



# IN CAB DRIVER DISTRACTION DETECTION

Nishanth Chennagiri Keerthi 24212022

Ashish Mohamed Usman 24201306

ACM40960 Projects in Maths Modelling, MSc Data and Computational Science,  
University College Dublin



## Abstract

This project addresses the growing issue of **in-cabin driver distractions** by developing a deep learning-based image classification system to identify **unsafe driving behaviours**. Using a curated subset of the **State Farm Distracted Driver Detection dataset**, we focused on three key classes: **safe driving**, **using phone**, and **drinking**. A baseline Convolutional Neural Network was implemented and enhanced with a **custom CNN model** using dropout regularization and class balancing, achieving over **98% test accuracy** with balanced precision and recall. To extend its applicability, we built a **video-to-image inference pipeline** that flags and annotates distracted behaviour in uploaded driving videos, highlighting the potential of computer vision for improving road safety.

## Motivation

Distracted driving is a leading cause of **road accidents** worldwide, responsible for millions of crashes and preventable deaths each year. Actions like **using a phone**, **drinking**, or adjusting in-car controls reduce driver focus and raise accident risk. The **World Health Organization** reports over **1.19 million** road traffic deaths annually, with distraction as a major factor. In Ireland, the **Road Safety Authority** links **20–30%** of collisions to distraction, causing over **1,400** serious or fatal crashes yearly. Our project addresses this issue by using deep learning and computer vision to analyse in-cabin driving videos, automatically flagging distracted behaviour to help reviewers identify risks and take preventive action.

## Dataset Used

Our project uses the **State Farm Distracted Driver Detection** dataset, focusing on three key safety behaviours: **safe driving**, **using a phone** (merged from multiple phone-related categories), and **drinking**. We worked with about **14,000 images**, splitting them into training, validation, and testing sets, each with metadata for quick access. The classes are imbalanced, with using a phone being the most common and drinking the least, which we kept in mind during model development.



## Video Pipeline & Webpage

Report Unsafe Driving

Driver ID: 24201306  
Upload Video: Choose File | my\_uber\_driver.mp4  
Submit

Flagged Drivers

- 24480028 – bus\_driver.mp4  
Flagged at: 2025-08-06 17:06:04
- 2794307 – dangerous\_driver.avi  
Flagged at: 2025-08-11 16:29:51
- 24201306 – my\_uber\_driver.mp4  
Flagged at: 2025-08-11 17:53:01

Dashboard Flagged Drivers Logout

Flag this driver?  
Yes No

Using Phone [99.9%] From 5.05 To 9.85  
DRINKING From 10.05 To 14.85

## Methodology

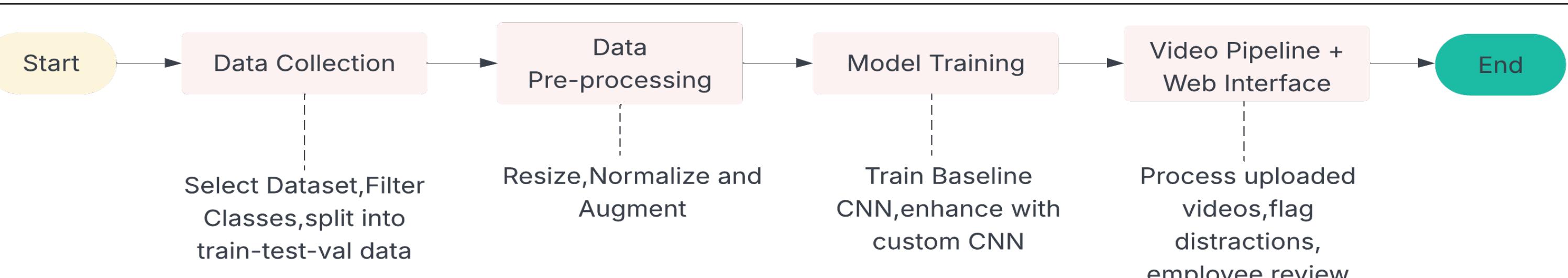
**Data Collection:** Used the State Farm Distracted Driver Detection dataset, focusing on three key classes: safe driving, using phone, and drinking, organised into train, validation, and test sets with metadata (60-20-20 Split).

**Preprocessing:** Resized, normalised, and augmented images to standardise inputs and improve generalisation.

**Model Training:** Developed a baseline CNN and a custom CNN with dropout and class balancing, achieving over 98% test accuracy.

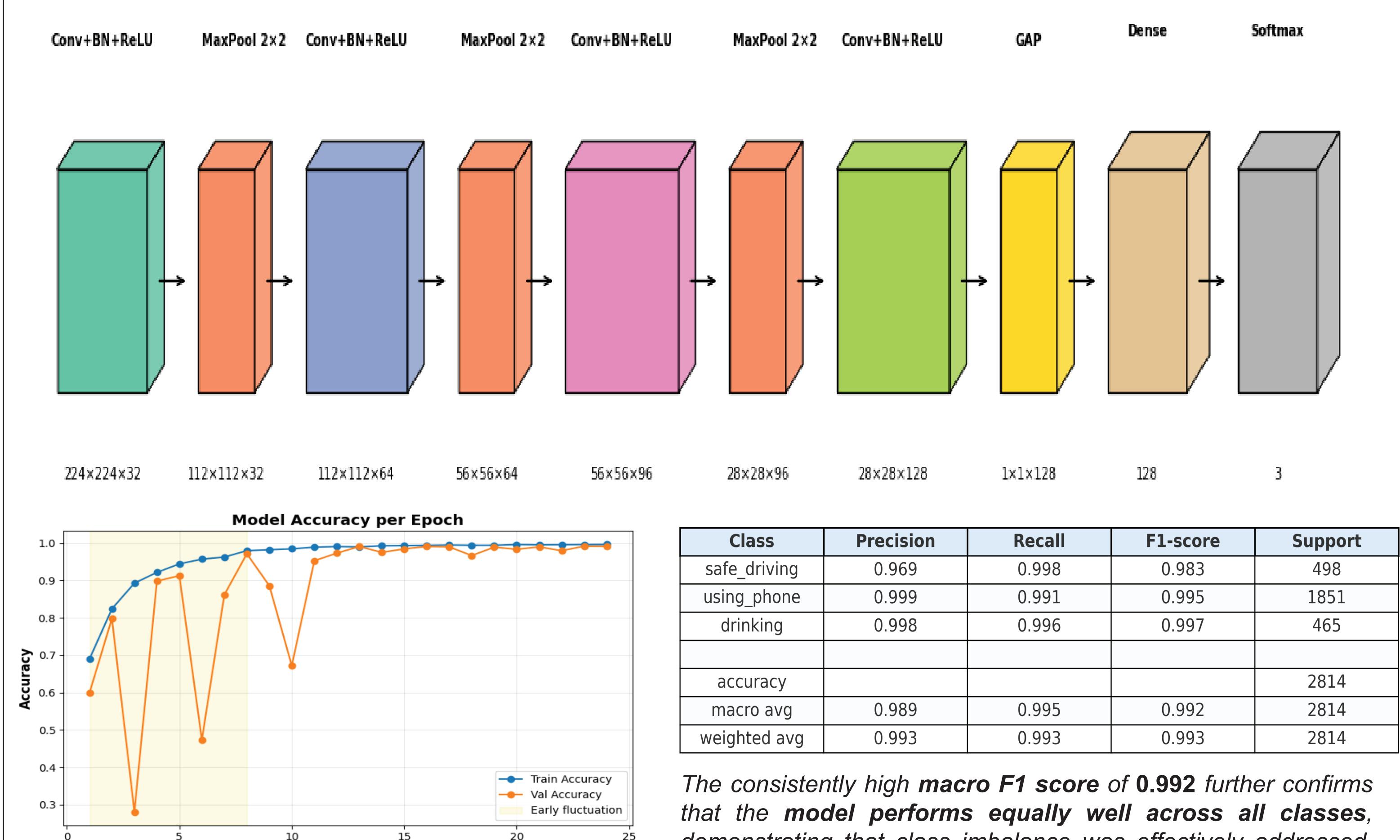
**Video Pipeline:** Extracted frames from uploaded videos, classified them, and flagged potential distractions for review.

**Web Interface:** Allowed public video uploads and provided reviewers with tools to assess flagged frames and record decisions.

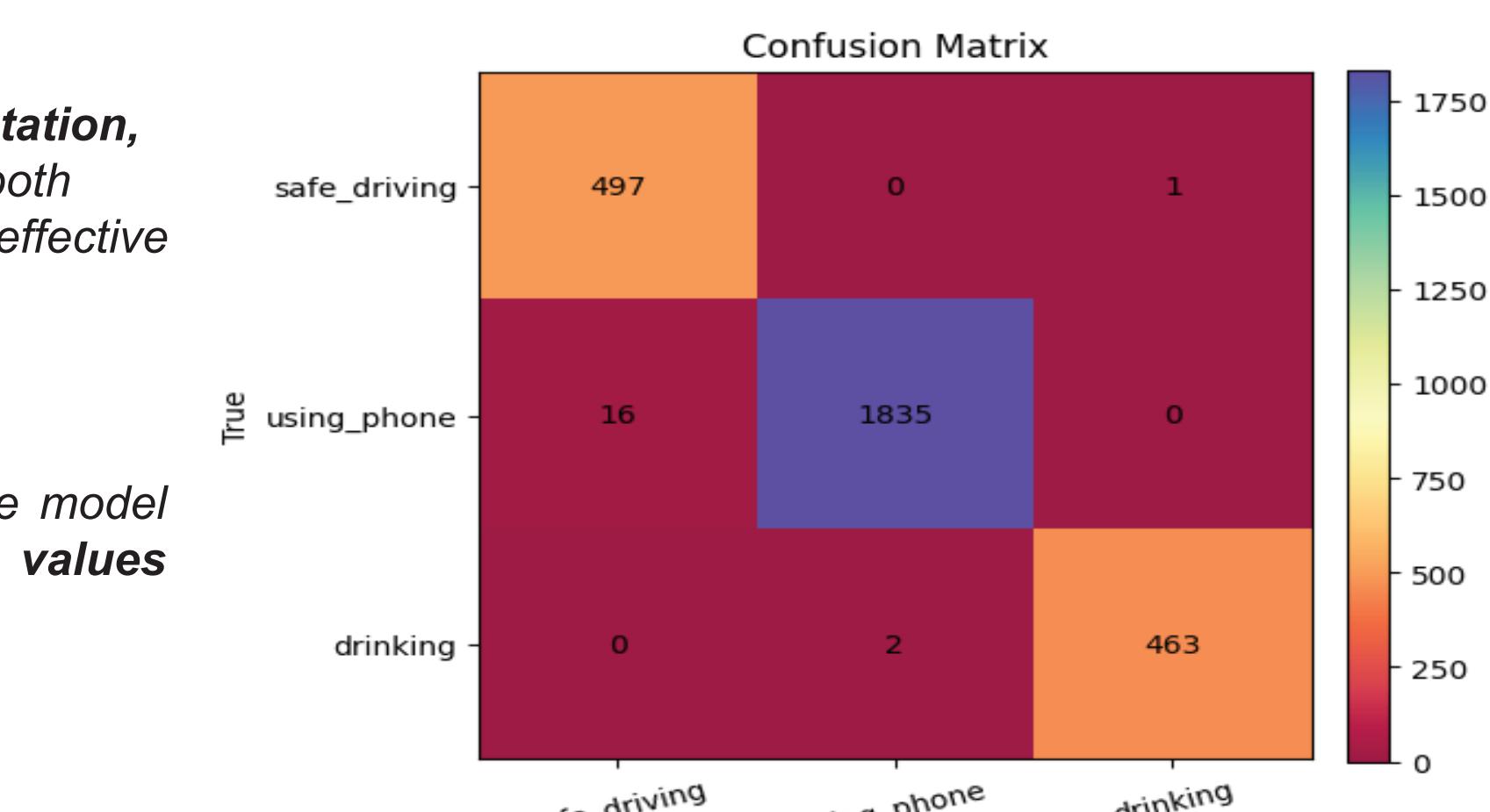


## Model Training

To handle **class imbalance**, we applied targeted augmentation to minority classes and used **class weights** during training, ensuring balanced performance across categories. The **custom CNN** has **four convolutional layers** with **batch normalization** and **ReLU activation**, **max pooling** for downsampling, **global average pooling**, and a dense layer with **regularization** and **dropout**, ending with a **softmax** output for the three driver behaviour classes.



The consistently high **macro F1 score** of **0.992** further confirms that the model performs equally well across all classes, demonstrating that class imbalance was effectively addressed.



The **confusion matrix** on the right shows how well the model distinguishes between classes, with **strong diagonal values** indicating **high accuracy**.



## Future Scope

Enable **real-time detection** within vehicles, allowing drivers to receive **quick alerts** that can help **prevent accidents**.

Combine video analysis with **sensor data** such as **eye-tracking** or **vehicle telemetry** to capture a more complete picture of driver behaviour.

Implement **privacy-focused** continuous learning, allowing the system to **improve over time** without storing or exposing **sensitive** driver footage.

## References:

- Kaggle. (n.d.). State Farm Distracted Driver Detection. Retrieved from <https://www.kaggle.com/competitions/state-farm-distracted-driver-detection>
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770–778. <https://doi.org/10.1109/CVPR.2016.90>
- World Health Organization. (2023). Global status report on road safety. Retrieved from <https://www.who.int/publications/item/9789240066783>

