Mitigating Driving Hypnosis and Drowsiness for Enhanced Safety on Samruddhi Mahamarg

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COMPUTER SCIENCE AND ENGINEERING (Artificial Intelligence and Machine Learning)

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CERTIFICATE

This is to certify that the Thesis on **"Mitigating Driving Hypnosis and Drowsiness for Enhanced Safety on Samruddhi Mahamarg"** is a Bonafide work of Aashi Khanna, Ketaki Tank, Atharva Rewatkar, Vedant Padole submitted to the Rashtrasant Tukdoji Maharaj Nagpur University, Nagpur in partial fulfillment of the award of a Degree of Bachelor of Technology (B.Tech), in Computer Science and Engineering. It has been carried out at the Department of Computer Science and Engineering, Shri Ramdeobaba College of Engineering and Management, Nagpur during the academic year 2023-2024.

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DECLARATION

We hereby declare that the thesis titled "**Mitigating Driving Hypnosis and Drowsiness for Enhanced Safety on Samruddhi Mahamarg**" submitted herein has been carried out in the Department of Computer Science and Engineering of Shri Ramdeobaba College of Engineering and Management, Nagpur. The work is original and has not been submitted earlier as a whole or part for the award of any degree/diploma at this or any other institution / University.

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APPROVAL SHEET

This report entitled "**Mitigating Driving Hypnosis and Drowsiness for Enhanced Safety on Samruddhi Mahamarg**" by **Aashi Khanna, Ketaki Tank, Atharva Rewatkar, Vedant Padole** is approved for the degree of Bachelor of Technology (B.Tech).

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ABSTRACT

The Samruddhi Mahamarg, a vital expressway, witnesses numerous accidents each year due to driving hypnosis and drowsiness, especially on its long stretches. This thesis proposes a novel approach to enhance safety by addressing these issues through the identification of drowsy eyes and yawning using state-of-the-art deep learning models.

The system employs two YOLOv8 models, one dedicated to detecting drowsy eyes and the other for recognizing yawning behavior. Remarkably high accuracy rates of 99.92% for drowsy eyes and 99.95% for yawning demonstrate the robustness and reliability of the proposed models. By accurately identifying these critical signs of driver fatigue, the system provides timely alerts, mitigating the risks associated with driving hypnosis.

This research emphasizes the importance of mitigating driving hypnosis to reduce the frequency of accidents on Samruddhi Mahamarg, emphasizing the potential to save lives and prevent injuries. The incorporation of cutting-edge technology in real-time monitoring showcases the commitment to advancing road safety in high-risk environments.

Keywords: Driving hypnosis, Drowsiness detection, YOLOv8, Samruddhi Mahamarg, Road safety, Accident prevention.

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1 Introduction

1.1 Background

The Samruddhi Mahamarg, a critical infrastructure project, stands as a testament to progress and connectivity. This extensive expressway, connecting major cities and regions, has undoubtedly enhanced economic activities and brought about unprecedented growth. However, the increasing traffic volume on Samruddhi Mahamarg has also raised concerns about road safety, particularly regarding the phenomena of driving hypnosis and drowsiness.

Understanding driving hypnosis as a trance-like state induced by prolonged, monotonous driving, and drowsiness as a significant contributor to accidents, it becomes imperative to address these issues comprehensively. The background of this project lies in recognizing the potential risks associated with long-distance driving and the need for innovative solutions to mitigate these risks and ensure a safer driving experience on Samruddhi Mahamarg.

1.2 Problem Statement

Despite the advancements in automotive safety technologies, the persisting problem of driving hypnosis and drowsiness poses a serious threat to the safety of commuters on Samruddhi Mahamarg. The monotony of long stretches of highway, combined with factors like fatigue and distractions, leads to a heightened risk of accidents. Current mitigation measures are often inadequate or not widely adopted, necessitating a focused investigation into tailored strategies to address the specific challenges faced on this expressway.

The problem statement revolves around identifying the factors contributing to driving hypnosis and drowsiness on Samruddhi Mahamarg and developing effective countermeasures to enhance road safety for all users.

1.3 Objectives

The primary objectives of this project are

1. To investigate and understand the patterns and factors contributing to driving hypnosis and drowsiness on Samruddhi Mahamarg.

2. To explore and evaluate existing technologies and methodologies aimed at mitigating driving hypnosis and drowsiness.
3. To develop and implement innovative strategies for real-time detection and prevention of driving hypnosis and drowsiness.
4. To assess the feasibility and effectiveness of integrating these strategies into the existing infrastructure of Samruddhi Mahamarg.
5. To provide recommendations for long-term sustainable measures to ensure continuous improvement in road safety.

1.4 Scope of the Project

This project focuses on the identification and mitigation of driving hypnosis and drowsiness specifically on Samruddhi Mahamarg. The scope encompasses a thorough examination of technological and behavioral interventions that can be applied both at the individual driver level and integrated into the expressway's infrastructure. The project also considers the practicality and scalability of proposed solutions within the context of the expressway's unique characteristics and the diverse range of vehicles and drivers using it.

1.5 Significance of the Project

The significance of this project lies in its potential to revolutionize road safety on Samruddhi Mahamarg. By addressing the challenges posed by driving hypnosis and drowsiness, the project aims to significantly reduce the number of accidents and enhance the overall safety of commuters. Furthermore, the project's outcomes could serve as a model for similar expressways and long-distance routes globally, contributing to advancements in intelligent transportation systems and promoting safer driving practices on a broader scale.

2 Literature Review

2.1 Driving Hypnosis and Drowsiness

Driving hypnosis and drowsiness are critical factors contributing to road accidents, particularly during long-distance travel on expressways like Samruddhi Mahamarg. The literature reveals a growing body of research aimed at understanding the underlying mechanisms, identifying risk factors, and proposing effective mitigation strategies. Driving hypnosis is described as a trance-like state induced by prolonged, monotonous driving conditions. Drivers experiencing hypnosis may exhibit reduced attention, slower reaction times, and impaired decision-making skills. Drowsiness, on the other hand, involves a state of fatigue and sleepiness, significantly impacting a driver's alertness and overall cognitive function.

Studies highlight various factors contributing to driving hypnosis and drowsiness. Monotonous road environments, extended travel durations, and lack of stimuli have been identified as triggers for hypnosis. Fatigue, inadequate sleep, and circadian rhythm disruptions are common contributors to drowsiness. Additionally, external factors such as environmental conditions, vehicle design, and individual health play pivotal roles.

2.2 Previous Study

Pastor Cerezuela et al. conducted a study comparing drowsiness levels on motorways and conventional roads during different driving periods. Their findings revealed a peculiar trend, with drowsiness being higher on motorways during the final driving period but not during the starting stage. The authors suggest that this result may be attributed to the cumulative effects of long drives. However, the study did not provide a clear solution to prevent or mitigate highway hypnosis, leaving a crucial gap in our understanding of effective interventions. Another paper titled "Research on Recognition of Road Hypnosis in the Typical Monotonous Scene" proposed by Shi et al. proposed a road hypnosis recognition model that combined Principal Component Analysis (PCA) and a Long Short-Term Memory network (LSTM). The model demonstrated impressive accuracy rates of 93.27% in simulated driving experiments and 97.01% in vehicle driving experiments. Despite this success, a notable gap exists in the focus on using eye tracker data for road hypnosis detection. Since highway hypnosis is a complex psychological phenomenon, relying solely on facial expressions may limit the model's effectiveness.

Similarly, Wang et al. presented a recognition method for road hypnosis based on physiological characteristics, employing ECG and EMG features. While their approach achieved promising results, the study's limitation lies in the inability of parameters to distinguish between road hypnosis and cognitive distraction. Moreover, the dataset focused solely on monotonous scenes, raising concerns about the model's generalizability to varied driving conditions.

Arif, Munawar, and Ali explored driving drowsiness detection using spectral signatures of EEG-based neurophysiology. Their study involved 12 healthy subjects and demonstrated remarkable results in inter-class classification, with high accuracy, recall, F1-score, specificity, Matthews correlation coefficient, and Cohen’s Kappa Score. However, a gap in the research emerges regarding the need for improvement in detection with statistical temporal and spatiotemporal features in smaller detection windows or the incorporation of deep learning-based automatic feature extraction methods.

In conclusion, existing research provides valuable insights into the challenges posed by driving hypnosis and drowsiness. While recognition models and physiological measures show promise, the literature underscores the need for holistic and context-aware mitigation strategies.

2.3 Existing Mitigation Technologies

2.3.1 Wearable gloves

Wearable technologies have emerged as promising tools for mitigating driving hypnosis and drowsiness, providing direct interaction with drivers to enhance their alertness. One notable advancement is the development of smart gloves designed to monitor and address cognitive states during driving.

1. Sensory Feedback: Smart gloves incorporate sensors that track physiological indicators such as skin conductance and temperature. These sensors can detect changes associated with drowsiness and alertness, providing real-time feedback to the driver.
2. Haptic Alerts: In addition to monitoring physiological signals, smart gloves can deliver haptic alerts. Vibrations or subtle pressure changes on the driver's hands serve as tactile warnings, effectively countering the monotony-induced trance associated with driving hypnosis.
3. Integration with Vehicle Systems: To optimize their effectiveness, these gloves can be integrated with vehicle systems. This integration allows for seamless communication between the wearable device and the vehicle, triggering additional safety features or alerts if the driver's state poses a potential risk.
4. User Comfort and Acceptance: Wearable technologies like smart gloves prioritize user comfort, ensuring that drivers can wear them without hindrance. Comfortable and unobtrusive designs contribute to increased user acceptance and adherence to using such technologies during extended drives.

2.3.2 Human-Machine Interaction

Human-machine interaction (HMI) is a key area where technology interfaces with the driver to enhance road safety. Voice-based alerts represent an innovative approach within this category, leveraging auditory cues to combat driving hypnosis and drowsiness.

1. Speech Recognition Technology: Advanced speech recognition algorithms enable vehicles to interpret and respond to verbal commands from the driver. In the context of combating hypnosis and drowsiness, these systems can analyze the driver's speech patterns for signs of fatigue or distraction.
2. Customizable Alerts: Voice-based alerts offer the advantage of customization. Drivers can personalize the types of alerts they receive, ranging from gentle reminders to more assertive warnings, creating an individualized experience that aligns with their preferences.
3. Real-time Feedback: By providing real-time feedback through voice alerts, drivers are prompted to engage with the vehicle actively. This interaction helps break the monotony of long drives, keeping the driver cognitively engaged and reducing the risk of succumbing to hypnosis.
4. Integration with Navigation Systems: Voice-based alerts can also be integrated with navigation systems, leveraging information about upcoming turns, rest areas, or traffic conditions to deliver context-aware warnings. This integration enhances the relevance and effectiveness of the alerts.
5. Cross-Modal Integration: To cater to drivers with different preferences, voice-based alerts can be integrated with other modalities, such as visual displays or haptic feedback, creating a multi-sensory approach to counteracting hypnosis and drowsiness.

3 Methodology

3.1 Overview

Our methodology is designed to provide a comprehensive understanding of driving hypnosis and drowsiness. We employ a mixed-methods approach, integrating quantitative analysis of Kaggle image datasets with qualitative insights from a Google Forms survey. This dual-pronged strategy aims to capture both the visual indicators of drowsiness and the subjective experiences of individuals. The subsequent analysis will guide the development of targeted interventions for enhanced highway safety.

3.2 Quantitative Phase (Data)

3.2.1 Data Collection

Our data collection from Kaggle involves a meticulous categorization of images, providing a diverse set to capture the nuances of driving hypnosis. The datasets encompass the following categories:

3.2.1.1 Drowsy Eyes

Drowsy eyes exhibit characteristics such as drooping eyelids, reduced eye movement, and a glazed appearance. Image data of the drowsy eyes of multiple drivers have been considered for this dataset. The drivers being recorded depicted varying levels of drowsiness, to ensure a more detailed composition of drowsiness data. Variations in lighting conditions and facial orientations are considered to ensure robust feature extraction.

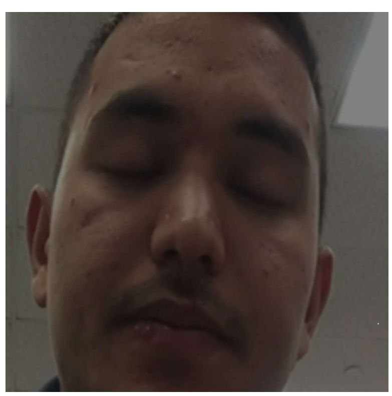

Fig. 3.1 - Drowsy image data

- Feature Extraction:
  a. Eye Closure Analysis:
     - Quantifying the degree of eye closure during drowsy states.
     - Identifying patterns associated with different levels of drowsiness.

  b. Facial Muscle Tension:
     - Analyzing changes in facial muscle tension, particularly around the eyes.
     - Correlating muscle tension with the severity of drowsiness.

3.2.1.2 Non-Drowsy Eyes

Non-drowsy eyes showcase characteristics associated with alertness and attentiveness. Emphasis has been put on diverse facial expressions, varying driving backgrounds, and multiple drivers with different facial and temporal cues to capture a comprehensive baseline of non-drowsiness.

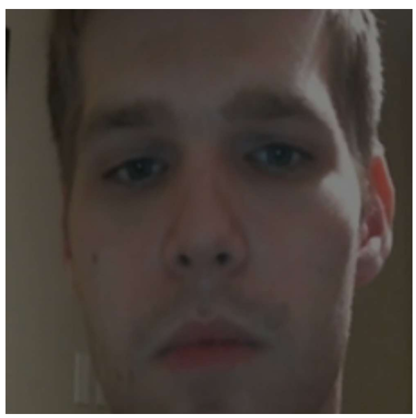

Fig. 3.2 - Non-drowsy image data

- Baseline Feature Analysis:
  a. Pupil Dilation:
     - Measuring pupil dilation as an indicator of alertness.
     - Exploring variations in dilation under different conditions.
  b. Eye Movement Patterns:
     - Analyzing natural eye movement patterns in non-drowsy states.
     - Identifying consistent features associated with wakefulness.

3.2.1.3 Yawn

Yawning is considered a potential indicator of fatigue and drowsiness. Capturing a range of yawning expressions to study associated features is significant for the detection of fatigue and drowsiness among drivers. Images depicting yawning inside a vehicle with incorporation of noise have been used in the dataset. The people who have been recorded yawning were of diverse ethnicity, age, different facial cues, wearing eyewear, etc. This diverse selection of the target population ensures the detection of fatigue in all kinds of drivers.

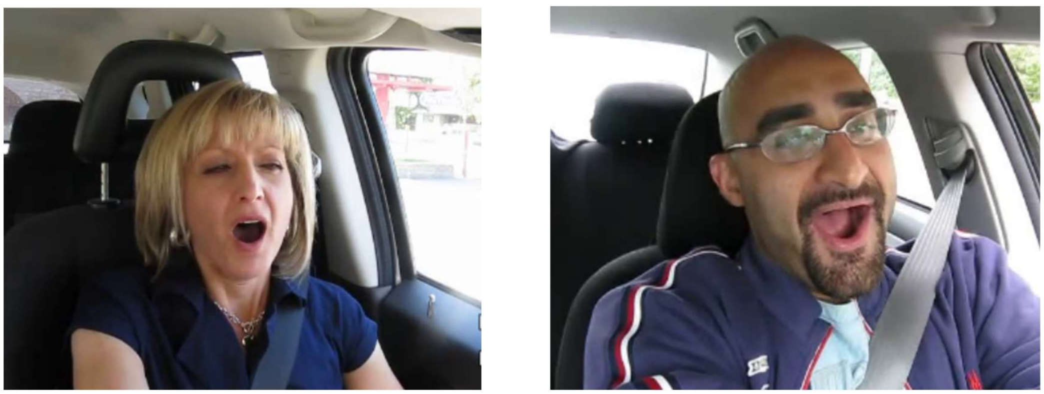

Fig 3.3 Yawning image data

➢ Yawn-Related Feature Analysis:

a. Facial Contortions:

- Identifying facial contortions during yawning episodes.
- Analyzing changes in facial muscles and expressions.

b. Temporal Patterns:

- Investigating the temporal patterns of yawning in relation to drowsy states.
- Correlating yawning frequency with reported drowsy incidents.

3.2.2 Annotation

The Kaggle datasets have been meticulously annotated using Roboflow. Annotation is a critical step in object detection, and its significance is particularly pronounced when working with models like YOLO (You Only Look Once), which we have made use of in the development of our project. This annotation process involves labeling key features in each image, providing valuable ground truth data for supervised learning, and enhancing the effectiveness of our subsequent analyses.

Annotation provides labeled data that serves as ground truth for training machine learning models. In object detection, it helps the model learn the spatial characteristics of objects within an image. Annotations often involve creating bounding boxes around objects of interest. These boxes define the extent of the object, enabling the model to recognize and locate it within an image. The box includes the coordinates of the object's center, its width, and its height.

While curating the drivers, we've made sure to promote inclusivity and personal differences. Thus, there are drivers from various races to make sure the model detects people with differences in facial features. There are drivers wearing eyewear and headgear to ensure detection even in the presence of such obstructions. Since not all individuals yawn the same way, recording multiple drivers ensures the inclusion of different ways of yawning (covering mouth with hands, yawning with teeth being visible, etc.).

3.2.2.1 Drowsy

The carefully selected images conveying drowsy eyes have been annotated in the Roboflow environment. The bounding boxes are created to include the region of interest, eyes, highlighting areas of eye closure, while also identifying variations in facial muscle tension. These annotations aid in the detection of drowsiness based on eye features.

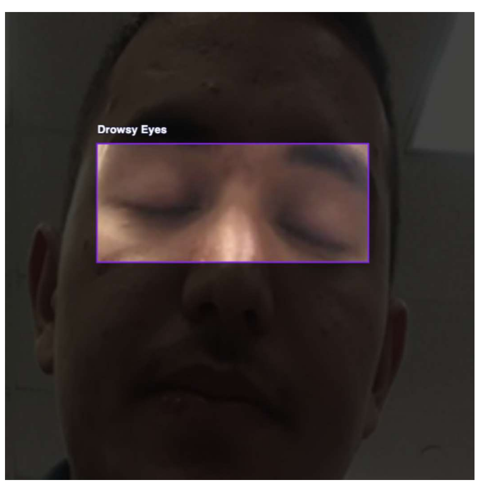

Fig. 3.4 - 'Drowsy' annotation

3.2.2.2 Non-Drowsy

To provide a baseline that stands for non-drowsy or alert eyes, we have included annotations of the feature 'Non-Drowsy Eyes'. Just as in the case of drowsy eyes, the region of interest includes the eyes, and the bounding box is drawn to include the same. The labeled images highlight areas of natural pupil dilation and outline patterns in normal eye movements.

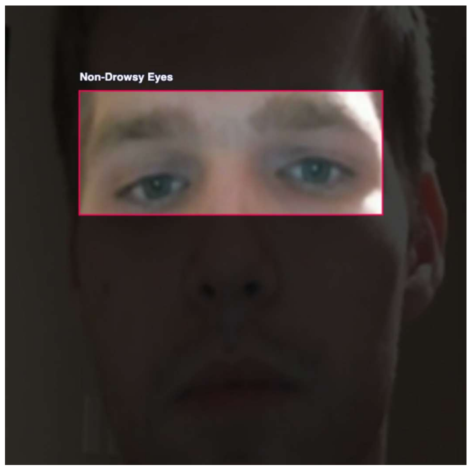

Fig. 3.5 - 'Non-Drowsy' annotation

3.2.2.3 Yawn

After a meticulous selection of images that distinctly depict a driver yawning inside a vehicle, we included those images in our annotation set. The region of interest in this case would be the entire face. This is because yawning causes facial variations through a series of involuntary muscle movements and changes in facial expression. While a person yawns, there are distinct features observed, such as mouth opening, facial contortions, eye closure, changes in expression, muscle tension and relaxation, temporal patterns, and individual differences. To account for these changes, we include the entire face of the driver in the bounding box.

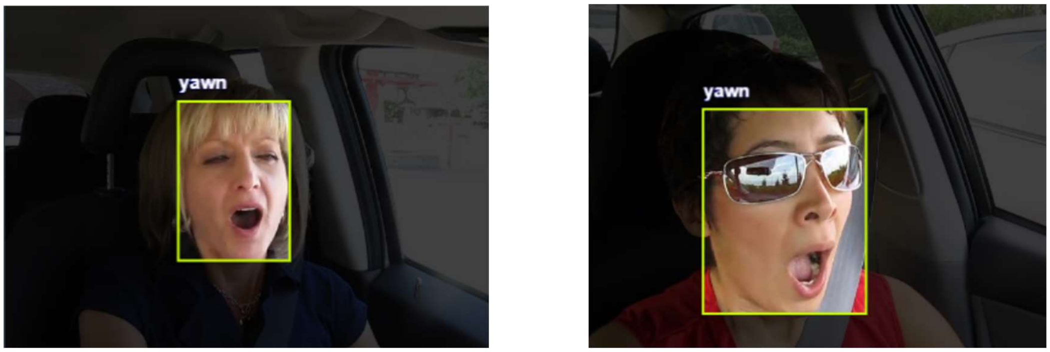

Fig. 3.6 - ‘Yawn’ annotation

3.3 Qualitative Phase (Survey)

To complement the image data, a Google Forms survey was designed to collect qualitative insights into individuals' experiences with driving drowsiness. The survey includes open-ended questions about past incidents, challenges faced, and coping mechanisms employed during instances of drowsiness. The survey also intends to shed light on the composition of the survey-takers and their preference for driver mitigation systems. This qualitative survey paves the way for a more holistic understanding of the human experience of driving fatigue.

We collected a total of 60 responses from people of all age groups. A few of the questions and their summarized responses have been included below.

- Age composition

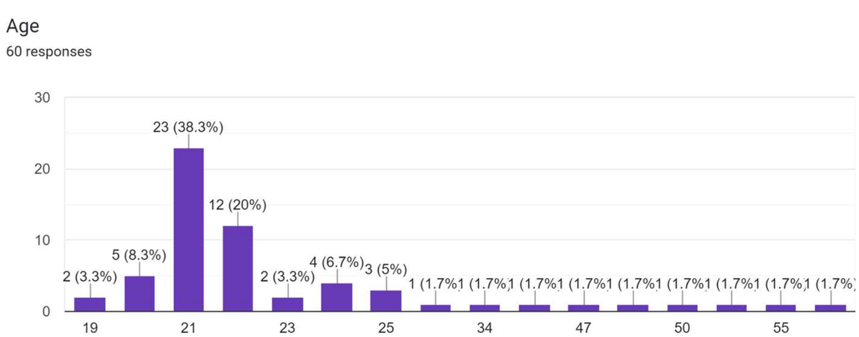

Fig. 3.7 - Age distribution

Survey takers belong to age groups ranging from 19 to 57 years old, with the majority being 21 years old. Age also casts light on the question of the relation of driving hypnosis with age-related factors. If the cases of hypnosis increase with age, then age-related mitigation measures can be incorporated.

- Driving experience of respondents

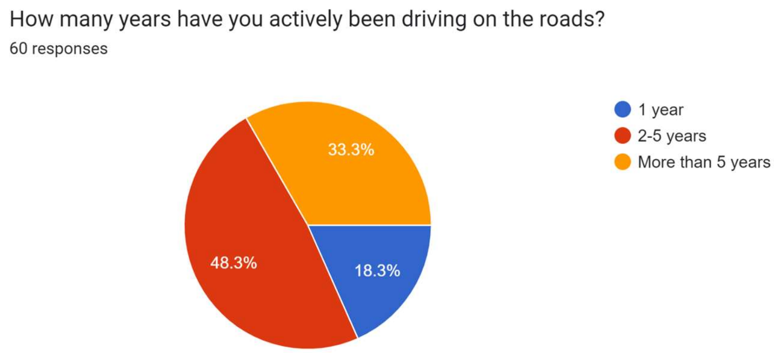

Fig. 3.8 - Driving experience distribution

Collecting data about the driving experience helps us understand whether there exists a relationship between the amount of experience drivers have and their experience with driving hypnosis or drowsiness. If more experienced drivers have less experience of driving hypnosis, then suggestions can be made to novice drivers, to avoid highway stretches for their safety.

- Experience with driving hypnosis

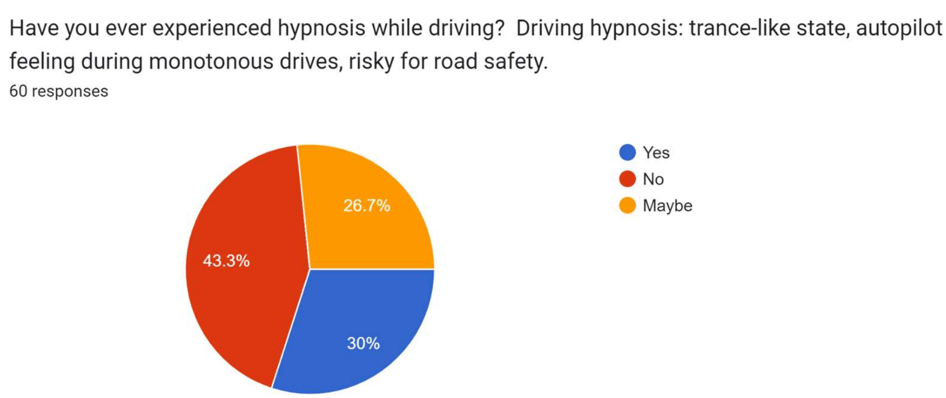

Fig. 3.9 -Experiencing driving hypnosis distribution

The above chart depicts a striking 30% of survey-takers being sure of the fact that they have experienced driving hypnosis. There are also 26.7% of respondents who are unsure whether they've experienced it or not. This shows that there is less awareness about the symptoms and effects of driving hypnosis among the populace. This helps us understand that to be able to manage and monitor the state of hypnosis, one needs to be aware of what they are experiencing.

- Experience with driving drowsiness

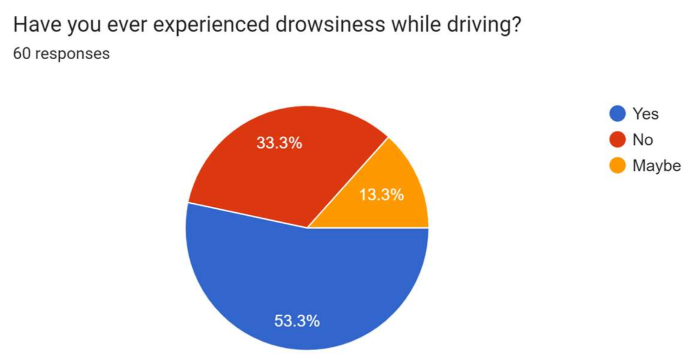

Fig. 3.10 - Experiencing driving drowsiness distribution

The most commonly understood and experienced phenomenon is drowsiness, which was experienced by over 50% of the survey-takers. This shows that since people understand what being drowsy is, they are more likely to understand if they are experiencing it and hence monitor it.

- Accidents

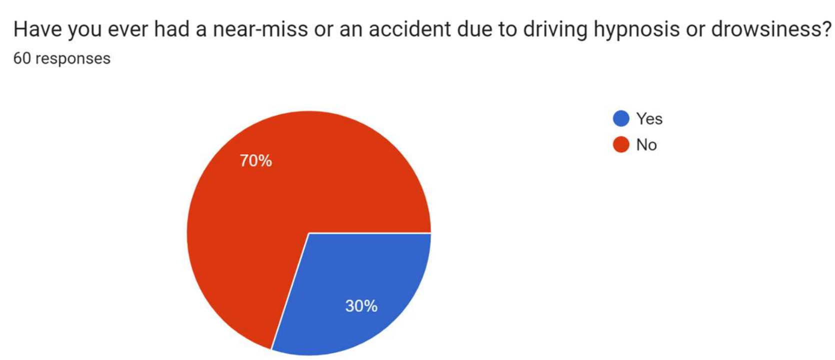

Fig. 3.11 - Accident distribution

To make it clear how pressing the phenomenon of driving hypnosis is, we asked if the drivers had experienced a near-miss or an accident due to driving hypnosis. Interestingly, about 30% of the drivers had experienced the same, indicating how fatal driving hypnosis and drowsiness is. This proved how urgent it is to develop driver monitoring systems to avoid accidents and ensure safety.

- Willingness to use technology to battle driving hypnosis

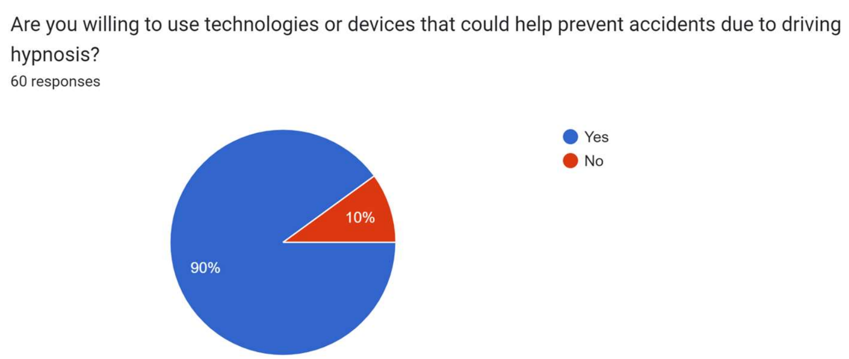

Fig. 3.12 - Willingness to use mitigation technology distribution

A vast majority of the drivers were eager and willing to incorporate the usage of technology to help prevent accidents. This showed how valuable it is to develop and research technology to help mitigate driving hypnosis and how well it would be accepted by the population.

The amalgamation of visual data from Kaggle datasets and qualitative insights from the survey will pave the way for the development of targeted interventions. These interventions aim to create mitigation systems that enhance highway safety by addressing the identified factors contributing to driving hypnosis and drowsiness.

4 Driver Monitoring System

4.1 Overview

The Driver Monitoring System (DMS) developed in this project is designed to enhance highway safety by detecting and mitigating driver drowsiness and hypnosis. The DMS utilizes annotated images from Kaggle datasets, capturing features related to drowsy eyes, non-drowsy eyes, and yawning. The YOLO (You Only Look Once) model serves as the technical framework for object detection, allowing the system to efficiently process and analyze real-time visual cues from a driver's face. The detection interface provides real-time feedback to the driver, alerting them to potential signs of drowsiness. Visual indicators, such as warnings or alarms, can be triggered based on the model's analysis of the driver's facial features. This proactive approach aims to prevent accidents by prompting the driver to take corrective actions, such as taking a break or adjusting their driving behavior.

4.2 Dataset

To train the Driver Monitoring System, two separate models are trained on two distinct datasets:

a. Drowsy - Non-Drowsy dataset - The dataset comprises annotated images capturing features related to drowsy and non-drowsy states. Balanced representation ensures the model's ability to accurately detect both conditions. The two features were carefully annotated and the dataset was augmented to result in a size of 2963 images.

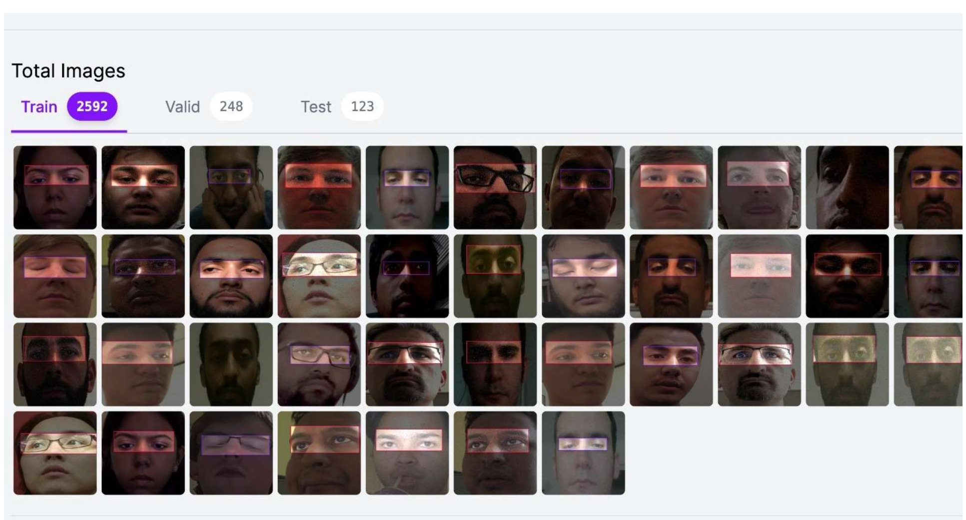

Fig. 4.1 - Drowsy-Non Drowsy dataset

b. Yawn dataset - Specifically annotated for yawning behavior, this dataset encompasses a diverse range of yawning expressions. After annotation, a total of 656 images are added to the dataset, and augmentations are carefully applied which results in the size of the dataset reaching a whopping 1548. In the preprocessing step, images in the dataset are also resized to 640x640 to maintain uniformity.

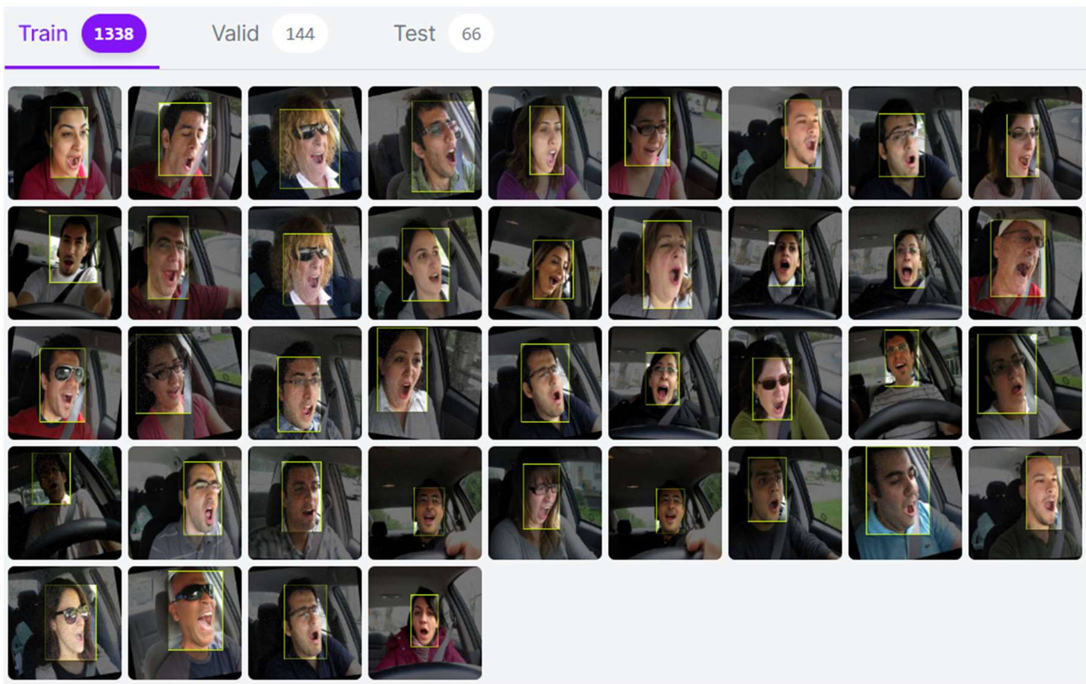

Fig. 4.2 - Yawn dataset

The table below summarizes the sizes and splitting patterns of both datasets.

Table 4.1 - Composition, sizes, and splitting of datasets

Sr. No.	Dataset name	Size	Train-valid-test split	Augmentations applied
1.	Drowsy - Non drowsy	2963	87-8-4	Brightness: Between -25% and +25% Exposure: Between -25% and +25% Blur: Up to 2.5px Noise: Up to 5% of pixels
2.	Yawn	1548	86-9-4	Crop: 0% Minimum Zoom, 20% Maximum Zoom Rotation: Between -15° and +15° Blur: Up to 2.5px Noise: Up to 5% of pixels

4.3 Model Framework

4.3.1 YOLOv8

YOLOv8, or modern object identification technology, was developed by Ultralytics' Alexey Bochkovskiy and his colleagues. This object detector is the newest model of the YOLO (You Only Look Once) series, which is known for its accuracy and speed.

An image must be split into a grid of cells with each cell's bounding box and class probability predicted for YOLOv8 to work. The network then combines these predictions to deliver the final detection findings. Because YOLOv8 was trained on a massive dataset of images and labels, it is capable of recognizing a broad variety of objects.

The You Only Look Once object detection system, or YOLOv8 is an improved version that shows potential uses outside of object recognition. YOLOv8, with its accuracy and real-time capabilities, is useful for sleepiness detection on roads. It effectively recognizes eye movements and facial clues that indicate driver fatigue because of its strong architecture. This implementation makes it possible to respond quickly and accurately to alerts or interventions when drowsiness is noticed, which enhances driving safety.

Because of its speed and adaptability, YOLOv8 is a powerful instrument for improving monitoring systems and, in the end, reducing the hazards related to driver sleepiness on highways.

4.3.2 YOLOv8 Architecture

The C2f module is the focal point of YOLOv8's core design, representing the creative use of the Cross Stage Partial (CSP) concept. This deviation from the C3 module of YOLOv5 represents a deliberate improvement in the model's capacity for information transmission and feature extraction. CSP helps convolutional neural networks (CNNs) learn more effectively by tying together the various neural network phases. The C2f module, which consists of two Conv Modules and one BottleNeck element, uses the Split technique to streamline information flow so that YOLOv8 can analyze complicated visual input efficiently.

Incorporating CSP into YOLOv8's architecture not only enhances its ability to learn but also shows a dedication to computational efficiency. A key component of the model's architecture is the reduction of computing effort, which guarantees the model's ability to carry out real-time object detection tasks effectively. This is especially important for applications like highway sleepiness detection, where quick and precise visual data analysis is necessary to guarantee driver safety. YOLOv8 distinguishes itself in the field of deep learning for object detection by striking a compromise between accuracy and processing efficiency through the integration of CSP and the optimization of the C2f module.

The C2f module's composition highlights how intricate YOLOv8's design is. Conv Modules and BottleNeck parts demonstrate a careful design that emphasizes dimensionality reduction and feature extraction. The Split mechanism highlights the model's flexibility even more by allowing for information fusion or parallel processing as needed. Together, these architectural details add to YOLOv8's effectiveness in real-world situations, making it a flexible tool for specialized applications like improving safety systems by detecting tiredness on highways, in addition to standard object identification jobs.

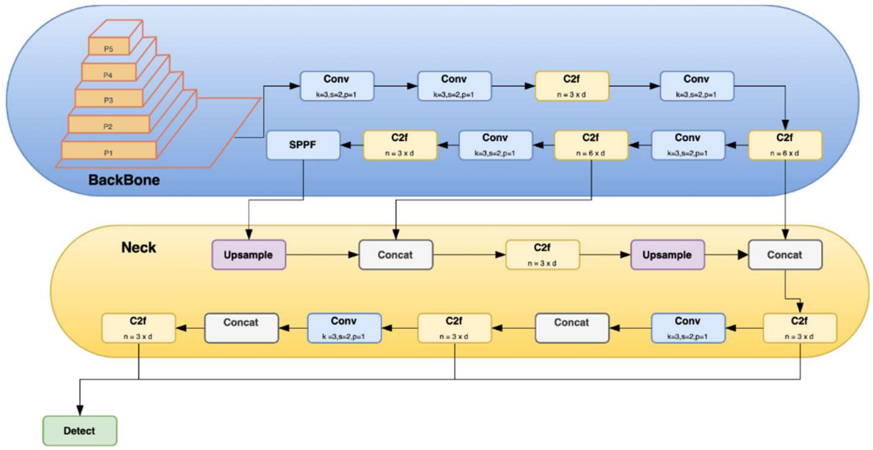

Fig. 4.3.1 - YOLOv8 Architecture

4.3.3 Training and Testing

Two separate YOLO models are trained, each on its respective dataset. The training process involves optimizing the model parameters for real-time detection while ensuring high accuracy.

Training parameters:

The following table Table 4.2 depicts the settings those are made for the YOLOv8 model training: a batch size of 16, a patience level of 50, and 100 epochs using an auto optimizer. These settings control the amount of training rounds, automatically optimise algorithms, batch size management, and tolerance for performance plateaus, all of which are integral to the way the model learns. During the course of 100 epochs, this optimised setup seeks to improve the YOLOv8 model's efficiency and accuracy by carefully adjusting important training parameters.

Table 4.2- YOLOv8 Training Parameters

	YOLOv8 training parameters
Epochs	100
Batch size	16
Patience	50
Optimizer	Auto

The figure 4.3.2 below, shows the extensive training procedure used for YOLOv8, highlighting the model's ability to identify driver tiredness and yawning. The first step is gathering a wide range of real-world photos, including portraits of sleepy people as well as people who are yawning. This dataset ensures that the model is flexible enough to be trained in a wide range of settings.

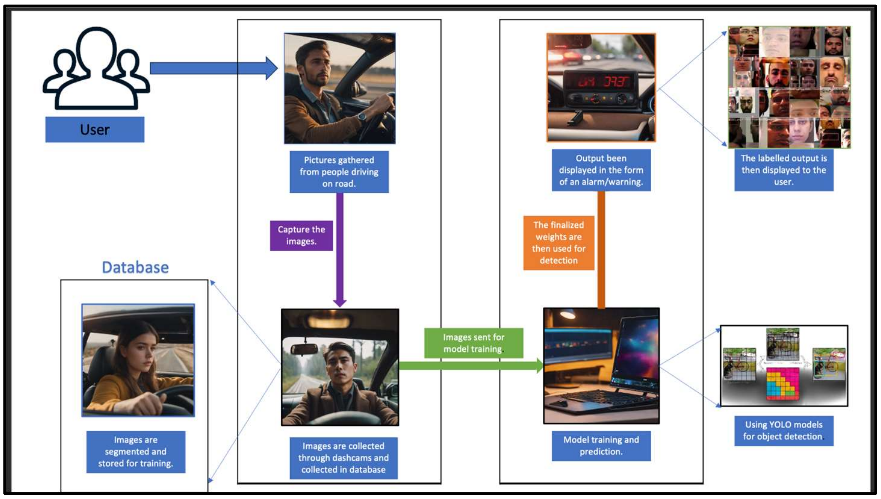

Fig 4.3.2 Model Architecture

The diagrammatic representation of augmentation techniques highlights the critical role they play in augmenting the model's robustness through the introduction of variations in lighting, angles, and backgrounds. Moreover, the incorporation of noise replicates real-world circumstances, readying the model for the unpredictable nature of on-road settings.

Through iterative training cycles, the YOLOv8 architecture's parameters are gradually adjusted to maximize tiredness and yawning detection. After training successfully, the model fits in with in-car systems with ease. The YOLOv8 is designed to identify indicators of tiredness or yawning and promptly trigger an alarm or warning to improve road safety and ensure timely driver response. This all-encompassing strategy, as seen in the diagram, highlights the painstaking measures made to give YOLOv8 the capacity to precisely recognize and react to crucial driving behaviors, enhancing overall transportation safety.

The trained models undergo rigorous testing and validation using the designated test and validation sets from their respective datasets. Performance metrics such as precision, recall, and F1 score are evaluated to assess the models' effectiveness in detecting drowsiness and yawning under various conditions.

4.4 Working

4.4.1 Detection Interface

The Driver Monitoring System (DMS) is equipped with an intuitive and user-friendly interface that seamlessly integrates into the driver's environment. The interface is designed to provide real-time feedback to the driver, facilitating timely responses to potential signs of drowsiness.

- Visual indicator

  The interface provides color-coded boxes for indicating various labels being detected:

  1. Green - Non-drowsy eyes
  2. Red - Drowsy eyes
  3. Yellow - Yawning

- Confidence percentage

  Along with the color, the confidence level of the particular label being detected in the real-time stream is also displayed which indicates how significant is the level of drowsiness or yawning in the driver.

4.4.2 Real-Time Detection

The heart of the DMS lies in its real-time detection mechanism, driven by the YOLO models trained on the Drowsy-Non Drowsy and Yawn datasets. The system processes each frame from the driver-facing camera in real-time. Frame-by-frame analysis ensures that the DMS remains responsive to dynamic changes in the driver's facial expressions and features. The model identifies characteristic features of drowsy eyes, such as drooping eyelids and reduced eye movement. Fine-tuned feature detection allows for accurate assessment of the driver's level of drowsiness. Yawning behavior is detected through the recognition of specific facial contortions and temporal patterns.

- Drowsy-Non drowsy detection

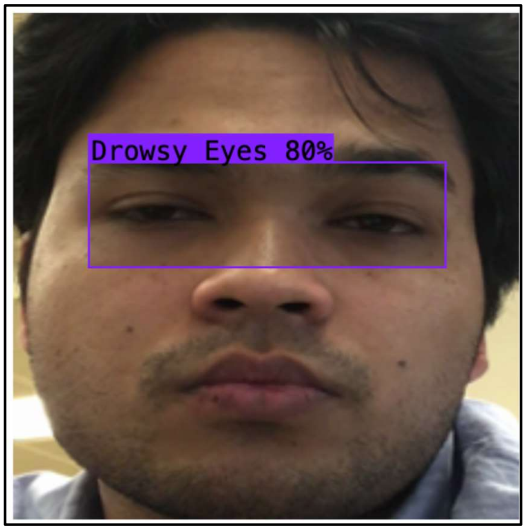

Fig. 4.4 - Drowsy detection

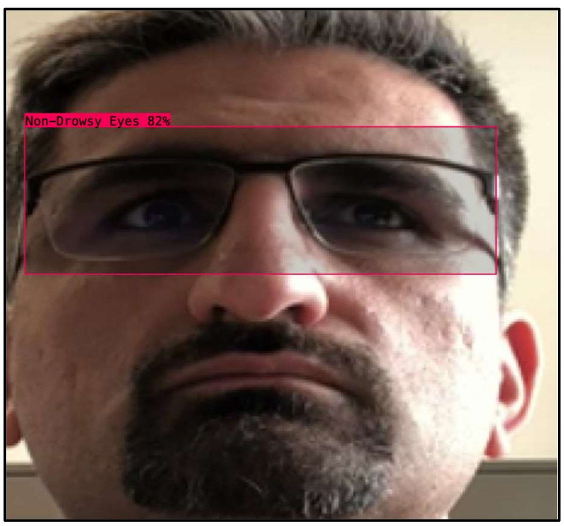

Fig. 4.5 - Non Drowsy detection

- Yawn detection

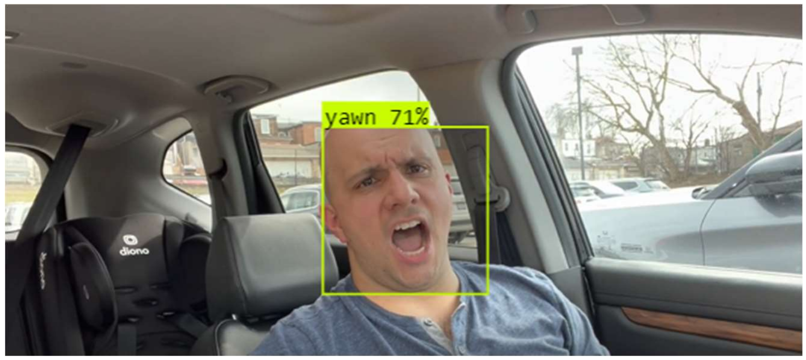

Fig. 4.6 - Yawn detection

With a confidence threshold of 70% and overlap threshold of 50%, the model detects the above instance as a 71% yawn.

5. Results

The YOLOv8 results showed a high degree of satisfaction and outperformed traditional Convolutional Neural Networks (CNNs) in many crucial areas. You Only Look Once version 8, also known as YOLOv8, demonstrated enhanced object identification and recognition skills, enabling quicker and more precise real-time processing of still photographs and moving pictures. YOLOv8 consistently outperformed conventional CNNs in comparison because of its cutting-edge design and effective object detection algorithms. YOLOv8 represents an intriguing development in computer vision and deep learning research because it greatly lowered processing time while simultaneously improving item recognition accuracy.

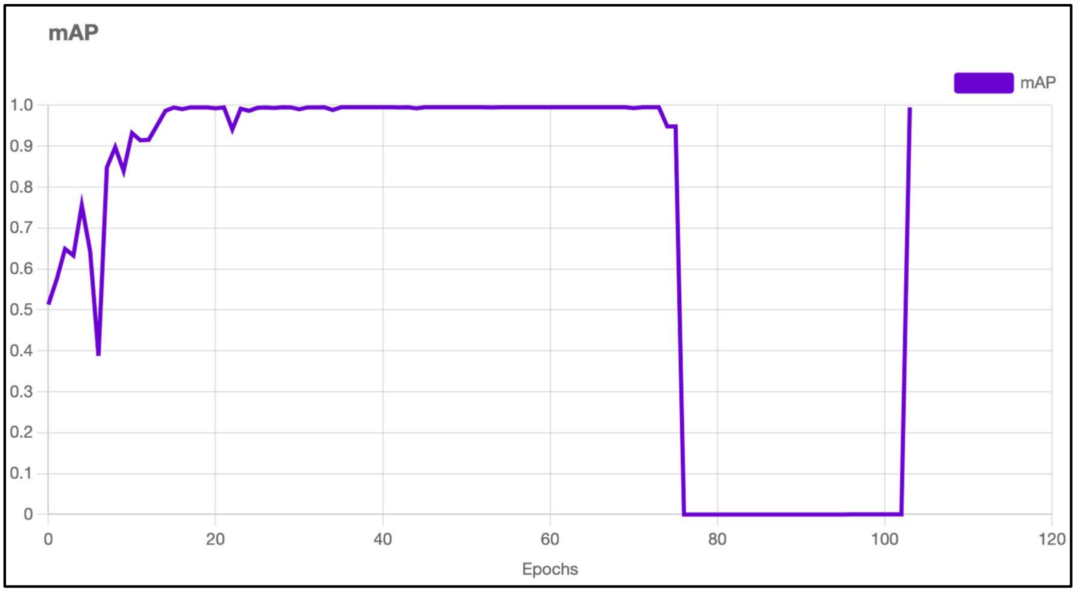

Fig 5.1 mAP vs Epochs for drowsy eyes

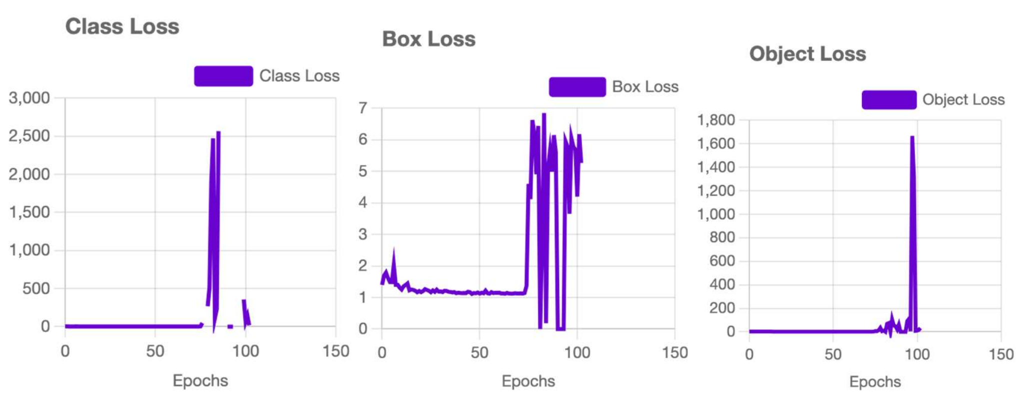

Fig 5.2 Box Loss, Class Loss, Object Loss vs Epochs for drowsy eyes

As the confidence threshold for classification changes, the F1 confidence curve shows how the F1 score—a gauge of a model's precision and recall trade-off—changes.

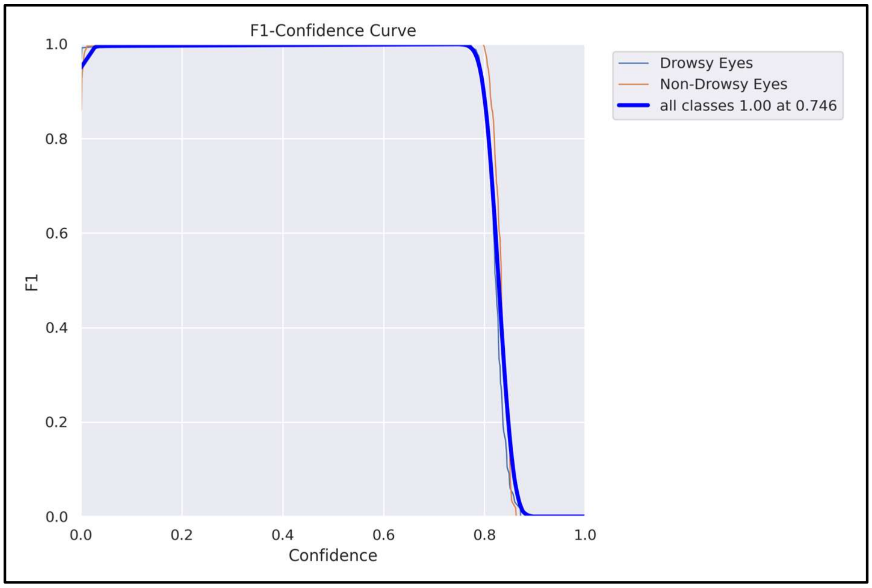

Fig 5.3 F1-Confidence Curve for drowsy eyes

An illustration of how a model's precision varies at various confidence thresholds is a precision-confidence curve. It aids in determining how precision and confidence are traded off in categorization or prediction tasks. The trade-off between precision and recall (sensitivity) for various classification thresholds is visually represented by a Precision-Recall curve. It offers perceptions on how effectively a model balances memory and precision as the classification threshold shifts.

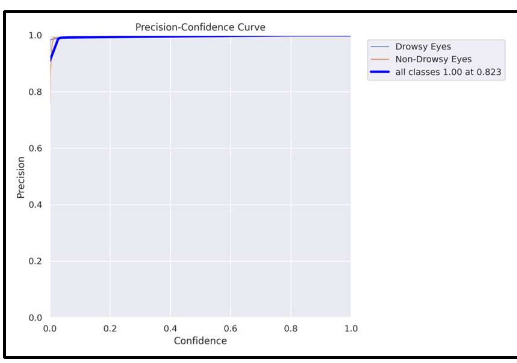

Fig 5.4 Precision Confidence Curve for drowsy eyes

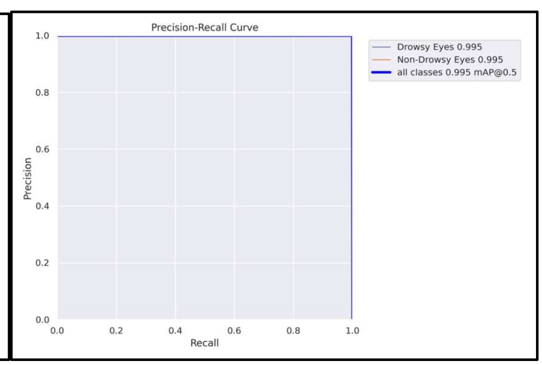

Fig 5.5 Precision-Recall Curve for drowsy eyes

A recall-confidence curve demonstrates how a model's recall (sensitivity) evolves when the categorization confidence threshold changes. It aids in assessing how recollection and confidence in categorization tasks relate to one another.

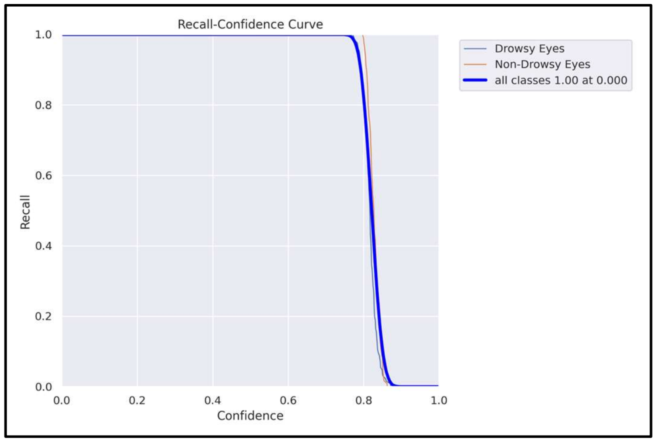

Fig 5.6 Recall Confidence Curve for drowsy eyes

Figure 5.7 below, depicts more YOLO-v8-related curves on loss, and metrics are shown.

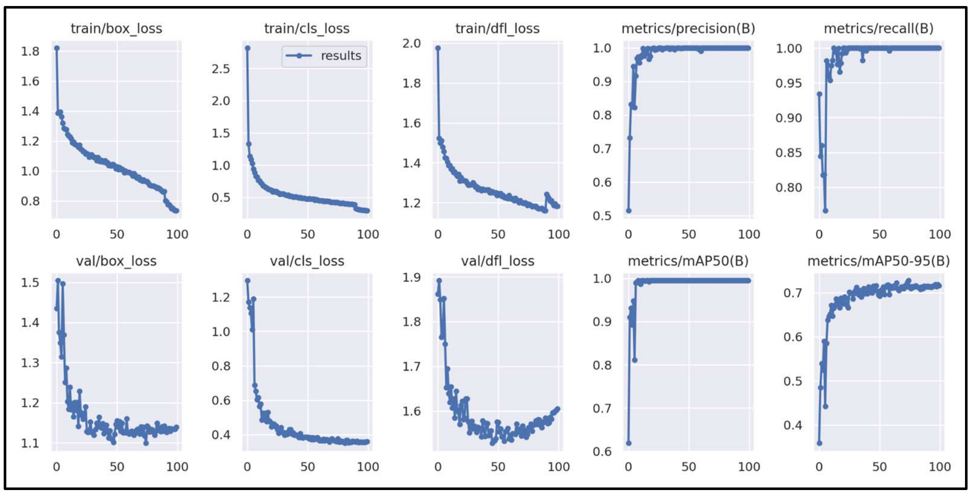

Fig 5.7 loss and metrics curves for drowsy eyes

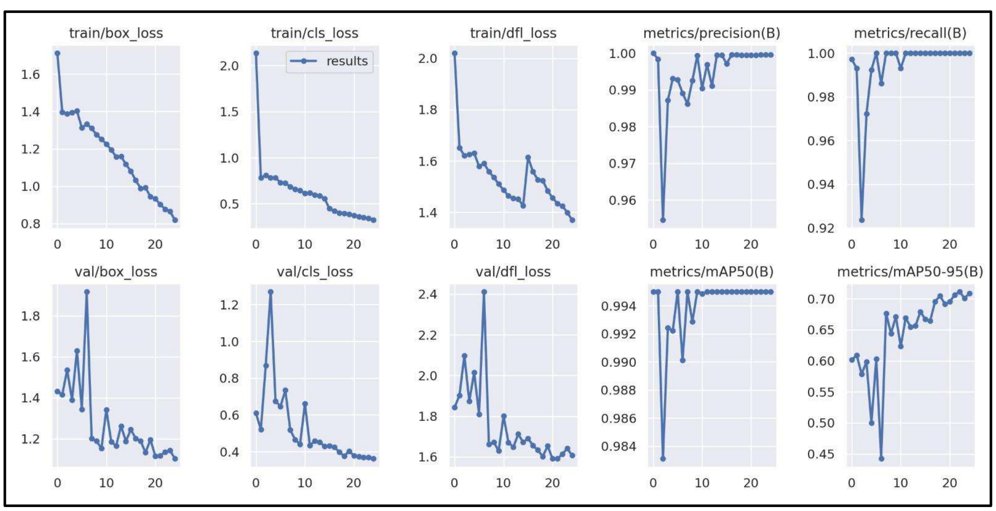

Fig 5.8 loss and metrics curves for yawning

The processes of building and training bounding boxes in batches, followed by our model's validation and prediction phases, are shown in the photos below.

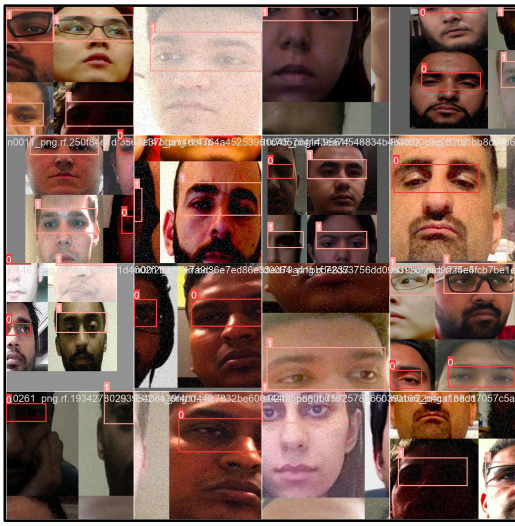

Fig 5.9 Training batch-0

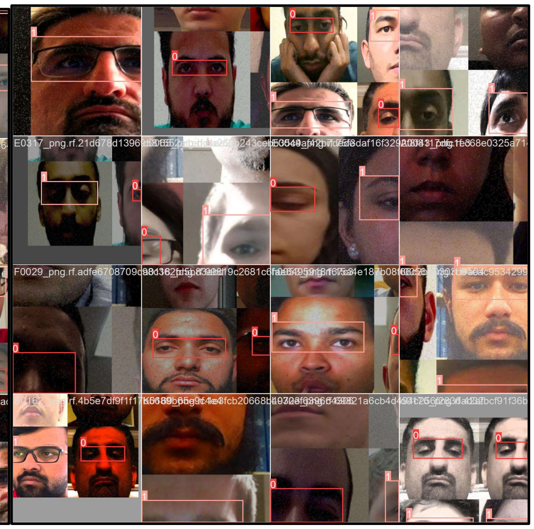

Fig 5.10 Training batch-1

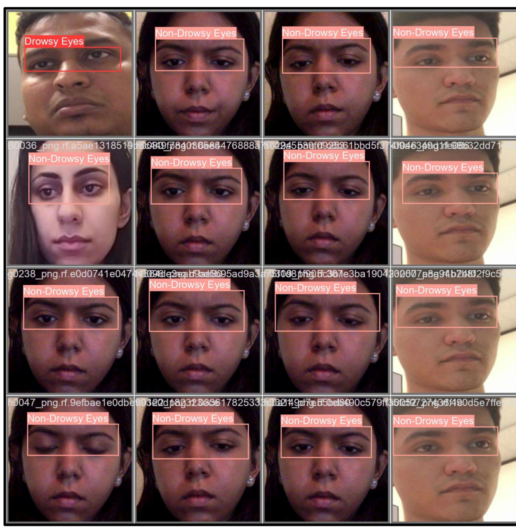

Fig 5.11 Validation batch-1 labels

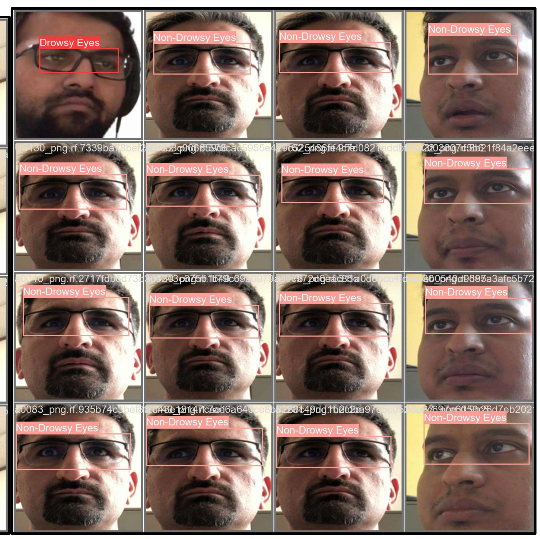

Fig 5.12 Validation batch-1 prediction

The following table depicts the maP50-90B, recall, and precision after epochs for yawning as well as drowsiness detection.

	Epoch 25	Epoch 50	Epoch 75	Epoch 100
Drowsy eyes	0.995	0.995	0.995	0.995
Yawning	0.995	0.995	0.995	0.995

Table 5.11 Epochs vs maP

	Epoch 25	Epoch 50	Epoch 75	Epoch 100
Drowsy eyes	1	1	1	1
Yawning	1	1	1	1

Table 5.12 Epochs vs Recall

	Epoch 25	Epoch 50	Epoch 75	Epoch 100
Drowsy eyes	0.9951	0.99913	0.99934	0.99927
Yawning	0.99949	0.99949	0.99951	0.99951

Table 5.13 Epochs vs Precision

6. Conclusion

To sum up, the project on Samruddhi Mahamarg which aims to reduce driving hypnosis and drowsiness is a thorough and creative way to deal with a serious problem related to road safety. This expressway's growing traffic volume has sparked worries about accidents brought on by drowsiness and driving hypnosis brought on by prolonged, monotonous driving. These problems continue even with advances in automotive safety technologies, so customized solutions are needed for this particular motorway.

The project's goals included determining what factors contribute, analyzing current technologies, creating creative plans, determining viability, and making suggestions for long-term solutions. The literature review emphasized the need for comprehensive mitigation strategies by highlighting the complexity of driving hypnosis and drowsiness. The project's methodology was established by earlier research that demonstrated a range of wearable technologies, physiological measures, and recognition models.

Driving hypnosis and drowsiness were thoroughly understood thanks to the mixed-methods approach, which combined quantitative analysis of Kaggle image datasets with qualitative insights from a Google Forms survey. The image datasets were painstakingly annotated to capture features such as yawning and non-drowsy and drowsy eyes. Important information about people's experiences, awareness, and readiness to use technology for mitigation was acquired through the survey.

A strong framework for the real-time detection of drowsiness and yawning was demonstrated by the Driver Monitoring System (DMS), which was created using YOLOv8. The system's usability was improved by the interface, which offered confidence percentages and color-coded visual indicators. The outcomes showed that the model performed well, outperforming conventional CNNs in many metrics. The model's precision and recall trade-offs at various confidence thresholds were demonstrated by the F1-Confidence Curve, Precision-Confidence Curve, Recall-Confidence Curve, and other visualizations.

The project's significance stems from its potential to address driving hypnosis and drowsiness, thereby revolutionizing road safety on Samruddhi Mahamarg. By warning drivers of possible indicators of fatigue, the developed DMS acts as a proactive tool to reduce the risk of accidents. The survey's findings add to our comprehensive understanding of what it's like for people to experience driving fatigue.

To summarize, this project offers a thorough and contextually-aware method of reducing driving hypnosis and fatigue, presenting workable solutions for improved road safety on Samruddhi Mahamarg. The project's results could be used as a template for similar motorways around the world, advancing the development of intelligent transportation systems and encouraging safer driving habits on a larger scale.

7. References

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[6]Research on Recognition of Road Hypnosis in the Typical Monotonous Scene

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