

Proposing

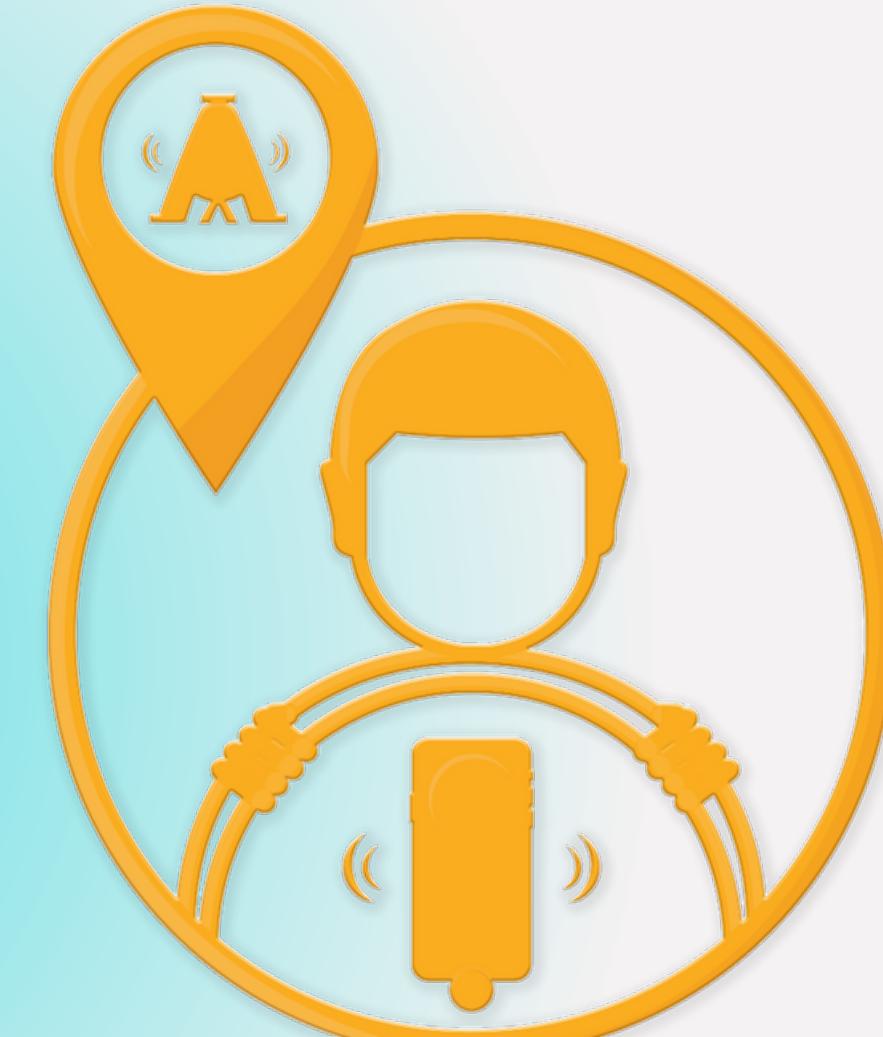


Alertawy

AI-Powered
Driver Monitoring System



Graduation Project Dissertation



ALERTAWY
YOUR ACTUAL SAVIOR



Outline

01 - Motivation

02 - Objective

03 - Methodology

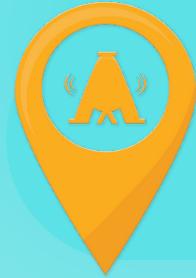
04 - Results

05 - Demo

06 - Constraints

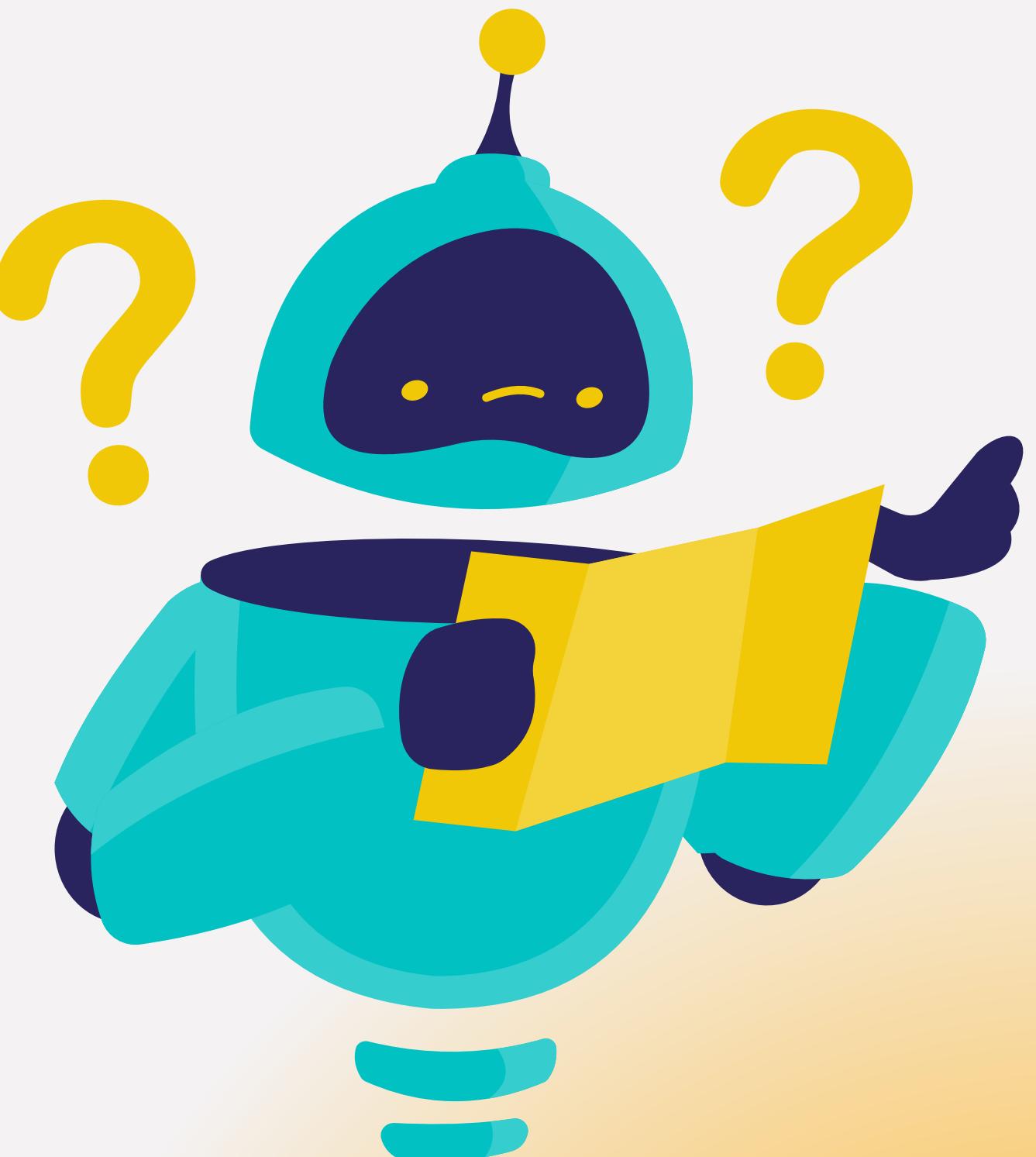
07 - Conclusion

08 - Future Work



01 - Motivation

How many lives are lost each year as a result of road accidents stemming from distracted and drowsy driving, as well as non-compliance with the speed limits enforced by radar cameras?





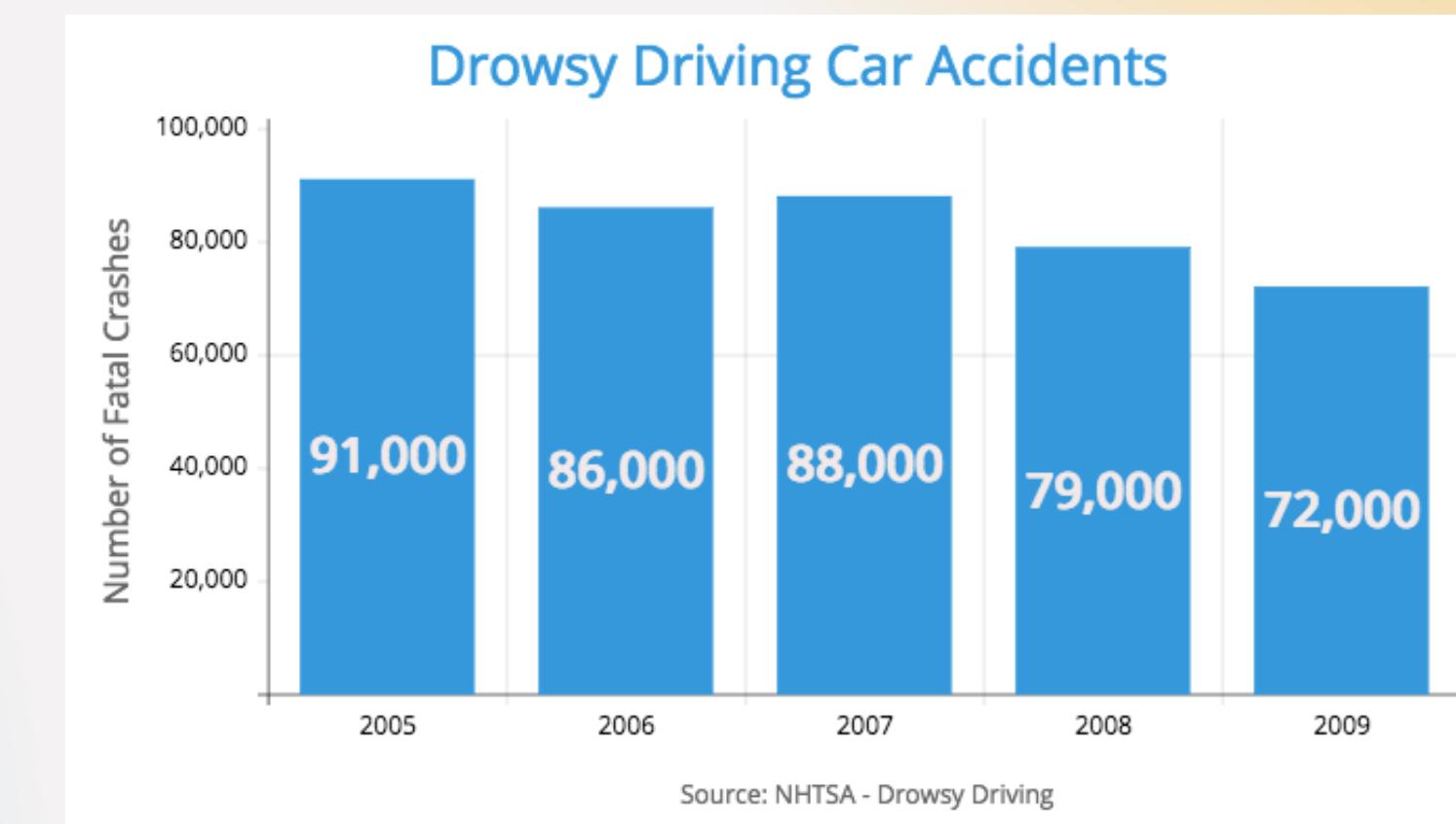
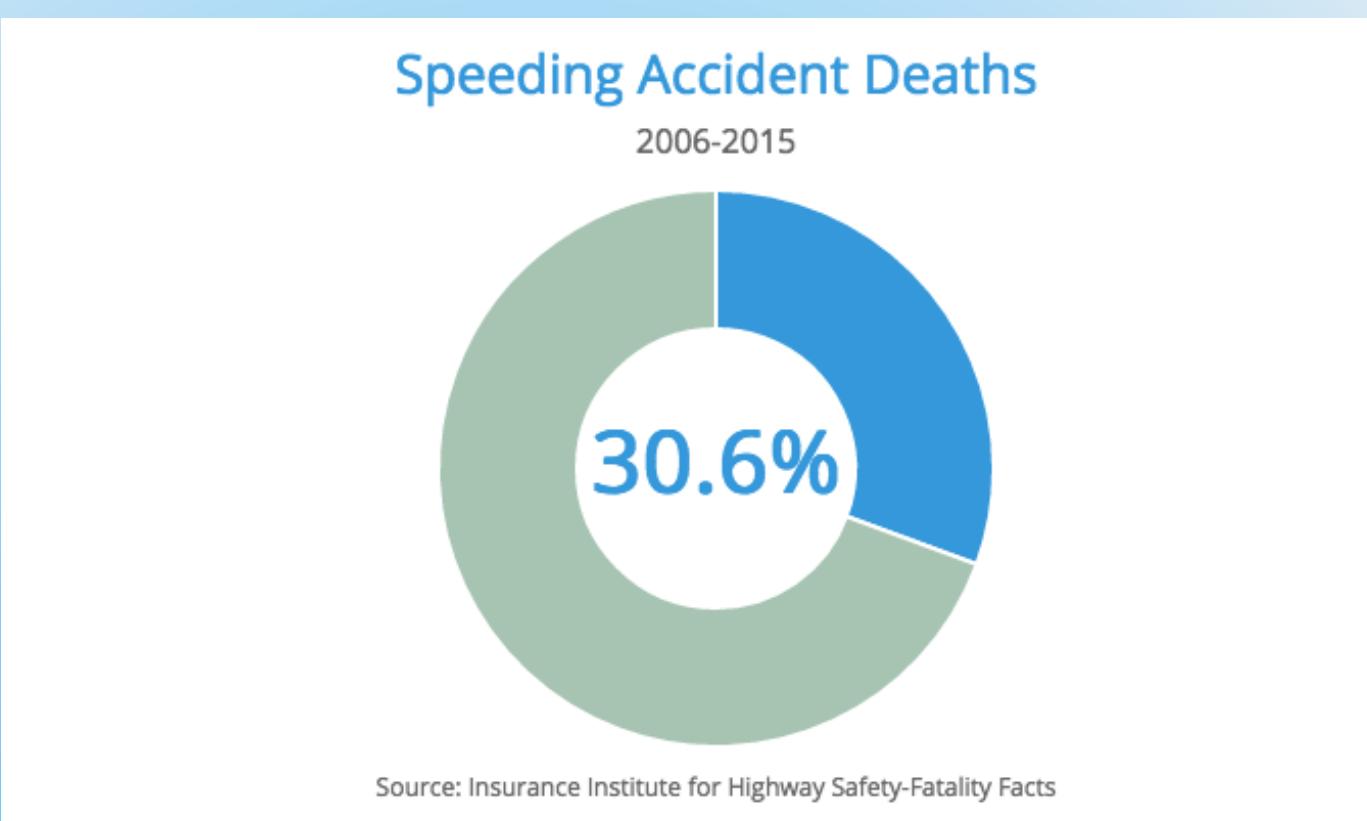
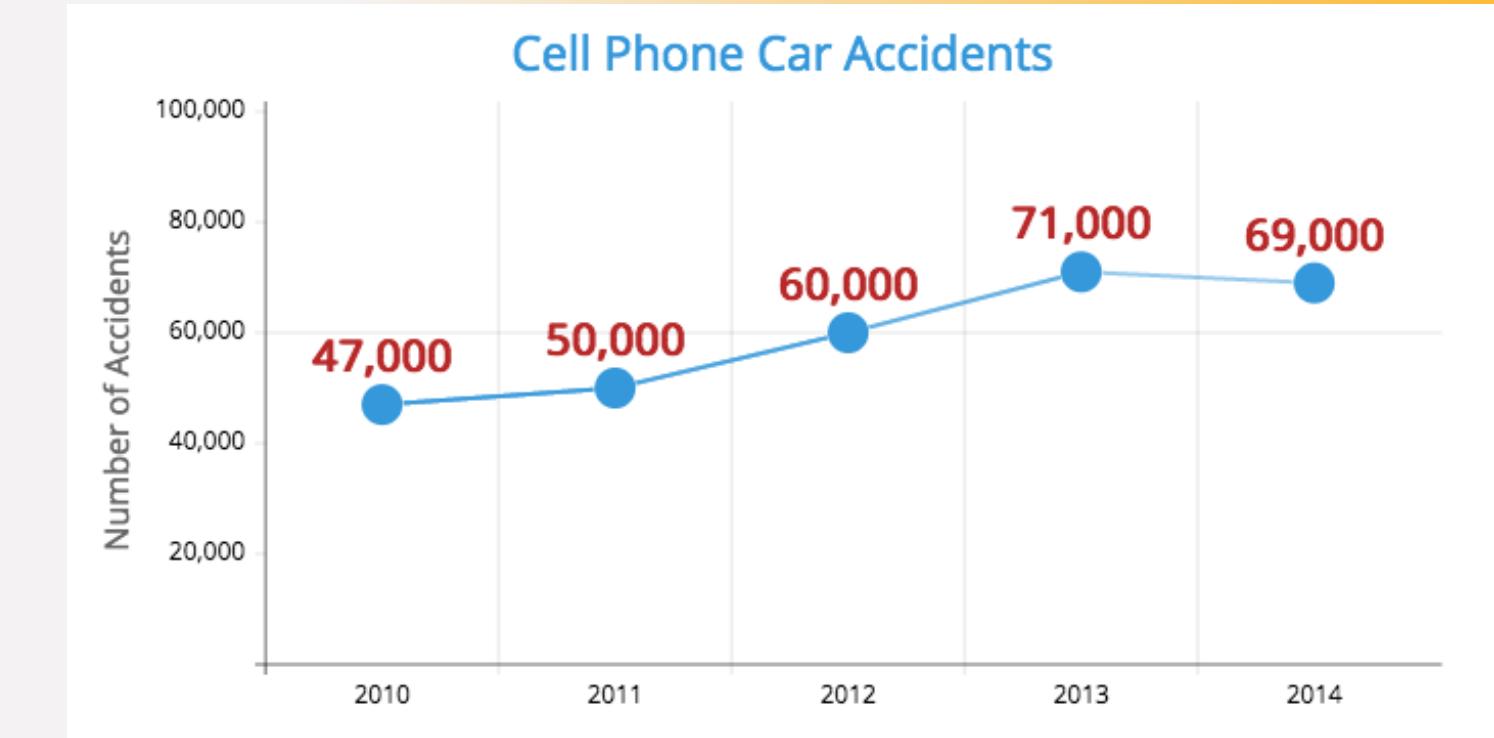
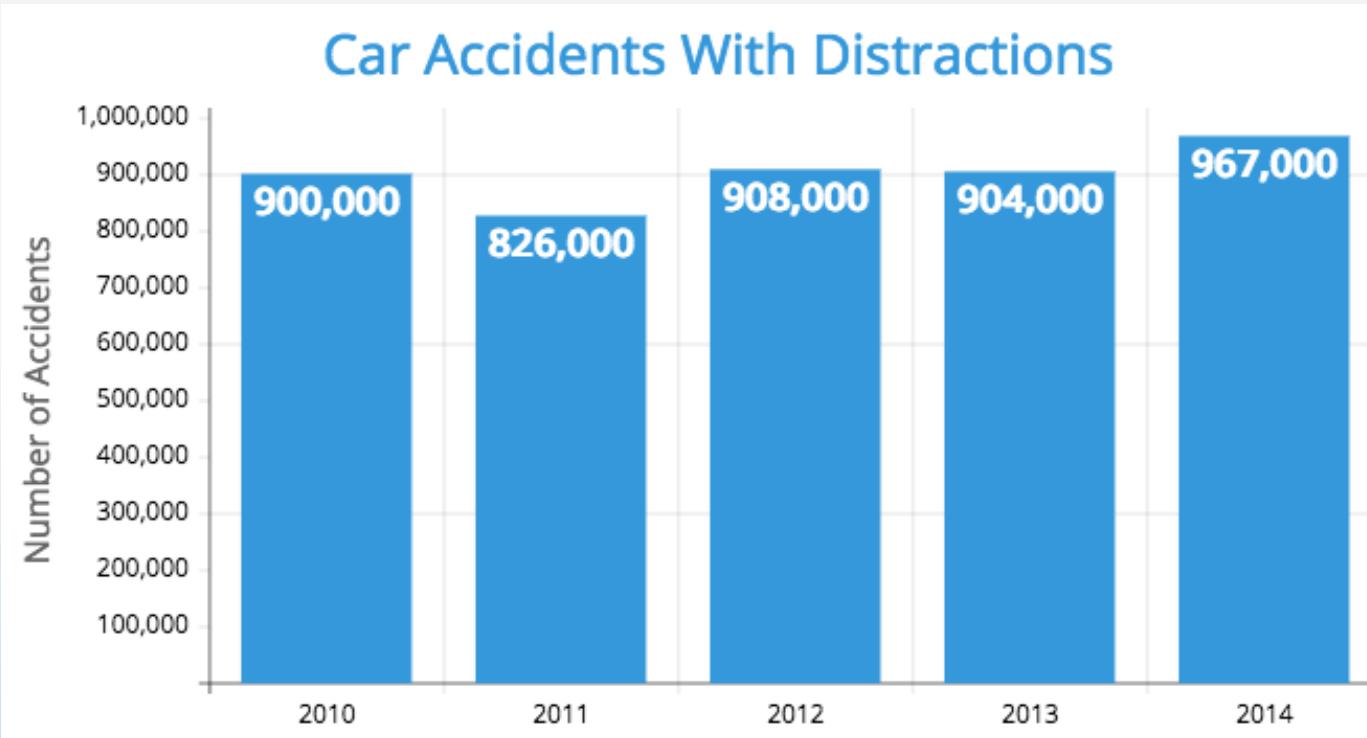
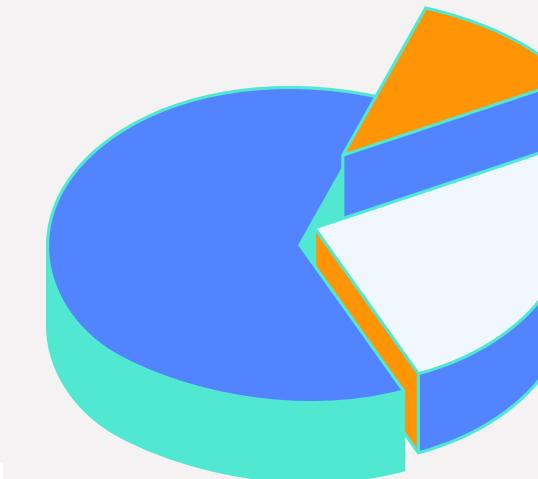
01 - Motivation

Actually, the numbers are large, Recent statistics show that distractions, drowsiness, cell phone use, and speeding are among the top seven causes of car accidents due to their significant impact.





01 - Motivation

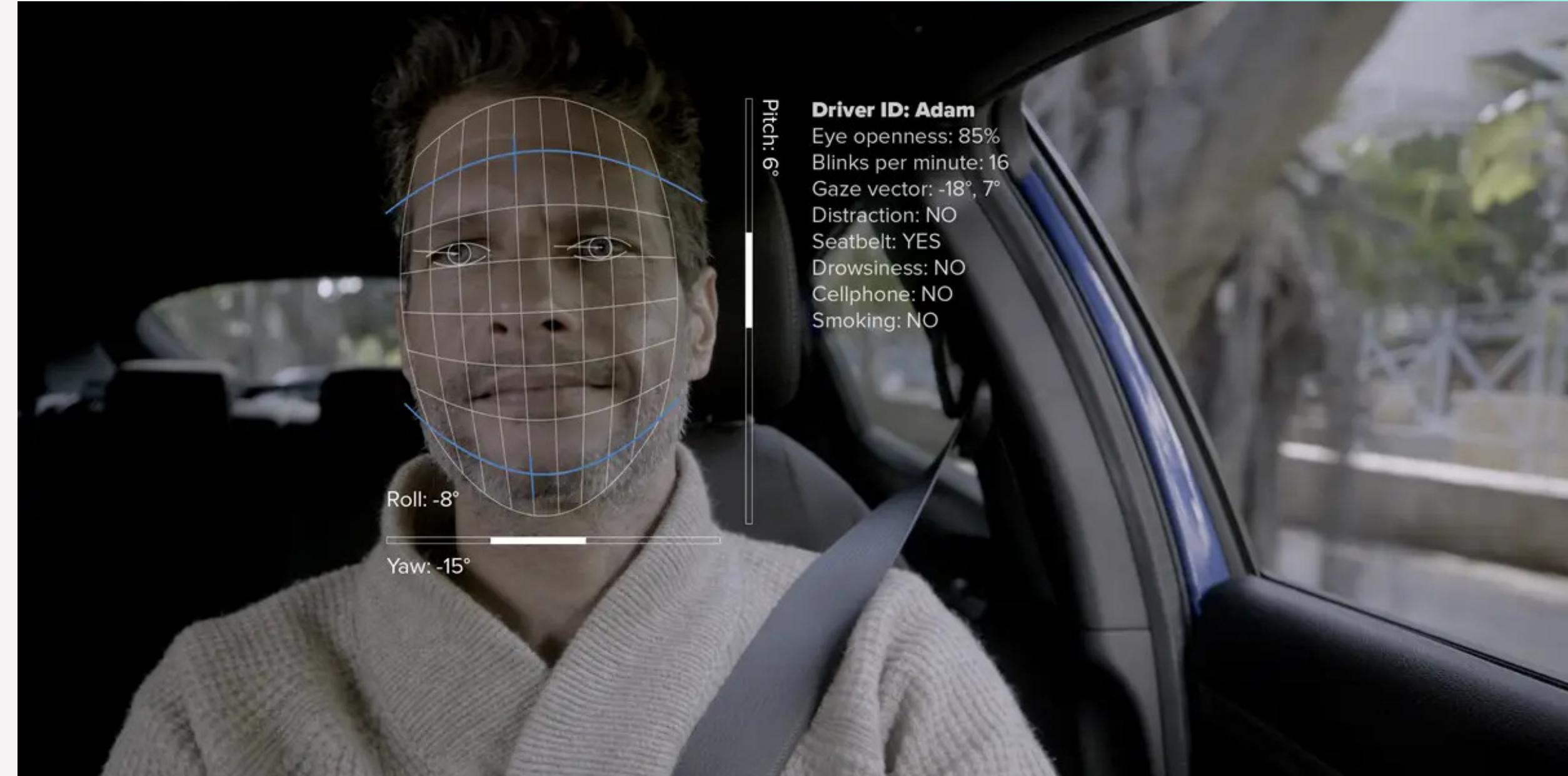
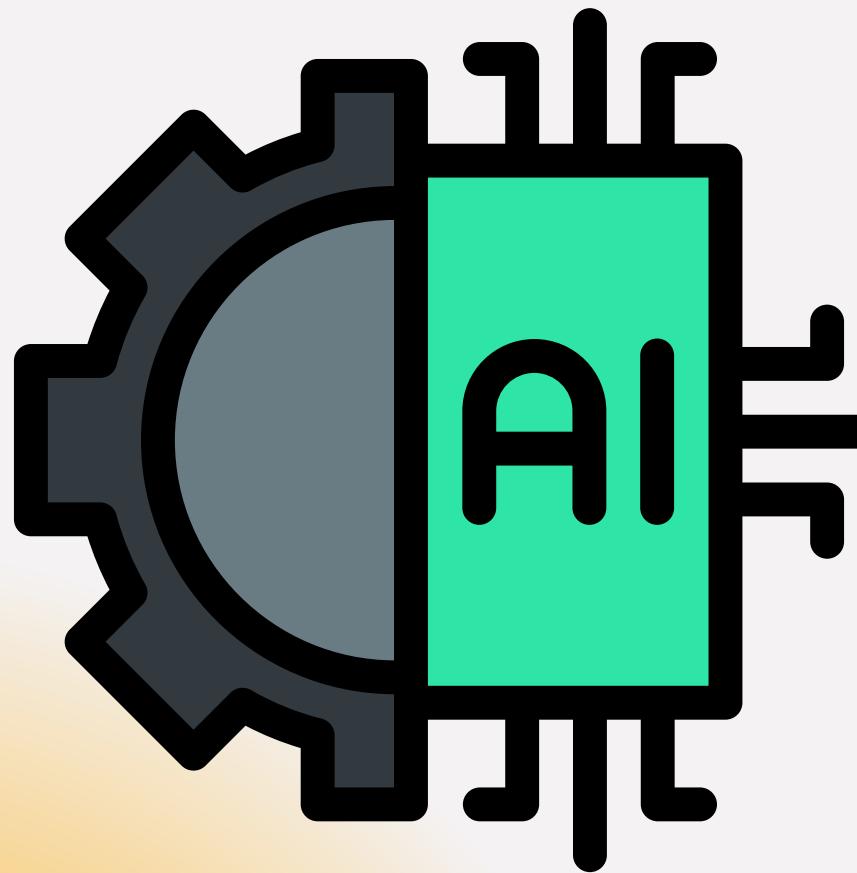




02 Objectives

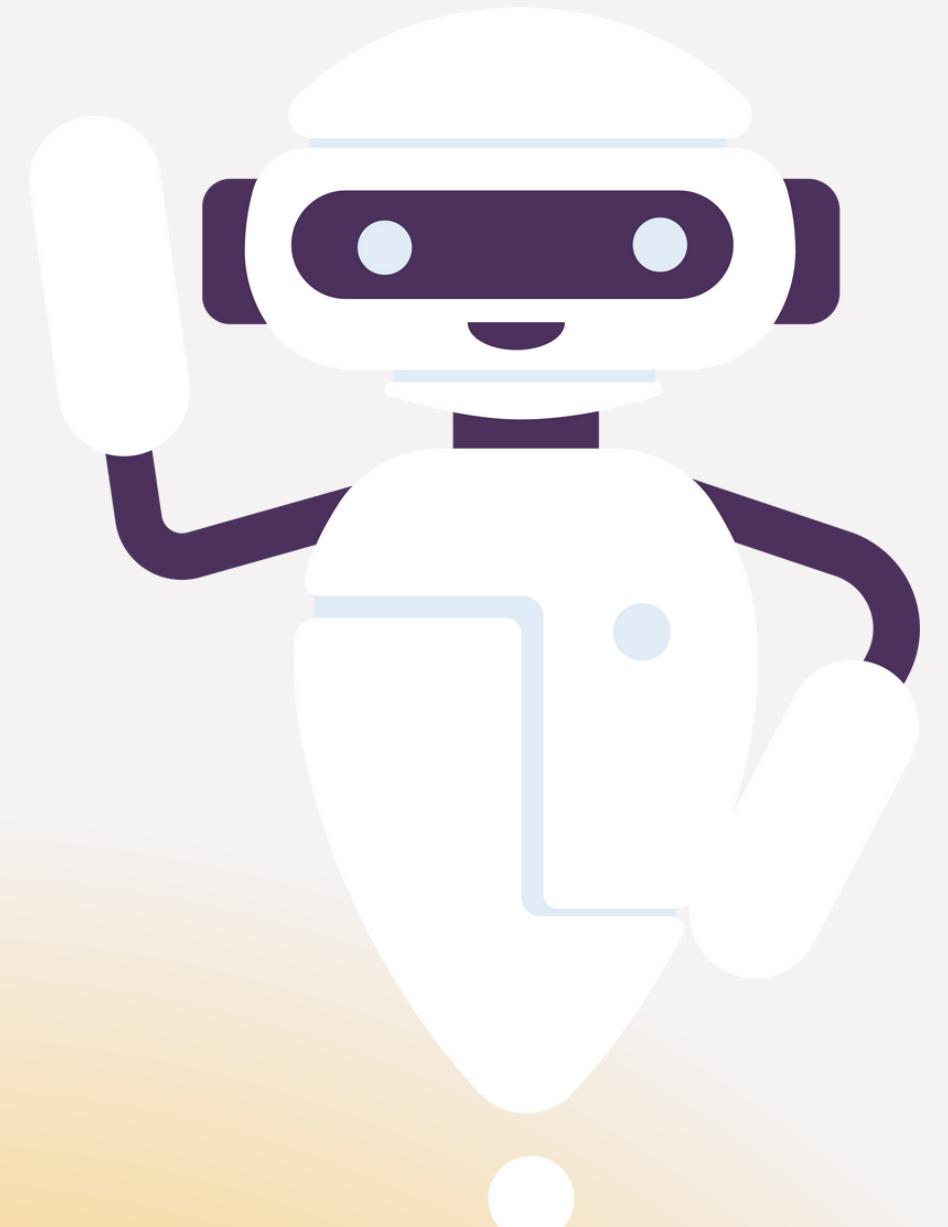
Enhancing Driver Safety through AI-Powered Monitoring System for All Users.

- The scope of our project is to address the critical issue of accidents caused by driver distractions, drowsiness, and lack of attention to the road.





02 Objectives

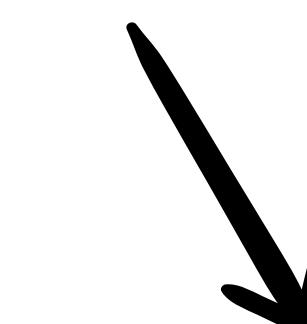


- Our aim is to develop and present a solid proof of concept illustrating how AI-powered driver monitoring effectively reduces the risks of drowsy or distracted driving.

Alertawy Integrated System



Mobile
application
for drivers



Web
application
for administration





02 Objectives

Key features of our Driver Monitoring System, "Alertawy"

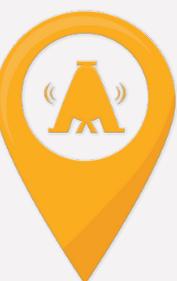


Real-Time Alerts: Utilizes advanced Deep Learning Computer Vision Techniques to detect and alert drivers of risky behaviors like phone use, drowsiness, and distractions.

Radar Avoidance Assistance: Helps drivers avoid radar detection by providing alerts for unsafe driving practices and speeding.

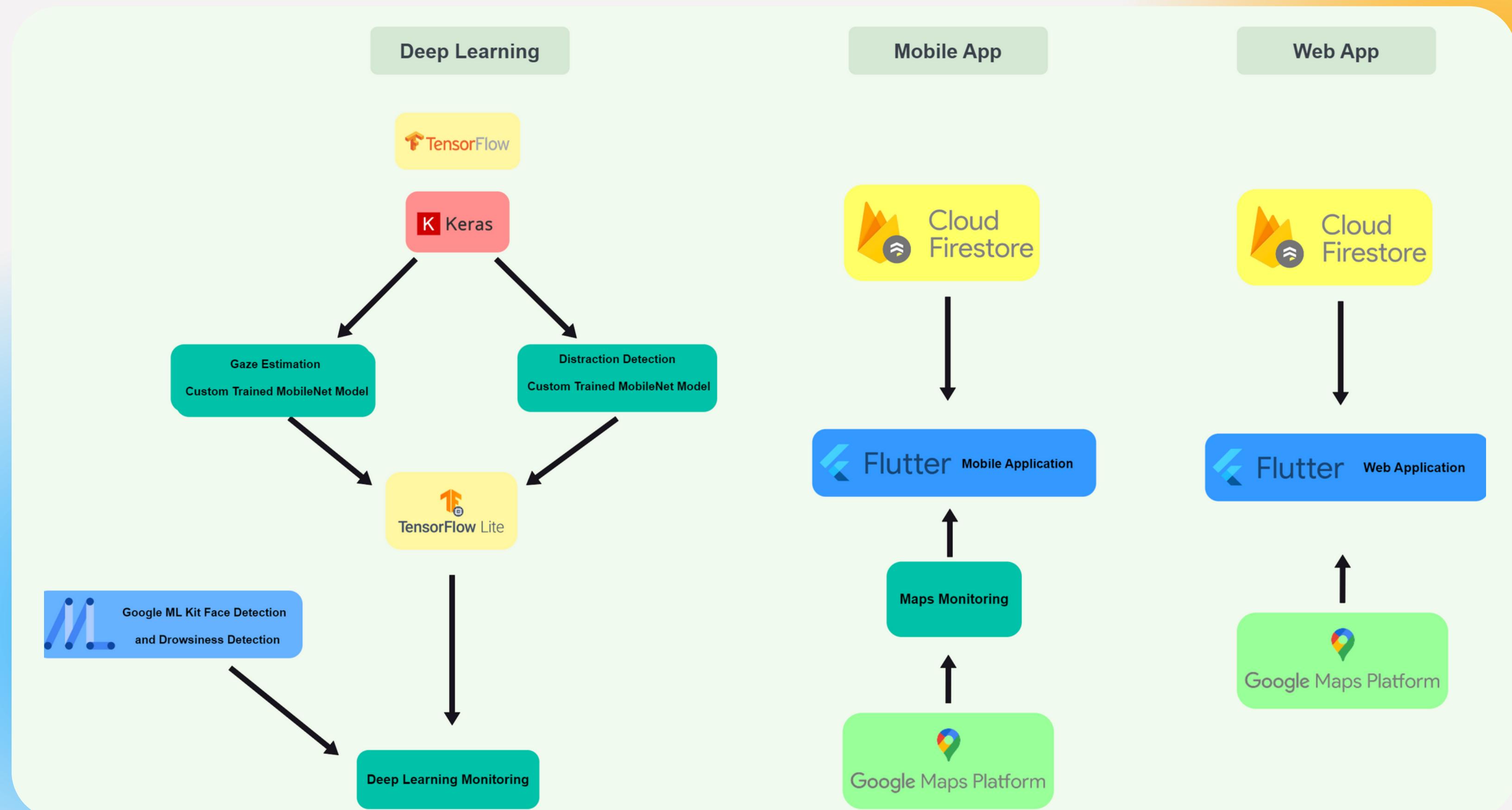


The web application: is an admin platform that provides a broader view of driver rides and reports. It facilitates evaluation, analysis, and proactive measures to enhance driver safety.



03 - Methodology

DMS Overview





03 - DL Methodology

Distraction Detection

- Combined three different datasets:
 - State Farm Distraction Kaggle competition Dataset
 - AUC Distracted Driver Dataset
 - Rabat University Distracted Driver Dataset
- Total of 80,000 images
- Utilized 40,000 images after removing unwanted classes.

Combined Distraction Dataset



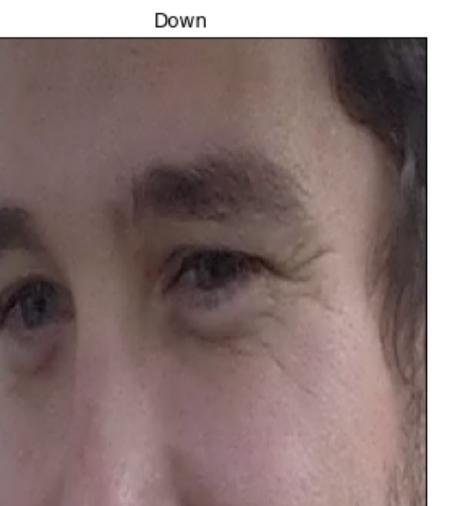
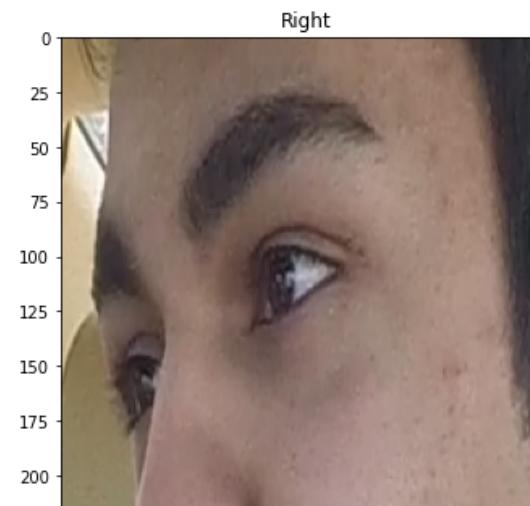
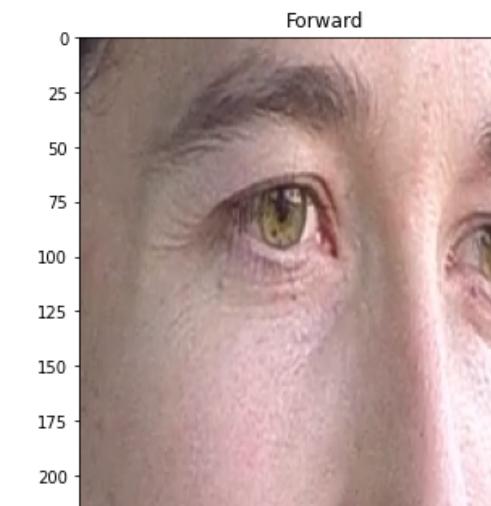
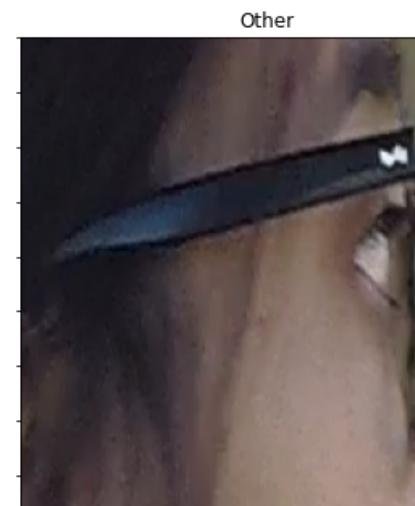
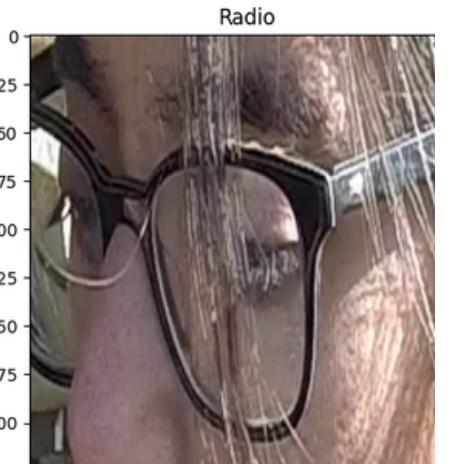
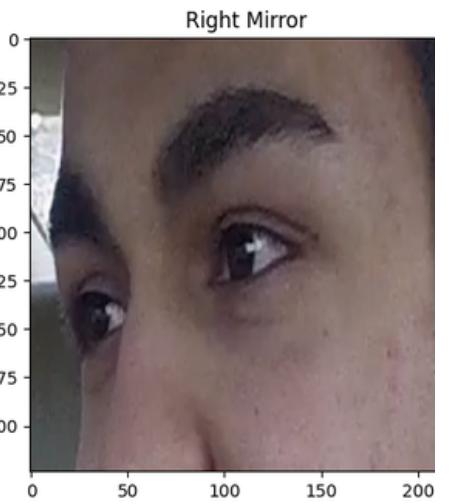
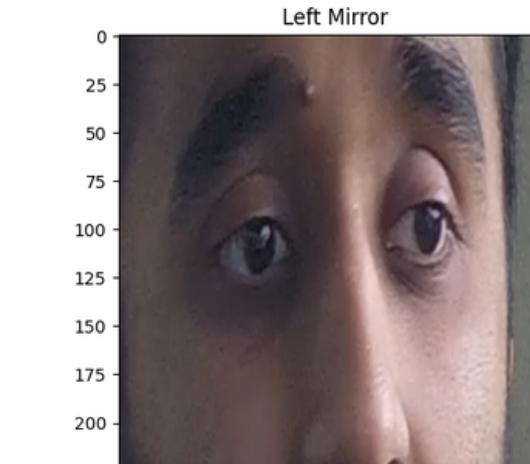
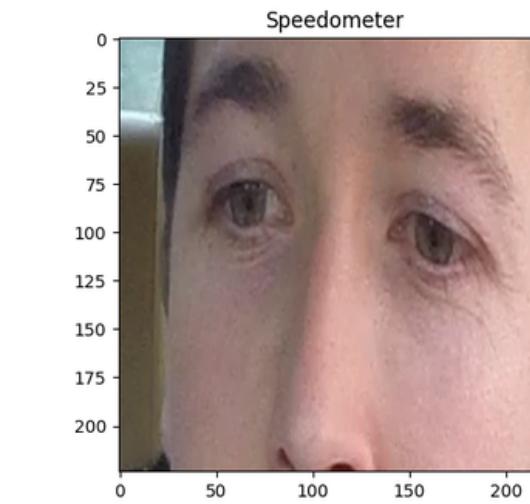
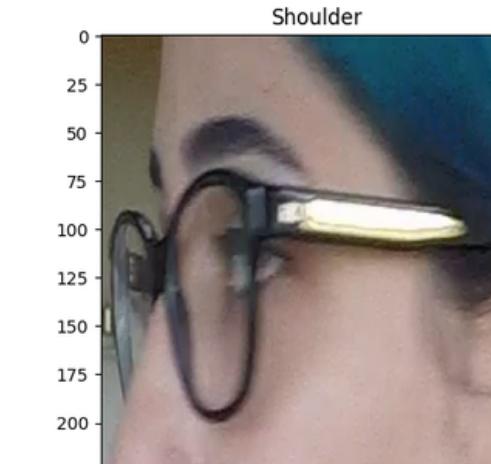
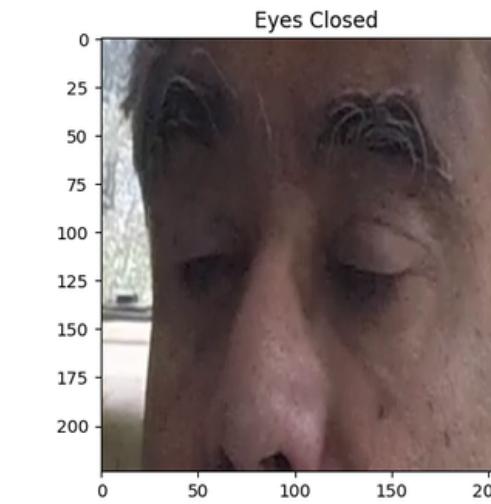
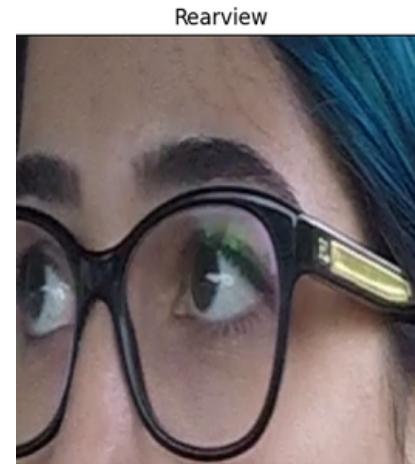


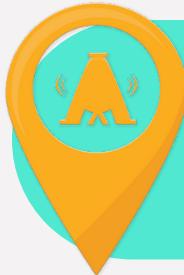
03 - DL Methodology

Gaze Estimation

- Total of 30,000 images
- Consist of 8 Classes called driver gaze zones.
- We Combined Some of the Classes to Focus only on the driver-eye direction.

Gaze Estimation LISA Dataset

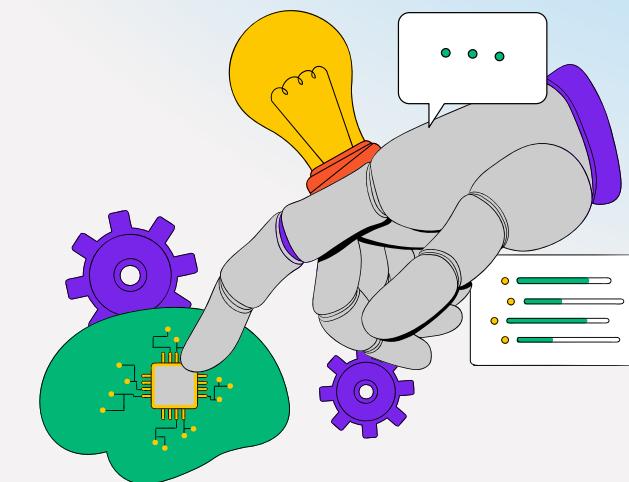
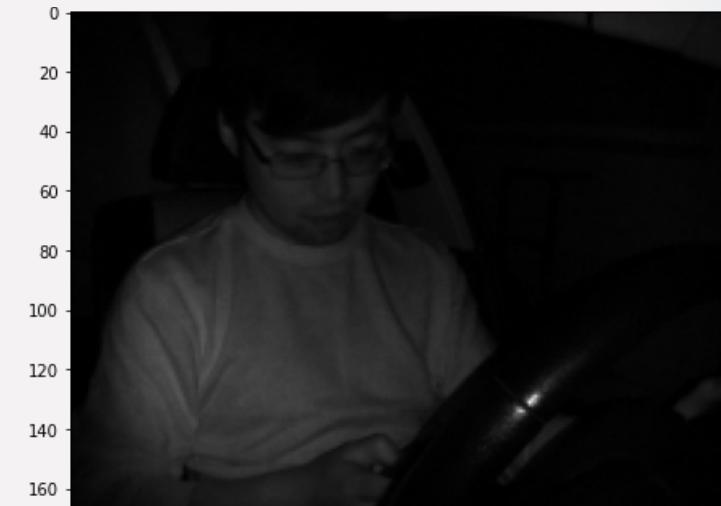




03 - DL Constraints

Limited Distraction Datasets: Overcoming the challenge of limited datasets containing the required shooting angles was crucial in training the distraction model, calling for innovative approaches to address this gap effectively.

Despite utilizing the DAD dataset: specifically captured from the desired camera angle, the model's performance was hindered due to the dimmed infra-red images, resulting in a limited accuracy of only 70%.



We attempted to develop a custom-trained object detection model for Drowsiness Detection, but encountered challenges regarding deployment and experienced **suboptimal performance** on mobile phones, necessitating further optimization efforts.

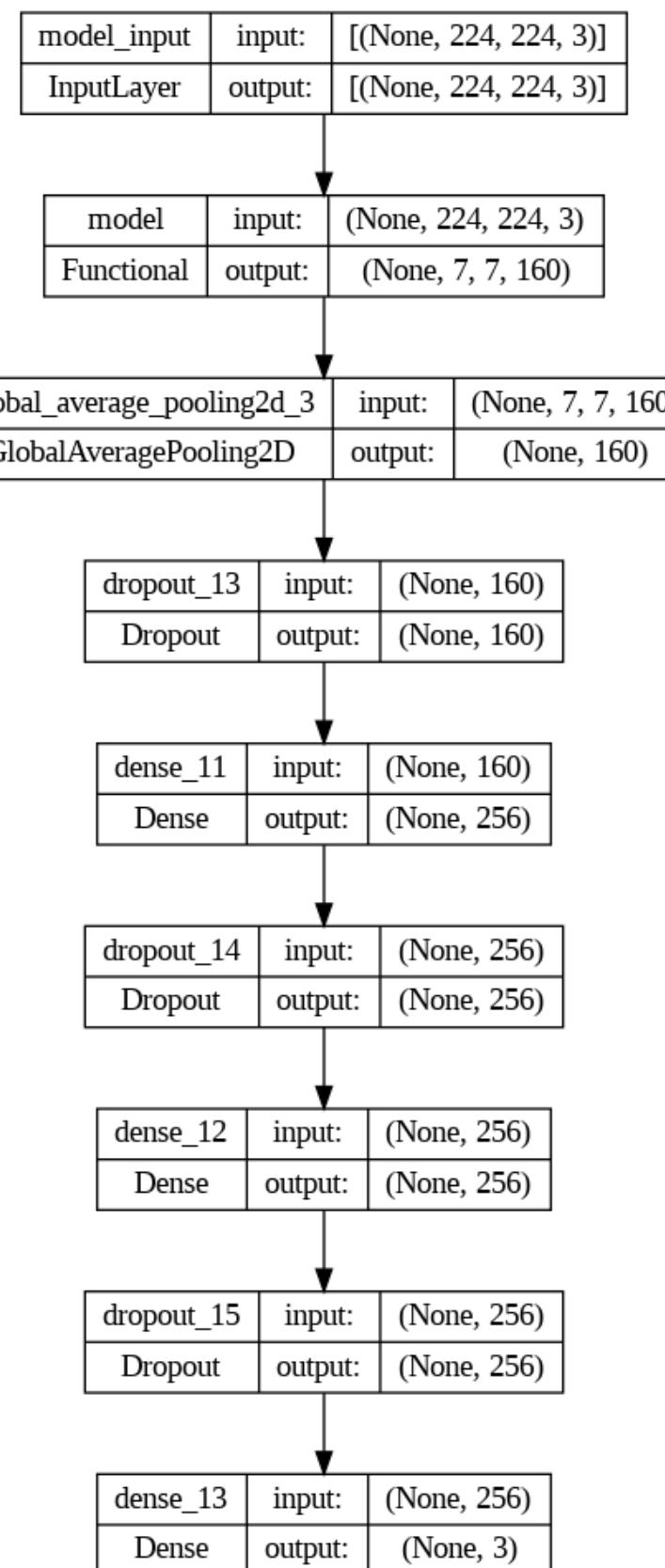
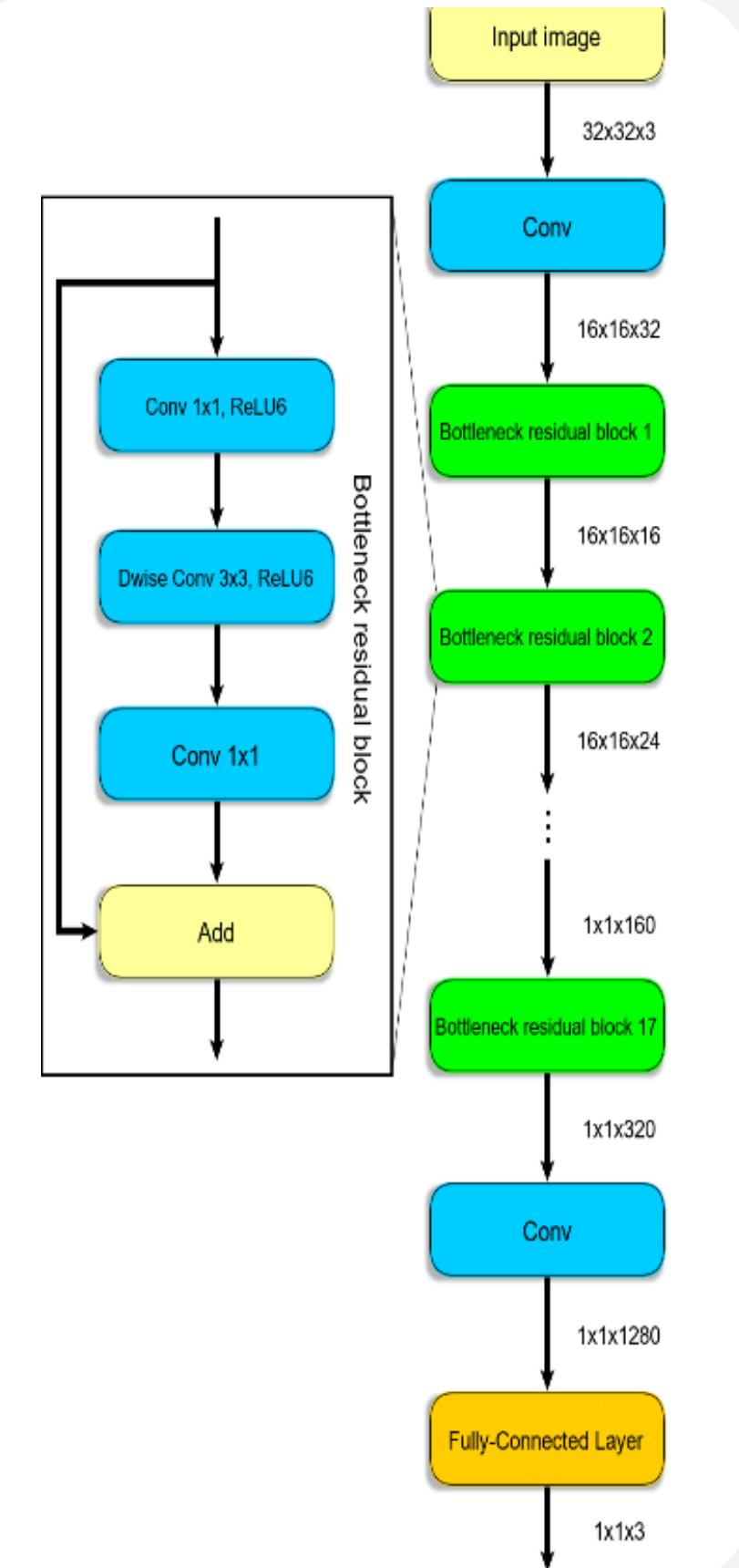
Exploring **fatigue detection** involved working with **video datasets**, which posed **challenges for mobile deployment**, emphasizing the need for tailored solutions to adapt and optimize such models for **real-time inference** on mobile devices.

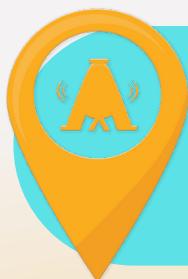


03 - Methodology

MobileNet

- **Lightweight Design:** designed to be compact and efficient, making it suitable for resource-constrained environments like mobile devices. Using depthwise separable convolutions reduces the number of parameters and computations required, resulting in a smaller model size.
- **Fast Inference:** optimized for speedy inference, allowing it to process data quickly. Its streamlined architecture and reduced computational complexity enable real-time or near-real-time predictions, making it ideal for applications with low-latency requirements.
- **Mobile-Friendly:** tailored to the constraints of mobile devices, striking a balance between model size, accuracy, and inference speed.

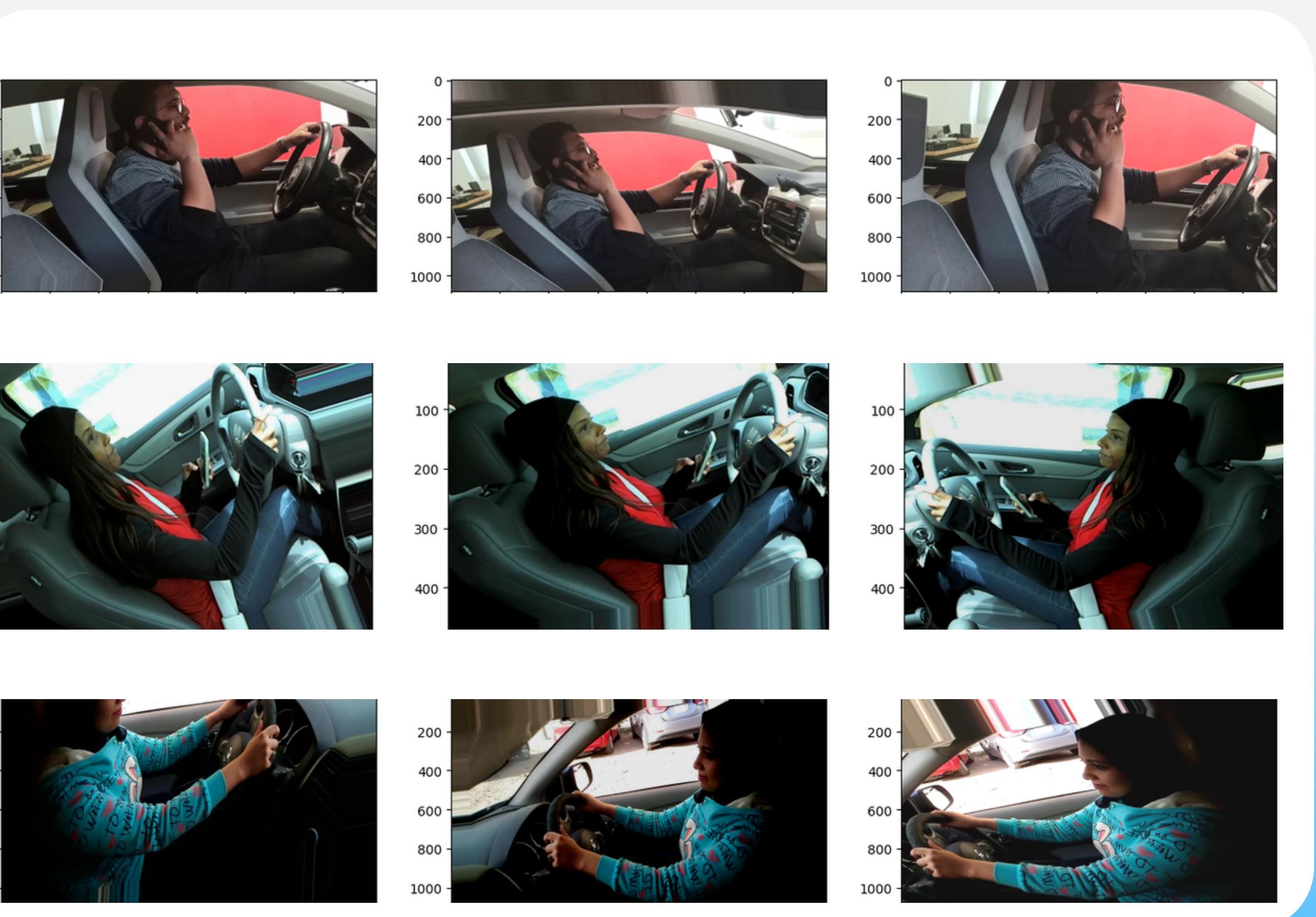




03 - DL Methodology

Deep Learning Training

- Data splitting was performed based on different drivers to prevent data leakage and ensure independence between the training and testing sets.
- Data augmentation techniques were applied to match desired camera angle and improve model generalization.
- Balancing Classes, certain classes were removed or combined to achieve a balanced representation of the different distraction categories

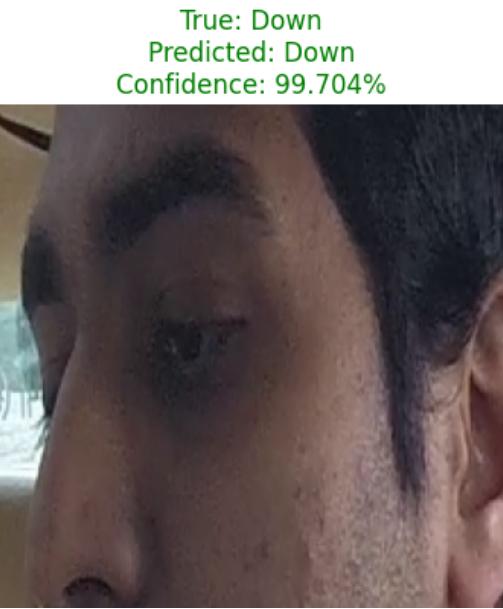
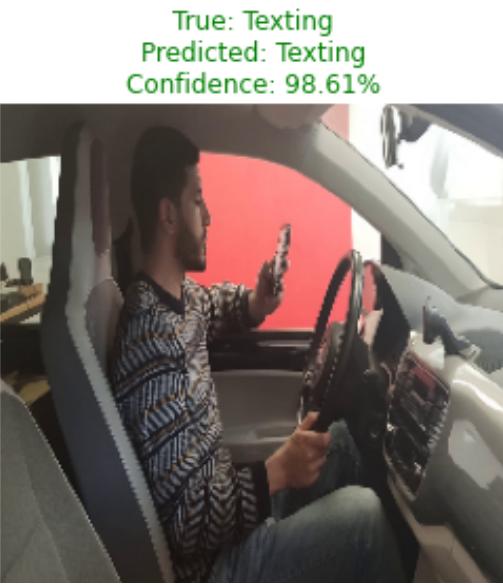




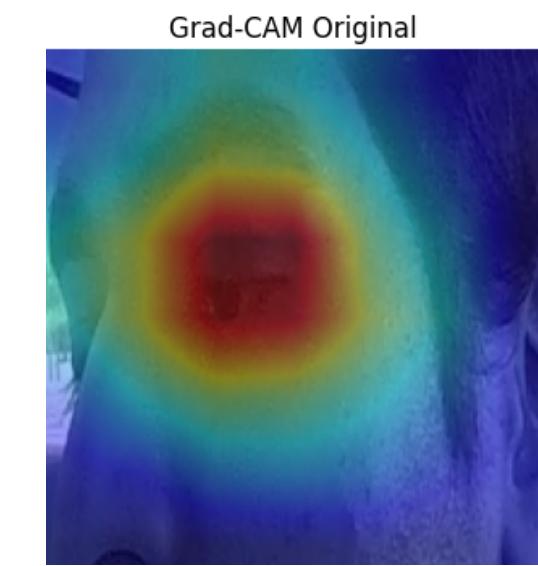
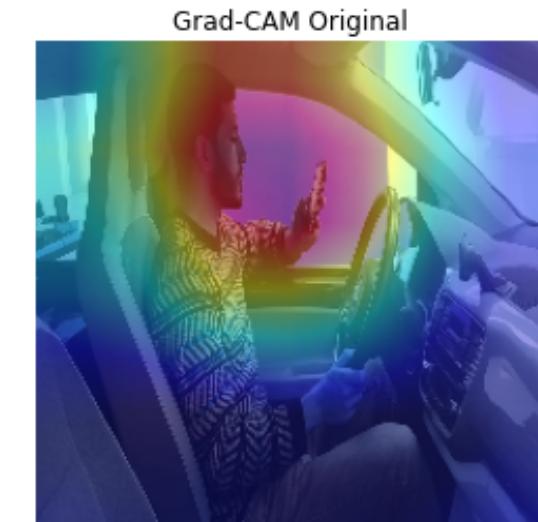
03 - DL Methodology

Deep Learning Results

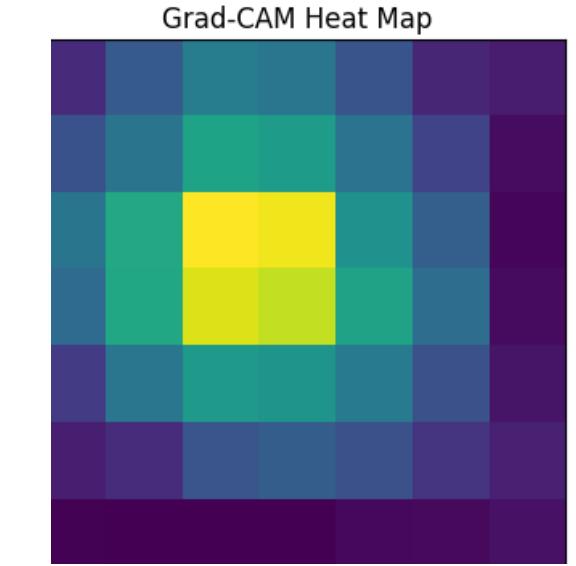
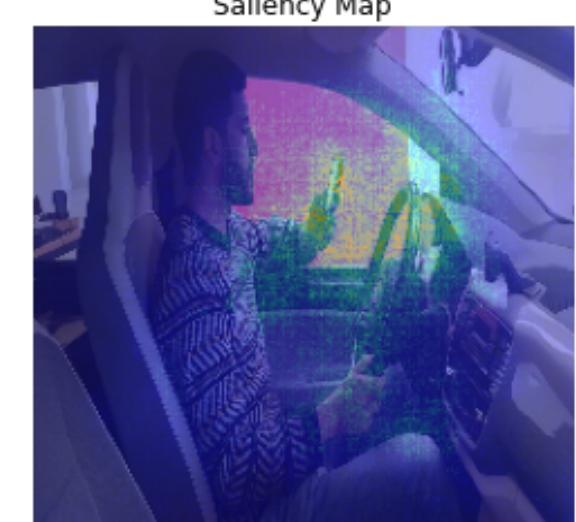
- Both DL models achieved a high accuracy of approximately **98% on the validation set** and **97% on the testing set**, showcasing their outstanding performance.
- In order to gain deeper insights into the models' inner workings, we explored their **black-box** nature by **interpreting model errors**, identifying confusing classes, and utilizing techniques like GRAD-CAM and Saliency Map to **explain predictions**, revealing the decision-making process and providing valuable insights into the models' inference mechanisms.
- To ensure the model's robustness and applicability in real-world scenarios, we incorporated **new images representative of the deployment environment**, allowing us to evaluate the model's **performance under realistic conditions** and validate its effectiveness in practical use cases.



Prediction: Talking on the phone
Confidence: 99.449%



Grad-CAM Original



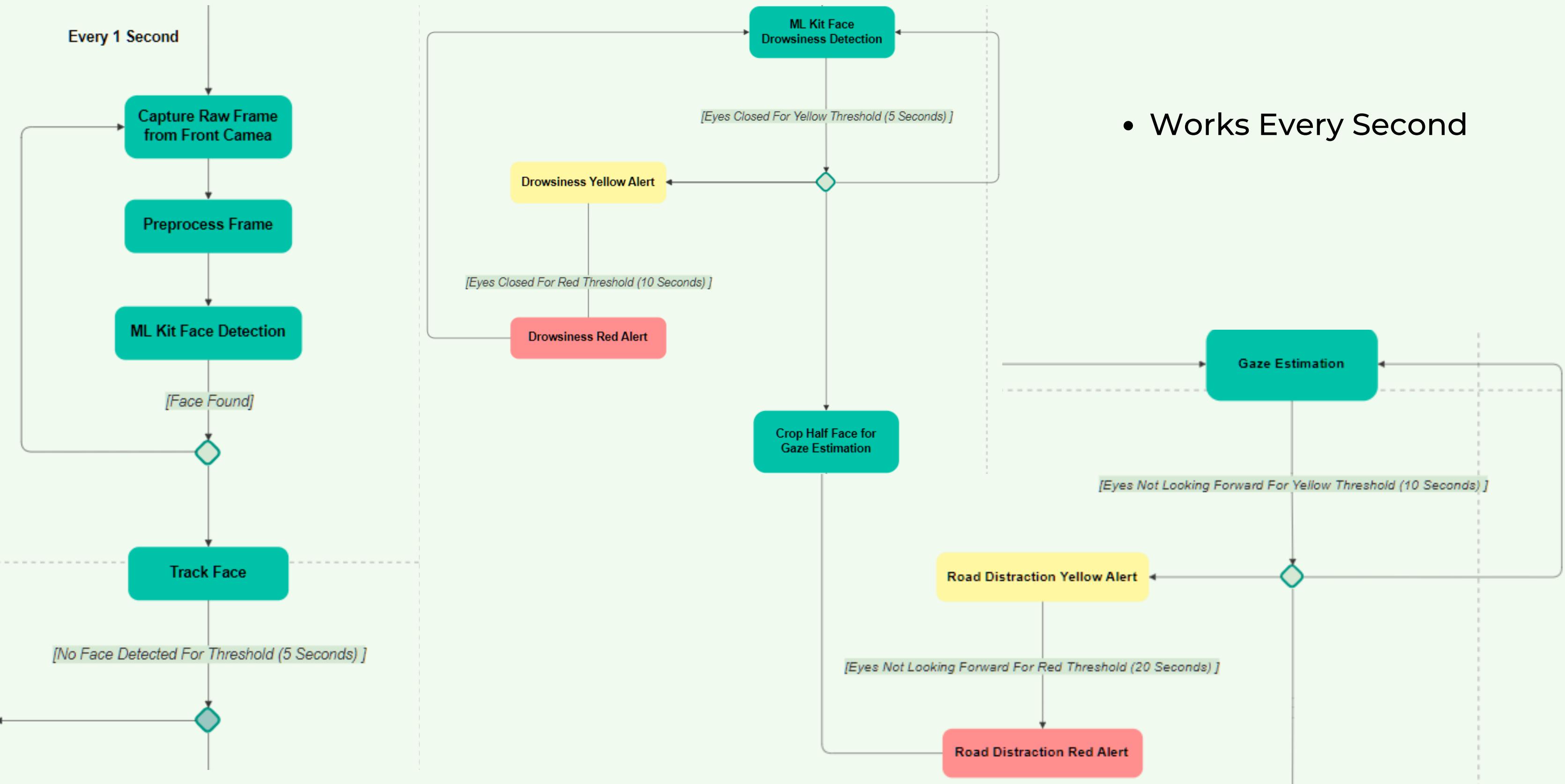
Saliency Map

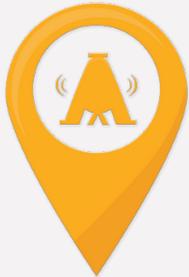




03 - Methodology

Deep Learning Monitoring

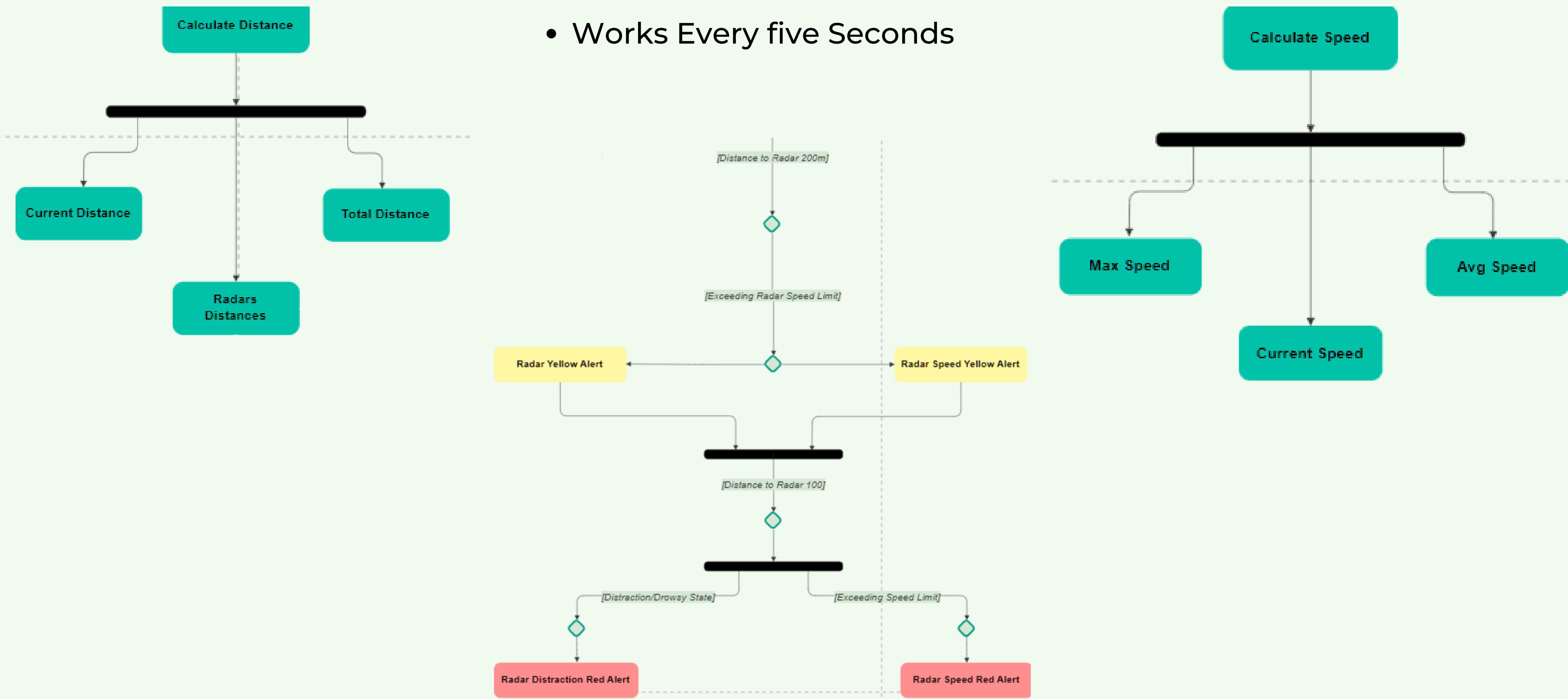


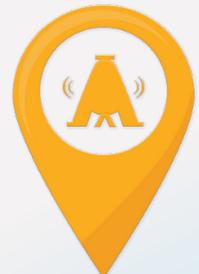


03 - Methodology

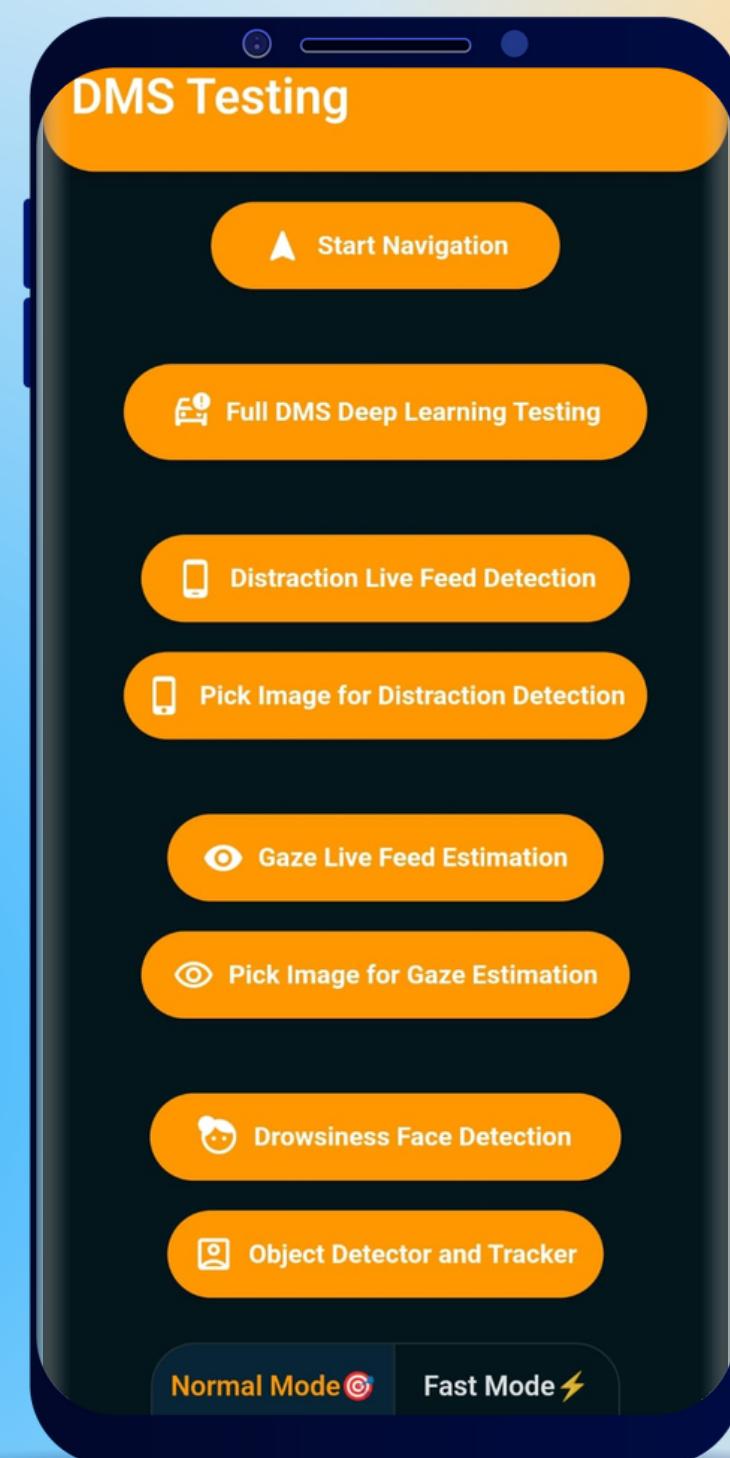
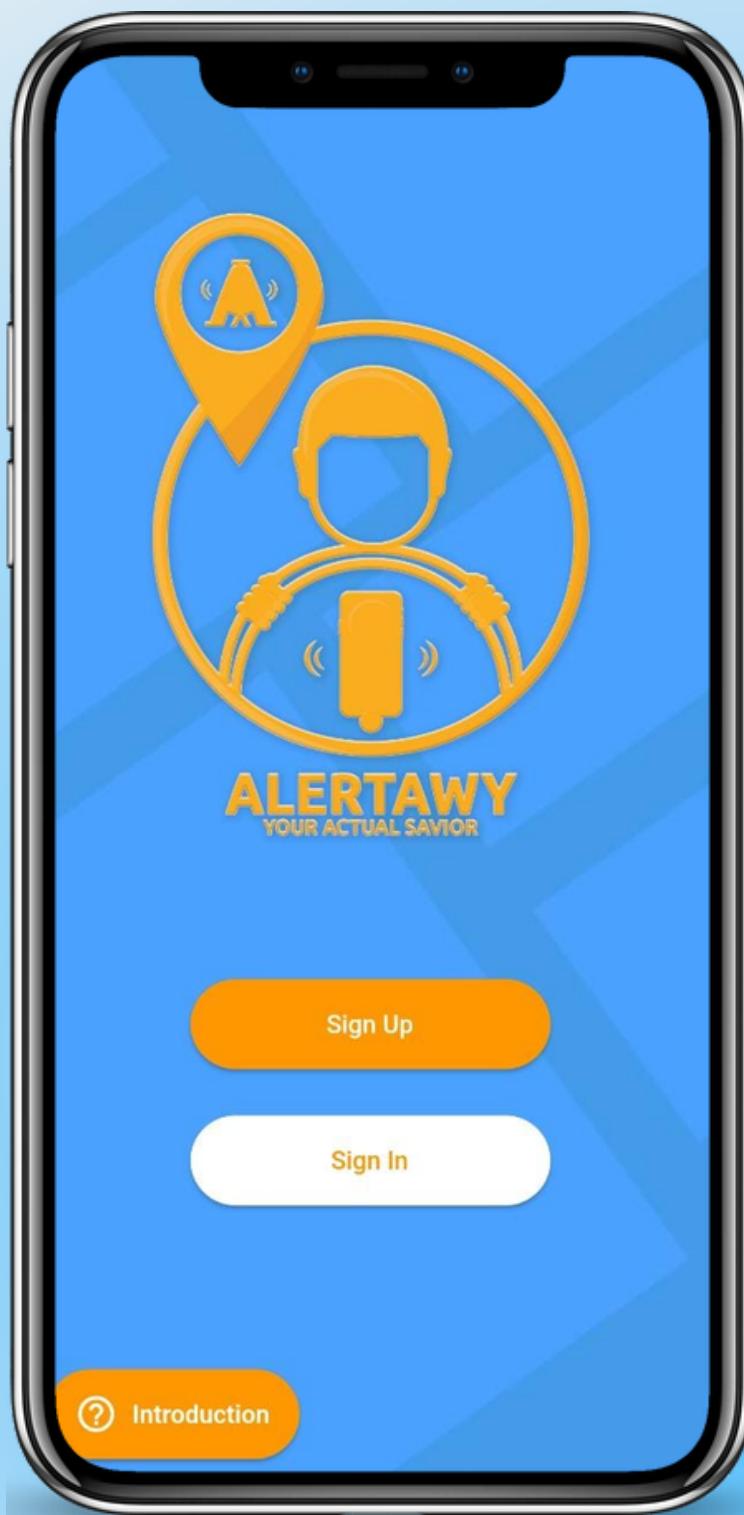
Maps Monitoring

- Works Every five Seconds





05 - Demo



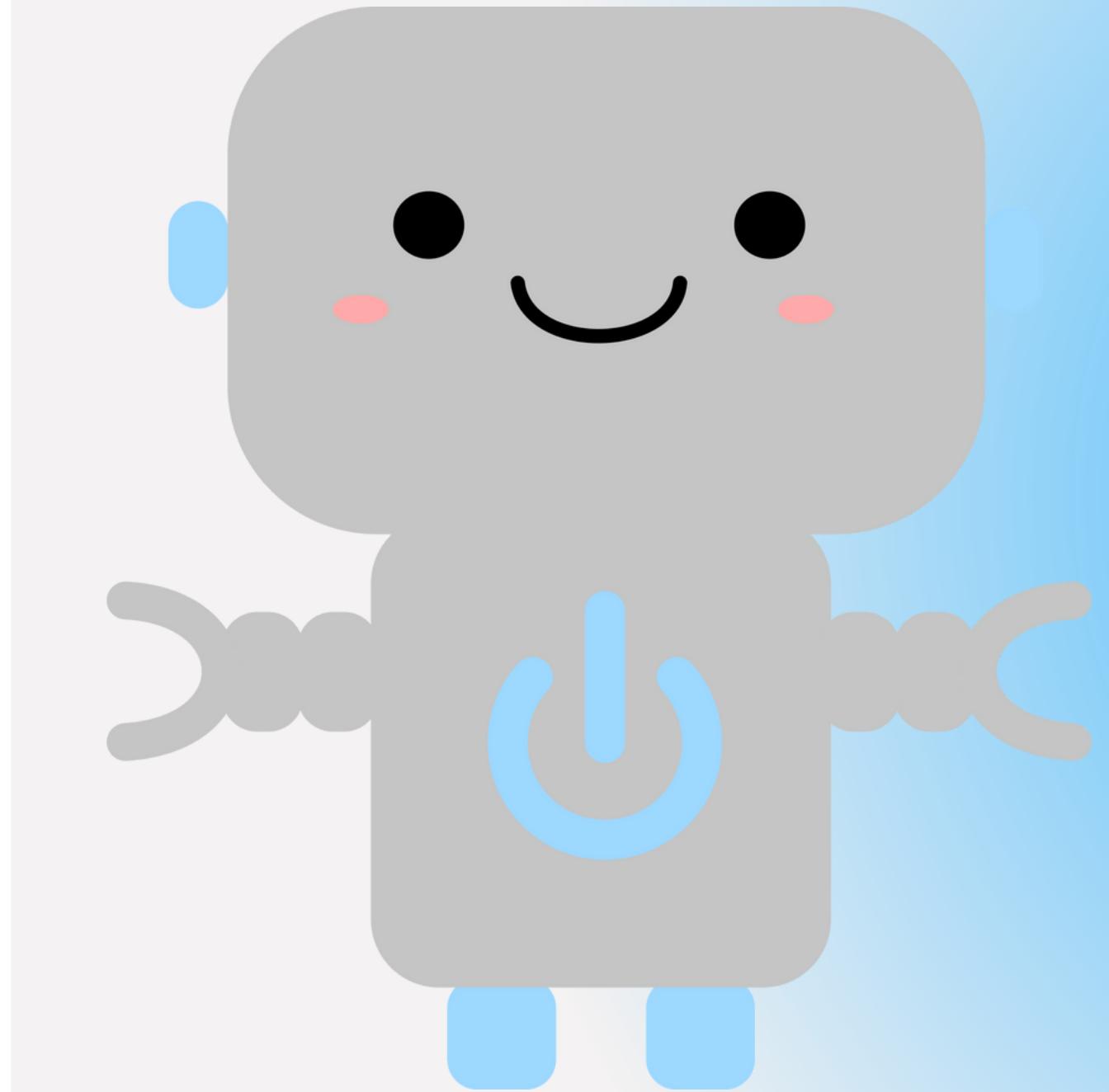


07 - Conclusion

At present, Our driving monitor system, Alertawy, includes features such as:

- Distraction detection.
- Gaze estimation.
- Drowsiness detection.
- Radar alerting.

Through the development of our mobile application, Our goal was to protect drivers, save lives, and reduce road accidents. Focusing on refining these features for improved accuracy and performance while keeping the application updated to meet user needs.





08 - Future Work



Cloud
Firestore

Cloud Services Constraints



if we expect each user to read 10 documents per day, write 5 documents per day, and delete 5 documents per day, then we can have up to 100 users before reaching the free tier limits per day.



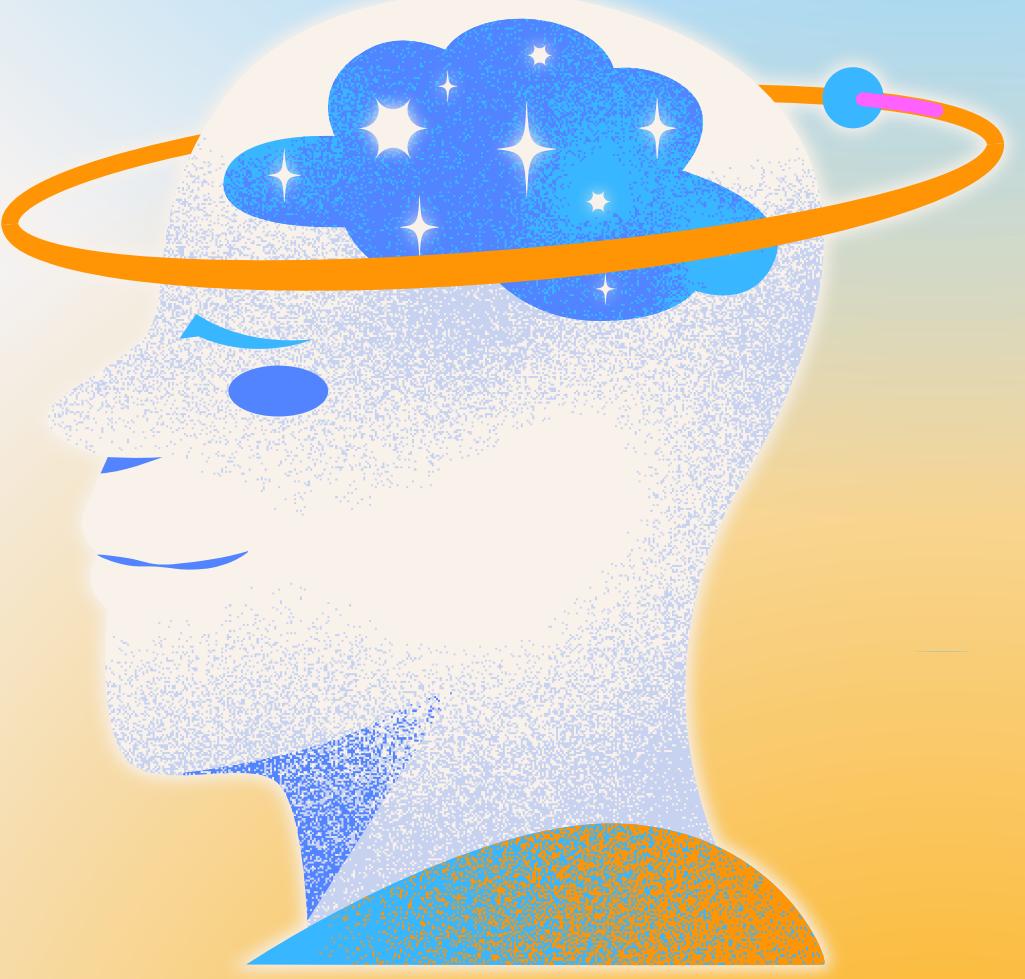
Google Maps Platform

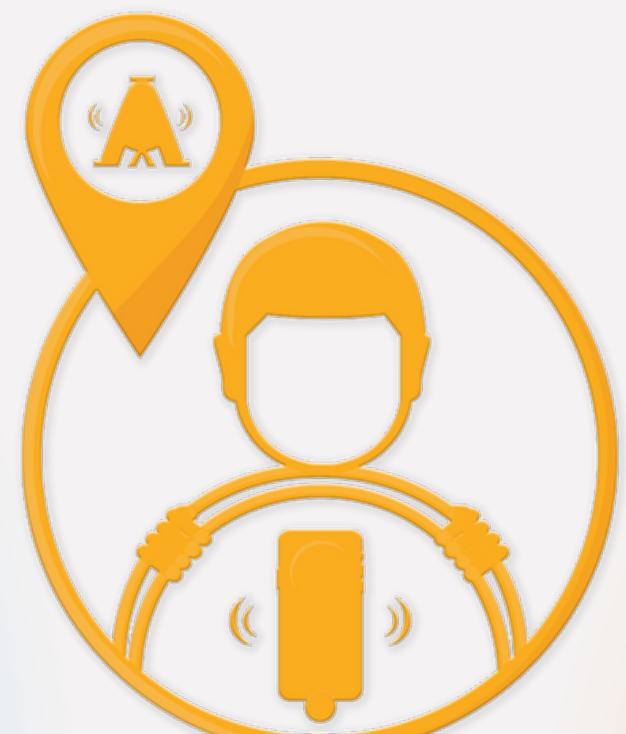
If the Driver uses 10 requests to the Google Maps API with every ride, then we can handle up to 20,000 rides per month on the Maps API free tier.



08 - Future Work

- Improve our deep learning models by retraining them with new datasets.
- Distraction with Object Detection.
- Fatigue Detection Model.
- Seat Belt Detection Model.
- Radar Camera Database.
- Release Beta Version for Testing.
- Web Application Server Hosting.





ALERTAWY
YOUR ACTUAL SAVIOR

Thanks
Questions...