**Technology Landscape Assessment**

Drivers who do not take regular breaks when driving long distances run a high risk of becoming drowsy. Driver drowsiness causes a decrease in cognitive ability and loss of control over the vehicle, increasing the probability of accidents. A report by the World Bank revealed that India accounted for 11 percent of the global death in road accidents and a quarter of serious accidents occur due to sleepy drivers.

A brief overview of the technology landscape of detection of the drowsy drivers is given below.

Control techniques help to prevent accidents or minimize their impact. It can be branched into active and passive systems. These systems help in monitoring the condition of the driver. The effect of the passive systems is visible when accidents occur, and it tends to minimize the impact on the people involved. It is the case with Airbags. The active systems are mainly electronic or electromechanical. They are actively engaged in studying the driver's behavior, the vehicle, and its behavior on the road. These systems are continuously involved in monitoring and giving feedback. Hence, help in preventing accidents.

The methods published in the literature to detect the drowsy driver has been classified into three main categories:

1. Analysis based on driving patterns
2. Analysis based on the change of physiological measurements
3. Analysis based on physical changes of the eyes and facial expressions using image processing

In this study, we have built a model that detects and sets off an alarm if a person is on the verge of falling asleep. There are two major parts to the model: eye detection and eye classification. We have used inbuilt haar cascade functions in OpenCV for eye detection. The region of interest detected in the haar cascade is converted to a grayscale image and resized to 130 x 130. Resizing is essential because the machine learning model takes an input of constant size. We have used a CNN-based model for classification with three conv2D layers, each followed by max-pooling (which imposes the limitation of constant input size). The output (taken from the final layer with two neurons) is a probability distribution over the state of eyes (Open/Closed). We compute loss using sparse categorical cross-entropy and train using an adaptive moment optimizer (ADAM, a variation of gradient descent) to train the model. We have obtained 0.9848 training accuracy, 0.9474 validation accuracy, and 0.9633 testing accuracy.