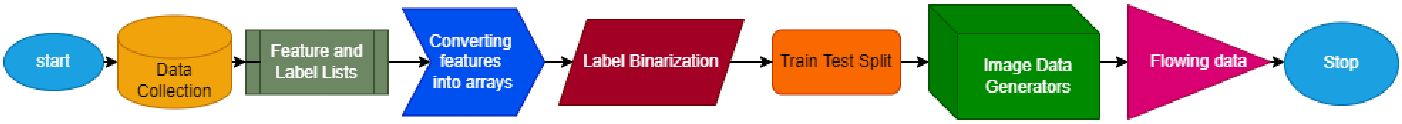

Figure 10: Eye Status Data Procesing Flowchart

2. **Yawn Dataset**:
The dataset was organized into a **pandas DataFrame**, with images categorized as **'yawn' or 'no yawn'**. A preprocessing **pipeline** was established to handle **image loading**, **resizing to 64x64 pixels**, and **rescaling pixel values.** Data augmentation techniques, including **random zooming, flipping, and rotation**, were applied to the training set to enhance model robustness. The dataset was subsequently divided into **training, validation, and testing sets** for model development and evaluation. The following has shown in the below figure 11.

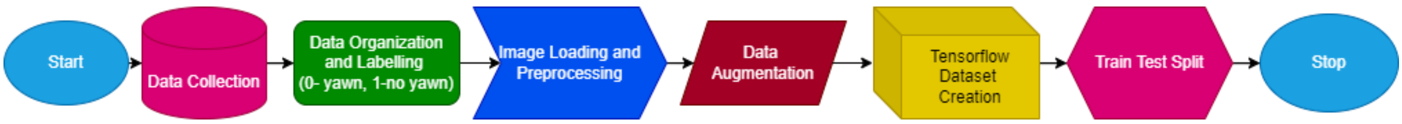

Figure 11: Yawn Status Data Procesing Flowchart

3. **Weather Dataset**:
Images were **categorized and labeled** based on their **directory structure**. They were subsequently resized to a **standardized dimension of 150x150 pixels**. To enhance model performance, **pixel values** were **normalized** to a **scale of 0-1.** The dataset was then divided into **training and testing subsets**, with **categorical labels converted into numerical representations using label encoding.** The following has shown in the below figure 12.

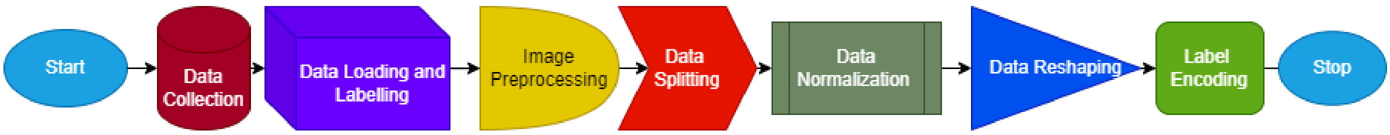

Figure 12: Weather Status Data Procesing Flowchart

C. Feature Extraction:

A. Histogram Colour extraction for Weather data:

To capture the color distribution within images, color histograms were computed for each image. The images were initially decomposed into their respective red, green, and blue components. Subsequently, histograms were generated for each channel, quantifying the frequency of pixel intensities. These histograms served as a foundational feature representation for subsequent image analysis and classification tasks. The following has shown in the below figure 13,14,15,16,17.

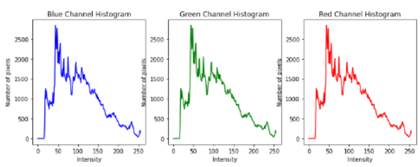

Figure 13: Cloudy graph

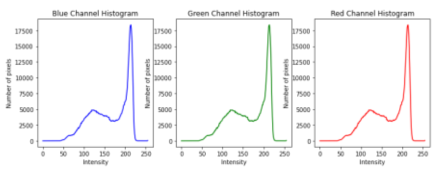

Figure 14: Foggy graph

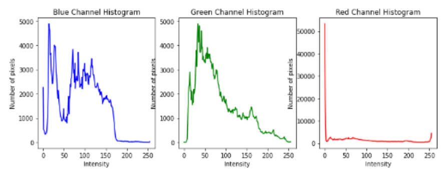

Figure 15: Sunrise graph

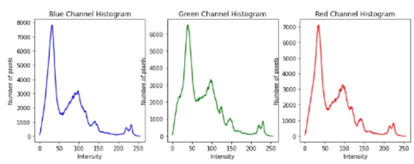

Figure 16: Rainy graph

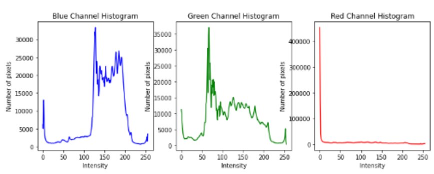

Figure 17: Shine graph

D. Model Building:

A. Eye status:

The proposed model is a convolutional neural network (CNN) comprising multiple convolutional and pooling layers. The architecture begins with an input layer processing 145x145 pixel images with three color channels. Subsequent convolutional layers extract features using 3x3 filters, while max-pooling layers downsample feature maps. The network concludes with flatten, dropout, and fully connected layers for classification. The following has shown in the below figure

Layer Type	Output Shape	Depth	Filter Size
Input	145x145	3	-
Conv2D	143x143	256	3x3
MaxPooling2D	71x71	256	2x2
Conv2D	69x69	128	3x3
MaxPooling2D	34x34	128	2x2
Conv2D	32x32	64	3x3
MaxPooling2D	15x15	64	2x2
Conv2D	13x13	32	3x3
MaxPooling2D	6x6	32	2x2
Flatten	1152	-	-
Dropout	-	-	-
Dense	-	-	64
Dense	-	-	4

Table 1: Eye Status Architechture in Texual and Numerical Representation.

B. Weather Status:

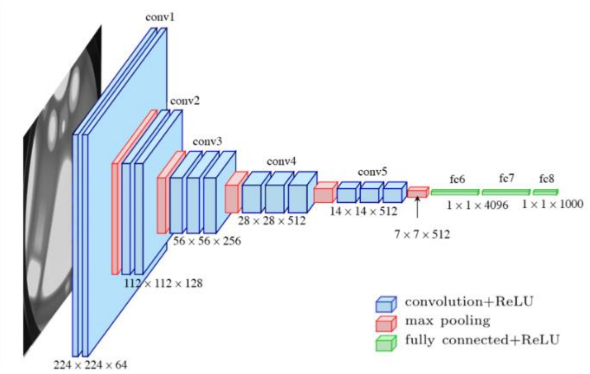

Figure 18: VGG-19 Architechture employed for weather module [17]

The model leverages transfer learning by utilizing the pre-trained VGG19 architecture. The initial convolutional layers of VGG19, trained on the ImageNet dataset, are employed as a robust feature extractor. To adapt the model to the specific classification task, the top fully connected layers are replaced with custom layers, including flattening, dense, and softmax activation for classification. This approach accelerates training and enhances model performance by capitalizing on the pre-trained knowledge.

E. Architecture Diagram

Description:

The architecture of the project is extended to include a Weather-Based Drowsiness Detection Model. This additional module enhances the system's capabilities by considering external factors such as weather conditions. The entire system is built upon the following components:

This system aims to monitor driver drowsiness and weather conditions using two separate cameras. The **figure 19** clearly demonstrates the entire systems functionality

Model Loading:

- Three pre-trained models (.h5 files) are loaded:
  - Eye Status Model (ESM) for detecting eye closure
  - Yawn Status Model (YSM) for detecting yawning
  - Weather Status Model (WSM) for classifying weather conditions

Haarcascade Loading:

- Haarcascade classifiers are loaded for face and eye detection:
  - haarcascade_frontalface_default.xml - Face detection
  - haarcascade_lefteye_2eye.xml - Left eye detection

- haarcascade_righteye_2eye.xml - Right eye detection

Camera Setup:

- **Camera 1 (driver-facing)** is opened for monitoring drowsiness.
- **Camera 2 (forward-facing)** is opened for weather detection.

Drowsiness Detection workflow:

1. Capture a frame from Camera 1.
2. Use the face cascade classifier to detect the driver's face.
3. Within the detected face region, use the eye cascades to identify both eyes.
4. Pass the eye region to the ESM for classification:
    - **Eyes Open:** Display "Eyes Open" message.
    - **Eyes Closed:** Increment a counter.
    - If the counter reaches a threshold (e.g., 3), trigger an alarm for potential drowsiness.

Yawning Detection workflow :

1. Continuously monitor Camera 1 for potential yawning gestures.
2. If a yawn is detected by the YSM, trigger an alarm for potential drowsiness.
3. Otherwise, display "Not Yawning" message.

Weather Detection workflow:

1. Capture a frame from Camera 2.
2. Extract features from the frame, such as histograms or color distributions.
3. Pass the extracted features to the WSM for classification:
    - **Cloudy:** Drive slow
    - **Foggy:** Drive slow
    - **Rainy:** Stop at any cost and trigger an alarm.
    - **Shine:** Potential for distraction
    - **Sunrise:** Be cautious of changing light conditions.

Double-Checking and Alerts:

- The system can leverage the weather conditions to influence drowsiness detection sensitivity. For example, in rainy conditions, a lower threshold for eye closure.

Architecture Visualization:

This architecture can be visualized as a block diagram with the following components:

- **Camera 1:** Driver-facing camera capturing frames.
- **Face Detection:** Detects the driver's face using Haarcascades.
- **Eye Detection:** Detects eyes within the face region using Haarcascades.
- **Eye Status Model (ESM):** Classifies eye state (open/closed) based on captured eye region.
- **Yawn Status Model (YSM):** Classifies yawning gestures based on video frames from Camera 1.
- **Alarm System:** Triggers an alarm for potential drowsiness.
- **Camera 2:** Forward-facing camera capturing frames.
- **Feature Extraction:** Extracts features (e.g., histograms) from the captured weather scene.
- **Weather Status Model (WSM):** Classifies weather conditions based on extracted features.
- **Alert System:** Displays messages and triggers alarms based on weather detection and potential drowsiness.

This high-level architecture provides a comprehensive overview of the system's functionality.

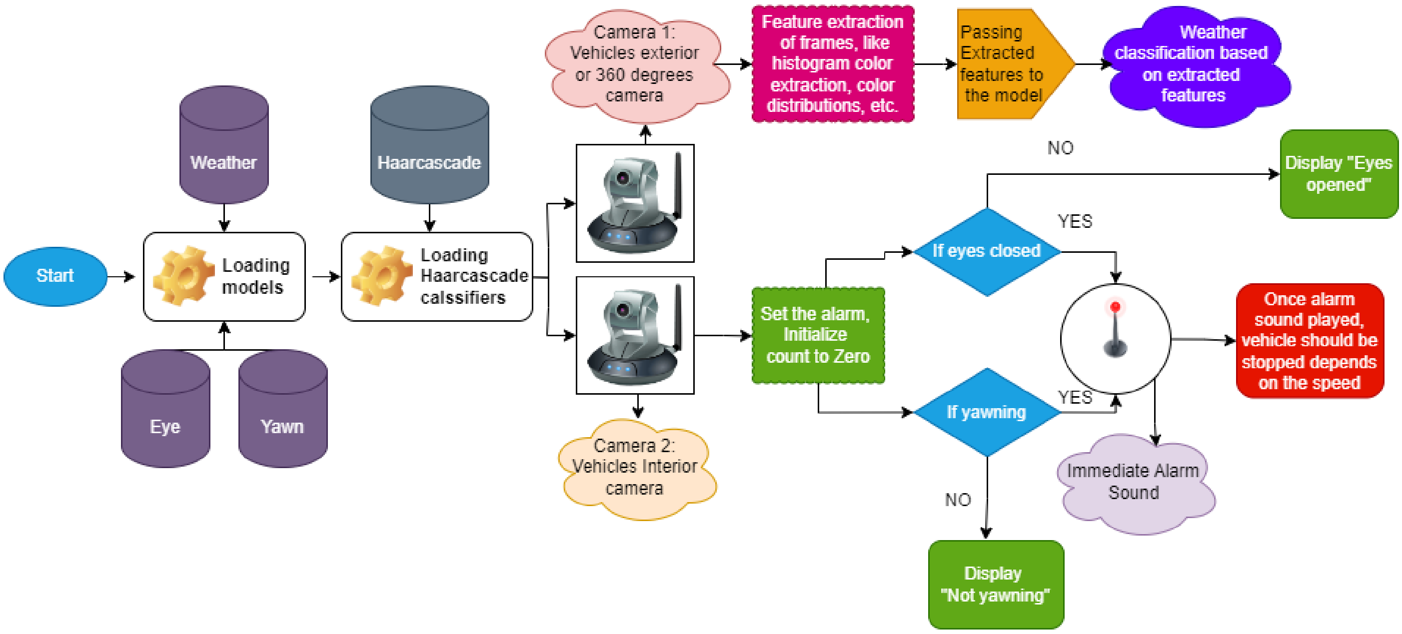

Figure 19: Overall system architecture which clearly shows the working of the system.

V. Results:

Weather Module:

A VGG19 convolutional neural network (CNN) architecture was employed for weather classification, leveraging transfer learning from a pre-trained model on ImageNet. The model was trained using Adam optimizer, categorical crossentropy loss, and accuracy metric. Hyperparameters included a batch size of 32, 15 epochs, early stopping after 5 epochs of no improvement, and model checkpointing for the best performing model.

Training Performance

The model achieved a training accuracy of 98.50% and a validation accuracy of 90.00%. While the high training accuracy indicates effective learning on the training set, the lower validation accuracy suggests potential overfitting. The training loss converged to 0.0948, and the validation loss was 0.2800, further supporting the overfitting hypothesis.

Testing Performance

The model demonstrated consistent performance on the unseen test set, achieving a loss of 0.2799 and an accuracy of 0.9033, similar to the validation results.

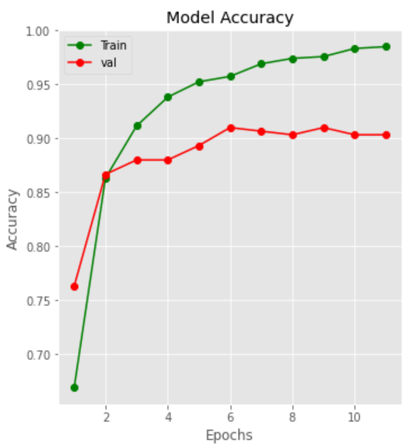

Figure 22: Traning and Validation Accuracy

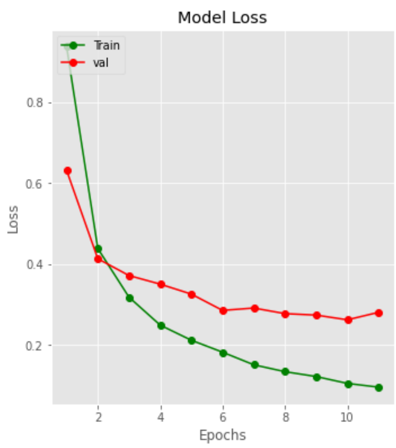

Figure 23: Training and Vlidation loss

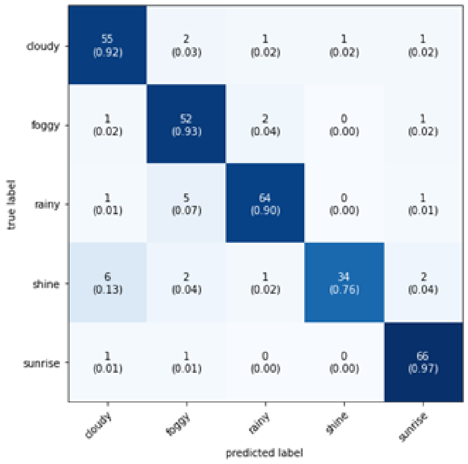

Figure 23: Confusion Matrix

Types	precision	recall	f1-score	support
0	0.86	0.92	0.89	60
1	0.84	0.93	0.88	56
2	0.94	0.90	0.92	71
3	0.97	0.76	0.85	45
4	0.93	0.97	0.95	68
accuracy			0.90	300
macro avg	0.91	0.89	0.90	300
weighted avg	0.91	0.90	0.90	300

Table 2: classification report of weather module

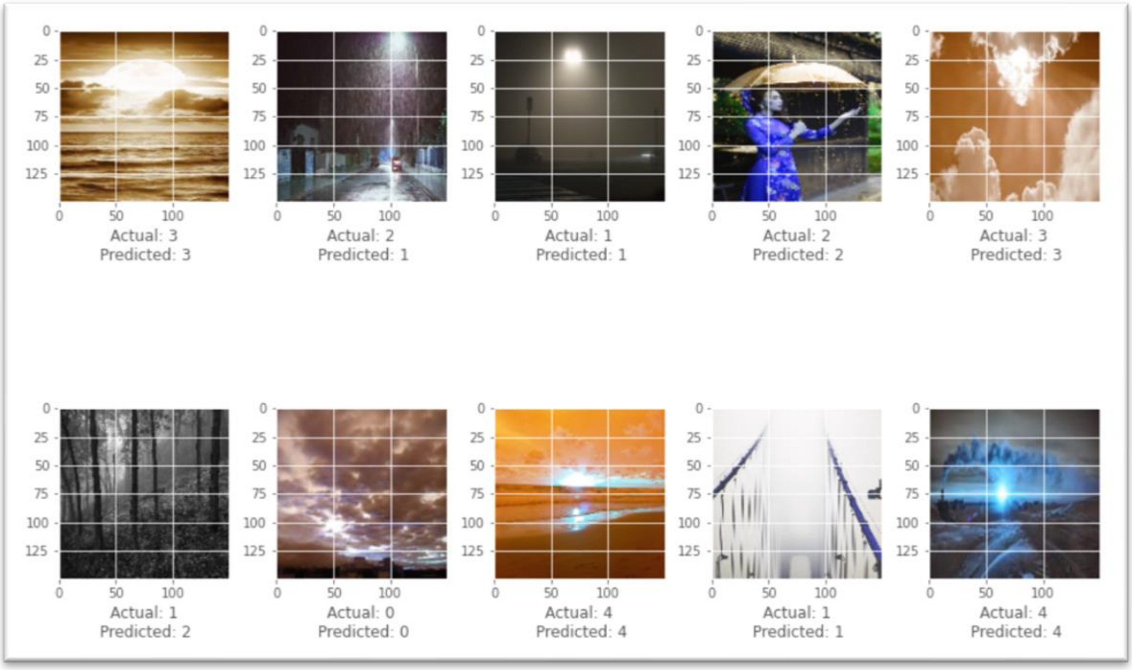

Figure 24: Weather Module Outputs with classes of 0,1,2,3,4

Weather System for Drowsiness:

Figure 11: Clear, Rainy, Foggy and Shine

Eyes and Yawn Module:

A. Eyes Model

The eyes model achieved strong performance, with training accuracy reaching 97.10% and validation accuracy at 97.06%. This indicates effective learning and good generalization to unseen data. The model's ability to differentiate between open and closed eyes is evident in the low training and validation loss values of 0.0934 and 0.0949, respectively. On the testing set, the model maintained a high accuracy of 93.4% and a loss of 0.043, demonstrating consistent performance.

B. Yawning Model

The yawning model also exhibited solid performance, achieving a training accuracy of 96.66% and a validation accuracy of 96.39%. The training and validation losses of 0.1065 and 0.1179, respectively, suggest effective learning without severe overfitting. On the testing set, the model demonstrated exceptional performance with an accuracy of 98.39% and a low loss of 0.0182. However, the F1 score of 0.5159 indicates potential class imbalance or difficulty in correctly classifying certain yawning instances.

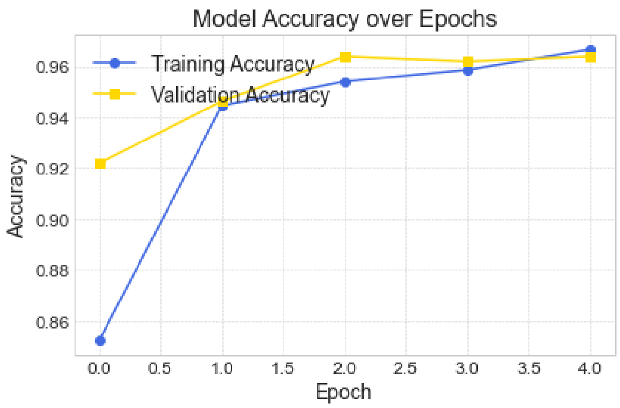

Figure 20: Traning and Validation Accuracy

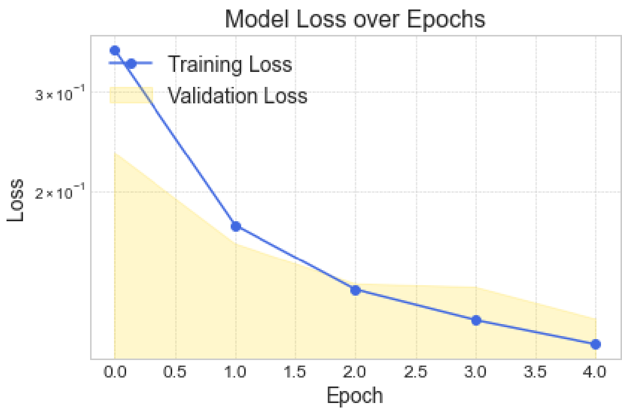

Figure 21: Training and Vlidation loss

Combined System:

Figure: 10 (Combined Systems output)

Overall Evaluation:

Both models demonstrated robust performance in their respective tasks. The eyes model excelled in distinguishing between open and closed eyes, while the yawning model effectively detected yawning instances. However, further analysis of the yawning model's performance, potentially through confusion matrices and precision-recall curves, is recommended to understand the reasons behind the lower F1 score.

VI. Conclusion:

In conclusion, our comprehensive drowsiness detection system, integrating eye status, yawning behaviour, and real-time weather conditions, has proven highly effective. The individual models for eyes and yawning prediction exhibit impressive precision, recall, and F1-scores, contributing to accurate drowsiness identification. The amalgamation of weather-based features enhances the system's robustness, providing a holistic approach to fatigue detection. The consolidated model, considering various combinations such as open eyes with yawning, open eyes without yawning, closed eyes with yawning, and closed eyes without yawning, achieves an overall accuracy of 96.18%. The system's versatility positions it as a valuable tool for real time fatigue monitoring in diverse scenarios.

VII. Future Scope:

Looking towards the future, the project holds substantial potential for improvement and expansion. Enhancing the models with larger and more diverse datasets will augment their generalization capabilities across different demographics and environmental conditions. Exploring real-world deployment possibilities, including integration into in-vehicle systems or wearable devices, is crucial for practical usability. Leveraging advanced machine learning techniques and investigating real-time video processing for continuous monitoring present promising avenues for technological advancement. Collaboration with industry stakeholders, particularly in the automotive and safety sectors, will facilitate the adoption of our drowsiness detection system, contributing to heightened road safety and accident prevention.

References:

[1] Kassem, Haider A., Morshed Chowdhury, and Jemal H. Abawajy. "Drivers fatigue level prediction using facial, and head behavior information." IEEE Access 9 (2021): 121686-121697.

[2] Nemcova, Andrea, et al. "Multimodal features for detection of driver stress and fatigue." IEEE Transactions on Intelligent Transportation Systems 22.6 (2021).

[3] Zhang, Zhimin, Huansheng Ning, and Fang Zhou. "A systematic survey of driving fatigue monitoring." IEEE transactions on intelligent transportation systems (2022).

[4] Ansari, Shahzeb, et al. "Driver mental fatigue detection based on head posture using new modified reLU-BiLSTM deep neural network." IEEE Transactions on Intelligent Transportation Systems 23.8 (2021): 10957-10969.

[5] Li, Zuojin, et al. "A novel learning model of driver fatigue features representation for steering wheel angle." IEEE Transactions on Vehicular Technology 71.1 (2021): 269-281.

[6] Jabbar, Rateb, et al. "Real-time driver drowsiness detection for Android application using deep neural networks techniques." Procedia computer science 130 (2018): 400-407.

[7] Celona, Luigi, et al. "A multi-task CNN framework for driver face monitoring." 2018 IEEE 8th International Conference on Consumer Electronics-Berlin (ICCE-Berlin). IEEE, 2018.

[8] Verma, Bindu, and Ayesha Choudhary. "Deep learning based real-time driver emotion monitoring." 2018 IEEE International Conference on Vehicular Electronics and Safety (ICVES). IEEE, 2018.

[9] Vural, Esra, et al. "Automated drowsiness detection for improved driving safety." (2008).

[10] Saini, Vandna, and Rekha Saini. "Driver drowsiness detection system and techniques: a review." International Journal of Computer Science and Information Technologies 5.3 (2014): 4245-4249.

[11] Duggal, Ravjyot Singh. Deep Learning for Driver Drowsiness Detection. Diss. Dublin, National College of Ireland, 2022.

[12] Singh, Jagendra. "Learning-based driver drowsiness detection model." 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS). IEEE, 2020.

[13] Minhas, Abid Ali, et al. "A smart analysis of driver fatigue and drowsiness detection using convolutional neural networks." Multimedia Tools and Applications 81.19 (2022): 26969-26986.

[14] Safarov, Furkat, et al. "Real-time deep learning-based drowsiness detection: leveraging computer-vision and eyeblink analyses for enhanced road safety." Sensors 23.14 (2023): 6459.

[15] Shan, Sama-E., et al. "IoT and computer vision based driver safety monitoring system with risk prediction." 2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2). IEEE, 2018.

[16] Savaş, Burcu Kir, and Yaşar Becerikli. "Real-time driver fatigue detection system based on multi-task ConNN." Ieee Access 8 (2020): 12491-12498.

[17] Bangar, S. (2020, February 24). VGG-Net Architecture Explained. Medium. https://medium.com/@sajals1146/vgg-net-architecture-880df59c37ea