PROTOTYPE OF DROWSINESS DETECTION

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Project Overview:

The Prototype of Drowsiness Detection aims to enhance road safety by detecting signs of driver drowsiness and alerting them in real-time. This prototype utilizes advanced technologies to monitor driver behavior and promptly issue alerts to mitigate the risks associated with drowsy driving.

Objectives and Motivations:

Creating a Prototype of Drowsiness Detection System that actively promotes road safety is our main goal. Driven by the concerning consequences of driving while intoxicated, our goal is to utilize cutting-edge technology to develop a prototype that not only keeps an eye on drivers but also warns them ahead of time, promoting a more secure and attentive driving environment.

Overview of Approach and Technologies Used:

- In our drowsiness detection prototype, we've developed a prototype of the real-time system designed to monitor a driver's facial features and identify signs of drowsiness. The approach revolves around the analysis of key facial landmarks using the dlib library, focusing particularly on areas such as the eyes and mouth.
- Our system employs a combination of computer vision and machine learning algorithms to analyze facial features and monitor eye movement patterns. A camera positioned within the vehicle captures the driver's face, and sophisticated image processing techniques are applied to detect signs of drowsiness, such as eye closure duration or opening of mouth for yawn. This integration of advanced technologies enhances the system's ability to recognize subtle indicators of drowsiness.
- The foundation of our drowsiness detection algorithm lies in the calculation of eye and mouth aspect ratios, providing insights into the openness of the eyes and the width of the mouth. These ratios play a pivotal role in determining whether the

driver is feeling drowsy or not which in turn forms the backbone of our detection system.

- To enhance the system's sensitivity and specificity, we've implemented specific thresholds for the eye-aspect ratio and introduced flags to keep track of continuous frames. These elements enable us to distinguish between normal variations and prolonged signs of drowsiness.
- Yawn detection is a crucial component of our system, achieved through the analysis of mouth aspect ratios. Upon identifying a yawn, the system triggers appropriate alerts to bring attention to the driver.
- Our system operates in real-time, continuously processing frames using a while loop. This ensures constant vigilance to changes in the driver's facial features, allowing for prompt detection of drowsiness indicators.
- In terms of technology, our prototype is built using Python, making use of powerful libraries such as OpenCV, dlib, and imutils for image processing and facial feature extraction.

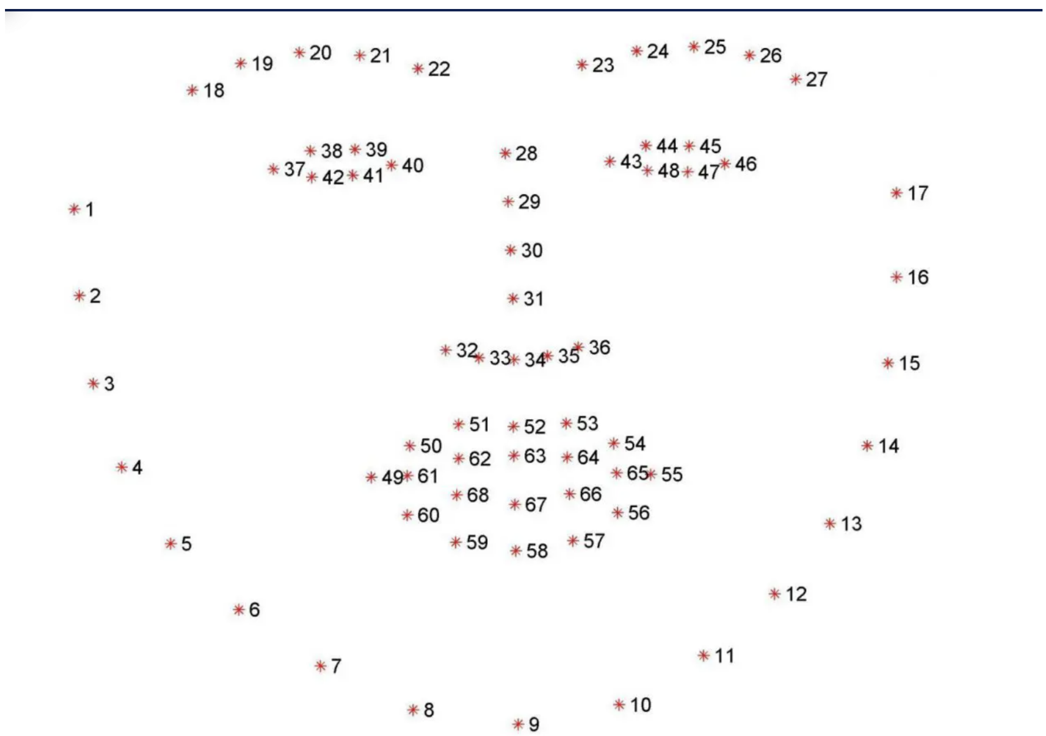
Key technologies include:

1. **Computer Vision with OpenCV:**
    a. We harness the power of OpenCV for real-time image processing. This technology allows us to continuously monitor mouth expressions and eye movements, providing crucial input for identifying signs of drowsiness.
2. **Facial Landmark (mouth, eyes) Detection with dlib:**
    a. We integrate the dlib library for facial landmark detection. This library enables us to precisely identify key facial features, such as eyes and mouth. The accurate extraction of facial landmarks is fundamental to our drowsiness detection algorithm, enhancing the system's sensitivity and accuracy.
3. **Image Processing with imutils:**
    a. We leverage imutils for streamlined image processing operations. This utility library simplifies tasks such as resizing frames, drawing contours around facial features, and implementing other essential image processing functions.
4. **Data Analysis:**
    a. In our exploration, we utilized a pre-trained model within the dlib library to map 68 facial points, constructing a dataset that captures diverse scenarios indicative of drowsiness. With a meticulous approach, we leveraged the one-rule threshold technique to precisely classify instances of drowsiness. Additionally, our analysis involved the creation of ROC curves, providing a comprehensive visual representation of the system's performance based on both average Eye Aspect Ratio (EAR) and average Mouth Aspect Ratio (MAR).

These technologies, including OpenCV, dlib, imutils, and others, work cohesively to create a comprehensive solution for drowsiness detection.

Technical Implementation / Results

- **Detailed description of the technical approach**



  - **Data Collection:**
    - Captured facial images using a camera during various driving conditions. Leveraged the shape_predictor_68_face_landmarks.dat file to precisely locate 68 facial landmarks, enriching the dataset with detailed facial feature information.
  - **Preprocessing:**
    - Extracted facial landmarks to identify key points on the face, crucial for subsequent feature analysis.
  - **Real-time Monitoring:**
    - The integration of the trained model into the real-time video stream from the camera involved a multi-step process to accurately monitor driver behavior. Leveraging the dlib face detector, the system efficiently located faces within each frame, providing a foundational step for subsequent analysis.
    - The shape predictor associated with the dlib library was then applied to extract crucial facial landmarks, including those representing the eyes and mouth. This information was pivotal in the computation of the Eye Aspect Ratio (EAR), enabling the system to monitor eye closure duration and identify potential signs of drowsiness.

- Additionally, the Mouth Aspect Ratio (MAR) was employed to specifically detect instances of yawning, a key indicator of driver fatigue. To enhance the interpretability of the system's output, convex hull operations were utilized, visually highlighting the regions around the eyes and mouth.
- Furthermore, a sophisticated algorithm was developed to analyze continuous frames, allowing the system to distinguish between momentary lapses and sustained periods of drowsiness, triggering appropriate alerts. This integration of advanced techniques ensures a robust and effective drowsiness detection system, prioritizing driver safety in real-world driving scenarios.

Explanation of algorithms, models, or techniques used

- **Eye Aspect Ratio (EAR):**
    - Calculated the EAR to monitor eye closure duration, a key indicator of drowsiness.
    - EAR is computed as the ratio of the average distance between vertical eye landmarks to the average distance between horizontal eye landmarks.
    - If EAR goes below the threshold value for 15 consecutive frames, It Consider it as drowsiness.
- **Mouth Aspect Ratio (MAR):**
    - Employed MAR to detect instances of yawning, another sign of drowsiness.
    - MAR is calculated as the ratio of the average distance between vertical mouth landmarks to the average distance between horizontal mouth landmarks.
- **Convex Hull Operations:**
    - Applied convex hull operations to obtain bordered regions around the eyes and mouth, visually highlighting these areas for better interpretation.
    - Enabled visualization of eye and mouth contours, aiding in the identification of drowsiness-related patterns.
- **Data Analysis:**
    - We employed the Otsu method as a technique to determine an optimal threshold for image segmentation. After applying the Otsu method, we leveraged the generated threshold to perform image segmentation.
    - Following the segmentation process, we sought to evaluate the performance of the applied model, especially in a binary classification context. To achieve this, we plotted a Receiver Operating Characteristic (ROC) curve. The ROC curve visually depicts the trade-off between sensitivity (true positive rate) and specificity (true negative rate) across different classification thresholds.
    - The ROC curve is instrumental in identifying the optimal threshold that balances sensitivity and specificity based on the specific requirements of the application. By analyzing the ROC curve, we gain insights into the efficiency and discriminatory power of the model. The area under the ROC curve

provides a quantitative measure of the overall performance of the model, with higher AUC values indicating superior discriminative ability.

- The application of the Otsu method and subsequent ROC curve analysis allowed us to determine the correct threshold for image segmentation and assess the efficiency of the model in distinguishing between different classes. This approach provides a robust framework for threshold selection and model evaluation in scenarios where accurate classification is critical.

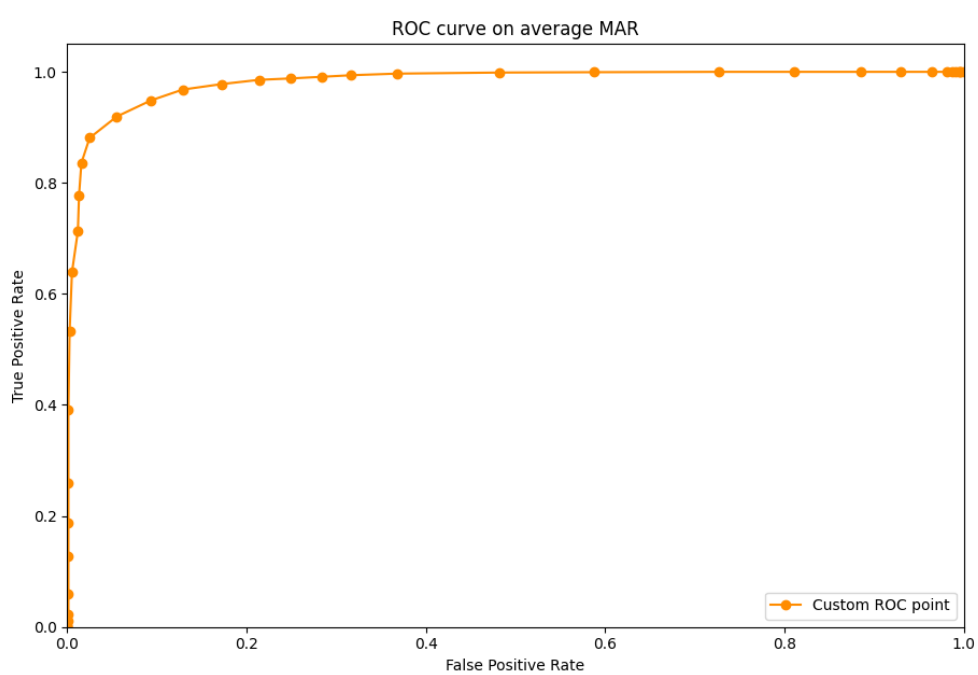
Intermediate Results:

Image1: EAR below threshold -> Drowsiness Detected

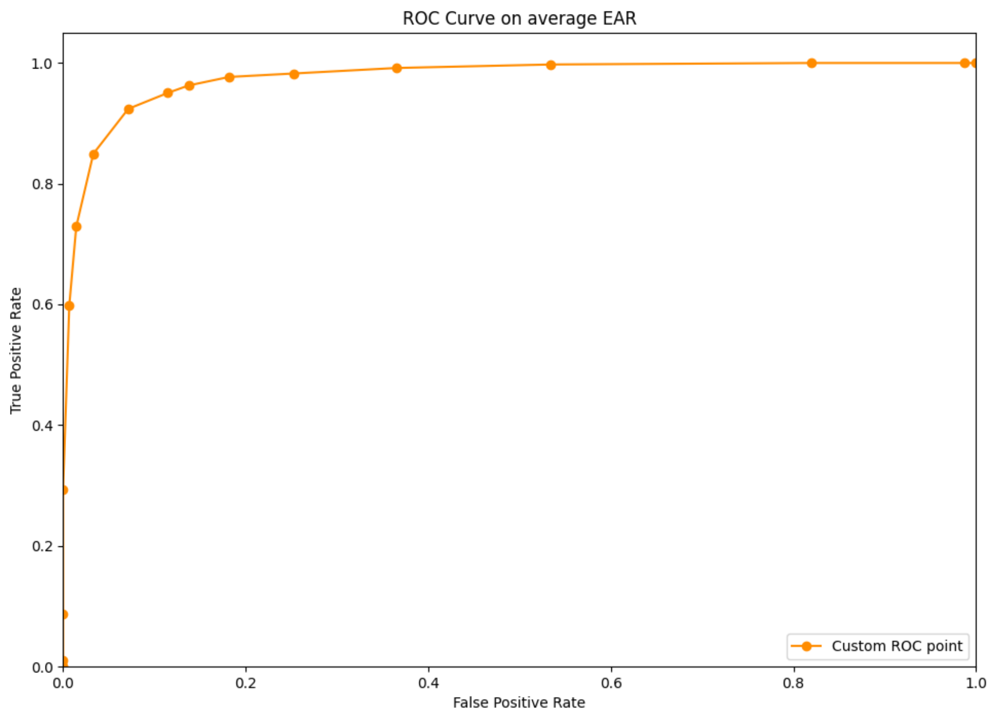
Image2: EAR above threshold -> Drowsiness Not Detected

Results:

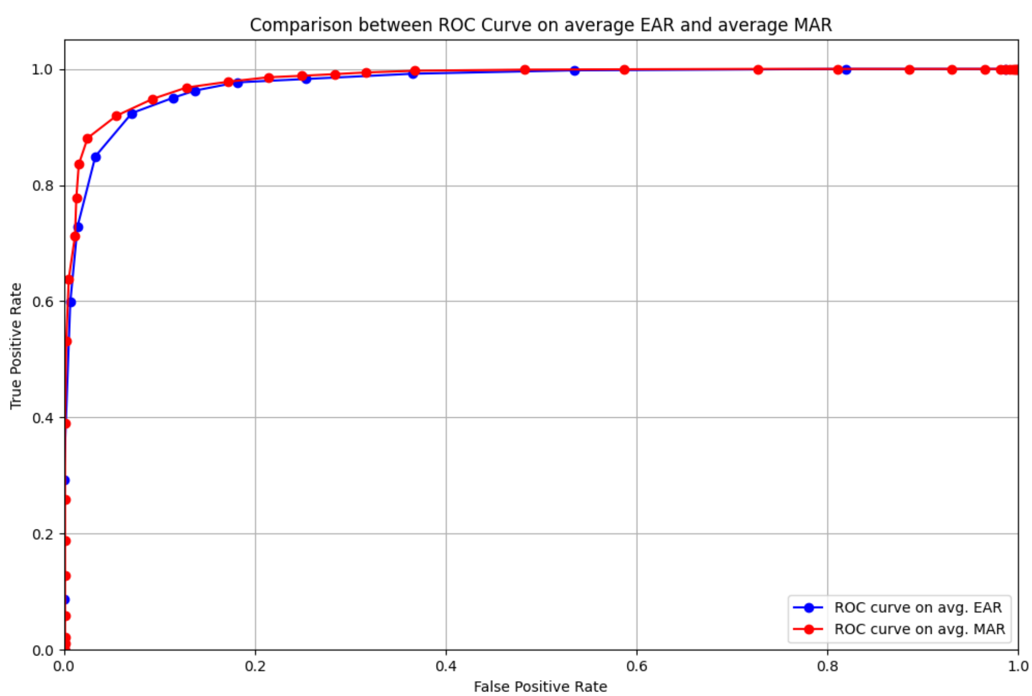
- Upon executing our model in a real-time scenario, the outcomes were remarkably promising.
- The prototype consistently provided accurate outputs, effectively distinguishing between instances of drowsiness and wakefulness. To optimize reliability, we meticulously calculated the best thresholds for both Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) using the one-rule threshold technique, minimizing false positives and false negatives.
- The derived thresholds stand as critical benchmarks for our drowsiness detection system:
    - **Best Threshold for Mouth Aspect Ratio:** 0.5855645444146671
    - **Best Threshold for Eye Aspect Ratio:** 0.2675092419954906
- In the real-time implementation, if the MAR and EAR of an individual's mouth and eyes surpass these optimal threshold values, it triggers a drowsiness flag. Beyond this threshold for flagging, the system promptly issues an alert to the user, providing a proactive measure against potential risks associated with drowsy driving.
- Furthermore, our comprehensive analysis extended to the plotting of Receiver Operating Characteristic (ROC) curves for EAR, MAR, and their combined values. These curves not only offered a graphical representation of the trade-off between true positive rate and false positive rate for various threshold values but also played a crucial role in guiding the selection of an appropriate classification threshold.



Plot1: ROC Curve on average MAR



Plot2: ROC Curve on average EAR



Plot3: Comparison between ROC Curve on average EAR and average MAR

- In our Prototype of drowsiness detection system, alerts are intelligently triggered through a combination of key indicators. The interplay of Eye Aspect Ratio (EAR), sustained drowsy frames, and the identification of yawning events forms the basis for activating alerts.
- When the EAR and MAR values exceed predefined thresholds, signifying potential drowsiness, and continuous frames indicate an extended period of drowsy behavior, our system takes proactive measures. Additionally, the detection of yawning events further refines the alert mechanism, capturing a comprehensive understanding of the driver's condition.
- Our alert system goes beyond mere notifications by incorporating informative text overlays directly onto the user interface. Phrases such as "Drowsiness Detected" and "Yawn Detected" serve as clear, user-friendly indications, enhancing the communication between the system and the driver. This thoughtful approach not only ensures the timely conveyance of critical information but also contributes to a more intuitive and responsive driving assistance system.
- In our prototype of drowsiness detection system, we've seamlessly integrated visual and auditory warnings using the VLC library as well which responds effectively to identified instances of drowsiness. With VLC, we ensure that drivers not only receive immediate visual cues but also auditory alerts, creating a comprehensive alert mechanism.
- In instances where prolonged drowsiness is detected, our system takes proactive measures. We initiate a web browser search for nearby hotels or motels, providing automated break assistance. This feature aims to make it convenient for drivers to find suitable places to rest. By combining audio alerts and automated break reminders, we, as a team, prioritize driver well-being and contribute to an enhanced level of road safety.

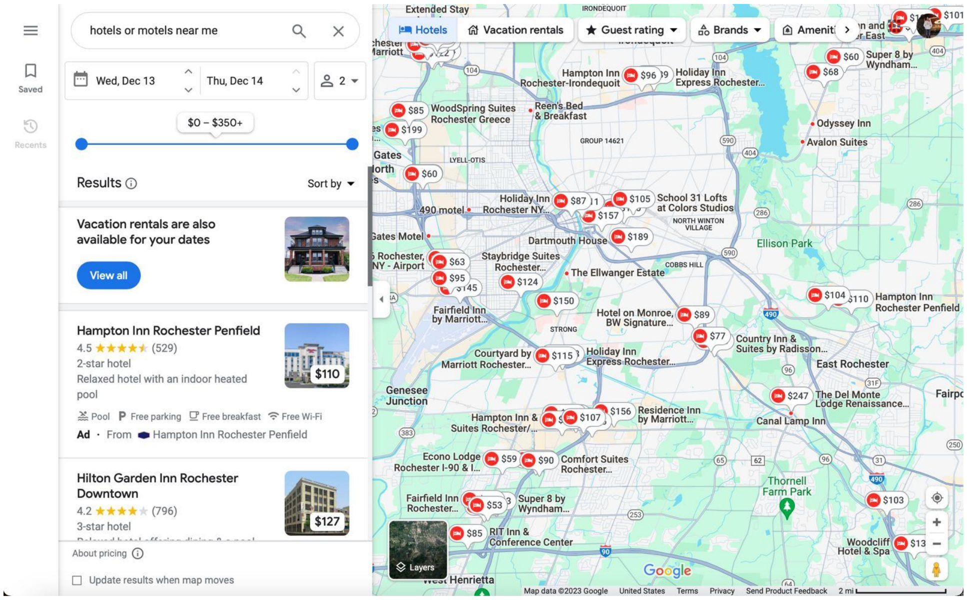


Image3: Webpage/Map showing nearby hotels and motels

OUR PROTOTYPE WORKING IN REAL TIME:
https://drive.google.com/drive/folders/1OL5zxbo-8SaWziKEPCjJKU8LaLsPJ9Dy?usp=drive_link

Image4: Eyes Open, Mouth Closed -> No Alert

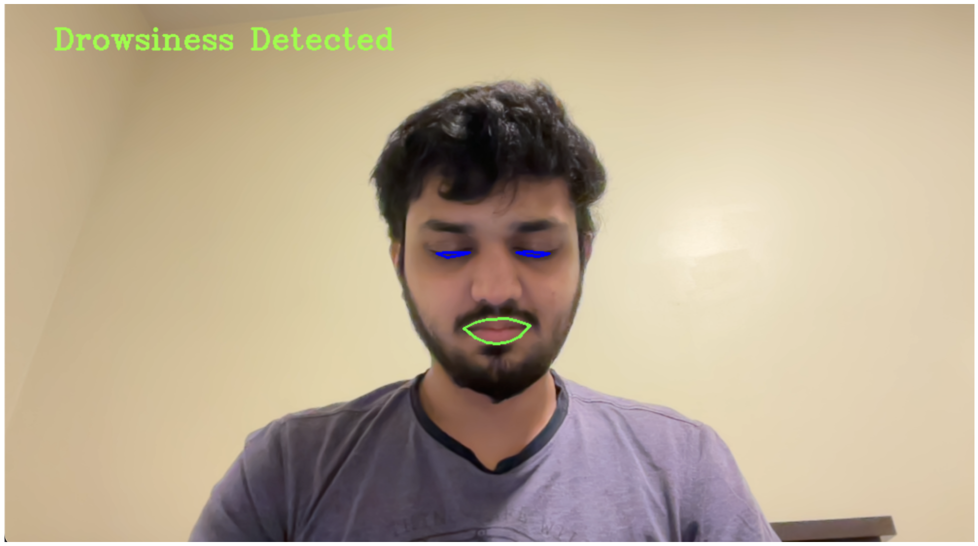


Image5: Eyes Closed, Mouth Closed -> Drowsy

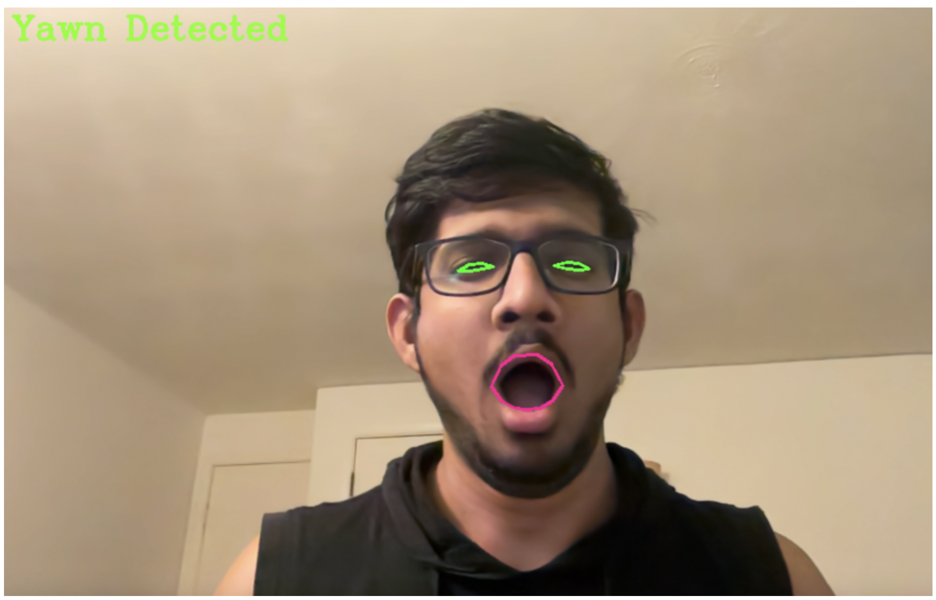


Image6: Eyes Open, Mouth Open -> Yawn Detected

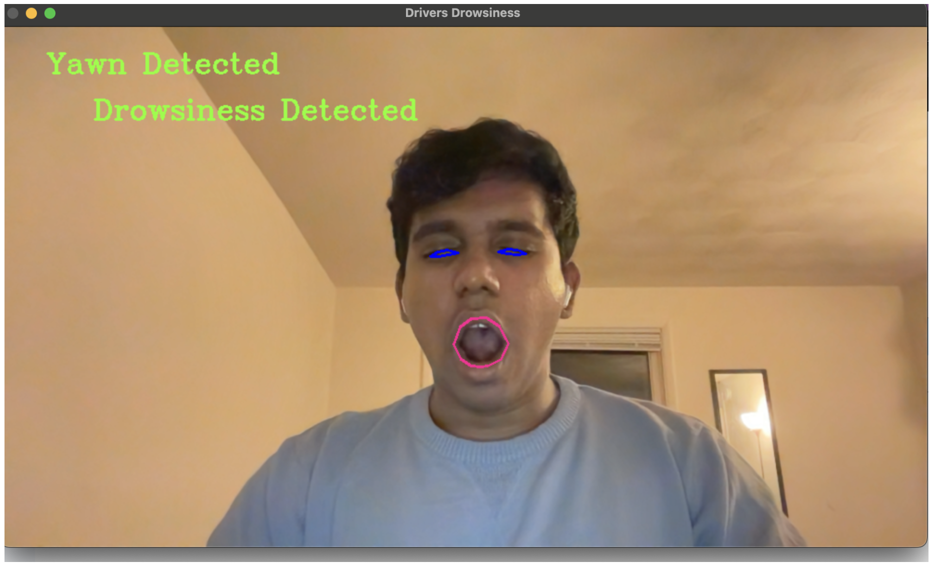
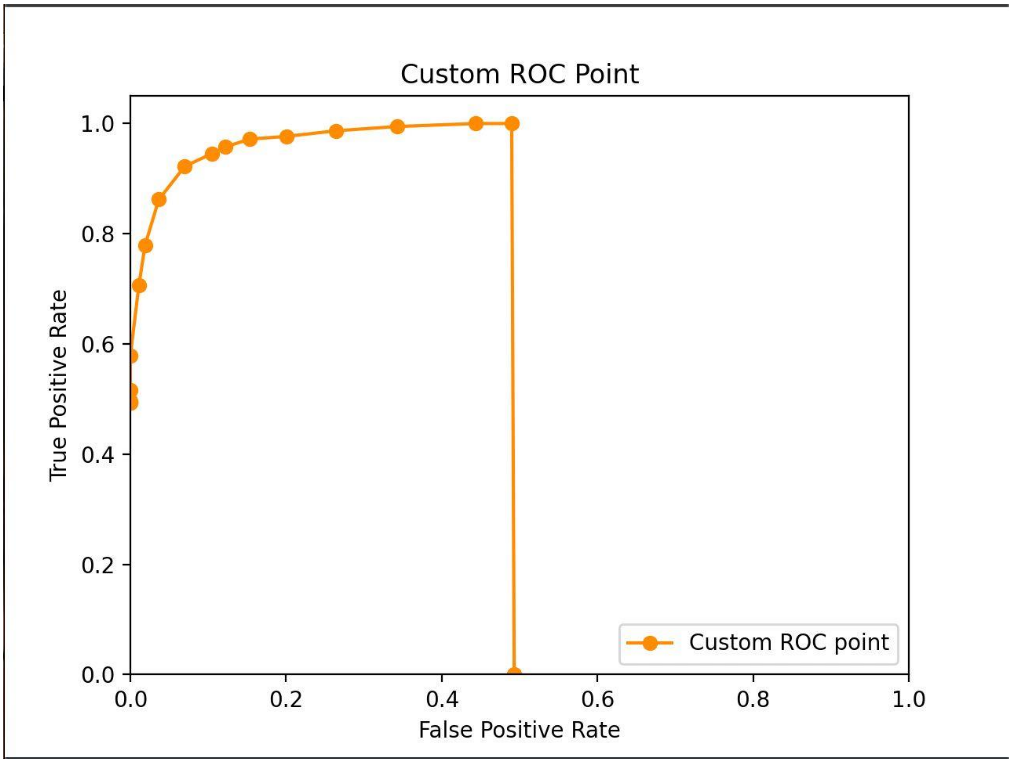


Image7: Eyes Closed, Mouth Open -> Drowsy and Yawn Detected

Hurdles, bugs, setbacks, problem-solving

- Acquiring a dataset containing both yawning and drowsy eyes presented a formidable challenge. To address this hurdle, we took the proactive step of creating our dataset. This initiative not only allowed us to tailor the dataset to our specific needs but also ensured the inclusion of essential instances of both yawning and drowsy eyes.
- The task of determining optimal thresholds for both Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) posed a significant challenge. To tackle this complexity, we employed a dual approach. First, we utilized the one-rule threshold method to establish initial thresholds. This technique allowed us to navigate the intricate landscape of EAR and MAR values and lay the foundation for subsequent refinement.
- During the EAR threshold calculation, we encountered a hurdle where the initial threshold value was unexpectedly low. This discrepancy stemmed from an oversight in the dataset, emphasizing the importance of dataset accuracy. Swift corrective measures were taken to rectify this anomaly, underscoring the iterative nature of our approach.
- The calculation of Receiver Operating Characteristic (ROC) curves brought its own set of challenges. Initially, the curve failed to commence from the conventional starting point (0,0) due to inaccuracies in false positives and false negatives calculation. A keen observation allowed us to identify and rectify the

miscalculation, ensuring the ROC curve accurately represented the trade-off between true positive and false positive rates. This iterative refinement underscores our commitment to precision in our analytical methodologies.



Plot4: Incorrect ROC Curve Hurdle

Mastery of Course Material

- **Face Detection Techniques:** During the course, we gained proficiency in various face detection techniques, including the utilization of the HAAR CASCADE frontal face detector. This classical approach, widely employed in computer vision, is specifically designed for grayscale images. We successfully integrated this technique into our initial project phase, demonstrating a solid grasp of fundamental image processing concepts.
- **Advancements with dlib Library:** Building upon our foundational knowledge, we explored more advanced face detection capabilities using the dlib library. In particular, we leveraged the get_frontal_face_detector() function from the library, allowing us to detect faces in colored images. This marked a significant enhancement, as it enabled our system to operate on images with more complex color information.
- **Integration of dlib for Face Landmark Detection:** Beyond face detection, we further extended our proficiency by incorporating the dlib shape predictor. This tool enabled us to identify facial landmarks with precision, allowing for the extraction of detailed facial features. The inclusion of facial landmarks enhanced

our Prototype of drowsiness detection algorithm, contributing to more accurate and robust results.

Ethical Considerations

We have given careful thought to ethical issues when developing our drowsiness detection prototype, especially about data gathering, potential abuse, and process biases.

- **Data Collection:**

  We are well cognizant of the delicate nature of collecting face data. We have taken moral action to allay privacy worries by getting consent documents signed by two people—friends who kindly offered to be included in our research. These consent papers clearly state what information is being collected, how it will be used, and how long the video footage will be used.

- **Potential Misuse:**

  We have put safeguards in place to prevent unauthorized use of face data since we are aware of the potential for misuse. The completed agreement forms limit the usage of the data acquired to our drowsiness detection research and clearly specify the goal of the project. Ensuring the ethical and responsible treatment of the obtained information is ensured by the stringent prohibition of unauthorized access or usage outside the stated scope.

- **Biases in Data:**

  We openly acknowledge the possibility of biases in our dataset, which are prevalent in many real-world data projects. Although we acknowledge that biases may still exist and actively work to diversity our sample, we are dedicated to addressing and reducing them. We also recognize how crucial contextual correctness is to our project. We acknowledge the need of customizing the dataset to the particular deployment location in the best-case scenario where our prototype of drowsiness detection technology is put into operation.

  Although the values of the eye aspect ratio (EAR) and mouth aspect ratio (MAR) might fluctuate between locations, the goal of this strategic approach is to improve accuracy. Through the use of region-specific information, we want to offer a more accurate and dependable system that takes into consideration the subtle differences between each unique location. This pledge demonstrates our commitment to accuracy and equity in the real-world use of our sleepiness detection technology.

Learning Objectives and Outcomes

As we reflect on the journey from our project's inception to its current state, we find a sense of accomplishment in achieving and, in many instances, surpassing our initial learning objectives.

- Our system, designed to identify signs of driver fatigue using facial landmarks, eye aspect ratio, and yawning detection, has exceeded expectations in terms of accuracy. This success underscores our dedication to precision and effectiveness in drowsiness detection.
- The seamless functionality of our alert system has been a notable achievement. By avoiding false positives and ensuring timely alerts, we've prioritized driver safety without introducing unnecessary distractions. This reliability in alert mechanisms aligns with our commitment to user-centric design. This is evident from our ROC curves of both EAR and MAR and the average threshold of EAR and MAR generated by our code. Our UI also clearly differentiates when a person is drowsy/not drowsy or when he is yawning or not yawning which can be seen in the drive we have presented earlier with our real time videos.
- Ethical considerations were woven into the fabric of our project. From documenting potential biases to implementing privacy measures and safeguards against misuse, our commitment to high ethical standards has been unwavering.
- Beyond meeting the minimum goal, our drowsiness detection system has proven itself to be functional and reliable. It effectively identifies various signs of drowsiness, showcasing its capability.
- In essence, our journey has not only met but often surpassed our initial learning objectives. It's a testament to the collaborative effort, innovation, and dedication that we, as a team, have invested in creating a drowsiness detection system that not only fulfills its goals but sets a high standard for future advancements.

Conclusion

- As we conclude our sleepiness detection research, the results highlight the importance of our efforts. By utilizing the pre-trained model of the dlib toolkit, we were able to map 68 facial locations in detail and produce a large dataset that represented a variety of sleepiness conditions.
- We applied the one-rule threshold method and found that it was effective in accurately categorizing cases of drowsiness A more detailed analysis of our system's performance was made possible by the construction of ROC curves, notably for average eye aspect ratio (EAR) and average mouth aspect ratio (MAR). Specifically,

our thresholds (MAR: 0.5855645444146671 and EAR: 0.2675092419494906) are important standards for precise drowsiness identification.

- **Suggestions for Future Work or Improvements:**
  - In the future, a potentially fruitful path of improvement would be to customize our dataset to target areas for increased precision. Given the possible differences in facial features across various geographic regions, developing and using region-specific datasets might greatly improve our system's ability to identify tiredness. Through taking into consideration regional variations in facial expressions and traits, we hope to personalize our system so that it is not just precise but also sensitive to the many driving conditions it can come across. This tactical approach is consistent with our dedication to ongoing enhancement and a more targeted, efficient application of our sleep detection technology.

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